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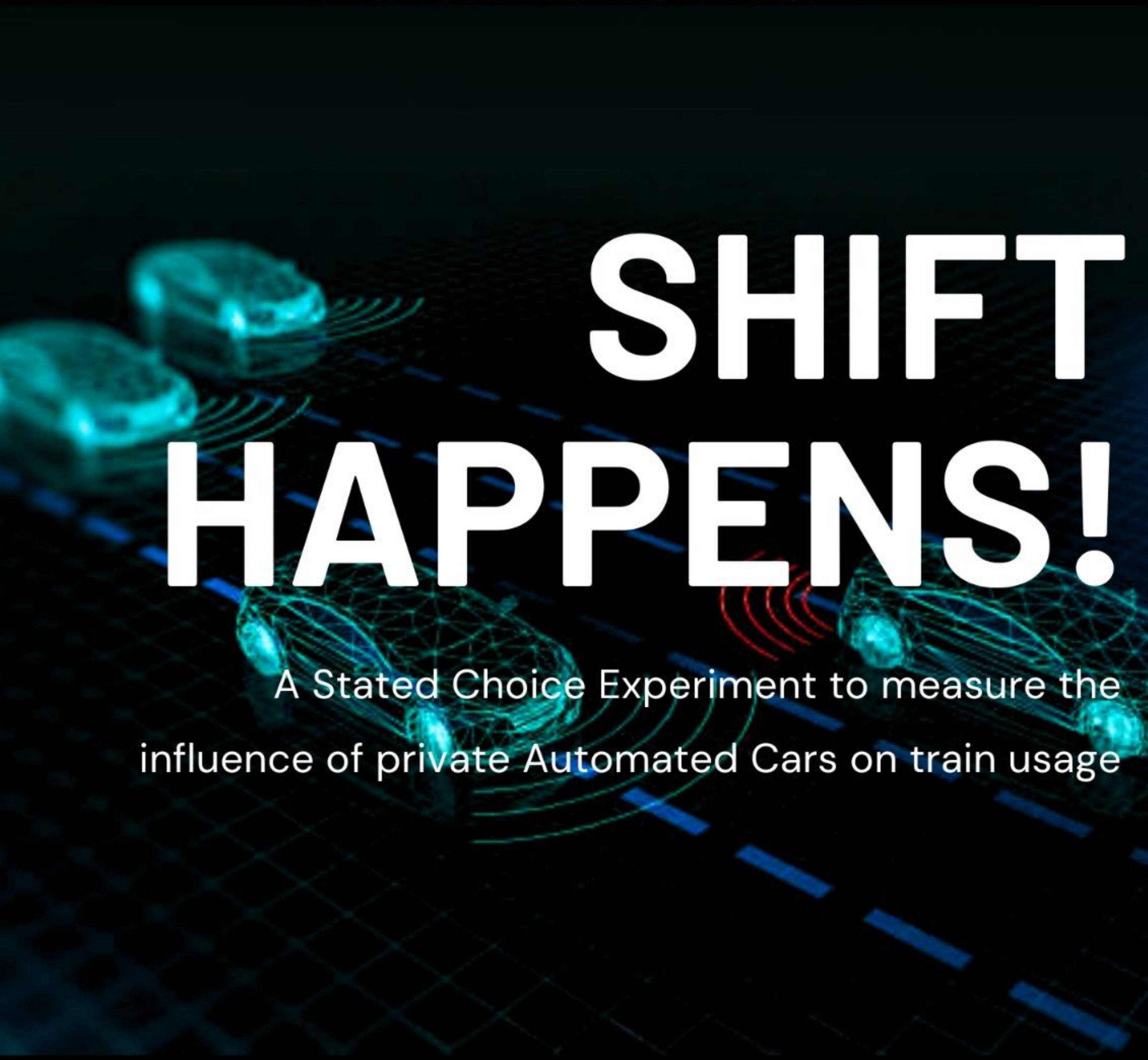

SHIFT HAPPENS!

A Stated Choice Experiment to measure the influence of private Automated Cars on train usage

30 October, 2023
TU Delft

Goudappel
MOBILITEIT BEWEEGT ONS

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Master thesis submitted to Technical University of Delft for

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By:

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Foreword

Before boarding on my thesis journey, I knew I wanted to delve into the domain of Smart Mobility – a term I now realize is quite broad. At the start, I could not imagine how I would find my topic or conduct my research. Yet, as I am reflecting upon this report, I can confidentially say that I am pleased with what I am presenting to you. Writing this thesis has been both an enjoyable and demanding process, requiring countless hours and substantial effort to conclude my Msc Complex Systems Engineering and Management. I did not go through this journey alone, and therefore I would like to express my gratitude to several individuals.

First, I would like to extend my appreciation to my committee, without whom this thesis would not have been possible I want to thank professor Dr. Bert van Wee, the chair of my committee, for his invaluable feedback and unwavering encouragement during the feedback sessions. I would like to thank Dr. Jan-Anne Annema, my first supervisor, for dedicating his time to review my papers and to guide me in the right direction when necessary. His candid and direct approach to providing feedback has been of great value to me. Additionally, I would like to thank Dr. Mark de Bruiijne, my second supervisor, for his extensive feedback, even though this was not entirely his area of expertise. Without him, my committee would have not been complete.

I wish to express my special gratitude towards Ir. Arthur Scheltes, my supervisor at Goudappel, for his solid support throughout my whole thesis. He consistently took the time to thoroughly review my papers and offer detailed feedback. He guided me into the, for me, unfamiliar research area. His enthusiasm and readiness are truly appreciated. I would also like to thank Dr. Mariska van Essen, a colleague from Goudappel, for her assistance in modelling my Stated Choice Experiment, a task that proved to be more challenging than I had initially anticipated.

I would like to express my gratitude to all the respondents who participated in my survey, as well as my Goudappel colleagues who generously offered their time and input during brainstorming sessions. Lastly, I want to express my deepest gratitude to my friends and family for their support throughout my thesis and my entire journey at TU Delft.

As I reflect on the intensive process of completing my thesis, I do so with a sense of fulfilment and optimism for the future.

Lola Lydia Geertruida van Zeijl
Delft, Oktober 2023

Summary

The development of automated cars has the potential to reduce global CO_2 emissions by enabling cars to drive closer to their predecessor, maintaining consistent speeds, and therefore requiring less energy. However, counter-research suggests that the use of automated cars may actually increase CO_2 emissions due to higher speeds and increased congestion on highways. This latter issue is particularly relevant in the densely populated Netherlands, where highway capacity is an issue which leads to frequent traffic jams. It is projected that congestion may double within a few years compared to 2018, potentially resulting in a gridlocked network in the future.

When former regular car users shift to automated cars, there is a modal shift within the road sector. Conversely, when former train users shift to automated cars, there is a modal shift from the rail sector to the road sector. This shift results in increased car density on highways, hence worsening the congestion issue. Train passengers have chosen train travel over car travel. However, automated cars differ from regular cars in three key aspects of the user experience; safety, motion sickness, and comfort. Automated cars offer a unique comfort feature, namely the ability to engage in other activities that regular cars do not permit. Additionally, people express more significant concerns towards the safety of automated cars compared to regular cars, and individuals are more likely to experience motion sickness when riding in an automated car as opposed to driving a regular car. This thesis aims to investigate how these differentiating factors influence the decision of train passengers for choosing automated cars. Therefore, the main research question addressed in this thesis is:

"To what extent do the factors of comfort, safety and motion sickness influence the decision among train passengers in selecting automated cars as their transportation mode?"

This thesis focuses on the Rotterdam-Amsterdam route, one of the most popular routes in the Netherlands, which exemplifies the congestion issue. Furthermore, there exist numerous definitions of automated cars. In this thesis, the automated car definition that formed the scope is semi-fully automated cars, which require off-highway control over the steering wheel, and the automated system can be activated on the highway. This automated car scenario is chosen due to its short-term feasibility.

As discussed in the methodology chapter, a Stated Choice Experiment is selected to examine this research topic, given that this research topic includes a not-yet-implemented technology. A Stated Choice Experiment is a methodology used to measure individual's preferences in specific scenarios. In this experiment, participants are presented with scenarios comparing the characteristics of a trip by train and by automated car. These characteristics and their interrelationships are identified through literature research and visualized in a conceptual model. In this literature analysis, the factors that influence the choice between train and regular car transport were identified. The identification of these factors provides insight into the choices people make when choosing between train and car transportation. These decision factors form the attributes and the data from the Rotterdam-Amsterdam form the attribute levels. Attributes are characteristics of a transportation mode, such as the trip costs, attribute levels are the different degrees of those characteristics, such as €16.25 for a trip with the car and €17.50 for a trip with the train.

To identify the factors that influence a choice for an automated car, the factors that influence a choice for regular car are first identified. These are the factors resulting from the literature review and encompass attributes such as costs and travel time. To measure the pure effect of the factors influencing the choice for an automated car, the attributes from the literature review are fixed in the Stated Choice scenarios. This means that these attributes do not have variating levels. As this thesis examined whether automated cars cause a shift, the key user experience factors of safety, motion sickness, and comfort are the factors that vary within the Stated Choice scenarios. The fixation of the attribute levels allows for the isolation and measurement of the pure impact of the three key factors.

After determining the attribute level values based on the corridor data, the Stated Choice scenarios underwent validation by expert M. van Essen. Subsequently, a clarification video was created to present to respondents before starting the survey, to ensure that all participants had a uniform understanding of automated cars and how to activate the automated system, in order to enhance the survey's robustness. The concept survey design and clarification video were then tested with a diverse group of potential respondents, encompassing individuals both knowledgeable about automated cars and those lacking that knowledge. This allowed for an assessment of both accuracy and clarity. The concept survey was finalized based on this test session and distributed through online platforms and physically at train stations.

The collected data was analysed using a Multinomial Logit model to determine the weights of the factors. Initially, all variables were included in the model. After eliminating non-significant and irrelevant variables through five iterative rounds of refinements, according to the existing literature, the final model was established. The results from the model showed that the factor comfort had the most significant impact on train passengers' modal choice, followed by the factors safety and motion sickness. Notably, the distance to the train station indirectly has the biggest influence on the modal choice, due to the multiple attribute levels of distance compared to the binary attribute levels 'on' (1) or 'off' (0) of the three key factors.

However, the impact, as represented by beta coefficients, does not necessarily mean that this also applies to the actual probability of a shift in modal choice. The beta coefficients in this study are numbers that indicate how much impact a factor has on the decision of an individual. If a factor indicates a high likelihood of shifting in a specific group, but this group is relatively small in reality, the actual impact and shift will also be minimal. Hence, the results obtained from the Multinomial Logit model are cross-referenced with real-time data to measure the actual shift and impact. This comparison is referred to as a 'what-if' scenario and is conducted with three variables of which concrete data of the route is available. A what-if scenario is a situation in which it is considered what could happen in a certain situation. These scenarios are based on three variables; the distance to a train station, the degree of motion sickness, and the class of travel.

In the first what-if scenario, the population was divided into five groups based on their proximity to a train station, ranging from living close to a train station to living far away from it. Notably, the results revealed that train passengers have a high probability of shifting to automated cars when the comfort level of automated cars exceeds that of trains. However, this high probability to shift is only the case for train passengers living more than 10 kilometres from a station. In both Rotterdam and Amsterdam, no postal code area has a proximity to a train station beyond a 10-kilometre radius. This shows that the beta coefficient, the probability of a shift, cannot be directly applied to real-world situations. Nevertheless, by considering the probability of a shift for each population group with specific attribute levels. the actual probability to shift is determined. Similar results were obtained from the other two 'what-if' scenarios, indicating that in the scenario where the comfort level of an automated car surpasses that of a train, there is a probability that more than half of the train passengers considers to shift. While this is a one-time study, and actual impact figures may vary, it does point to a substantial potential shift.

The study's results reveal that comfort is the most influential factor, even after comparing the results with existing literature. This can be explained by the fact that comfort is a satisfier, while safety and motion sickness are dissatisfiers in the NS customer requirements pyramid. Dissatisfaction represents a 'need', which is a prerequisite for choosing a transportation mode. In contrast, satisfiers are 'wishes'. When safety and motion sickness are neutralized, comfort becomes the satisfier and the decisive factor in choosing a transportation mode. This explains why the factor comfort holds the highest level of influence.

Yet, if such a major shift of train passengers towards automated cars were indeed to take place, it would have negative consequences for both the public transport sector, and the congestion issue on the Dutch highways. NS is still dealing with financial losses due to COVID-19, highlighting the significant impact the reduction of train passengers can have. Additionally, the shift of these passengers to the road sector would result in worsening the current congestion issue in the Netherlands, longer travel times, increased stress for passengers, and a higher likelihood of accidents.

This study fills a significant research gap as it investigates the impact of automated cars on train usage, particularly considering factors that in what an automated cars differs from a regular car: safety, motion sickness, and comfort. Nevertheless, it's worth noting that this study relies on a Stated Choice Experiment, where respondents are asked about hypothetical scenarios. To mitigate hypothetical bias, future research could involve allowing respondents to experience driving automated cars. Moreover, this research has only explored private and semi-fully automated cars, which limits the generalizability of the findings to shared or fully automated cars. Thus, these latter two topics serve as recommendations for future research, which could delve deeper into the influence of automated cars on train usage.

List of abbreviations

-2LL = -2 Log-Likelihood
AC = Automated Car
ACC = Adaptive Cruise Control
AEB = Automatic Emergency Braking
BSD = Blind Spot Detection
CBS = Central Bureau of Statistics
DCE = Discrete Choice Experiment
DCM = Discrete Choice Modelling
FAP = Fully Automated and Private
FSD = Full Self-Driving system
HOH = Hands Off on Highway
ICNG = Intercity New Generation
KiM = Knowledge Institute for Mobility policy
LKA = Lane Keeping Assist
MaaS = Mobility as a Service
MaSA = Multimodal and Shared Automation
MNL = Multinomial Logit model
MS = Motion Sickness
MSE = Motion Sickness Experience
NS = Nederlandse Spoorwegen
NVP = National Movement Panel
PA = Parking Assistance
PRISMA = Preferred Reporting Items for Systematic Reviews
R2 = McFadden R-squared
SAC = Shared Automated Car
SAE = Society of Automotive Engineers
SCE = Stated Choice Modelling
SPSS = Statistical Package for Social Sciences
TJA = Traffic Jam Assistance

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1. Introduction

The concept of automated cars (hereafter; AC) has been a topic of discussion for numerous years. However, the potential of ACs to mitigate traffic congestion and decrease CO_2 emissions from road transport remains uncertain.

The Dutch government has made commitments to reduce climate change through a coalition agreement. This agreement states that the Netherlands aims for a 55% CO_2 emission reduction by 2030. To achieve this goal, a climate and transition fund of €35 billion will be made available for the next 10 years (Waterstaat, 2013). Not only the Netherlands but also countries with significant economies such as China and the United States, have set targets to address climate change. This commitment stems from the fact that almost all countries in the world have signed the Paris Agreement, an international climate treaty focused on reducing global warming (Waterstaat, 2013).

The Paris Agreement encourages the development of technologies to lower CO_2 emissions, as investing in new technologies is often easier than focusing solely on consumption reduction (Nidumolu et al., 2013). One of these technological developments is ACs. According to Harb et al. (2021), the automated vehicle industry is undergoing unprecedented technological change. The industry is expected to be worth €7 trillion by 2050. Major companies are currently active in building ACs such as Tesla, Uber, Ford, General Motors and Waymo. Automated vehicles are gaining popularity because they provide the convenience of personal transportation but with the multitasking and relaxing benefits of public transport (Harb et al., 2021). The development of the AC has not been a gradual process, which already emerged in the 1980s and 1990s (Newcomb, 2015). Since then, technologies have been introduced into the car step by step. However, complex traffic situations and the unpredictable factor of human behaviour still make it challenging to have fully self-driving cars on the roads (B. Brown et al., 2018).

In theory, ACs have the potential to reduce CO_2 emissions. They maintain more consistent speeds due to AI algorithms, whereas human drivers change their speed more often by braking and accelerating (Banu, 2023). This could result in a 15% reduction in individual energy consumption. Furthermore, ACs can drive closer to their predecessor, reducing wind resistance. This could lead to an additional 10% energy reduction per car. Additionally, by optimizing traffic flow, ACs could contribute to a 30% reduction in traffic congestion (Silva et al., 2022).

However, in reality, there are often overlooked consequences. According to Massar et al. (2021), ACs can make travel easier and faster, resulting in increased highway congestion, and therefore in a 41.24% rise in CO_2 emissions, surpassing the intended reduction of 30% (Massar et al., 2021). In addition, Fagnant and Kockelman (2015) expect a 13% speed increase due to improved traffic flow outside rush hour, resulting from the introduction of ACs on the highway (Fagnant & Kockelman, 2015). However, given that there will not be a 100% adoption rate for automated vehicles, with many regular and electric cars remaining on the roads, this speed increase could lead to higher energy consumption (Wu et al., 2018).

In essence, whether the implementation of ACs will effectively reduce CO_2 emissions remains uncertain. To determine this, it is important to consider the origin of AC users. If former fuel-based car users shift to ACs, it is expected that the shift will have a positive effect on CO_2 emissions (Ercan et al., 2022). However, if former train passengers shift to ACs, it will result in a negative effect on CO_2 emissions due to the sustainable nature of rail transport and the shift in transportation sector (Ercan et al., 2022).

A shift from train usage to ACs is not desirable for several reasons. Firstly, if a shift occurs, there is a risk of not only failing to mitigate CO_2 emissions but also potentially increasing the emissions. Trains are the most sustainable transportation modes, besides active modes. In the Netherlands, 11% of the total greenhouse gas emissions come from the transport sector, with road transport accounting for 28%, and train use for only 3% (CBS, 2022d). Namely due to the fact that Dutch trains operate on 100% green electricity. Train emissions are not reduced to zero due to the fact that the production of green energy has also been taken into account when calculating emissions (Kloosterman et al., 2021) (IEA, 2022).

Secondly, a shift to ACs could result in a significant increase in the car concentration on highways, potentially leading to higher CO_2 emissions. A similar trend occurred with the introduction of electric cars (Rizet et al., 2016). While electric cars have a higher purchase price, their operational costs are relatively low due to the minimal taxes imposed on them (Boerop, 2018). Consequently, as the number of charging stations is rising fast with an average increase of 38% per year, the use of electric vehicles is increasing even more, which, in turn, increases road congestion (CBS, 2022).

Currently, Dutch highways face capacity limitations, and it is estimated that traffic congestion in the Netherlands will double within a few years compared to 2018 (Mistele, 2015; Klein & Kersten, 2022). Consequently, even outside peak hours, minor disturbances can escalate into major traffic jams. Unless investments are made in infrastructure, the Dutch highway network is at risk of becoming completely gridlocked in the future. In addition to the rise in passenger car usage, the transportation of goods on Dutch highways is expected to increase by 5% annually at low economic growth, and by 27% at high economic growth, worsening the congestion issue (Post, 2022; van Nieuwenhuizen Wijbenga & van Veldhoven – Van der Meer, 2021).

One significant factor contributing to the traffic congestion issue in the Netherlands is the high single-occupancy rate, where the only occupant in the car is the driver (Park, 2007). The Netherlands has the lowest average number of passengers per car in Europe, with an average of only 1.38 individuals per vehicle (European Environment Agency, 2021). The Netherlands is a densely populated country with limited available space. These geographical constraints make it challenging to construct new roads or widen existing ones in order to solve the traffic congestion issue (Bull et al., 2003; Rongen et al., 2022).

Numerous studies have been conducted on how different characteristics of transportation modes influence travellers' transportation mode choices, considering factors such as time and costs (Hamadneh et al., 2022). Train passengers chose the train over the car after considering these factors of both transportation modes. However, there are significant differences between regular cars and ACs, not only in terms of technology but also in user experience. This raises the question of whether these differences might trigger train passengers to shift to using ACs.

One advantage of train travel is the comfort it offers (Huang & Shuai, 2018). Research conducted by Huang and Shuai (2018) indicates that train comfort encompasses multiple aspects. Trains offer comfortable seating, ventilation and temperature control, and, importantly, the ability for passengers to engage in other activities such as working and sleeping, which travellers find most valuable (Horjus et al., 2022; Huang & Shuai, 2018; Lehtonen et al., 2022). This latter aspect of comfort sets ACs apart from regular car travel. This is attributed to the fact that these activities cannot be performed in a regular car, but can in ACs. Besides comfort, according to R. Happee in an expert interview, there are two other important factors in which an AC differentiates itself from the regular car, and influences user experience: motion sickness and safety. The summary and highlights of the expert interview with R. Happee are attached in Appendix A (Happee, 2023).

Safety is of greater concern when choosing an AC than a regular car, because people express apprehension about the safety of automated cars systems in ACs, while this factor is nearly negligible when selecting a regular car (Greaves & Ellison, 2011; Kyriakidis et al., 2015; Othman, 2021; Rezaei & Caulfield, 2020; Schoettle & Sivak, 2014). Although car accidents are considerably more frequent than train accidents, this does not deter people from predominantly choosing regular cars over trains (CBS, 2021). However, the introduction of ACs has suddenly raised safety concerns, which does impact the choice of ACs (Kaye et al., 2020). Therefore, safety is a differentiating factor between ACs and regular cars, in addition to comfort.

Regarding motion sickness, passengers in ACs are more prone to experiencing it compared to those in regular cars. The occupants' brains struggle to process the movements in ACs when they are not the ones driving (Bertolini & Straumann, 2016). Therefore, occupants in ACs experience motion sickness to being a co-driver in a regular car (Schmidt et al., 2020). This means that that AC occupants are more prone to motion sickness than drivers of regular cars (Diels & Bos, 2016). Hence, motion sickness is the third differentiating factor between ACs and regular cars, besides comfort and safety.

Consequently, it can be concluded that comfort, motion sickness and safety are three factors in which the AC distinguishes itself from the regular car, an assertion that is supported by literature (Bin Karjanto et al., 2017; Karjanto et al., 2018; Keshavarz & Golding, 2022; Nordhoff et al., 2021; Yoon et al., 2019).

Despite the confirmation in the literature that these three factors differentiate the AC from the regular car, no previous study has yet research the effects of ACs on train usage. Additionally, no study has examined the dynamics of these three crucial factors – safety, motion sickness and comfort – in the context of train passengers' mode choice. Given the influence these three factors can have on the transportation mode choices, and the knowledge gap in the existing literature, this study's primary focus lies in investigating these factors. Consequently, the primary objective of this study is to examine and quantify the impact of these three factors on train usage.

1.1 Research question

A shift from train use to the use of ACs is not desirable due to the existing capacity issues within the Dutch highway network. In order to mitigate this shift, the impact of ACs needs to be identified. Given that ACs distinct themselves in the domains of safety, motion sickness and comfort, it is pivotal to measure the impact of these three factors on train passengers' transportation mode choice. Hence, the main research question that will be assessed in this study is as follows:

> *" To what extent do the factors safety, motion sickness, and comfort, influence the decision among train passengers in selecting automated cars as their transportation mode?"*

A set of sub-research questions is developed to help answering the main research question:

1. *What factors influence individuals' to decide on utilizing trains or cars?*
2. *What are the weights assigned to the three factors as determined through a Stated Choice Experiment?*
3. *What is the real-world applicability of the Stated Choice Experiment results when exposed to hypothetical what-if scenarios?*

1.2 CoSEM related

To analyse the impact of a new technology on a modal shift, various stakeholders are involved. These stakeholders each have their own interests and are engaged in interactions, resulting in complexity. A transportation system is a large physical system with many uncertainties. When a modal shift occurs, it necessitates extensive coordination and cooperation. All of these elements contribute to the complexity of this socio-technical system. From a design thinking perspective, it is essential to evaluate the impact of ACs and to lay a solid foundation for policy interventions. Lastly, the research topic aligns with the CoSEM track Transport and Logistics, as it explores the concept of mobility transition.

1.3 Thesis outline

This section outlines the structure and framework of the thesis. Chapter 1 introduces the overarching social challenges and delineates the research gap that this study addresses. Chapter 2 provides the methodology, explaining the reasoning behind its selection and detailing the approach taken in this study. Chapter 3 provides an in-depth literature review, followed by the exploration of the conceptual model. Chapter 4 delineates the attributes, specified the levels at which these attributes are assessed, and outlines the design of the survey for data collection. Chapter 5 represents the empirical findings derived from the survey, interpreting the model specification of these results. Chapter 6 describes the hypothetical scenarios to link the model specification to real-world data and exploring the potential outcomes in the varying key factors as AC scenarios. Chapter 7 describes the conclusion of this study, an extensive discussion of the findings, and a series of recommendations. The study's research outline is illustrated in Figure 1.

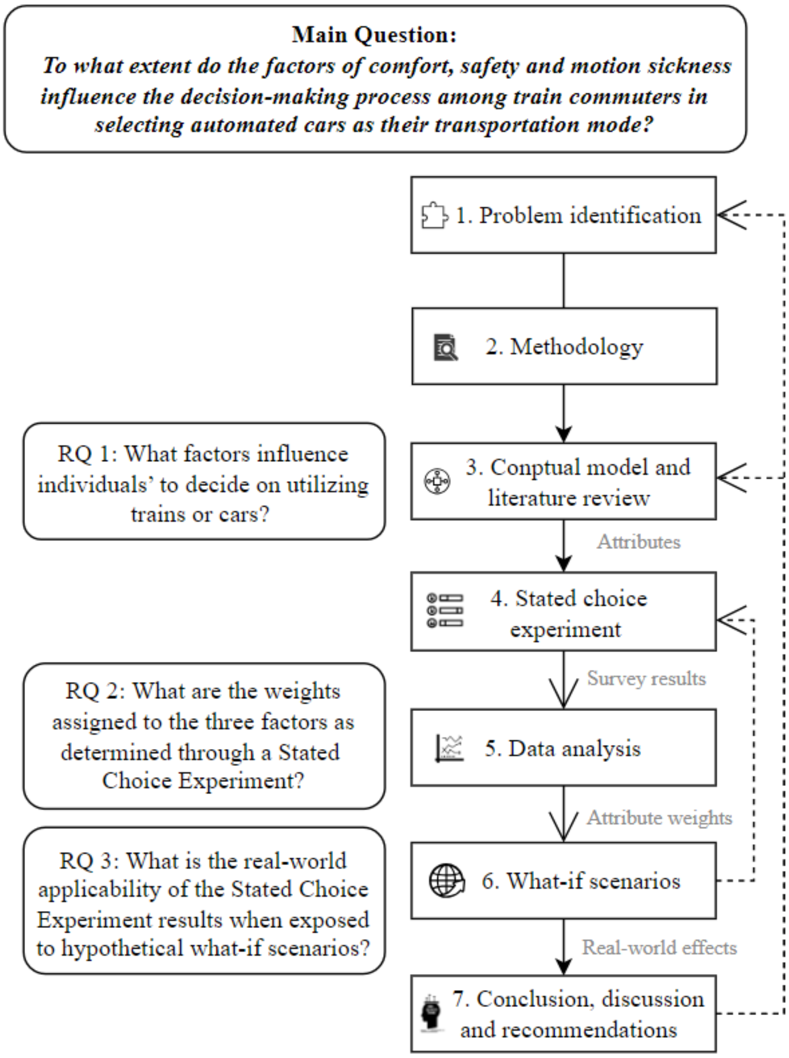


Figure 1 - Thesis outline

2 Methodology

This chapter provides an overview of the methodologies employed in this study. This chapter begins with the research approach that is used to answer the main question in Section 2.1. This is followed by an introduction to discrete choice modelling and selecting the choice experiment in Section 2.2. Subsequently, the chapter delves into the conceptualisation of the Stated Choice Experiment in Section 2.3. Next, the process of creating the survey design and collecting the data is explained in Section 2.4, followed by the description of the data analysis method that will be used in this study in Section 2.5. Lastly, the model specification and the discussion on which methodology is used will be described in Section 2.6. Additionally, this method differs from the traditional form, which is described in Section 2.7, ending with a conclusion in Section 2.8.

2.1 Research Approach

The main research question concerns a hypothesis, specifically, whether the three key factors are independent variables that each influence travellers' transportation mode decisions. Because this study investigates a hypothesis it falls under the theory-testing research, rather than exploratory research (Acton et al., 1991; Anderson et al., 2019). Exploratory research focuses on investigating a topic with little existing knowledge, in order to generate a hypothesis (Chuang et al., 2009; De Haes & Van Grembergen, 2009). While the concept of ACs is still relatively unfamiliar, and its impact remains uncertain as indicated in Chapter 1, there is sufficient knowledge to formulate the hypothetical research question. Moreover, this research question fits within the modal shift domain, in which choice hypotheses are assessed using quantitative data (Tsamboulas et al., 2007).

2.1.1 Modelling Method Selection

The research question involves independent variables that are quantifiable to determine their degree of influence. Since this study concerns a decision for a transportation mode, choice behaviour is measured (Bohte et al., 2009). This can be achieved through various choice models. Discrete Choice Modelling (hereafter; DCM) is selected as the modelling method, instead of Agent-Based Modelling (hereafter; ABM), Conjoint Modelling (hereafter; CM), and Machine Learning (hereafter; ML).

DCM specifically focuses on understanding choices between different alternatives, in this study the AC and the train as alternatives (Ben-Akiva & Lerman, 2018; Hensher & Johnson, 2018). ABM focuses primarily on measuring individual behaviour and simulating systems, which is overly complex for measuring solely choice behaviour (Bonabeau, 2002; Macal & North, 2005). ML focuses on predicting a choice and recognizing patterns, but this method is less suitable for assessing the impact of specific variables (Lieder et al., 2020). CM is particularly useful for optimizing product characteristics and services, and it is less suitable for investigating large shifts, such as a shift from the rail sector to the road sector (Gustafsson et al., 2003; Verma & Chandra, 2018). Consequently, DCM is the most suitable modelling method for this study and will be further discussed in the next subsection.

2.2 Discrete Choice Modelling

A DCM identifies the factors that influence a decision between multiple alternatives (American Automatic Control Council, 2011). DCM is an application of the Utility Theory in real-world scenarios (Fosgerau & Bierlaire, 2009). The Utility Theory is a concept where an individual chooses an alternative with the aim of maximizing their overall utility, which represents their preference and needs (Ben-Akiva & Lerman, 2018). When an induvial aims to maximize its utility, trade-offs must be made in order to make a decision. There are features of the alternatives that influence these trade-offs called attributes. Attributes are factors that are considered by individuals to compare the alternatives. Individual's alternative choice is besides the alternative features, additionally influenced by individual-specific features. Because when individuals consider the same alternative features, but they have characteristics, then the final alternative choice can vary considerably (Ren et al., 2023).

Based on the methodology process of Weber (2021), a visual representation has been developed for this study to present the methodology process, as displayed in Figure 2 (Weber, 2021). Each step of this process is discussed in detail further in this chapter.

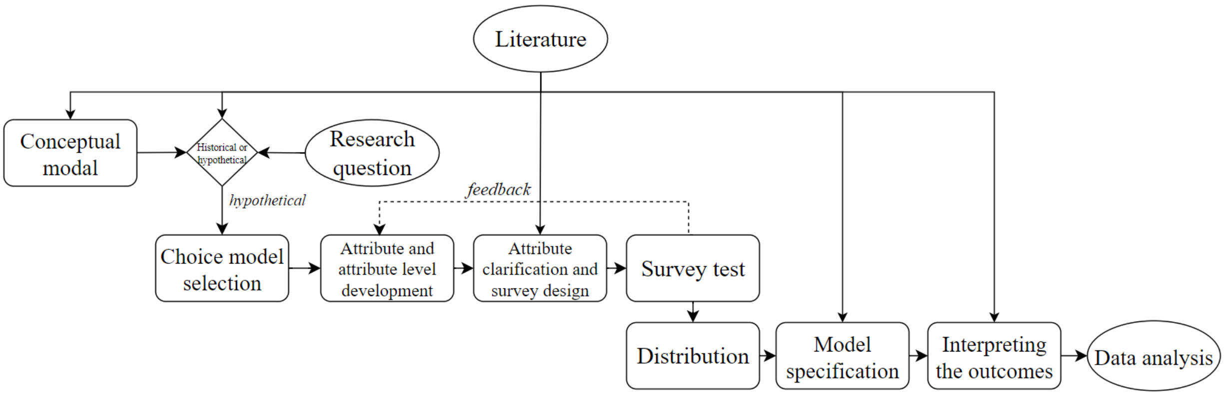


Figure 2 - Visual process diagram of the selected methodology

The multiple alternatives and their varying attribute levels form the different scenarios. These scenarios can be presented in a choice experiment, which can be approached in two possible ways: through a Stated Choice Experiment (hereafter; SCE) or a Discrete Choice Experiment (hereafter; DCE). The SCE involves choice scenarios based on hypothetical situations, while the DCE is based on existing data. As of now, AC has not yet been implemented on Dutch highways, thus there is no available data, consequently, selecting an AC as a modal choice remains a hypothetical scenario. Therefore, this study employs a Stated Choice Scenario (Lambooij et al., 2015).

2.3 Conceptualisation

An SCE is a specific method within the broader framework of DCM. Due to the use of hypothetical scenarios, an SCE allows for the inclusion of new attributes in comparison to a DCE. Therefore, an SCE gives the opportunity to examine the three critical factors in this study – safety, motion sickness and comfort, which highlights why an SCE is more suitable for the objective of this study.

The design of an SCE encompasses the design of attributes and their attribute levels, addressed in the subsequent chapter. These attributes build the foundation for the hypothetical scenarios and the subsequent model specification.

2.3.1 Attribute development

Since an SCE consists of hypothetical scenarios, the attributes and attribute levels themselves must be determined. An attribute is a characteristic and an attribute level is the degree of the characteristic. To identify the characteristics that constitute the attributes, a literature review is conducted (Coast & Horrocks, 2007). The literature review also assesses to what extent these characteristics influence the individuals' choices. Once all relevant characteristics have been identified, they are integrated into a visual conceptual model. This conceptualization provides the framework for understanding choice behaviour in a SCE (Kløjgaard et al., 2012). The links within this conceptual model represent the relationships between the variables. The SCE quantifies these relationships to gain insight into how the variables, outlined in the conceptual model, influence the modal choice (Seiferling et al., 2014).

Subsequently, these characteristics from the conceptual model become the attributes (Coast & Horrocks, 2007). Some attributes may not have a significant influence on the modal choice, as the literature review suggests because they are not relevant to the decision-maker. However, it still remains important to include them as attributes to prevent assumptions, which could negatively influence the validity of the results (Lancsar & Louviere, 2006).

2.3.2 Attribute level development

After determining the attributes, the next phase is to establish the attribute levels. This phase is pivotal in the SCE design process as these attribute levels define the choice scenarios in an SCE, directly influencing the decision (Adamowicz, Louviere, et al., 1998; Kemperman, 2021). In this study, the focus is on a specific corridor, the route Rotterdam - Amsterdam. Some attribute levels can be derived from the existing data available from the corridor. This approach ensures that the levels are aligned with the actual corridor, enabling the comparison of the results with the same real-world corridor for the most realistic examination (Abiiro et al., 2014). However, data is unavailable for the remaining attributes. For these attributes, the levels are derived based on potential designs and consumer preferences for the alternatives (Huber, 1974). By doing so, the attribute levels are aligned with potential reality situations, ensuring an examination of the most realistic future situation. Furthermore, it is crucial that attribute levels are comprehensible to all respondents, and that they capture the decision motifs. In other words, the range of levels must highlight the involved trade-offs (Green & Srinivasan, 1978).

2.4 Survey design

After establishing all attribute levels, the choice sets for the scenarios can be generated. To ensure a consistent understanding of all alternatives and attributes among all respondents, clarification is necessary. Subsequently, the survey undergoes testing before the final survey is ready for distribution.

2.4.1 Alternative and attribute clarification

To construct a choice set, a comprehensive description of the alternatives must be provided to the individuals making the trade-offs, in addition to presenting the scenarios. However presenting an excessive amount of information can overwhelm respondents, making it challenging to fully understand the alternatives (Hensher, 2006). The inclusion of a visual representation of the attribute levels can facilitate a better understanding. As individuals become more acquainted with the attributes and the levels, the resulting outcomes are more robust and valid (Johnson et al., 2011).

Alongside the visual representation of the attribute levels, a visual representation of the alternatives is also incorporated. In this study, one of the alternatives is a not-yet-implemented transportation mode. This could be a challenge for respondents in forming a clear understanding of this particular transport mode. To ensure uniformity in respondents' understanding of the alternatives, an explanatory visualization is presented to the respondents before making their choices. This approach enhances the robustness of the resulting outcomes (Johnson et al., 2011).

2.4.2 Survey test

A survey test is also called a pilot test. The test is conducted via a testing panel, involving individuals who have knowledge of the alternatives, and those who are unfamiliar with the alternatives. The individuals acquainted with the alternatives must verify the content and accuracy of the survey questions. The individuals unacquainted with the alternatives assess the survey's comprehensibility, ensuring that they understand each scenario in the survey and can complete it without ambiguity.

This approach enables the validation of the experimental design, encompassing attributes, attribute levels, choice sets and the set of survey questions (Obadha et al., 2019). Furthermore, this method facilitates the detection of issues that may arise during the survey test, including technical, substantive, or clarity-related issues, which provide insights for improving the final survey design (Barthold et al., 2022).

Lastly, a survey test serves as a tool to estimate the time and effort required to complete the survey. Choice sets are often more complex than initially apparent by the experimenter conductor. By gaining a better understanding of the time needed to complete the survey, the data collection can be planned more efficiently (Cleave, 2021).

2.5 Data collection

The survey is distributed to train passengers, with no exclusion of any particular passenger from the target group, as the study aims to investigate all passenger characteristics. The objective is to ensure that the distribution of the sample aligns with the characteristics of the actual population. This can be compared with actual data obtained from CBS.

2.5.1 Survey distribution

In partnership with NS, Goudappel maintains a panel of respondents with train passengers. However, due to budgetary constraints, the survey cannot be distributed through this panel.

As a result, the survey is distributed via platforms and personal networks. There are no cost limitations associated with this distribution method, but it may present limitations related to the target group. Given that the study is being conducted at a consultancy for mobility issues, and at a technical university, respondents within personal networks are likely to possess prior knowledge and enthusiasm regarding alternative transportation modes. However, forcibly approaching a diverse group of respondents may potentially influence the sample distribution, and therefore the validity of the results negatively (Bush & White, 1985).

Additionally, to expand the sample size, a physical distribution method can be employed. Apart from increasing the respondent sample, this approach allows face-to-face interactions and clarifications of any ambiguities present in the survey. By employing platform distribution, personal network distribution, and physical distribution, a diverse sample can be collected.

In order to draw valid conclusions from survey results, a minimum number of respondents must be obtained. The required sample size is calculated with Equation 1.1 of Orme (1998) (De Bekker-Grob et al., 2015).

$$N \geq 500 * \frac{l}{J * S} \tag{1.1}$$

Where:
l = largest number of levels of the attribute
J = number of alternatives in each choice task
S = number of choice sets

2.6 Modal specification

After collecting the respondents' data, the subsequent step involves its analysis. Initially, an explanation of the random utility theory will be provided, followed by the selection of the Logit model chosen for the analysis of choice data.

2.6.1 Utility theory

The respondents' data are used to estimate the parameters for the choice models. These parameters are derived using the Utility Theory, which implies that respondents select the alternative with the highest utility, often referred to as the measure of satisfaction for a given alternative (Chorus, 2012). The decision for the utility theory stems from its ability to provide insights into individuals' decisions, a crucial aspect when comparing two transportation mode alternatives (Birnbaum, 2001).

The primary objective of an SCE is to determine how attributes influence the utility perceived by every respondent (Hanley et al., 1998). Utility includes both a systematic component, related to the attributes, and a random component that encompasses individual characteristics and random variation (Kemperman, 2021; Lizin et al., 2022). The utility functions are defined as follows:

$$U_{ijc} = V_{ijc} + e_{ijc} \tag{1.2}$$

$$V_{ijc} = \sum \beta_k X_{ijk} \tag{1.3}$$

An SCE consists of *N* choice sets. Each choice consists of *m* options. The respondents are asked which option they would choose. Each option is described by *k* attributes (Fayyaz et al., 2021). Here, *U_ijc* is the total utility of respondent *i* for alternative *j* in choice set *c*, *V_ijc* is the systematic utility and *e_ijc* is the error term, i.e., the random component. *β_k* is the parameter that is associated with attribute *k* and *X_ijk* is the value associated with attribute *k*, chosen by respondent *i*, considered for alternative *j* (C. G. Chorus, 2012). In other words, Equation 1.2 represents an individual's estimated level of satisfaction when selecting a specific alternative, which is in this study referred to as a transportation mode with a set of specific characteristics.

The software employed to use the Utility Theory is the Statistical Package for Social Sciences (hereafter; SPSS). The selection of SPSS is based on several factors; its familiarity with the software, its user-friendly interface, and its seamless integration with the survey tool LimeSurvey (Baarda et al., 2014). Due to the higher familiarity with SPSS, compared to other more advanced statistical software packages, such as R and Biogeme, errors can be identified more easily, leading to time savings.

2.6.2 Multinominal Logit Model

To examine choice probabilities regarding the selection of transportation mode alternatives, several models are considered. Table 1 outlines the objectives, execution and selection criteria for the considered models; Mixed Logit model, Nested Logit model, Latent Class Cluster analysis, and Multinomial Logit Model.

Model	Objective	Execution	Selection criteria
Mixed Logit model (Cantillo & Ortúzar, 2005; Ryan et al., 2008)	This model measures individual's preferences and choice patterns.	Statistical advanced software packages such as R or Biogeme are needed to run this model, as SPSS does not have a Mixed Logit function.	This model is valuable for a highly diverse group of respondents, but it is not well-suited for this study, which specifically targets train passengers.
Nested Logit model (Greene & Hensher, 2003; Ryan et al., 2008).	This model orders choices and measures correlations between alternatives, such as various brands within the same transportation mode alternative.	The use of this model requires a lot of theoretical background knowledge of the model. Only a simple run can be done with the software SPSS, for larger models, the software R or Biogeme should be used.	In this study, transportation mode alternatives do not correlate, making this model unsuitable.
Latent Class Cluster analysis (Greene & Hensher, 2003; Ryan et al., 2008)	This model identifies groups of individuals based on their preference patterns.	The implementation of this model requires software specific to this model such as Latent Gold or Mplus.	This model identifies the specific types of individuals who will shift, instead of the extent to which train passengers shift. Therefore, this model is not suitable for this study.
Multinomial Logit Model (Cantillo & Ortúzar, 2005; Ryan et al., 2008)	This model predicts an individual's choice between two or more discrete alternatives.	This model is used to estimate the parameters of the variables. SPSS has a built-in MNL function.	This study measures discrete alternatives, namely different, uncorrelated modes of transport: train and AC. This does make the MNL suitable for this study.

Table 1 - Model objective and execution comparison

In conclusion, the Mixed Logit model is unsuitable for this study as its primary purpose is to measure choice patterns, which does not align with the object of this study. Furthermore, this study targets a homogenous group, namely train passengers, whereas the Mixed Logit model is suited for a diverse and heterogeneous group (Cantillo & Ortúzar, 2005; Ryan et al., 2008). Similarly, the Nested Logit model is not a suitable fit for this study since it is designed to explore alternatives that correlate, while the alternatives in this study, AC and train, do not correlate (Greene & Hensher, 2003; Ryan et al., 2008). Additionally, the Latent Class Cluster analysis is not a suitable option for this study due to its aim of categorizing groups (Greene & Hensher, 2003; Ryan et al., 2008). The primary focus of this study is to assess the extent to which various factors influence shifts, rather than to identify the specific types of individuals who will shift.

Consequently, it was determined that the MNL model is the most suitable choice for this study, compared to the other three models. This selection is based on its alignment with the study's objective, which focuses on choices for discrete transportation modes (Cantillo & Ortúzar, 2005; Ryan et al., 2008).

An MNL model measures the probability of a respondent choosing alternative j, in the total set of all alternatives *J*. The Equation is added in Equation 1.4 (C. Chorus, 2022; Peng & Nichols, 2003).

$$P = \frac{e^{Vij}}{\sum_{j=1}^{J} e^{Vij}} \tag{1.4}$$

Where:

P	= the probability of individual i to choose alternative j in the set of alternatives J
e^{Vij}	= the utility of individual i to choose alternative j
$\sum_{j=1}^{J} e^{Vij}$	= the sum of all utilities of individual i choosing alternative j; the entire choice set.

2.6.3 Analysing model fit

The results from the SCE must be analysed. In order to interpret the results, the model must have a good fit. The fitness of the model can be checked via the -2 Log-Likelihood (hereafter; -2LL). A better model fit is indicated by a lower -2LL, or in other words, the closer -2LL is to zero (Chorus, 2012). In addition to -2LL, the Rho-square can also determine the model fitness. The higher the McFadden Rho-square, the better the model fits. (McFadden, 1974).

An excess of variables can lead to model overfitting (Babyak, 2004). Enhancing the model fit is achievable through the elimination of non-significant variables from the model, if literature supports their exclusion. Once the model achieves its optimal fit, the parameters can be analysed and interpreted.

2.7 Methodological decisions

2.7.1 Fixed attribute levels

In this study, the SCE is conducted differently from traditional SCEs. In a traditional SCE, various attributes and their levels are determined, and these levels vary for each choice set (Ryan et al., 2008). In this study, the methodological choice is made that certain attribute levels are kept constant throughout the whole SCE, also referred to as fixed attribute levels. These attributes concern the characteristics of the transportation modes that are drawn from the literature review and have been identified as factors that influence the decision for a transportation mode. Given that these attributes have been extensively researched before, and will be further elaborated in Chapter 3, this study places its primary focus on the three key factors from the research question, rather than re-examining the previously studied attributes.

Even though the focus is on the three key attributes, the attributes identified in the literature review are still included in the choice sets. As discussed in Chapter 1, the characteristics of the transportation modes influence the decision for a transportation mode. This results in individuals continuing to consider them in their decisions if they are not part of the choice sets (Kuchler & Zafar, 2019; Manski, 2018). To prevent respondents from filling in these attribute levels themselves, they are fixed in this study.

By keeping these attributes fixed, the results are more realistic, directly aligning with the actual contextual scope. Outlining a realistic situation helps to mitigate hypothetical biases, a phenomenon in which individuals' answers may deviate from their actual choice due to the scenarios being hypothetical situations, as discussed in more detail in Section 7.3 (Caplan et al., 2010; Ehmke et al., 2008). In addition, fixing attribute levels reduces the overall number of scenarios (Hensher, 2006). Attempting to fully vary all attributes would result in an excessive number of scenarios, which is time-consuming both for the survey compiler and analyst and for respondents. An excessive amount of scenarios in a survey could result in a low respondent count (Hensher, 2006). To ensure a significant respondent count, it is essential to keep the survey length manageable. As a general guideline, a Stated Choice Experiment should involve a maximum of three alterable attributes, with a total of eight scenarios (Van Essen 2023).

Because this approach introduces an innovative element to the traditional SCE, it can be categorized as innovative thinking (Orlandi, 2010). A new variation of the method has been established to depict more realistic scenarios while incorporating all influential variables and ensuring a manageable number of choice sets.

However, it is essential to acknowledge that fixed attribute levels do not give modelling outcomes, thereby restricting the generalizability of the results and preventing the ability to draw significant conclusions about these fixed attributes (Adamowicz, Boxall, et al., 1998; Lokkerbol et al., 2019).

2.7.2 Corridor

Since fixed attribute levels are employed in this study, they are assigned specific values. Consequently, the decision was made to focus on a particular corridor. The Netherlands features a diverse geographic landscape, encompassing both densely and sparsely populated areas. Given these significant density differences, a specific corridor is selected to avoid ambiguity among respondents when multiple corridors are presented. By countering this ambiguity, clearer results can be obtained that other researchers can build on (Elsner, 2017). While this could have been achieved by using a hypothetical corridor, the translation of the results to real-world data, as further explained in Chapter 6, necessitates the use of an existing route.

The decision was made to opt for one of the Netherlands' most critical routes in both the rail and road network: the Rotterdam – Amsterdam corridor, rather than a hypothetical one. Rotterdam and Amsterdam are the two largest cities in the Netherlands, containing significant populations and economic activity (Thomas, 2022). These cities also have well-developed train connections, including a high-speed train connected between the two cities (NS, 2022).

This route also exemplifies the traffic congestion problem in the Netherlands. According to the 2022 traffic data, both the A4 and A2 highways, connecting Rotterdam and Amsterdam, are consistently ranked in the top 10 congested roads (ANWB, 2022). The A4 highway appeared twice in the top 10 due to congestion in both directions, despite recent expansion and improvements on this highway (Dossier A4, 2022.; Rijksoverheid, 2023).

In addition to the possibility of translating model results to actual effects using an existing corridor, this approach also provides valuable insights into the actual behaviour of train passengers. This eliminates reliance on overly optimistic assumptions. Consequently, the results become more straightforward to interpret and can be directly translated into real-world contexts. This approach also assists in maintaining the manageability of the study's scope (Munn et al., 2018).

2.8 Conclusion

To summarise, DCM is the method used to quantitate the relations from the conceptual model. SCE was selected as the method for this study due to its applicability to non-tangible situations. Finally, the choice was made to select MNL over a Mixed Logit model, a Nested Logit model, and a Latent Class Cluster model because an MNL model is the best-suited model for analysing two discrete choice alternatives. In addition, this study diverges from a traditional SCE by incorporating fixed attributes with constant values. These fixed variables are derived from an existing route, as they capture actual behaviour and provide insights into the practical implications of the study's findings.

3 Literature review and conceptual model

In order to examine whether train passengers are going to shift towards AC, this chapter begins by defining the specific form of AC that forms the scope of the study in Section 3.1. Additionally, the ongoing developments within the train sector are analysed in Section 3.1 for a fair and accurate comparison.

Train passengers have chosen train travel over regular car travel as their preferred transportation mode choice. To examine whether ACs cause a shift from rail travel to road travel, whereas regular cars did not, the impact of the factors in which the AC differs from a regular in terms of user experience will be measured. The factors are safety, motion sickness, and comfort. To measure the pure effect of these three key factors, the factors that made train passengers choose train travel instead of regular car travel need to be controlled. To identify these factors, a literature review is conducted in Section 3.2. Once these factors are known, the factors with the greatest influence can be added to the conceptual model in Section 3.3.

3.1 State of the Art

3.1.1 Automated car concept

ACs, also known as self-driving cars or autonomous vehicles, operate without human intervention, using advanced technology, sensors and algorithms for navigation and control (Dimitrakopoulos et al., 2021). They reduce collisions by monitoring their surroundings, detecting hazards, and intervene to prevent accidents (Bachute & Subhedar, 2021; Barla, 2022; Frąckiewicz, 2023a, 2023b; Silva et al., 2022, 2022; Zhang et al., 2023).

In addition, these vehicles use AI to enhance safety by minimizing accidents caused by human error (Ravindra, 2023). However, it is important to note that the human factor also prevents accidents by intervening, a factor that cannot be replaced by AI in an AC (Bengler, 2023). Challenges for AC remain present, including regulatory issues, public acceptance, technological advancements, and ethical concerns in complex decisions (Fleetwood, 2017; Hussain & Zeadally, 2019; Wang et al., 2022).

While fully ACs are in development, automatic components are already being integrated into regular cars, also serving as a test for public acceptance. These features include:

- *Blind Spot Detection* (hereafter; BSD) monitors blind spots using radar sensors and alerts the driver of potential hazards (SerVision, 2020).
- *Adaptive Cruise Control* (hereafter; ACC) uses radar sensors to maintain a safe following distance to the car ahead and adjusts speed accordingly (Hijiki, 2021).
- *Automatic Emergency Braking* (hereafter; AEB) detects possible collisions and provides warnings or intervenes with braking (Wardlaw, 2021).
- *Lane Keeping Assist* (hereafter; LKA) uses cameras and sensors to keep vehicles within their lane and prevent unintentional lane changes (Golson, 2022).
- *Parking Assistance* (hereafter; PA) uses sensors and cameras to identify parking spots and obstacles, assisting with parking manoeuvres (Edkinds, 2022).
- *Traffic Jam Assist* (hereafter; TJA) combines ACC and LKA to help drivers in traffic jams by automatically adjusting speed and steering (Choksey, 2021).

Presently, 92% of newly manufactured cars are equipped with ACC, and 50% are equipped with LKA, PA and TJA, indicating the increase in the popularity of automatic systems (Bartlett, 2021). This represents a gradual shift towards automation in cars, often unnoticed by drivers. These automated components each require energy to function. Hence, the energy consumption of an AC must not be underestimated. Consequently, the increasing number of automated components in a car corresponds to higher energy consumption (Baxter et al., 2018).

3.1.2 AC scenario scope

As outlined in Section 2.4.1, an alternative clarification is presented to all survey respondents to provide a consistent definition of an AC. This is done because the role of ACs in a traffic system can be viewed from various perspectives. Tillema et al. (2015) from the Knowledge Institute for Mobility Policy (hereafter; KiM) categorized these perspectives based on two criteria: the level of automation and the degree of sharing (Tillema et al., 2017). Additionally, the Society of Automotive Engineers (hereafter; SAE) has established six levels of automation, serving as the standard for measuring automation (On-Road Automated Driving (ORAD) committee, 2015).

The categorization based on these two criteria results to four AC scenarios: I) Mobility as a Service (hereafter; MaaS), II) Multimodal and Shared Automation (hereafter; MaSA), III) Hands Off on the Highway (hereafter; HOH) and IV) Fully Automated and Private (hereafter; FAP). The visualization of these scenarios is attached in Appendix B. To delineate the scope, the HOH scenario is selected as AC scenario. An explanation why it was chosen is additionally included in Appendix B.

In brief, the HOH scenario involves SAE level 4 automation, wherein drivers are still responsible for taking control of the car when exiting the highway, while the car operates autonomously on the highway. Unlike the MaaS and MaSA scenarios, this scenario does not necessitate as much societal support, which presents the most significant challenges in those scenarios. However, governmental intervention is essential to ensure safety and certification (Hancock et al., 2019; Olsson et al., 2023). Recent studies indicate that this scenario is the most feasible in the short term because it addresses the primary challenges of FAP and SAE level 5 automation, where numerous external human factor are active in urban traffic areas (Agbe & Shiomi, 2021; Kyriakidis et al., 2019; McKinsey, 2023). Section 2.4.1 mentioned the need to provide an alternative clarification to all survey respondents for a uniform understanding. Section 4.5 addresses this by utilizing the HOH scenario.

3.1.3 ICNG

There are not only developments in the automation car sector but also in the rail sector. Since April 2023, NS and ProRail have been testing the New Generation Intercities (hereafter; ICNG) on the route Rotterdam-Amsterdam (NOS, 2023a). In three months, the two test InterCitys have travelled more than 100,000 kilometres on that route (NL Times, 2023). This subchapter discusses the features of the new ICNG train design, focussing on the three key factors from this study; its passenger comfort enhancements, considerations for motion sickness, safety measures, and additionally, its contribution to sustainability.

The ICNG trains replace the trains with older equipment and will cope with the growing demand for train passengers. The trains are primarily intended for the core of NS’s and ProRails’ railway network. The ICNG can reach a speed of 160 km/h with a maximum of 200 km/h, while the current Intercity can reach a maximum speed of 130 km/h. Additionally, the ICNG incorporates Belgium's power and safety systems, allowing for seamless cross-border operations (NL Times, 2023). Additionally, the ICNG trains are designed with distinct sections for work, being quiet and socializing (Ariën, 2017).

Comfort

Numerous enhancements have been introduced in the ICNG to improve the comfort of train travel for passengers. These improvements focus on providing a better work environment, improved seating, and enhancing the overall atmosphere. Real tables have been integrated into the train wagons and each seat now features a more spacious fold-out table. Passengers have access to Wi-Fi, while power outlets for both smartphones and laptops are conveniently available at every seat (Collet et al., 2022). Moreover, the seats have been widened to provide sufficient room for comfortable armrests on both sides. The space between seats has also been expanded to accommodate more luggage (Collet et al., 2022). Lastly, the ICNG contains an aerodynamic design, utilizing advanced materials to minimize noise emissions. An automatic air-conditioning system has been installed to enhance passenger comfort further (Collet et al., 2022).

Motion sickness

With the new design, consideration has also been given to how to reduce motion sickness. Although trains inherently cause less motion sickness compared to other modes of transportation, the implementation of regenerative braking ensures that the level of motion sickness does not intensify during track or rail changes (Collet et al., 2022).

Safety
The ICNG is equipped with the European Rail Traffic Management System (ERTMS), a European specification for railway signals and train controls (Olsson et al., 2023). This enables international travel, elevating the train's reliability and maintaining a high level of safety. However, it is worth noting that the train remains a public space, and while the new design offers improvements, it may not necessarily enhance the overall feeling of safety within the wagons (Collet et al., 2022).

Sustainability
The high-speed train stands out as a more sustainable option than electric cars, and even ACs (Kamga & Yazici, 2014). Primarily due to the numerous automatic components an AC has that demand energy (StatsMan, 2019). However, this difference is increased further by the fact that there is separate waste collection on the balconies of the trains, along with LED lighting featuring an Intelligent Light Control. An Intelligent Light Control system can reduce energy consumption by up to 45%. (Martirano, 2011; Ariën, 2017).

3.1.4 Conclusion

The automotive industry focuses on advancing automated systems. However, achieving MaaS or MaSA depends on significant government involvement and societal support. Conversely, the Netherlands is nearing the HOH scenario, which aligns with the development of AC components. This suggests that the adoption of SAE level 4 ACs will precede the adoption of SAE level 5 ACs on Dutch roads, hence the HOH scenario with SAE level 4 AC will form the scope of this research. Additionally, the ICNG has implemented developments related to the three key factors within this study. These developments address all three aspects of user experience, which may influence the modal shift after the entrance of ACs to the opposite direction.

3.2 Modality choice factors

Train passengers have selected trains over regular cars. To assess whether the AC would lead to different choices, the factors that influence passengers' decision between the train or the regular must be identified. These factors will be identified through a literature review. The Preferred Reporting Items for Systematic Reviews and Meta-Analysis method (hereafter; PRISMA) is used for conducting the literature review. PRISMA was chosen because it is internationally used and it enables readers to evaluate if the conclusions drawn from the literature review are legitimate (Liberati et al., 2009). To gather data, this method is used as a formal systematic review guideline. The criteria for selecting articles, the search approach, the methods for extracting data, and the methods for analysing the results are extensively outlined in the review process in Appendix C (Abelha et al., 2020).

3.2.1 Literature review method

The literature review method involves multiple phases. Initially, determining the keywords is essential. Subsequently, it is necessary to assess the volume of results obtained from the search terms. Following that, papers are selected based on specific criteria. Lastly, there will be a brief discussion on excluded papers.

The process of selecting search terms started broadly and generically. The initial search terms, 'Travel behaviour' AND 'rail' AND 'road' gave an extensive number of results. Consequently, the search terms were progressively refined until all the important components from the research topic were in the search terms. The search terms are added in Table 2. Even though the number of hits remained very high, a decision was made to proceed to the scanning the titles and to assess them against the inclusion and exclusion criteria.
The table is organized chronologically from top to bottom. The top row represents the initial search terms for general information gathering about the subject, while the bottom row lists the final search terms.

Search terms	Database	Hits
‘travel behaviour’ AND ‘rail’ AND ‘road’	ScienceDirect	4,201
‘travel behaviour’ AND ‘train’ AND ‘road’	ScienceDirect	3,550
'travel behaviour' AND 'train' AND 'car' AND 'modal shift'	ScienceDirect	2,648
'travel behaviour' AND 'train' AND 'car' AND 'modal shift' AND ‘factors’	ScienceDirect	1,658
'travel behaviour' AND 'train' AND 'car' AND 'modal shift' AND ‘factors’ AND ‘preferences’	ScienceDirect	1,205

Table 2 - Literature review search terms

The selection of titles was based on various inclusion and exclusion criteria. These criteria were employed to determine whether to include or exclude an article. The language of the report is English. However, Dutch papers are also considered readable, and can therefore be additionally selected. Furthermore, due to the substantial volume of papers available, only peer-reviewed articles were selected. Given the extensive numbers of papers investigating this topic, preference was given to papers that incorporate more than 10 variables in their studies.

This approach allows for comprehensive conclusion to be drawn from a single paper, rather than necessitating comparisons among multiple papers. Finally, as the study focuses on trains and cars, research on buses, trams, metros, and shared mobility options were excluded from consideration. The criteria can be found in Table 3.

Criteria	Inclusion	Exclusion
Period	≥ 2015	≤ 2014
Language	English or Dutch	Non-English or non-Dutch
Resource medium	Peer-reviewed scientific articles	Blogs, forums and patents
Database	ScienceDirect	Other
Transportation subtopic	Rail, Train, Car, Road	Busses, Trams, Metros, Shared Mobilities
Number of variables	≥ 10	≤ 9

Table 3 - Literature review inclusion and exclusion criteria

It is important to note that there is a possibility of unintendedly excluding highly specific papers that are relevant for this study. Some articles may pertain to smart transportation projects, with only the project name mentioned. Such articles may only be discovered through the process of snowballing (Wohlin, 2014). Snowballing is the method of searching for secondary articles which are cited by primary articles (Jalali & Wohlin, 2012).

3.2.2 Literature analysis

The findings from this literature review, identified as [1] to [10], are presented in Table 4. Numerous studies have investigated the factors that influence the decision for a transportation mode, as outlined in Table 2. The decision is made to include only ten articles as the key references. These ten were selected based on their comparison research encompassing at least both trains and cars.

Furthermore, there key references explore a wide array of variables, and ultimately, they all arrive at the same conclusion. Including an addition reference would not contribute significantly to the existing literature body. Consequently, the literature review was limited to these ten key references.

#	Authors	Title
[1]	(Madhuwanthi et al., 2016)	Factors Influencing Travel Behaviour on Transport Mode Choice
[2]	(Mwale et al., 2022)	Factors that affect travel behaviour in developing cities: A methodological review.
[3]	(Ettema & Nieuwenhuis, 2017)	Residential self-selection and travel behaviour: what are the effects of attitudes, reasons for location choice and the built environment?
[4]	(Lekshmi et al., 2016)	Activity-based travel demand modelling of Thiruvananthapuram urban area.
[5]	(Shen et al., 2016)	Factors affecting car ownership and mode choice in rail transit-supported suburbs of a large Chinese city.
[6]	(Zheng et al., 2016)	Preference heterogeneity in mode choice based on a nationwide survey with a focus on urban rail.
[7]	(Guerra et al., 2018)	Urban form, transit supply, and travel behaviour: Evidence from Mexico's 100 largest cities.
[8]	(Shariff & Shah, 2008)	Factors influencing travel behaviour and their potential solution: a review of current literatures
[9]	(Nguyen-Phuoc et al., 2018)	How do public transport users adjust their travel behaviour if public transport ceases? A qualitative study
[10]	(Tembe et al., 2019)	The demand for public buses in sub-Saharan African cities: Case studies from Maputo and Nairobi

Table 4 - Article titles

The articles were compared side by side based on the factors that resulted from the studies of the articles, as can be seen in Table 5.

	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[9]**	**[10]**
Passenger characteristics										
• Gender	X	X	X	X	X	X	X			X
• Age	X	X	X	X	X	X	X			X
• Income	X	X	X	X	X		X	X		X
• Education level		X	X				X			
• Vehicle ownership	X		X	X					X	X
• Household size	X	X	X		X		X		X	
• Travel frequency		X			X		X	X	X	X
• Possession of driver's license	X		X	X		X			X	X
• Residential density	X					X	X	X		X
• Social status		X		X						
Trip characteristics										
• Trip purpose	X							X	X	X
• Subsidy					X					
• Time of day	X			X				X		X
• Availability								X		
• Single-occupancy	X									X
• Transferring						X				
Transport mode characteristics										
• Waiting time	X	X				X		X		X
• Time of trip					X	X			X	
• Walkability			X	X	x	X	X	X	X	X
• Costs	X	X		X	X	X		X	X	X
• Parking availability	X	X	X							X
• Reliability	X	X				X			X	X
• Comfort	X	X			X	X				X
• Safety	X	X			X					X
• sustainability			X				X	X		

Table 5 - Literature review of factors influencing the modal choice

The factors identified as having the most significant impact on travel behaviour between train and car are summarized. An extensive textual literature review of these factors is attached in Appendix C.

3.2.3 Results

From analysing these articles, the dominant factor affecting the choice between train and car travel is possessing a driving license and owning a car (Ettema & Nieuwenhuis, 2017; Mwale et al., 2022; Nguyen-Phuoc et al., 2018; Shariff & Shah, 2008; Shen et al., 2016; Tembe et al., 2019). If passengers do not own a driving licence or car, it is natural for them to choose the train over the car. The studies where this did not emerge as the biggest factor in the survey did not include the characteristics of having a driving licence or a car in their research scope. Having a driving licence and owning a car is intertwined with income levels, which, in turn, are influenced by education level and employment (Guerra et al., 2018; Lekshmi et al., 2016, 2016; Shen et al., 2016; Tembe et al., 2019).

In addition to the characteristics of travellers that impact their modality choice, there are also characteristics of the transportation modes, the attributes, that influence this decision. For instance, one of the most significant attributes is the distance to the nearest train station (Nguyen-Phuoc et al., 2018; Shen et al., 2016; Tembe et al., 2019; Zheng et al., 2016). The further the train station, the less likely travellers are to use the train. Especially when these travellers have to go to the station by car. By contrast, in densely populated areas, travellers are more likely to take the train, as train stations are closer to residents, and there are fewer parking spaces available (Guerra et al., 2018). Lastly, travellers are more likely to choose a particular transport mode when the (variable) costs and travel times are lower. It's important to note that sunk costs are often not considered by travellers when making their choice (Lekshmi et al., 2016; Mwale et al., 2022; Shen et al., 2016; Zheng et al., 2016).

3.2.4 Conclusion

It is important to distinguish and isolate the influence of specific factors that influence a decision between train travel or regular car travel, in order to measure the pure effect of a shift to AC usage. The characteristics of passengers; gender, age, employment, ownership of car and/or driver's license, and income, and the characteristics of the transportation modes, attributes; proximity, cost and travel time, form a framework. The variables in this framework will be fixed, of which the definition will be described in Section 4.3, in order to measure the shift from train to AC, without obscuring the observations as these factors are the same factors that affect the decision between train and regular car travel (Hensher, 2006).

3.3 Comparative literature review analysis

The results of this literature review are compared with the literature review conducted by Mwale et al. (2023) (Mwale et al., 2023). This comparative analysis aims to critically evaluate the identified factors and their degrees of influence by cross-referencing with the existing paper. Both studies employed the same method, PRISMA, and review a similar number of studies. The primary analytical methods in the studies which are reviewed by Mwale et al, are SCE and MNL, which aligns with the methods employed in this study to analyse the survey results. Hence, the literature review by Mwale et al. serves as a suitable refence paper for this comparison.

3.3.1 Categorization of factors

A notable difference arises in the categorization of the factors. In this study, factors are categorized into characteristics of travellers and characteristics of transportation modes, which is not delineated in Mwale et al.’s literature review. However, factors with significant influence largely align but may fall under different categories. For example, proximity to the nearest train station is categorized under urban density, fares and fuel costs fall under travel costs, travel time under service quality, and age, income, gender, employment, and travel frequency fall under the demographic and socioeconomic factors. Ownership is categorized under transport modes. While this categorization enhances clarity, it may create less obvious policy categories.

The rationale behind distinguishing between traveller-based and transport mode-based factors is of policy relevance. Policy interventions can be made more readily on transport mode-based factors than on person-based factors.

3.3.2 Key similarities and differences

The paramount point of comparison is the factors with the greatest impact. Both traveller and transport mode characteristics have consistent findings. Proximity, travel costs, and travel time are found to be influential factors in transportation mode choice in both literature reviews. Similarly, age, gender, employment, ownership, income and travel frequency are established as influential factors for travellers in both studies.

It is important to note that while there are substantial similarities between the two literature reviews, there are also minor differences that can be explained. Mwale et al. included tolls as a factor, which is not relevant in the context of the Netherlands. Additionally, lifestyle is considered a demographic factor in Mwale et al.'s study, focusing on travel patterns and motifs. This did not result from the literature review of this study. However, the impact of this factor appears to be minor and is therefore not added to the results of the literature review in this study.

3.3.3 Conclusion

These shared similarities affirm the consistency of the literature review. The comparison strengthens the credibility of the review's findings, illustrating the effectiveness of employing the PRISMA method and employing inclusion and exclusion criteria to identify valid literature. The difference in categorization is attributed to the fact that there are varying purposes for which the literature reviews are intended. In this study, they serve as foundational components for possible future policy interventions, which is further explained in Section 7.3.2. Lastly, the similarities of this comparison confirm that the inclusion of ten key references is sufficient for a valid literature review, and that the addition of more key references would not significantly lead to a different set of influential factors.

3.4 Conceptual model

Both the characteristics of transportation modes and the characteristics of train passengers are in the modal choice. When measuring the effect of the inclusion of ACs as a potential mode of transportation, safety, motion sickness, and comfort are expected to influence the mode selection (Bin Karjanto et al., 2017; Happee, 2023; Karjanto et al., 2018; Keshavarz & Golding, 2022; Nordhoff et al., 2021; Yoon et al., 2019). To measure the extent of the impact of these three factors, the characteristics of transportation modes and the characteristics of train passengers derived from the literature review, in Section 3.2, will be kept fixed (Hensher, 2006). Section 4.3 will discuss this fixation further in detail.

Sustainability is anticipated to have minimal to no impact on the choice of ACs (Happee, 2023). To examine this, it was decided to incorporate the level of environmental awareness as a passenger characteristic, and CO_2 emissions as a transportation mode characteristic. These elements have also been integrated into the conceptual model, which is presented in Figure 3.

Conceptually, there is also an input labelled 'other'. Indeed, there are additional components that influence a transportation mode choice, as indicated by the literature review in Section 3.2.2. These components could encompass factors such as parking availability, reliability, and the probability of delays. However, for the purposes of this study, these factors have been excluded from the research scope. Their exclusion allows for maintaining focus on the primary variables while still acknowledging their relevance. Additionally, it enhances the transparency of the study and facilitates its reproducibility.

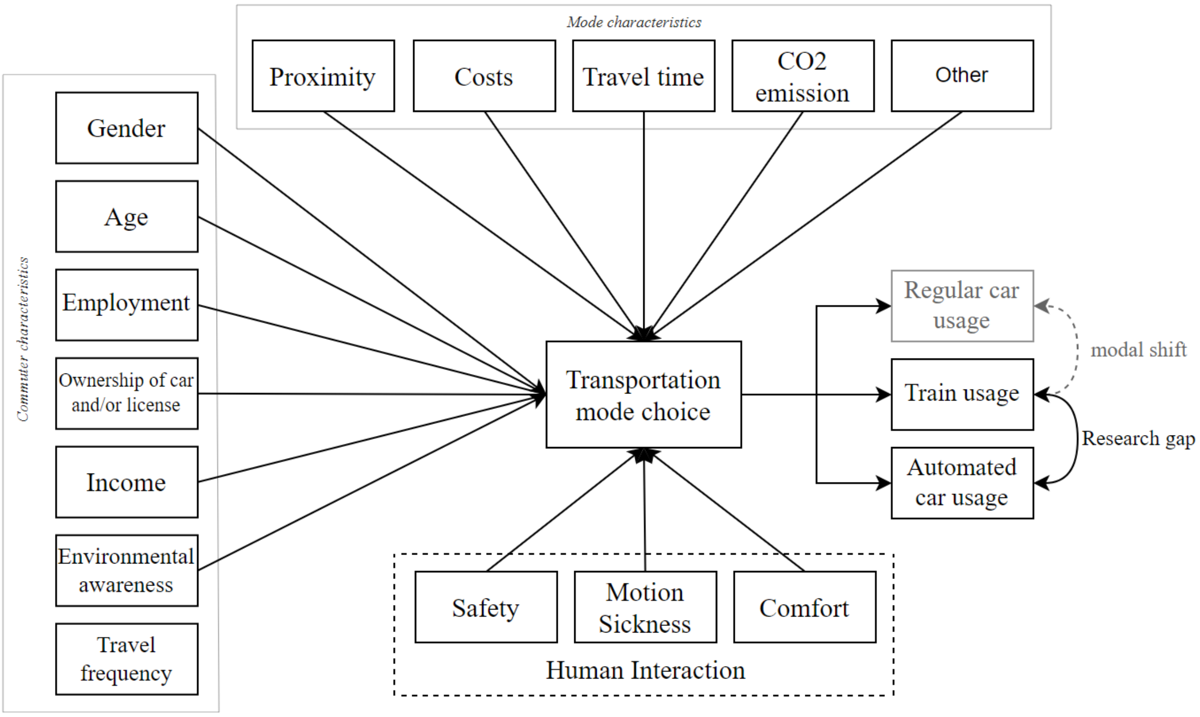


Figure 3 - Conceptual model for the transportation mode choice

3.5 Conclusion

Various AC scenarios were considered. The selected scenario is where the driver has to maintain control over the steering wheel off the highway, and the automated system can be activated on the highway, aligning with SAE level 4, semi-full automation. In parallel, developments take place in the train sector, with the ICNG forming the scope to represent the train developments.

Train passengers have a preference for train travel over regular car travel. To assess whether the AC can induce a shift where regular cars cannot, factors influencing passengers' choice between train and regular cars were identified through a literature review. Two key categories emerged: transport mode characteristics and passenger attributes. A comparative analysis between the current literature review and Mwale et al.'s (2023) study reveals that, despite the differences in categorization, the most influential factors align. This affirms the validity of the results from the literature review from this study and highlights that the inclusion of ten key references suffices, obviating the need for additional references. The factors with the greatest influence were incorporated into the conceptual model. The transport mode characteristics encompass proximity to the nearest station, travel costs, travel time, and the examination of sustainability through CO_2 emissions. The passenger attributes include gender, age, employment status, ownership of a driver's license and car, income, and environmental awareness- similarly addressing sustainability considerations. These variables will shape the attribute levels in the following chapter.

4 Attributes, attribute levels and survey design

As previously discussed in Section 2.7, this study focuses on the Rotterdam – Amsterdam corridor. This particular route is important for both the rail and road network. Additionally, the characteristics of the transportation modes and passengers, as identified through the literature review, are quite similar along this route for both car and train travel. This similarity allows for the use of real-world data from the route to establish the attribute levels. Furthermore, the similarity ensures that the attribute levels can accurately estimate the pure impact of the three key factors on the decision. These characteristics are described in Section 4.1.

In Section 4.2, the attributes and attribute levels of the key factors are discussed. Following that, in Section 4.3, the attributes and attribute levels of the fixed characteristics, derived from the literature review, are described. Attributes from both sections form the SCE scenarios, which are validated by an expert in Section 4.4. After the validation, a clarification video is created to ensure a uniform understanding among all respondents in Section 4.5. Subsequently, this video and the concept survey design are tested in Section 4.6. The final survey design outline is outlined in Section 4.7, followed by a conclusion in Section 4.8.

4.1 Descriptive statistics of the route Rotterdam – Amsterdam

Descriptive data is presented in this section to offer an overview of the current situation of the route. This data provides more context before going into more detail about the SCE and forms the basis for defining the attribute levels that are drawn from the literature review (Cooksey, 2020; Snyder, 2019).

4.1.1 Characteristics of the transport modes

This subsection connects the characteristics of the transportation modes from the conceptual model with the figures on the corridor. These encompass proximity, costs, travel time, and CO_2 emissions. As shown in the conceptual model, proximity to a train station affects the modal choice (Nguyen-Phuoc et al., 2018). The average distance from all postal codes in Rotterdam to a train station is 2.74 km, while in Amsterdam, it is 2.17 km, resulting in an overall average distance of 2.5 km, equivalent to 2,500 metres (Postcodes.nl, 2023). The data per postal code area can be found in Appendix D. This figure will be used further in Section 4.3.

Costs and travel time additionally influence the modal choice. CO_2 emissions are also included as a factor in the conceptual model. Figure 4 shows the Rotterdam – Amsterdam corridor.

Figure 4 - CO_2 emissions, travel time and travel costs on the Rotterdam-Amsterdam route

Travelling by train takes 40 minutes and costs €17.50, resulting in a CO_2 emission of 172 grams of CO_2. Travelling by car takes outside rush hour 60 minutes, and in rush hour 1 hour and 45 minutes, incurring a cost of €16.25 and emitting 268 grams of CO_2 during the trip (NS, 2023). These figures are derived from electric car data, because equivalent data for AC do not exist yet. Figure 4 shows only the A4, as mentioned in the introduction, highway A2 also connects Rotterdam with Amsterdam (GoogleMaps, 2023). The A2 data is very similar to that of the A4, but the A2 has been excluded from the figure for the sake of clarity in the illustration.

Goudappel, along with two other companies Kantar and MobidT, has the Dutch Travel Panel (hereafter; NVP). This is a dataset which started in 2019 through smartphones. There are 10,000 daily participants in the panel. Travellers on the Rotterdam-Amsterdam route can be measured through this movement panel. Four so-called shapes have been determined in a GIS file; I) the A4, II) the A2, III) the high-speed rail line, and IV) the intercity between Rotterdam and Amsterdam. These are the four ways people can travel by train or car from Rotterdam to Amsterdam and vice versa. Data was then requested for 2 years for these 4 routes. This became a dataset of 3887 trips on this route. From this dataset, the car-train distributions can be extracted and the characteristics of the travellers, which are further discussed in Section 4.1.2.

Using the NVP dataset, the travel time from Figure 4 can be verified. The NVP dataset shows that it takes 58 minutes for car users outside rush hour, which is assumed before 07:00, between 9:00 and 16:00, and after 19:00. In the morning rush hour was the average travel time of 106 minutes, in the evening rush hour was the average travel time 93 minutes. The average travel time for the train ride between Rotterdam and Amsterdam is 42 minutes. From this, it can be concluded that the NVP has real numbers and is generalisable to passenger characteristics in addition to transport mode characteristics.

The difference between car and train travel on the route Rotterdam – Amsterdam may appear large, but a comparison table, Table 6, has been made with other routes with the same distance to illustrate the relatively minor difference on this route. Two random relatively large cities, located at approximately the same distance, were selected for this comparison. The table compares for both travel time (hereafter; TT) and travel costs (hereafter; TC) (NS, 2023).

From	**To**	**Distance**	**TT train**	**TC train**	**TT car**	**TC car**	**Δ TT**	**Δ TC**
Rotterdam	Amsterdam	83 km	40 minutes	€17.50	60 minutes	€16.25	*20 minutes*	*€1.25*
Rotterdam	Den Bosch	83 km	98 minutes	€21.34	55 minutes	€17.94	*43 minutes*	*€3,40*
Amsterdam	Apeldoorn	85 km	95 minutes	€19.30	56 minutes	€16.86	*39 minutes*	*€2,62*

Table 6 - Travel time and travel cost comparison of three routes

Both the TT and TC are approximately twice as high, indicating that there is a relatively little difference between car and train travel on the route Rotterdam – Amsterdam. In other words, this represents the corridor where the variations in attribute values, as outlined in Section 3.4's conceptual model, are minimal. Essentially, by keeping attribute levels at constant levels, there is a risk of losing the broader perspective of travel behaviour (Beirão & Sarsfield Cabral, 2007; Clifton & Handy, 2003). However, by assigning actual values to these fixed attributes that are closely aligned, the understanding of travel behaviour is preserved.

4.1.2 Characteristics of the train passengers

To ensure the generalisability of the NVP dataset across the corridor, a comparison with Central Bureau of Statistics (hereafter; CBS) data is conducted. Namely, CBS has mapped the transport use among Dutch citizens (Statistiek, 2022). There are specific categories where the NVP dataset and CBS share identical category levels. Consequently, the comparison is focused exclusively on these matching categories to ensure the most accurate comparison. As a result, this comparison is undertaken for two categories; age-related preferences in train or car, and travel motifs. The graphs are added in Figure 5.

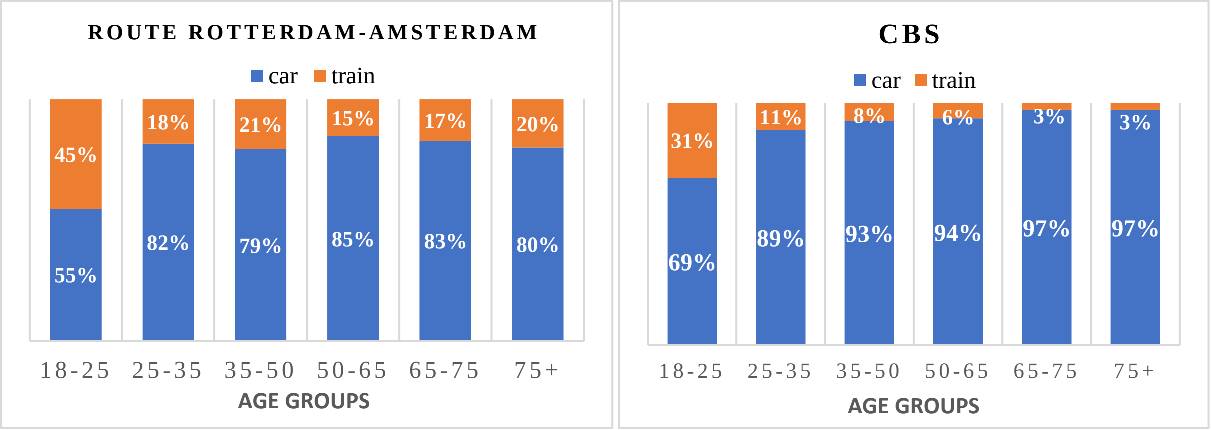


Figure 5 - Graphs of the car-train distribution on the Rotterdam-Amsterdam route and CBS

The datasets show a similar pattern. The train is used more often along the Rotterdam-Amsterdam route than across the Netherlands. This can be explained by the fact that there are places in the Netherlands where there are no train stations or train tracks (Givoni & Rietveld, 2007). Additionally, Rotterdam and Amsterdam are the largest cities in the Netherlands with one of the largest train stations in the Netherlands. This allows the conclusion that the NVP data is generalisable over the entire Rotterdam-Amsterdam route.

The chart shows that in the 18-25 age group, train use is much higher than in other age groups. In the 25 to 35 age group, train usage has decreased slightly, and in the later age categories, train usage drops even further (Statistiek, 2022). This can be explained by the fact that there are many students in this age group. In the Netherlands, students can use free weekend or weekly public transport (Cats et al., 2017).

Lastly, the travel motifs in the NVP dataset are compared with the data from CBS to further assess the reliability of the NVP dataset. Both the NVP and CBS results in Figure 6 have the same patterns and indicate a higher number of individuals travelling by train for leisure and accommodation purposes compared to commuting for work. Travelling to work is in second place (CBS, 2022c).

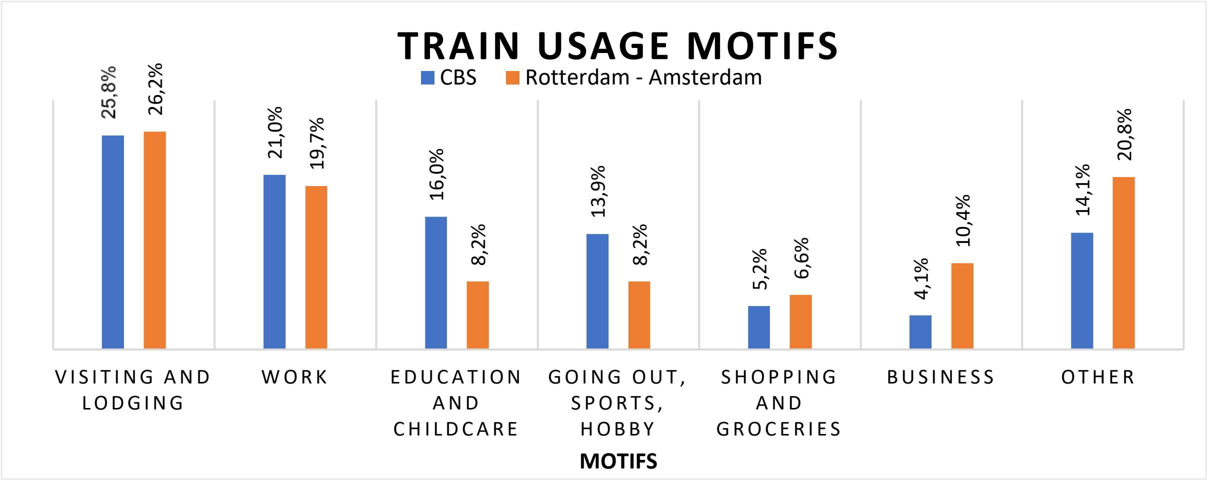


Figure 6 - Train usage comparison between CBS and NVP

In conclusion, the NVP data for the Rotterdam-Amsterdam route is a valid data set because it matches Dutch travel distribution data from CBS. This allows the characteristics of transportation modes to be extracted from the NVP dataset and form the basis for the traveller profile.

4.2 Varying attributes and attribute levels

The literature review has identified the factors influencing travellers' mode choice between trains or regular cars. While ACs differ from regular cars in various aspects, as discussed in Chapter 1, there are three key areas where passengers experience noticeable differences, which in turn influence their mode choice; safety, motion sickness and comfort (Bin Karjanto et al., 2017; Karjanto et al., 2018; Keshavarz & Golding, 2022; Nordhoff et al., 2021; Yoon et al., 2019). This section elaborates on these three components, how they differ from regular cars, and outlines the attribute levels.

4.2.1 Motion sickness

Motion sickness is a phenomenon where passengers experience discomfort and unease due to conflicting sensors between their inner ear's vestibular system and their brain (Bertolini & Straumann, 2016). Individuals seating in different positions in a car, passenger or driver, can have varying degrees of motion sickness. A driver's brain is able to associate an observed event with the movement that follows. A passenger has a lack of direct control and their brain can therefore not assimilate the movement, resulting in motion sickness (Schmidt et al., 2020).

The emergence of ACs introduces a novel scenario regarding motion sickness. Passengers in ACs act akin to passengers in regular cars, as the car's system generates movements instead of the human driver. Consequently, occupants in ACs are more vulnerable to motion sickness, and may therefore choose not to engage in automated driving or to not activate the automated system. This was highlighted by Diels & Bos (2016), who published an article on the severity of motion sickness in ACs for SAE level 4 and up (Diels & Bos, 2016).

Moreover, research by Cowings et al. (1999) and Kato and Kitazaki (2008) shows that built-in automation systems worsen motion sickness compared to the train (Cowings et al., 1999; Kato & Kitazaki, 2008). This results from the greater frequency of vehicle movements, such as turns, braking and acceleration, compared to trains, where motion is more consistent and gradual (Happee, 2023; Iskander et al., 2019).

Additionally, Schmidt et al. (2020) concluded that 66% of Dutch travellers suffer from motion sickness, and globally, the motion sicken rate is 59% (Schmidt et al., 2020). Given the influence of motion sickness on passenger engagement with the automation system (Diels & Bos, 2016) and the global occurrence of motion sickness, it could significantly impact the decision to shift from train to AC travel.

Siddiqi et al. (2023) conducted research into algorithms for reducing motion sickness for different car manoeuvres of ACs. Their hybrid algorithm solution proved to be the most effective solution, leading to a reduction of motion sickness by 75% (Siddiqi et al., 2023). Other studies by Li & Chen (2022), Kremer et al. (2022) and Siddiqi et al. (2021) investigated different technologies, each of which led to a reduction in motion sickness (Kremer et al., 2022; D. Li & Chen, 2022; Siddiqi et al., 2021).

In conclusion, it is likely that travellers in ACs, who as occupants of regular cars experience motion sickness, will also experience it in an AC. However, developments are taking place to reduce the experience of motion sickness. To examine whether these developments cause a shift for train passengers to ACs, these two scenarios will be the attribute levels of motion sickness. To measure the impact of motion sickness on AC passengers, the level of the train remains the same.

Train	Automated car
Level 1: As an occupant on a train, your experience of motion sickness is similar to any average train ride.	*Level 1*: As an occupant of an AC, your motion sickness experience is equivalent to that of a passenger in a regular car.
	Level 2: Due to pioneering technology, motion sickness in an AC is mitigated. Hence, as an occupant of an AC, you experience less motion sickness, and your experience is equivalent to that of a train passenger.

Table 7 - Motion sickness attribute levels

Level 2 of the AC states 'equivalent to that of a train passenger'. This is the maximum level of this attribute. Some travellers always suffer from motion sickness, even on the train. Research by Förstberg (2005) shows that reducing motion sickness among train passengers very difficult (Förstberg, 2005). Consequently, it was determined that the level of motion sickness experiences on the train represents the upper limit, and the attribute levels of the AC cannot surpass this level (Kremer et al., 2022; D. Li & Chen, 2022; Siddiqi et al., 2021). Setting this as a maximum enables the most realistic answers to be obtained and prevents unrealistic optimism. This will result in more valid results and thus more accurate interpretations of these results.

The two levels represent different ends of the car sickness aspect. However, because level 2 is caused by an external factor, a new technology, the two levels are not dependent on each other. As a result, the levels are orthogonal, meaning they do not correlate. Because the levels do not correlate, the parameters can be determined separately from each other (Rose & Bliemer, 2009). As a check question, respondents were asked at the end of the survey whether they suffer from motion sickness, and to what extent. The possible answers to this question were based on the Motion Sickness Severity Scale (MSSS) (Polymeropoulos et al., 2020).

4.2.2 Safety

While safety plays a minor role in choosing a regular car, it plays a major role in choosing an AC (Kaye et al., 2020). In the Netherlands, car passengers face an accident risk of 1.48 per billion kilometres, while train passengers encounter only 0.01 per billion kilometres. Although car accidents are nearly 150 times more likely, regular cars are still preferred over trains by the general population (CBS, 2021). The degree of impact on the decision changes when people have to choose ACs. Multiple studies show that there is a high concern, 70% or more, about the safety of automated systems (Greaves & Ellison, 2011; Kyriakidis et al., 2015; Othman, 2021; Rezaei & Caulfield, 2020; Schoettle & Sivak, 2014).

The definition of safety differs between trains and ACs. Dutch trains have a remarkably low accident rate, making passenger sentiment an important safety aspect. Given the communal nature of train travel, safety perceptions are influenced by fellow passengers. Conversely, this dynamic does not apply to private ACs. To ensure an equal comparison between trains and ACs in terms of safety, the study uses the attribute safety perception instead of general safety.

In a study by Molin & Kroesen (2022), attribute safety perception is tested with a numerical rating scale. On the scale, the lowest number is labelled 'very unsafe' and the highest number is labelled 'very safe'. However, Molin & Kroesen (2022) indicated that respondents' characteristics may influence the meaning of 'very unsafe' (Molin & Kroesen, 2022). Since it is a perception, this limitation cannot be completely removed, but by giving more explanation to the scores, this can be reduced.

- **Level 10 - High safety perception**
  Travellers are confident in the safety measures of both the train and the self-driving car. They feel comfortable, and relaxed and have no worries about possible dangers during the journey.
- **Level 8 - Reasonable safety perception**
  Travellers still have a considerable sense of safety, but perhaps there is a slight doubt or concern about safety in certain situations. Overall, however, they are confident in the safety arrangements and believe the risk of accidents or incidents is low.
- **Level 6 - Average safety perception**
  Travellers experience a moderate level of safety. They have some doubts and concerns about safety during the journey regarding reliability or possible technical failures. They do not feel completely reassured but still see enough potential in the safety of both vehicles.
- **Level 4 - Moderate safety perception**
  Travellers experience some insecurity while using the vehicle. They have low confidence in the safety of the vehicle and worry about possible accidents or incidents. They feel vulnerable and do not have much confidence in the protection and safety measures.
- **Level 2 - Low safety perception**
  Travellers feel extremely unsafe when using these vehicles. They believe the vehicle poses serious safety risks and avoid using it. They lack confidence in technology and consider it dangerous.

The attribute levels need to have an equidistance, which means that in a stated choice experiment the distances between levels must be the same size, in order to perform statistical analysis (Sanko, 2001).

Since the perception of safety for an AC is low according to the literature, it should be investigated whether safety perception is a driver for a shift from train passengers to ACs. Therefore, the levels have a linear rise to examine whether a shift will happen and when.

A score of 10 for trains is not realistic due the fact that the elimination of technical errors and unpleasant human behaviour can never be fully eliminated (Branton & Grayson, 1967; Kobayshi, 1994). In addition, because such a large percentage of people have concerns regarding the safety in an AC, it is unrealistic to completely lessen these concerns in the short term (Greaves & Ellison, 2011; Kyriakidis et al., 2015; Othman, 2021; Rezaei & Caulfield, 2020; Schoettle & Sivak, 2014). Therefore, giving AC an attribute level of 10 is not achievable in this SCE.

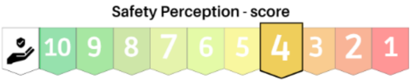
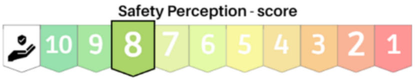
Train		**Automated car**	
Level 1:		*Level 1*:	
		Level 2:	
		Level 3:	

Table 8 - Safety perception attribute levels

Additionally, based on research by Cann and Calhoun (2001), it should be acknowledged that there could be a significant difference between a rating of 1 and a rating of 2 (Cann & Calhoun, 2001). However, since this is a hypothetical scenario, it is expected that nearly as many people will be discouraged by a rating of 2 as by a rating of 1, even though in reality there could be a substantial difference between them.

Due to the low number of train accidents in the Netherlands, only six occurred in the last 10 years, train passengers have a very high safety perception for trains. However, as mentioned earlier, the train does not get a score of 10, therefore the train is rated at 8 (Pel et al., 2014; Swuste et al., 2010). As this score is based on reality, there will not be varying attribute levels of the safety perception for the train, leading to the most realistic results.

Since the score of 10 for an AC is not realistic, and with a score of 2 the respondent will not likely choose the mode of transportation, making an attribute level of 2 redundant, the attribute levels of ACs are formed by the safety perception levels of are 4, 6 and 8.

4.2.3 Comfort

Comfort is an AC aspect and its impact on train usage is not yet researched, while research has been done on improving comfort for automated driving (Asua et al., 2022; Bae et al., 2019; Du et al., 2018).

Comfort is quantifiable into environmental and spatial factors. Environmental factors consist of temperature and noise, and spatial factors consist of workspace and seating (Asua et al., 2022). However, it was decided to split the factors from the latter category due to variations in interiors, usage and travel motivation. The seating category focuses on chairs and relaxation, while the workspace category focuses on the designated areas for work-related activities. As a result, comfort is split into three categories:

1. Environmental
2. Seating
3. Work-space

These three categories align with the developments of the ICNG in Section 3.1.3. In addition to this alignment, the accuracy of this categorization was also assessed during an oral session. Close contacts were asked about their interpretation of comfort in a transportation mode. Their responses aligned with the findings of Asua et al. (2022), highlighting environmental conditions, seating quality and workspace availability. To validate these findings, another group was asked to select their preferred comfort element among the three elements. All three components were selected multiple times, indicating that none could be eliminated. The results of both sessions are attached in Appendix E. Given the diverse range of respondents' perspectives on comfort, they were initially questioned about what the most important aspect of comfort is for them. Then, based on their chosen answers, they were presented with a specific scenario question, related to their selected aspect of comfort, while the other two comfort elements remained concealed. This approach measures each respondent's actual preference, while still allowing a comparative analysis of responses.

Workspace

Numerous articles discuss working in ACs, portraying various scenarios such as a fold-out table or even a flexible pull-out table. To measure whether the level of workplace comfort influences respondents' choice, these two degrees of impact form the two levels (R. Happee, 2023; Mizielińska-Chmielewska, 2018; Roy, 2019; Spance10, 2017). The attribute level for the train remains the same in every scenario, due to the fact that this level is based on the developments of the ICNG, as described in Section 3.1.3 (Collet et al., 2022; NL Times, 2022).

Train	Automated car
Level 1: • Individual workstations are provided, each equipped with a stationary table or fold-out tables by the seats. • There are electrical power sockets located by the seats. • Wifi connectivity is available	*Level 1*: • A fold-out table is provided for placing your laptop or other items. • There is an electrical power socket located under the seat. • Mobile internet connectivity is available
	Level 2: • The steering wheel can be folded away, and there will be a spacious and flexible pull-out table. • This pull-out is equipped with a wireless charger. • High-speed 5G internet connectivity is available.

Table 9 - Comfort workspace attribute levels

Seating

The same principle applies to seating in an AC. Numerous news articles have been published featuring the concept of the 'ideal' seat. These range from seats that can slide back and have adjustable arms, to seats that can be fully reclined, with adaptable resting pads designed for the passengers. To assess whether the degree of seating comfort impacts the respondent's modality choice, the two levels of influence are considered (Adient, 2021; D. Brown, 2020; Sokurenko, 2023; Tangemann, 2019). The attribute level for the train remains consistent and is based on the ICNG, as described in Section 3.1.3 (Collet et al., 2022; NL Times, 2022).

Train	Automated car
Level 1: • The train seats are spaced far apart, allowing enough room for a big to fit between them. • On both sides, there are wide arm supports. • The seats are wide and have soft cushioning.	*Level 1*: • When the self-driving system is engaged, the seat automatically slides back. • Solid and adjustable armrests are located on both sides. • The seat is spacious and deep.
	Level 2: • During the ride, the seat can be fully reclined and flattened. • The armrests have reclining pads adapted to the passenger's comfort. • The seat has adjustable sides, enabling customization for wider seating space.

Table 10 - Comfort seating attribute levels

Environment

Lastly, developments are also taking place in the area of environmental comfort, ranging from the implementation of a ventilation system to a comprehensive noise-cancelling interior. These varying degrees of environmental comfort form the attribute levels to measure whether increased comfort causes a shift in modal choice (Keene, 2021; Maniar, 2021; Nissan, 2023). The attribute level for the train remains the same and is derived from the ICNG, as described in Section 3.1.3 (Collet et al., 2022; NL Times, 2022).

Train	Automated car
Level 1: • There are multiple vents present, equipped with a filtering system. • Sensors are utilized to measure and automatically regulate the temperature. • The wagons' walls are equipped with sound insulation.	*Level 1*: • There is a ventilation system is present, allowing passengers to adjust the direction of airflow to their preferences. • The temperature is automatically adjusted based on current weather conditions. • The interior is made of sound-absorbing materials that reduce noise pollution.
	Level 2: • An air purification system actively detects and eliminates harmful pollutants. • Passengers can set their preferred climate zone for each individual seat. • The car's floor, walls and roof are equipped with sound insulation, complemented by designed tires aimed at minimizing noise pollution.

Table 11 - Comfort environment attribute levels

In summary, the comfort attribute levels for the train remain consistent as they align with the actual comfort aspects of the ICNG. However, for the AC, this remains uncertain, implying potential fluctuations in the degree of comfort. These levels are derived from the potential designs outlined in the (grey) literature. This allows for the assessment of the impact of transitioning the focus by AC manufacturers from less comfort to more comfort in an AC.

4.2.4 Methodological Decision

For the variable 'comfort', the decision was made to treat this attribute as independent in order to assess its influence on the probability of a mode shift. The attribute levels described in this section remain unaffected by the presence of other individuals, regardless of whether there is one or thousand other travellers. This approach enables the isolation and measurements of the specific impact of 'comfort', thereby avoiding the situation where 'comfort' becomes a confounding variable. Confounding variables may appear to explain certain aspects, but are in reality influenced by unmeasured third variables, such as the human factor or crowding in this context (Austin & Brunner, 2004; Frank, 2000). Such situations can introduce bias into the results and lead to inaccurate conclusions. To circumvent this issue, the methodological decision was made to base the attribute levels on independent components.

Safety perception poses a challenge as a confounding variable, given the inherent nature of the term 'perception', when comparing the safety of trains and cars. The ability to assess safety takes precedence over the risks of safety being a confounding variable, and can therefore not be altered (Wilson & Gordon, 1986). Negative consequences may arise from wrong cause-and-effect relationships; however, these can be mitigated through the inclusion of control variables and their significance level (Austin & Brunner, 2004; Frank, 2000). In this study, the attribute safety encompasses three variables, with two of them serving as control variables. The significance of these variables is further discussed in Chapter 5. Lastly, Motion sickness, being an individual characteristic, does not function as a confounding variable by itself. Therefore, the choice of attribute levels is primarily pertinent to the comfort attribute.

4.3 Fixed attribute and attribute levels

In addition to the varying attributes discussed in Section 4.2, this SCE also encompasses fixed attributes, as described in Section 2.7 (Guerra et al., 2018; Mwale et al., 2022; Shen et al., 2016; Tembe et al., 2019; Zheng et al., 2016). These fixed attributes are not the main focus of this SCE and are therefore fixed and require one level each.

4.3.1 Fixed levels

The fixed attributes are the transportation mode characteristics derived from the conceptual model. In Table 12 these attributes have been assigned names that are more comprehensible to the respondents. Additionally, this table includes fixed levels accompanied by brief descriptions of the calculations (Hensher, 2006). All attributes are based on the actual data of the train and (automated) car of the Rotterdam - Amsterdam route, as described in Section 4.1.

Attribute	Train	(Automated) Car	Brief description
Distance from origin to transport mode	• 2,500 meter	• 50 meter	From Section 4.1: The average distance to a station in Rotterdam is 2.74 km, while in Amsterdam, it is 2.17 km. This results in an average distance of approximately 2,500 metres when rounded up. Private AC distance approximated at 50 metres.
Time in the main transport	• 40 minutes • Every 15 minutes	• Peak: 1 hour and 45 minutes • Off-peak: 60 minutes	From Section 4.1: Travel time by car outside of rush hour is 60 minutes, and during rush hour it is 105 minutes (NVP, 2023). By train, it takes 40 minutes (NVP, 2023).
Price	• €17.50 • 2nd class	• €16.25	From Section 4.1: Costs of a car trip on the R-A route are €16.25, including expenses for fuel, maintenance, and depreciation (NS, 2023; NIBUD 2023). The cost of a train ticket for the R-A route is €17.50 (NS, 2023; NIBUD 2023).
Distance from transport mode to destination	• 400 meter	• 400 meter	The distance between the ending of the journey with the transport mode and destination has minimal effect, therefore it is the same for both transportation modes.
CO_2 emission	• 40 times less than a fuel car • 5 times less than an electric car	• 1.5 times more than an electric car	From Section 3.1.1: CO_2 emissions comparison indicates Dutch trains emit 40 times less CO_2 than gasoline cars and five times less than electric cars, with ACs emitting 1.5 times more than electric cars.

Table 12 - Fixed attribute levels

Detailed calculations from this table are provided in Appendix F.

It is important to acknowledge that for scope for this study, these variables are fixed. In reality, the costs of the AC will likely be higher since a private AC is expected to be more expensive than an electric car. Additionally, train fares increase annually, a factor not accounted for in this current study.

4.4 Expert validation

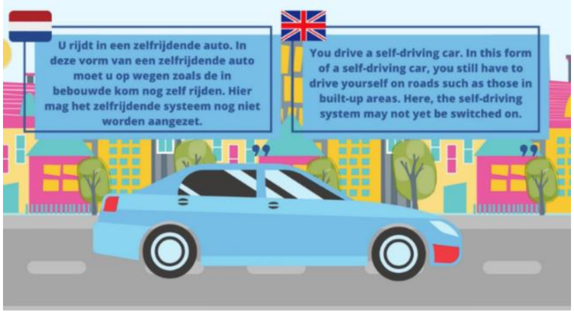
A traditional Stated Choice Experiment typically involves varied attributes in each scenario, creating unique combinations. However, this study has adopted a different approach to the Stated Choice Experiment by interpreting the identified attributes from the literature review as fixed attribute levels. This approach enables to measure the pure effect of ACs. If the different levels of these attributes were measured, no distinction can be made within all scenarios between when train travellers choose an AC or a regular car (Van Essen, 2023). Additionally, fixation eliminates choices through excessive optimisation. These fixed levels are the attribute features of both transportation modes operating on the Rotterdam – Amsterdam route.

This study's Stated Choice Experiment deviates from the traditional method. Because of this, it is essential to subject the methodology and final survey design to expert validation. For this, the expert is Mariska van Essen, an academic expert in stated choice experiments. Van Essen's involvement included two sessions: contributing to the design of the attribute levels and validating the alternative stated choice method. The latter session led to the conclusion that this approach facilitates the collection of more detailed information on how the three attributes (comfort, motion sickness and safety) that are not yet investigated, influence the decision for choosing a given transportation mode (Van Essen, 2023).

4.5 Concept clarification

When respondents are questioned about the definition of an AC, it is likely that individuals may have varying perceptions regarding the operation of an AC level 4. In the context of a study investigating the impact of ACs, it becomes paramount to establish a standardized, accurate understanding of what an AC is and how it works. In order to ensure robustness in the results derived from the stated choice experiment, uniformity in the understanding among respondents of what an AC is necessary. To achieve this, a video is made to explain how an AC SAE level 4 works. The video highlights three primary aspects:

Explaining when the self-driving system may/should be activated and deactivated. Figure 7 displays a screenshot from the video, highlighting when to activate the system.



U rijdt in een zelfrijdende auto. In deze vorm van een zelfrijdende auto moet u op wegen zoals de in bebouwde kom nog zelf rijden. Hier mag het zelfrijdende systeem nog niet worden aangezet.

You drive a self-driving car. In this form of a self-driving car, you still have to drive yourself on roads such as those in built-up areas. Here, the self-driving system may not yet be switched on.

Figure 7 – Screenshot of the moment of activating the automated system

Visualisation of the activation process. *Figure 8* displays a screenshot from the video, highlighting the activation process.

U drukt de auto pilot knop in en het systeem activeert

You press the auto pilot button and the system activates

Source: Volvo Concept 26

Figure 8 - Screenshot of how the activation process works

Visualisation of the execution of other tasks while the automation system is in operation. Figure 9 displays a screenshot from the video, highlighting the performance of other activities.

U kunt andere activiteiten uitvoeren zoals lezen en liggen

You can do other activities such as reading

Source: Volvo Concept 26

Figure 9 - Screenshot of performance of other activities

4.6 Survey design test

Prior to distributing the survey to the intended target group, the survey design needs to be tested in order to identify and correct any potential issues or ambiguities within the survey questions, instructions, or overall structure (Hoyos, 2010). The survey validation process of the survey design comprises two components, question validation and video validation.

4.6.1 Test Group

Both the video and the survey design underwent an examination from three distinct groups: one expert, three acquainted and four individuals unacquainted with automated driving. To ensure the correctness of the questions and video content, expert S. Nordhoff underwent an interview, aiming to validate accuracy (Nordhoff, 2023). Participants who are unfamiliar with automated driving were tasked with evaluating the video's comprehensibility and the clarity of the AC concept. The group was asked to repeat the automation concept and activation process. This last step was designed to check whether the survey was simple and clear for respondents to complete. Lastly, the results of the sessions with both groups were shared with the opposite group.

The characteristics of the two test groups are added in Table 13.

Attendee	Age	Gender	Highest education level	Employment	Acquainted with automated driving
1	42	Female	PhD	Researcher Mobility and Behaviour	Yes
2	35	Female	PhD	Postdoctoral Researcher	Yes
3	62	Male	PhD	Professor	Yes
4	35	Male	PhD	Researcher Mobility and Behaviour	Yes
5	22	Female	Higher Professional Education (HBO)	Student	No
6	57	Female	Master's Degree	Human Resource Manager	No
7	28	Male	Higher Professional Education (HBO)	Team leader IT consultant	No
8	61	Male	Higher Professional Education (HBO)	Economist	No

Table 13 - Characteristics of test group

4.6.2 Results from Test Group

During the validation session, Nordhoff's main observation suggested that in an SAE level 4 car, the driver is not obligated to turn off the automation system upon exiting the highway (Nordhoff, 2023). However, when this dilemma was presented to individuals unfamiliar with automated driving during the validation session, it led to a lack of clarity regarding the content of the video and resulted in confusion about the concept of ACs. As a result, it was decided to exclude Nordhoff's aforementioned comment.

In addition to the definition dilemma, five other dilemmas were presented to the test group. The key takeaways from this validation session are that all three components – seating, workspace, and environmental – were confirmed as comfort through an open questionnaire. Additionally, each of these three components was selected through a different multiple-choice question, leading to the decision not to eliminate any of the components in the survey design. The test group preferred a layout with illustrations over a table layout. To measure safety perception, the test group opted for a numerical score rather than a comparison score. The group additionally chose a numerical score that ranges from 1 to 10 instead of an A to E rating system. Lastly, the test group chose for the survey to be designed for mobile phones, rather than for laptops, as it facilitates easier access to the target group of train passengers. Further, the validation session is added in Appendix G.

Following the content validation round, the survey design was finalized. This was followed by the testing phase of the final survey, a critical stage in a stated choice experiment. The same test group constituted the group of potential respondents, including both train passengers familiar and unfamiliar with ACs. Feedback from the test was that out of the 8 respondents, the average time it took to complete the survey was 11 minutes. However, it was decided to reduce the completion time with 3 minutes, as the test group was asked to provide feedback on the survey. All eight respondents indicated that they understood everything in the finalized survey, and no feedback concerning comprehension was received. Due to a poor internet connection and issues with Firefox, some figures did not always load. Unfortunately, this falls under the category of force majeure, and no adjustments can be made to address

4.7 Survey structure

The survey was set up with LimeSurvey, an open-source survey software. This software makes it easy to analyse the results and relationships between them. In addition, respondents remain anonymous with this software. The survey consists of an introduction, scenarios, person-related questions and finally an open-ended question.

- Introduction
  Before the start of the survey, an introduction page is visible. This page includes the author’s personal details, encompassing the name, surname, study and a short statement outlining the purpose of the survey. Mentioning these elements serves to establish a connection and to ease engagement. Additionally, the structure of the questions is highlighted, and the explanation video is provided at the end of the introductory page.
- Scenarios
  The first scenario in the survey is the baseline scenario, which involves the fixed attribute levels based on the characteristics of both transportation modes on the route Rotterdam-Amsterdam. The responses to the baseline scenario provide an understanding of the respondents’ initial preferences and their motivations. Subsequently, the attributes of safety perception, motion sickness, and comfort were individually added to the fixed attributes. This approach designates the base case as the control group, making it possible to assess how specific attributes influence the choice and to what extent. This allows a direct comparison between the original and adjusted preference.
- Attribute rating
  As a cross-verification step, respondents are asked to rank the attributes according to their impact on their decisions. This ranking involves identifying the attribute that exerted the most influence on their choice in the first place, and the attribute with the least influence in the last place.
- Characteristics
  After the scenarios come the questions to build the respondent's profile. This is split into 3 parts: personal characteristics, car use and train use.
  - *Personal Characteristics*
    This section includes the characteristics added to the conceptual model: age, gender, employment, environmental awareness, and income. This is followed by a control question that assesses if respondents experience motion sickness and its severity. This question is designed to explain the results of the motion sickness scenario questions.
  - *Car use*
    This section contains questions to identify respondents’ current car usage. A target group control question is included as a preferred point. If train passengers don’t have a driving licence, their responses will be eliminated from the results as they aren’t the intended survey target group for research on ACs. Lastly, there are questions included examining their car payment, familiarity with AC features and their driving motive.
  - *Train use*
    This final section contains questions to map respondents’ train usage. To examine the walkability attribute, the distance to the nearest station is asked. Additionally, respondents are asked about their preferred means of travelling to the station, their frequency of train travel, their performed activities during the trip, and their motive to use the train. Moreover, respondents are asked to indicate their travel class and if they have to pay for their train use.

- Open question
  To end, an open question has been added for comments and a thank you is shown for completing the survey.

The final survey is added in Appendix H.1 and in Dutch in Appendix H.2.

4.8 Distribution

The goal is to ensure that the survey is distributed to a target group that matches the train passenger population. To achieve this, the survey will be randomly distributed through both personal and non-personal contacts, as aforementioned in Section 3.4. LinkedIn and WhatsApp are the selected platforms for this distribution, with the addition of the explanation video to avoid potential understanding problems due to technical issues. The personal contacts were requested to share the survey with other train passengers they knew. A possible drawback of this approach is that it could attract mainly respondents who are still studying. This biasing effect could lead to unbalanced results, a limitation whose occurrence should be tested in the data analysis.

In addition to online distribution, the survey was also distributed offline. Train passengers were directly approached, and the survey's purpose was explained. To facilitate ease, a plasticized QR code was provided, enabling respondents to complete the survey at their convenience, whether this was at the station or during their train journey. This approach offers the advantage of reaching respondents who are harder to reach online, such as the elderly. However, it is important to acknowledge that an unconscious selection occurs due to the human factor in the selection process. This limitation also increases the chance of a biased respondent group and is further explained in Section 7.5.

5 Results

This chapter discusses the survey sample in Section 5.1. Section 5.2 presents descriptive statistics to offer a comprehensive view of the sample. In Section 5.3, the results are analysed to assess the model's fitness. Following that, Section 5.4 interprets the model's outcomes. The chapter ends with a conclusion in Section 5.5

5.1 Survey sample

In this section is the sample size discussion, followed by the established measurements to safeguard personal data, followed by the discussion of excluding data in the analysis.

5.1.1 Sample size

In order to draw valid conclusions from survey results, a minimum number of respondents must be obtained. In Section 2.4, Equation 1.1 was introduced to determine the minimum required number of participants. With the attributes and attribute levels established in Chapter 4, the calculation for the minimum number of respondents is performed, resulting in a minimum requirement of 94 respondents.

$$N \geq 500 * \frac{l}{J{*}S} = N \geq 500 * \frac{3}{2{*}8} = 93.75 \approx \text{minimum 94 respondents}$$

The data were collected from July 19 to August 24, 2023, and the minimum requirement of 94 respondents was met, as the survey collected 171 respondents. The survey was opened by 228 individuals, thus 57 (25%) individuals did not complete the survey.

5.1.2 Personal Data Protection

Throughout this study, measurements have been taken to safeguard personal data. This has been achieved by ensuring complete respondent anonymity, where no IP addresses, email addresses, or names have been collected (Iversen et al., 2006). Any unintentional exposes in the open question at the end of the survey has been removed. Furthermore, data security is ensured through password protection, limiting access to the creator's account. Lastly, the survey data will be deleted the day after the final thesis is submitted. This approach ensures data availability if needed and removes it once it becomes unnecessary. No backups of the data are maintained.

5.1.3 Excluded respondents

In advance, the requirement was set that respondents without driving licenses would be excluded from the dataset. It was expected they would likely be in their early twenties and still students. However, upon closer examination of the dataset, it became apparent that the profiles of the respondents without driving licenses (n = 17) spanned an age range from 20 to 60 years old, with a mean of 45. This contradicted the initial assumptions.

Subsequently, during the data analysis, further discussed in paragraph 5.3, the first round of analysis was conducted both with and without the group of respondents without driving licenses. While the results showed no substantial differences, there was a slight decrease in the significance level. Therefore, it was decided to retain the group of respondents without driving licenses in the analysis.

5.2 Descriptive data

In this section, the descriptive statistics are provided to introduce the dataset. These statistics reveal how the data is spread and how closely it aligns with the real distribution of the Dutch population. This comparison allows for the identification of unusual data points, known as outliers, within the data set.

5.2.1 Respondent characteristics

Mapping the socio-demographic characteristics of the respondents provides additional context, enhancing the understanding of the respondents' profiles and the distribution of the data. Furthermore, this approach enhances transparency and reproducibility in the study. The characteristics are added to Table 14. A column has been added to the table with actual population figures for comparison.

The survey included age as a continuous variable. However, for the purpose of analysis, age was categorised into three groups: 18 to 24 years, 25 to 50 years, and 51 years and older. These categories are consistent with those employed by CBS (CBS, 2022a). Furthermore, the data were coded in order to compute an MNL, which is added to Table 14.

Name	Code choices	Freq	%	NL %
Age	18 to 24 years	47	27	11.1
	25 to 50 years	86	50	46.6
	51 years and older	38	38	42.3
Gender	1 = Female	61	36	50,3
	2 = Male	110	64	49.7
Employment	1 = Employed	139	81	68.4
	2 = Studying	26	15	6.7
	3 = Retired	6	4	22.6
	4 = unemployed	0	0	2.3
Income	1 = €0 to €1500	22	13	19.0
	2 = €1500 to €2500	16	9	22.4
	3 = €2500 to €3500	50	29	20.2
	4 = €3500 to €4500	37	22	22.9
	5 = €4500 to €6000	20	12	12.5
	6 = €6000 or more	19	11	3.0
	7 = I prefer not to tell	7	4	/
Level of motion sickness	1 = Never	60	35	16
	2 = Seldom	62	36	29
	3 = Sometimes	35	20	26
	4 = Often	14	8	16
	5 = Always	0	0	13
Degree of environmental awareness	1 = I see myself as not environmentally aware at all	3	2	3
	2 = I see myself as a little environmentally aware	36	21	11
	3 = I see myself as moderately environmentally aware	117	68	66
	4 = I see myself as very environmentally aware	15	9	20
Distance to the nearest train station	1 = 0 to 2.5 km	112	65	9.4
	2 = 2.5 to 5 km	34	20	42.4
	3 = 5 to 7.5 km	11	6	25.9
	4 = 7.5 to 10 km	6	4	12.9
	5 = more than 10 km	8	5	9.4
Train travel frequency	1 = Once or less per year	2	1	7.4
	2 = Several times a year	17	10	9.4
	3 = Several times a month	41	24	45.2
	4 = Several times a week	111	65	38.1
Class	1 = 1nd class	22	13	20
	2 = 2nd class	133	78	80
	3 = I have no preference	16	9	/
Ownership of an NS business card	1 = No, I do not have an NS BC.	65	38	/
	2 = Yes, I have an NS BC. and it is subsidised from my work.	104	61	/
	3 = Yes, I have an NS BC. but it is not subsidised from my job.	2	1	/
Ownership of a driving license	1 = Yes	154	90	65.9
	2 = No	17	10	34.1
Years of driving experience	1 = 0 to 5 years	26	17	6.3
	2 = 6 to 15 years	74	48	29.7
	3 = 16 years or more	54	35	64.0
Ownership of a car	1 = Yes	80	52	58
	2 = No	74	48	42
Type of car	1 = A fuel-based car	72	90	89.1
	2 = A hybrid car	4	5	4.8
	3 = An electric car	4	5	6.1
Presence of automatic parts	1 = No, there are no automatic systems present in my car.	44	55	/
	2 = I don't know if these parts are present in my car.	1	1	/
	3 = Yes, there are one or more automatic systems in my car. but I do not use them.	3	4	/
	4 = Yes, there are 1 or more automatic systems present in my car and I use them.	32	40	/

Table 14 - Descriptive statistics including codes and population comparison (sources; CBS, 2018, 2022b, 2022a, 2023c, 2023a, 2023d, 2023b; Czeisler et al., 2023; Gemiddeldgezien.nl, 2023)

Of two variables, the data of the distribution of the Dutch population is not available. While there is existing data on the ownership of NS business cards, there is a lack of information on whether their cards are subsidized by their company (Hildebrand, 2017). Additionally, there is no existing research on whether individuals utilize the automated components in their cars. It is expected that this lack of research in this latter area may be attributed to the fact that it has not yet gained significant interest within the research community.

The variable "distance to nearest station" shows a notable difference from the distribution within the Dutch population. This difference is attributed to the fact that the survey respondents consist of only train passengers. Individuals who have a preference for train travel tend to choose for residences in close proximity to a train station. This is evident from the significant percentage of respondents falling in the "0 to 2.5 km to a train station" category. This phenomenon is commonly referred to as residential self-selection, where individuals choose their place of residence based on their personal preferences (Van Wee, 2009).

5.2.2 Completion time

The average time taken by all survey participants to complete the survey was 12 minutes en 31 seconds. However, there were four instances of unusually long completion times, which were 7 hours en 18 minutes, 2 hours and 6 minutes, 1 hour and 54 minutes, and 1 hour and 24 minutes. Based on research by Matjašič et al. (2018), it was decided to classify only completion times exceeding one hour as outliers, as there was not enough information to consider completion times under an hour as outliers (Matjašič et al., 2018).

Upon further examination of these four responses, it was evident that one particular question required significantly more time to answer. It is assumed that respondent have eft the survey open to return later to it. After removing these outliers from the dataset, the average completion time decreased to 8 minutes and 36 seconds. This aligns closely with the expected completion time, which had been communicated to respondents as a commitment.

5.2.3 Choice distribution

The distribution of choice scenarios has been included in Figure 10. For each scenario (1 to 8), the percentages of respondents choosing the train and those choosing the AC are provided. The survey's target audience comprised train passengers. Therefore, it is reasonable that in the base case (1), 85% chose the train. The 15% of respondents who chose the AC in the base case are likely to train passengers who were intrigued by the explanatory video on ACs.

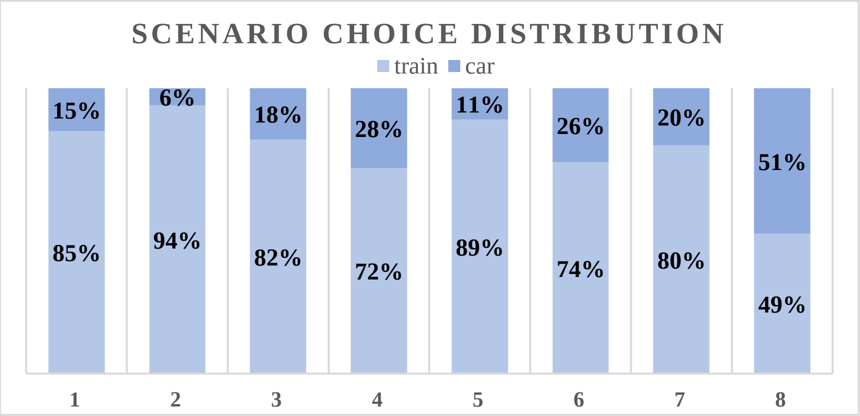


Figure 10 - Scenario choice distribution for train or automated cars

Interestingly, in each scenario, the train emerges as the preferred mode of transportation, except for the last scenario. In this particular scenario, the comfort level of an AC surpasses the comfort level of a train. A Multinominal Regression Analysis is performed to statistically capture this occurrence.

5.2.4 Coding design

In order to conduct a Multinominal Regression Analysis, it is necessary to code the scenarios using a dummy coding scheme (Hardy, 2010). A dummy coding scheme is created to transform nominal/ordinal variables into numerical values, making them suitable for regression analysis (El-Habil, 2012). The dummy coding scheme is provided in Table 15.

	Safety				Motion sickness			Comfort		
Scenario	**Basecase**	**8 and 4**	**8 and 6**	**8 and 8**	**Basecase**	**Car worse**	**Equal**	**Basecase**	**Equal**	**Car better**
1	1	0	0	0	1	0	0	1	0	0
2	0	1	0	0	1	0	0	1	0	0
3	0	0	1	0	1	0	0	1	0	0
4	0	0	0	1	1	0	0	1	0	0
5	1	0	0	0	0	1	0	1	0	0
6	1	0	0	0	0	0	1	1	0	0
7	1	0	0	0	1	0	0	0	1	0
8	1	0	0	0	1	0	0	0	0	1

Table 15 - Scenario coding design scheme

Subsequently, the answers of each respondent were integrated into this coding scheme. In Appendix I the complete dataset of one random respondent has been included to provide a clear demonstration of how the final dataset was assembled.

Dummy coding allows for the inclusion of different units in the model simultaneously, however, this leads to unstandardized beta coefficients. This is because it preserves the original units of measurements of the dependent variables in the regression model (Fassott et al., 2016; Whitt, 1986). Unstandardized coefficients can be valuable as they quantify the actual change in utility (J.-O. Kim & Mueller, 1976). Nevertheless, it is important to consider them carefully in interpretation and to not rely on them as mere numerical values. Section 5.4 reiterates this.

5.3 Modal specification

To determine the optimal set of parameters, all variables were initially included in the modal as dependent variables for the decision between train and AC. In the initial model encompassing all variables, the model was constructed twice: once with individuals who do not possess a driving licence included in the dataset, and once with them excluded from the data set. The disparity between these two datasets was minimal, and the model's fit remained the same. Further discussion on the model's fit is provided in Section 5.3.1. Since removing the data of respondents without a driving license did not improve the model, it was decided to retain this data within the dataset.

For the initial analysis, all variables were included in the model. In the set of parameter estimates resulting from this initial model, the base case values for comfort, safety and motion sickness were set to 0 as they served as the reference group. Furthermore, the parameters related to car ownership and having a driving license were also set to 0 because they are redundant. Redundant means that the variable has no significant influence on the model (Lei et al., 2019). These redundant variables were subsequently removed from the model, and the regression analysis was rerun without their inclusion.

In the next step, within the model without redundant parameters, variables with the highest significance levels were excluded if the removal was supported by the existing literature (Vakhitova & Alston-Knox, 2018). At each step, and assessment of the models' fitness was conducted to determine whether the removal of variables improved the models' fitness (Sentas & Angelis, 2006). This iterative process was repeated five times until the most optimal modal fit was achieved and the retained variables were logically justified. A comprehensive elaboration of the steps, along with textual explanations, is provided in Appendix J.

5.3.1 Modal fitness

To assess the model's fitness of the final model, the -2 Loh Likelihood (hereafter; -2LL) and the McFadden R-squared (hereafter; R^2) are considered and added in Table 16.

Statistical measures	Output
-2 Log Likelihood	536.1
McFadden R-squared	0.236

Table 16 - Model fitness data

The -2LL has a value of 536.1, which represents the lowest value among all steps of the elimination process, indicating the final model is the best-fitting version among all examined (Fagerland & Hosmer, 2012). An R^2 value of 0.236 means that 23,6% of the variation in the dependent model is explained. Given the large number of independent variables in the model, this is a substantial percentage, implying a reasonably strong fit (El-Habil, 2012).

5.3.2 MNL Equations

The final MNL model has been established, leading to the establishment of utility Equations for both train and AC alternatives. For attributes with two levels, one parameter is determined, and for attributes with three levels, two parameters are determined (He et al., 2012). Since each attribute has a reference base case as reference, the included levels correspond to the scenarios presented in the survey, and they serve as the parameters. The fixed attributes do not have a beta parameter.

The utility functions are specified as follows:

$$U_{train} = 0 \tag{2.1}$$

$$\begin{aligned} U_{AC} = {} & asc + \beta_{safety\_8and4} * safety_{8and4} + \beta_{safety_{8and6}} * safety_{8and6} + \beta_{safety_{8and8}} * safety_{8and8} \\ & + \beta_{motionsickness_{carworse}} * motionsickness_{carworse} + \beta_{motionsickness_{equal}} * motionsickness_{equal} \\ & + \beta_{comfort_{equal}} * comfort_{equal} + \beta_{comfort_{carbetter}} * comfort_{carbetter} + \beta_{travelfreq} * travelfreq \\ & + \beta_{autoparts} * autoparts + \beta_{age} * age + \beta_{neareststation} * neareststation + \beta_{levelmotionsickness} \\ & * levelmotionsickness + \varepsilon \end{aligned} \tag{2.2}$$

Where:

U_{train} = systematic utility of alternative train (the base alternative)
U_{AC} = systematic utility of alternative automated car (AC)
acs = alternative specific constant
$\beta_{safety_{8and4}}$ = parameter for the situation of train safety perception is 8 and AC safety perception is 4
$\beta_{safety_{8and6}}$ = parameter for the situation of train safety perception is 8 and AC safety perception is 6
$\beta_{safety_{8and8}}$ = parameter for the situation of train safety perception is 8 and AC safety perception is 8
$\beta_{motionsickness_{carworse}}$ = parameter for the situation where the MSE for the AC is equal to the MSE of a regular car
$\beta_{motionsickness_{equal}}$ = parameter for the situation where the MSE for the AC is equal to the MSE of a train
$\beta_{comfort_{equal}}$ = parameter for the situation where both comfort levels are qualified as 2/3 stars
$\beta_{comfort_{carbetter}}$ = parameter for the situation where the comfort level of AC is qualified as 3/3 stars
$\beta_{travelfreq}$ = parameter for train travel frequency
$\beta_{autoparts}$ = parameter for the presence and usage of automatic parts in an owned car
β_{age} = parameter for age
$\beta_{neareststation}$ = parameter for the nearest train station
$\beta_{levelmotionsickness}$ = parameter for the level of motion sickness experienced by travellers
ε = random error

5.4 MNL model results

To run the model, the software SPSS is used. Table 17 represents the parameters of the final model. The beta coefficients indicate whether the utility will increase or decrease as an attribute changes. In this model, 'rising' attribute levels signify the transition between 'on' and 'off', indicating whether a scenario is active or inactive. This subsection provides a general overview of the results, while a more in-depth quantitative analysis of the findings will be presented in Chapter 6.

Choice (0 = train 1 = AC)^a - Parameter estimates							
						95% confidence interval for Exp(β)	
Variable	**β**	**ε**	**Wald**	**Significance**	**Exp(β)**	**LB**	**UB**
(Intercept)	**-3.480**	1.004	12.006	.001*			
Safety_8and4	**-1.331**	.627	4.505	.034*	.264	.077	.903
Safety_8and6	**.308**	.455	.459	.498	1.361	.558	3.318
Safety_8and8	**1.250**	.426	8.613	.003*	3.491	1.515	8.045
motionsick_car_worse	**-.373**	.501	.553	.457	.689	.258	1.840
motionsick_car_equal_to_train	**1.181**	.427	7.655	.006*	3.259	1.411	7.526
Comfort_both_good	**.401**	.450	.793	.373	1.493	.618	3.610
Comfort_car_better	**2.255**	.427	27.932	.000*	9.534	4.132	22.000
often_traintravel	**-.969**	.152	40.378	.000*	.380	.282	.512
auto_parts	**.337**	.080	17.564	.000*	1.401	1.197	1.640
Age	**.027**	.008	11.666	.001*	1.027	1.012	1.043
class	**.824**	.198	17.283	.000*	2.280	1.546	3.363
neareststation	**.395**	.117	11.403	.001*	1.484	1.180	1.866
levelmotionsickness	**-.131**	.118	1.229	.268	.877	.696	1.106

Table 17 - Parameter Estimates for all included variables

Almost all parameters are statistically significant at a 95% confidence interval, which corresponds to a significance level of < 0.05 (Nakagawa & Cuthill, 2007). There are four variables that do not achieve significance; I) the scenario involving safety perception at level 8 for the train and level 6 for the AC, II) the scenario where motion sickness is more severe in the AC than in the train, III) the scenario where both comfort levels are equally good, and IV) the degree of motion sickness experienced by individuals.

Regarding the latter variable, while its effect on the transportation mode choice is supported in the literature, the MNL model does not provide statistical evidence of its effect on the model (Dam & Jeon, 2021; Diels et al., 2016; Edelmann et al., 2016; Salter et al., 2019). This could be due to the dataset's size or because the variable may correlate with transportation choice but not in a statistically significant matter (Shrestha, 2021). Due to the literature, it is expected that the level of motion sickness still has an influence on the transportation mode choice, and therefore it was decided to retain it in the model.

The first three non-significant variables representing the scenarios show a high correlation, above 0.5, with the base case from their factor (Masson et al., 2003). The correlation scheme is included in Table 18. This shows multicollinearity, the situation in a multiple regression where variables have a higher correlation with each other (Kløjgaard et al., 2012). However, these variables with multicollinearity can be kept in the analysis because they are important to the research question and thus have theoretical relevance (Kløjgaard et al., 2012). Hence, given that the study focuses on these scenarios, they are retained in the model.

Pearson Correlation	**Safety_base**	**Safety _8and6**	**motionsick _base**	**motionsickcar_ worse**	**Comfort_ base**	**Comfort_ both_good**
Safety_base	1	**-.588****	-.447**	.293**	-.447**	.293**
Safety_8and6		1	.218**	-.143**	.218**	-.143**
motionsick_base			1	**-.655****	-.333**	.218**
motionsick_car_worse				1	.218**	-.143**
Comfort_base					1	**-.655****
Comfort_both_good						1
** Correlation is significant at the 0.01 level (2-tailed).						

Table 18 - Correlation scheme of redundant variables

5.4.2 Interpretation results

This subsection discusses what exactly the parameters mean. It is important to note that these parameters represent unstandardized coefficients, as mentioned in Section 5.2.4. These coefficients show the change in utility of AC associated with a one-unit change in the independent variable. Unstandardized coefficients are more challenging to interpret than standardized coefficients. Conclusions are drawn cautiously when working with unstandardized coefficients. These coefficients are expressed in the original units of the variables. In the case of the safety, motion sickness, and comfort scenarios, they are binary, representing either occurrence (1) or non-occurrence (0). Furthermore, all variables are expressed in different units; age is measured in years, while the scenarios are in an 'on' or 'off' state. The parameters of the variables have been interpreted from this perspective.

The **ASC** represents the base value when all other variables are set to zero, which is *-3.480*, indicating a strong preference for the train which has a utility of 0.

Regarding the **safety perception** scenarios, as the safety level of the AC increases, its utility rises as well, influencing travellers to favour AC as their modal choice. Namely, with a safety level of 4, the beta coefficient is *-1.331*, indicating a strong negative influence on travellers' choice for AC. As the safety perception reaches level 6, the beta coefficient becomes *0.308*, essentially reversing its direction to a positive value. Finally, when the safety perception level for the AC matches that of the train at 8, the beta coefficient increases to *1.250*, further increasing the probability of train passengers choosing AC.

When passengers experience more **motion sickness** in the AC than in the train, the beta coefficient is *-0.373*. This suggests that as motion sickness worsens, train passengers are less likely to choose the AC. When a breakthrough technology mitigates the experience of motion sickness in the AC to match that of a train, the beta coefficient becomes *1.181*. In essence, when the experience of motion sickness in the AC is mitigated, the probability of passengers selecting AC over the train increases.

Comfort emerges as the most influential factor, with a positive preference for AC when both transportation modes offer a good comfort level. The beta coefficient is *0.401*, indicating a favourable direction towards choosing AC. When the comfort level of AC improves further, the beta coefficient increases to *2.255*, the highest parameter besides ASC. This highlights the large influence of comfort on the shift from train to AC.

The **travel frequency** has a beta coefficient of *-0.969*. This implies that individuals who frequently travel by train are less likely to choose an AC. One explanation for the direction of this parameter could be residential self-selection as explained in Section 5.2.1.

The beta coefficient for the **presence of automatic components** in a car is *0.337*, indicating that individuals with more experience in handling automatic car features are more likely to choose the AC as their mode of transport instead of the train.

In terms of **age**, the beta coefficient is *0.027*, implying that as age increases, so does the preference for AC as a transportation mode. This finding contradicts existing literature, but it can be clarified by considering the composition of the survey sample (Harper et al., 2016; Wadud & Mattioli, 2021). The survey was primarily distributed within close-knit networks, predominantly among individuals in the engineering field as mentioned before in Sections 2.4.1 and 4.8. The majority of older respondents are men, who typically show an interest in technology (Robinson & McIlwee, 1991). Consequently, they may have a preference for ACs, resulting in a positive beta coefficient.

Travel class has a beta coefficient of *0.824*, which indicates that second-class travellers have a higher likelihood of choosing the AC. This could be attributed to the fact that second-class wagons tend to be more crowded and, consequently, less comfortable, with comfort being the most influential parameter (Thompson, 2021).

The beta coefficient for the **distance to the nearest station** is *0.395*. This suggests that as the distance to the nearest station increases, passengers are more inclined to choose an AC as their transportation mode. This could also be clarified by residential self-selection as explained in Section 5.2.1.

The beta coefficient for the **degree of motion sickness** is *-0.131*, indicating that a higher level of motion sickness among individuals reduces their likelihood of choosing an AC. Despite the positive parameter associated with the scenario where the experience of motion sickness is mitigated in an AC, individuals who experience more motion sickness are still less likely to shift to the AC. This is likely due to the scepticism among people who suffer from motion sickness regarding the technology that will mitigate the motion sickness experience in an AC.

Nevertheless, it is essential to thoroughly analyse these effects. The safety, motion sickness, and comfort scenarios are binary, while on the other hand, travel frequency has a broader range with five levels, making its impact relatively lower on a per-level basis. When considering the full scale, the impact of travel frequency could be greater than that of comfort, especially at the highest level. While this clarification highlights the practical important of unstandardized coefficients, it is important to note that their interpretation can be challenging because their scale and magnitude can vary widely between different variables. It is therefore necessary to ensure a nuanced understanding of the unique contributions of each variable and their actual impact on passengers' mode choice.

5.5 Conclusion

In this chapter are the model parameters determined for the utilities of choosing between the train and AC with an MNL model. After determining the best model fit, four variables that were not significant, were retained in the model due to their theoretical relevance to the research question. This resulted in the final model from which the results were analysed. The findings indicated that comfort had the most significant influence, as indicated by its highest beta coefficient, followed by safety, and then motion sickness. It should be taken into account that these factors are binary, while the travel frequency factor is a multi-level variable, which therefore also has a significant impact on the choice between train and AC.

6 Hypothetical situation

The beta coefficient has been determined in Chapter 5, but are unstandardized. Therefore, it may not be immediately evident what these beta coefficient represents in practical terms. If a variable seems to have a significant influence on the potential shift within a specific group, then the impact of this variable on practical terms initially seems large. However, if this specific group is, in reality, quite small, the actual influence of this variable is relatively small. To address this, the utility values have been aligned with the actual data from the Rotterdam-Amsterdam route. In Chapter 4, the transportation data for this route was analysed using the NVP dataset, which will also be utilized to determine the actual impact. The actual impact will be measured through the use of what-if scenarios, which are discussed in Section 6.1 and mathematically supported in Section 6.2. Sections 6.3, 6.4 and 6.5 examine the three different what-if scenarios. The chapter ends with a conclusion in Section 6.6.

6.1 What-if scenarios

Since the AC has not been implemented yet, it is not possible to measure its real, tangible impact. Instead, the impact of ACs is assessed through 'what-if' scenarios. To assess the robustness of this study, three distinct what-if scenarios have been analysed. Measuring the robustness of a study involves evaluating the reliability of the results and the interpretations (Vaismoradi et al., 2013). In this study, this entails verifying whether the findings hold true in different circumstances (Berger et al., 2009). The choice for three scenarios serves to apply triangulation, a method that tests multiple theories to enhance the validity and credibility of the results (Carter et al., 2014; Jick, 1979). Triangulation requires at least three metrics. If there is minimal variation in the results across these three scenarios, these consistent outcomes serve as a critical indicator of the study's robustness. If this turns out to be the case, three scenarios are sufficient for triangulation. Section 6.7 provides a reflection on this approach.

Specific details about the travel class of train passengers, the degree of motion sickness they experience, their age, the level of automation in their cars, and their proximity to a train station are characteristics of passengers, and therefore no general data exists. In order to calculate the what-if scenarios, assumptions for these characteristics are made based on the NVP dataset and existing literature.

6.1.1 What-if variables selection

In order to put the variable into practical terms, the what-if scenarios are conducted with variables of which the population proportion per variable level is available. This is essential for conducting the analysis. Section 6.3 discusses the analysis further in detail. The three variables forming the 'what-if' scenarios are proximity to the nearest station, the level of motion sickness, and travel class. These scenarios were selected based on the existing literature highlighting the significance of proximity to a train station in terms of passenger accessibility as mentioned in Section 3.2 (Ha et al., 2020; Ingvardson et al., 2018; Nguyen-Phuoc et al., 2018; Shen et al., 2016; Tembe et al., 2019; Zheng et al., 2016). Given that both Rotterdam and Amsterdam are recognized for train accessibility, this factor is included as one of the three what-if scenarios (Séveno, 2023). Additionally, the NVP dataset provides data about the proximity to the nearest train station for both passengers with their origin in Amsterdam and Rotterdam. The second what-if scenario is formed by the factor level of motion sickness. While this particular scenario may not demonstrate statistical significance, the literature strongly supports its impact, as shown in Section 5.4 (Dam & Jeon, 2021; Diels et al., 2016; Edelmann et al., 2016; Salter et al., 2019). Consequently, it is likely that this factor will have a greater influence on the modal choice than indicated by the findings of this study, making it the second what-if scenario. Lastly, travel class forms the last what-if scenario because it offers a straightforward measure. This is attributed to the fact that passengers need to make a decision on whether they choose to travel first- or second-class, this results in a clear distinction between first- and second-class travel. This clear distinction makes the results from the what-if scenario very reliable, hence making it the third what-if scenario.

For the first what-if scenario, the difference between travel frequency and proximity to the nearest station is minor since they have a high correlation, 0.588. This high correlation indicates multicollinearity and therefore have overlap in explanatory data (J. H. Kim, 2019). For this reason, only one of these two variables is selected for the what-if scenario (Hair et al., 2012). However, due to the fluctuating nature of the travel frequency figures, the actual figures for the nearest station are more consistent and thus more stable. Therefore the nearest station will be used for the what-if scenario and not travel frequency. The presence of automated parts was excluded as a factor for the what-if scenarios due to a lack of available data. Lastly, age was not included as a what-if scenario, as it is anticipated this variable is influenced by the survey sample as mentioned in Section 5.4.2.

6.1.2 Assumptions

To measure the what-if scenarios, the remaining numbers must be entered into an MNL, which is further elaborated in Section 6.2. These entered numbers are assumptions which have been made for these variables. The assumptions underlying the what-if scenarios are outlined in Table 19, which also provides a brief explanation of the significance of each assumption for better clarity.

Variable	**Scenario**			**Explanation**
	1	**2**	**3**	
Distance to the nearest station	x	1	1	Regarding the proximity to the nearest station, calculations by postal code in Amsterdam and Rotterdam, detailed in Section 4.1.1, align with the empirical findings in Paragraph 6.3 that 64% of survey respondents live within 0 to 2.5 km from the nearest station, resulting in a classification of level 1.
Level of motion sickness	2	x	2	The degree of motion sickness is assumed to be mild, or seldom, based on research by Czeisler et al. (2023) research, categorizing this variable as level 2 (Czeisler et al., 2023).
Class	2	2	x	As for travel class, approximately 80% of train passengers opt for 2nd class travel, leading to the assumption of level 2 to represent the majority in the what-if scenarios (Traxx, 2022).
Travel frequency	3	3	3	The NVP data in Section 5.2.1 reveals that the largest group, constituting 45.2%, falls into level 3, which corresponds to frequent train travel several times a month. Therefore, the assumption for this variable is level 3.
Automatic parts	1	1	1	Regarding the presence of automatic parts, it is assumed that train passengers have a lower interest in automobiles due to the fact that they opt for the train over the regular car, indicating that they do not own cars with automatic parts, resulting in an assumption of level 1.
Age	42	42	42	The assumption for age is set at the average age of 42, based on the NVP dataset.

Table 19 - What-if scenario assumptions

6.2 Methodology

The first three variables form the what-if scenarios, with each scenario having an assumption left blank in the table. These blanks are filled with actual data to determine which factor has the highest probability of a shift. To quantify this probability, the parameters and assumptions are entered into the Utility function in Equation 3.1.

$$\begin{aligned} U_{AC} = {} & -3.480 + -1.331 * Safety\_8and4 + 0.308 * Safety\_8and6 + 1.250 * Safety\_8and8 \\ & + -0.373 * motionsick\_car\_worse + 1.181 * motionsick\_car\_equal\_to\_train \\ & + 0.401 * Comfort\_both\_good + 2.255 * Comfort\_car\_better + -0.969 \\ & * often\_traintravel + 0.337 * auto\_parts + 0.027 * Age + 0.824 * class \\ & + 0.395 * neareststation + -0.131 * levelmotionsickness \end{aligned} \tag{3.1}$$

Subsequently, the probability of choosing an AC is calculated using Equation 3.2.

$$\mathrm{P} = \frac{e^{UAC}}{e^{Utrain} + e^{UAC}} \tag{3.2}$$

This method is used to identify skewed interpretations of the unstandardized beta coefficients. For each level group, the probability of shifting to AC is calculated, which is then multiplied by the percentage proportion of that specific group. This computation allows for the determination of the overall possible shift for each population group. By summing up all the shifts within all five groups, the possible shift for the entire population in Rotterdam and Amsterdam is measured.

In mathematical terms, the probability, denoted as P, of a group shift, is determined by incorporating the utility values into MNL Equation 1.4. This result is then multiplied by the percentage sizes at that level to quantify the cumulative shift.

6.2.1 Scenario clarification

In Subsections 6.3 to 6.5, the probabilities of shifting per scenario are measured. In these subsections, the scenarios are denoted in numbers. For clarification, this subsection appoints the scenario numbering in a brief summary of the scenarios described in Section 4.2.

Number	Name	Explanation
1	Basecase	In this scenario, all fixed attribute levels of the AC and the train are added, without the designation of the factors safety, motion sickness and comfort.
2	Safety_8and4	In this scenario, on top of the fixed attribute levels, the safety perception for the AC is level 4, and for the train is level 8.
3	Safety_8and6	In this scenario, on top of the fixed attribute levels, safety perception for the AC has increased to level 6, and for the train it remains level 8.
4	Safety_8and8	In this scenario, on top of the fixed attribute levels, the safety perception for the AC increased to level 8, and equal to the level of the train.
5	motionsick_car_worse	In this scenario, on top of the fixed attribute levels, the experience of motion sickness in the AC is worse than in the train, and similar to that in the regular car.
6	motionsick_equal	In this scenario, on top of the fixed attribute levels, the experience of motion sickness in the AC is improved, and is similar to that in the train.
7	Comfort_both_good	In this scenario, on top of the fixed attribute levels, the comfort level of the AC and the train are both good in their own respective ways.
8	Comfort_car_better	In this scenario, on top of the fixed attribute levels, the comfort level of the AC exceeds the comfort level of the train.

Table 20 - What-if scenario assumptions

6.3 What-if scenario 1 – Proximity to train stations

This study investigates how people might change their choice of transportation when automated cars are available. Respondents were presented with the eight scenarios as mentioned in Section 6.2.1.

6.3.1 Population proportion

In this first what-if scenario, the probability of people shifting to automated cars at different train station proximity levels for each scenario is calculated using the MNL model. Regarding the distance to a train station, the population is categorized into five groups, which are the same levels as in the survey: those living 0 to 2.5 kilometres from the station, those living 2.5 to 5 kilometres from the station, those living 5 to 7.5 kilometres from the station, those living 7.5 to 10 kilometres from the station, and those living 10 kilometres or more from the station.

The data of the population proportions have been derived from Section 4.1, is attached in Appendix K. The proportions of the five groups is presented in Table 21. The proportions are calculated solely by postal codes and has not been further ranked based on population density within each postal code due to resource constraints and time scope.

Distance to a train station per postal code	
Level	**%**
1 (= 0 to 2.5 km)	69
2 (= 2.5 to 5 km)	27
3 (= 5 to 7.5 km)	2
4 (= 7.5 to 10 km)	4
5 (= 10 km or more)	0

Table 21 – City average postal code distribution

6.3.2 Probabilities to shift

For each population group, the probability that the train passengers will potentially shift to AC is measured for each scenario with Equation 3.3.

$$Total\ P\ for\ a\ scenario = (P(that\ people\ \ will\ shift) * \%\ population\ proportion) \tag{3.3}$$

This is done for each of the eight scenarios. The total probabilities to shift per scenario for the five population groups added in Table 22.

The probability that a group will shift	Level 1 (0 to 2.5km)	Level 2 (2.5 to 5 km)	Level 3 (5 to 7.5 km)	Level 4 (7.5 to 10 km)	Level 5 (10 km or more)
Scenario	P %	P %	P %	P %	P %
1	10	15	20	27	**36**
2	3	4	6	9	**13**
3	13	19	26	34	**43**
4	29	37	47	57	**66**
5	7	10	15	21	**28**
6	27	36	45	55	**64**
7	15	20	27	36	**45**
8	52	62	71	78	**84**

Table 22 - Probabilities that a population group will shift

This table shows that train passengers that fall in the last group, those who live further than 10 kilometres from a train station, are the most likely to make a shift to an AC. However, these are solely the percentage probabilities that the five population groups will shift to ACs. By multiplying the probability of a shift by the population proportion of each group, the actual percentage of train passengers who would be likely to shift is calculated. With this approach, it can be understood how the shift is distributed across the whole population based on the proximity characteristics of the five groups.

The probabilities to shift were multiplied by the population proportions from Table 21, and the results are added in Table 23.

The actual probability that a group will shift	Level 1 (0 to 2.5km)	Level 2 (2.5 to 5 km)	Level 3 (5 to 7.5 km)	Level 4 (7.5 to 10 km)	Level 5 (10 km or more)
Scenario	**Total P %**	**Total P %**	**Total P %**	**Total P %**	**Total P %**
1	10 * 69 = **7**	15 * 27 = **4**	20 * 2 = **0**	27 * 4 = **1**	36 * 0 = **0**
2	3 * 69 = **2**	4 * 27 = **1**	6 * 2 = **0**	9 * 4 = **0**	13 * 0 = **0**
3	13 * 69 = **9**	19 * 27 = **5**	26 * 2 = **1**	34 * 4 = **1**	43 * 0 = **0**
4	29 * 69 = **20**	37 * 27 = **10**	47 * 2 = **1**	57 * 4 = **2**	66 * 0 = **0**
5	7 * 69 = **5**	10 * 27 = **3**	15 * 2 = **0**	21 * 4 = **1**	28 * 0 = **0**
6	27 * 69 = **19**	36 * 27 = **10**	45 * 2 = **1**	55 * 4 = **2**	64 * 0 = **0**
7	15 * 69 = **10**	20 * 27 = **5**	27 * 2 = **1**	36 * 4 = **1**	45 * 0 = **0**
8	52 * 69 = **36**	62 * 27 = **17**	71 * 2 = **1**	78 * 4 = **3**	84 * 0 = **0**

Table 23 - Actual probabilities that a population group will shift

To summarize the data from Table 20, which are further elaborated in Appendix L, the highest probability of a shift occurs among people from population group level 5. However, within this population group, the proportion is approximately 0% on the Rotterdam – Amsterdam corridor. Conversely, it is evident that the highest probability to shift actually occurs among train passengers in the population group level 1, because this is the largest population proportion.

In practical terms, this means that the actual probability that train passengers potentially shift to AC is minimal for individuals living far from the train station. In contrast, the highest actual probability that train passengers might shift happens among individuals living close to a train station. This group is the least likely to shift due to their easy access to a train station. Nevertheless, since this group constitutes the majority of the city population, the actual probability to shift is the highest.

By summing up the percentages of all five population groups, the total probability that the entire population on the corridor might shift is measured, as shown in Equation 3.4.

$$\begin{aligned} Total\ impact = {} & (P(that\ people\ living\ 0\ tot\ 2.5\ km\ from\ the\ station\ will\ shift) \\ & * \%\ of\ people\ living\ within\ 0\ to\ 2.5\ km\ from\ the\ station) \\ & +\ (P(that\ people\ living\ 2.5\ tot\ 5\ km\ from\ the\ station\ will\ shift) \\ & * \%\ of\ people\ living\ within\ 2.5\ to\ 5\ km\ from\ the\ station) \\ & +\ (P(that\ people\ living\ 5\ tot\ 7.5\ km\ from\ the\ station\ will\ shift) \\ & * \%\ of\ people\ living\ within\ 5\ to\ 7.5\ km\ from\ the\ station) \\ & +\ (P(that\ people\ living\ 7.5\ tot\ 10\ km\ from\ the\ station\ will\ shift) \\ & * \%\ of\ people\ living\ within\ 7.5\ to\ 10\ km\ from\ the\ station) \\ & +\ (P(that\ people\ living\ 10\ km\ or\ more\ from\ the\ station\ will\ shift) \\ & * \%\ of\ people\ living\ within\ 10\ km\ or\ more\ from\ the\ station) \end{aligned} \tag{3.4}$$

For each scenario, the probability of a shift from rail passengers to AC was determined for the entire population travelling on the Rotterdam-Amsterdam route. For every scenario, the total shift is added in Table 24.

Total probability that people will shift on the R-A route	
Scenario	**%**
Base case	12
Safety_8and4	3
Safety_8and6	15
Safety_8and8	30
Motionsick_car_worse	7
Motionsick_equal	29
Comfort_both_good	16
Comfort_car_better	55

Table 24 - The total shift on the Rotterdam-Amsterdam route regarding the train station proximity level distribution

6.3.3 Conclusion

In short, depending on their distance to the train station, it can be concluded that if people do not yet feel safe in the AC, a very small group could potentially shift, i.e. only 3%. However, when the comfort level in ACs is higher than that in trains, a large group could potentially shift, namely 55%. Explanations of the percentages of the other scenarios are added in Appendix L.

6.4 What-if scenario 2 – Level of motion sickness

In this second what-if scenario, the population distribution of motion sickness levels is incorporated in Table 25. This data resulted from the studies by Bos and Bles (1998) and Czeisler et al. (2023) (Bos & Bles, 1998; Czeisler et al., 2023). Regarding the experience of motion sickness, the population is categorized into five groups, which are the same levels as in the survey: those who never experience motion sickness, those who seldom experience motion sickness, those who sometimes experience motion sickness, those who often experience motion sickness, and those who always experience motion sickness. The distribution encompasses the entire Netherlands, as a level-specific distribution of passengers on the Rotterdam-Amsterdam corridor is not available. The assumption has been made that this distribution is generalizable across the entire nation. Consequently, it is assumed that this distribution is also applicable to train passengers travelling on the Rotterdam-Amsterdam route.

MS level	SCE score	N %
None	1 = never	16
Mild	2 = seldom	29
Moderate	3 = sometimes	26
Severe	4 = often	16
Very severe	5 = always	13

Table 25 - Motion sickness level distribution in the Netherlands

The same methodology was applied to this what-if scenario as in Subsection 6.3. For each population group, the probability that the train passengers will potentially shift to AC is measured for each scenario with Equation 3.3. This is done for each of the eight scenarios. The total probabilities to shift per scenario for the five population groups are attached to Appendix M.

To summarize the data from total probabilities per scenario, as attached in Appendix M, the largest probability to shift occurs among train passengers who never experience motion sickness, level 1. However, only a small proportion of the population never suffers from motion sickness. As a result, this is not the highest actual probability to shift. Indeed, the highest actual probability to shift happens among train passengers who experience a seldom of motion sickness. They are less likely to shift to AC than passengers who never suffer from motion sickness. However, this latter group is considerably larger in size, resulting in the actual shift being almost twice as high.

This phenomenon is confirmed by the dataset from the survey, as every respondent who answer that they are willing to shift from train to AC when the experience of motion sickness is lessened, experiences some degree of motion sickness. There are no respondents in this group who never experienced motion sickness.

By summing up the percentages of all five population groups, the total probability that the entire population on the corridor might shift is measured, as shown in Equation 3.5.

$$\begin{aligned}
\mathit{Total\ impact} = {} & (P(\mathit{of\ individuals\ that}\ \boldsymbol{never}\ \mathit{experience\ motion\ sickness\ will\ shift}) \\
& * \%\ \mathit{of\ individuals\ that}\ \boldsymbol{never}\ \mathit{experience\ motion\ sickness}) \\
& + (P(\mathit{of\ individuals\ that}\ \boldsymbol{seldom}\ \mathit{experience\ motion\ sickness\ will\ shift}) \\
& * \%\ \mathit{of\ individuals\ that}\ \boldsymbol{seldom}\ \mathit{experience\ motion\ sickness}) \\
& + (P(\mathit{of\ individuals\ that}\ \boldsymbol{sometimes}\ \mathit{experience\ motion\ sickness\ will\ shift}) \\
& * \%\ \mathit{of\ individuals\ that}\ \boldsymbol{sometimes}\ \mathit{experience\ motion\ sickness}) \\
& + (P(\mathit{of\ individuals\ that}\ \boldsymbol{often}\ \mathit{experience\ motion\ sickness\ will\ shift}) \\
& * \%\ \mathit{of\ individuals\ that}\ \boldsymbol{often}\ \mathit{experience\ motion\ sickness}) \\
& + (P(\mathit{of\ individuals\ that}\ \boldsymbol{always}\ \mathit{experience\ motion\ sickness\ will\ shift}) \\
& * \%\ \mathit{of\ individuals\ that}\ \boldsymbol{always}\ \mathit{experience\ motion\ sickness})
\end{aligned} \tag{3.5}$$

For each scenario, the probability of a shift from rail passengers to AC was determined for the entire population travelling on the Rotterdam-Amsterdam corridor. Table 26 presents the summation of all the probabilities of all five population groups.

Total probability that people will shift on the R-A route	
Scenario	**%**
Base case	9
Safety_8and4	3
Safety_8and6	12
Safety_8and8	27
Motionsick_car_worse	7
Motionsick_equal	27
Comfort_both_good	13
Comfort_car_better	51

Table 26 - The total shift on the Rotterdam-Amsterdam route regarding the motion sickness level distribution

6.4.3 Conclusion

In short, depending on the extent of motion sickness train passengers experience, it can be concluded that if people do not yet feel safe in the AC, a very small group could potentially shift, i.e. only 3%. However, when the comfort level in ACs is higher than that in trains, a large group could potentially shift, namely 51%. Explanations of the percentages of the other scenarios are added in Appendix M. This is almost identical to the outcomes of the first what-if scenario.

6.5 What-if scenario 3 – Travel class

Finally, this approach is applied to the last what-if scenario, where the travel class distribution on the train is evaluated. As detailed in Section 5.2, and regarding the travel class, the population is categorized into two groups, which are the same levels as in the survey: those travelling first class, and those travelling second class.

Approximately 80% of passengers choose second-class travel on this route (Traxx, 2022). This distribution is presented in Table 27.

Class	N %
1	20%
2	80%

Table 27 - Train travel class distribution

For both the population groups, the probability that the train passengers will potentially shift to AC is measured for each scenario with Equation 3.3. This is done for each of the eight scenarios. The total probabilities to shift per scenario for the five population groups are attached to Appendix N.

To summarize the data from this appendix, the highest probability to shift occurs among train passengers who travel second class. This group also has the highest population proportion, resulting in the highest actual probability to shift from train usage to AC. Conversely, the probability of first-class train passengers shifting to AC Is exceedingly low. This can be attributed to the high comfort level that is already associated with first-class travel compared to second-class travel (Oborne, 1978). This phenomenon is further elucidated in Section 6.5.2. Additional to the low probability that first-class travellers will shift, the relatively small population proportion of first-class passengers further minimizes the actual shift among first-class passengers.

By summing up the percentages of both population groups, the total probability that the entire population on the corridor might shift is measured, as shown in Equation 3.6.

$$\begin{aligned} Total\ impact = {} & (P(of\ individuals\ that\ travel\ first\ class\ will\ shift) \\ & * \%\ of\ individuals\ that\ travel\ first\ class) \\ & + (P(of\ individuals\ that\ travel\ second\ class\ will\ shift) \\ & * \%\ of\ individuals\ that\ travel\ second\ class) \end{aligned} \tag{3.6}$$

For each scenario, the probability of a shift from rail passengers to AC was determined for the entire population travelling on the Rotterdam-Amsterdam corridor. Table 28 presents the summation of all the probabilities of both population groups.

Total impact on the R-A route	
Scenario	**%**
Base case	9
Safety_8and4	3
Safety_8and6	12
Safety_8and8	26
motionsick_car_worse	7
motionsick_equal	25
Comfort_both_good	13
Comfort_car_better	51

Table 28 - The total shift on the Rotterdam-Amsterdam route regarding the train travel class distribution

6.5.1 Conclusion

In conclusion, depending on the extent of motion sickness train passengers experience, it can be concluded that if people do not yet feel safe in the AC, a very small group could potentially shift, i.e. only 3%. However, when the comfort level in ACs is higher than that in trains, a large group could potentially shift, namely 51%. Explanations of the percentages of the other scenarios are added in Appendix N. This is almost identical to the outcomes of the first and fully identical to the outcomes of the second what-if scenario. A general conclusion of all three what-if scenarios is discussed in Section 6.7.

6.5.2. Impact of Excluded Factors

The probability of first-class travellers shifting to ACs is very low. This is further influenced by comfort-related aspects that were not included this this study. Specifically, this study solely encompassed independent comfort components, such as interior features, to prevent 'comfort' from becoming a confounding variable, as detailed in Section 4.2.4. However, factors such as crowding, heat, smell, or the availability of seating, depend on the presence of other passengers (Beirão & Sarsfield Cabral, 2007; Z. Li & Hensher, 2013; Mims et al., 2023; Nahrin & Rahman, 2012; Tirachini et al., 2013). These factors were deliberately excluded from the study, as additionally mentioned in Section 4.2.4. Nevertheless, due to these factors, first-class travel distinguishes itself from second-class travel regarding the influence of other passengers (Corbridge et al., 1989; Yap et al., 2016). In addition, fewer passengers travel first-class. Consequently, there is less crowding and more privacy in this class.

However, when there is less crowding and more privacy, as is the case in first-class travel, ACs may not necessarily represent a superior alternative for train passengers. Consequently, first-class passengers have less fewer incentives to shift. Yet, further research is needed to ascertain the true impact of factors such as crowding, heat, smell, or the availability of seating, which depend on the presence of other passengers. This will be discussed in more detail in Chapter 7.

6.6 Reflection

From this study, it is apparent that comfort emerges as the most influential factor, as indicated by its large beta coefficient. However, the variables of cost, time and CO_2 emissions are included as fixed factors, resulting in no beta coefficients from the MNL. Proximity is also included as a fixed variable, but is measured through the passenger characteristic variable ‘distance to the nearest train station’. Consequently, no statistical comparison can be done between the three key factors and the three fixed variables. The possibility exists that the three key factors have less influence on the modal shift than the fixed variables. To examine whether this is the case, a ranking question has been incorporated into the survey. This enables a direct comparison of the impact of the three factors with that of the fixed variables.

Ha et al. (2020) conducted a statistical analysis of these three fixed variables. The results from their research showed that travel time has the highest beta coefficient, followed by travel costs, with sustainability of the transport mode ranking last (Ha et al., 2020). These results can be cross-referenced with the survey results of the ranking question, to determine whether these three attributes are placed below or above the three key factors. The ranking is added in Table 29.

Variable	**Rank**
Comfort	1
Time	2
Safety	3
Costs	4
Sustainability	5
Motion Sickness	6

Table 29 - Variable ranking

Interestingly, this analysis confirms that the order of Ha et al. (2020) is indeed accurate; first travel time, then travel costs, and lastly sustainability. However, the variable comfort is ranked as the most influential factor in the survey, surpassing travel time. The MNL results have already shown that comfort has the most influence on the modal choice, and this comparison with the fixed attributes and ranking from the literature, further validates this finding.

The complete ranking and its calculation are provided in Appendix O. It must be acknowledged that tFhis ranking solely includes the characteristics of transportation modes and not those of passengers. This is done because if a policy intervention needs to be designed to counter the shift, only the characteristics of the transportation modes can be modified and not the characteristics of the passengers.

6.7 Conclusion

The analyses presented in this chapter highlight that the beta coefficients discussed in Chapter 5 do not necessarily guarantee a significant probability to shift in mode choice in practical terms. This is primarily attributed to the fact that, in certain scenarios, only a specific subgroup may opt for a mode shift, which could be relatively small in size. To accurately assess the probabilities in the real-world, the parameters are linked to actual data from the Rotterdam-Amsterdam corridor, allowing for the measurement of the actual probability to shift. This assessment was conducted for three different what-if scenarios to enhance the robustness of the study. The three what-if scenarios have extreme similar outcomes, indicating that three what-if scenarios suffice for triangulation, eliminating the need for additional what-if scenarios to reach the same conclusion.

The results of all three what-if scenarios indicate that when the comfort level of an AC surpasses that of the train, there is a probability that more than half of train passengers might shift to AC as a transport mode. Next, the impact of comfort is compared to the ranking of the fixed attributes to determine if the significance of comfort is indeed substantial and not a result of the absence of data for the fixed variables. This analysis demonstrated that the factor comfort has more influence on the modal choice compared to the fixed variables. While it is important to note that this study is a one-time execution, the prospect of the probability that more than half of the train passengers consider a shift is a significant and concerning finding, which will be further discussed in Chapter 7. In addition, it should be acknowledged that this is a predictive probability, and the actual shift depends on factors beyond just the comfort features installed in an AC.

7 Conclusion, discussion and recommendations

This study focused on the impact of private ACs on train passengers' transportation mode choice, particularly a shift from train usage to AC usage. Safety perception, motion sickness and comfort are the core factors in this study to measure this shift. This chapter describes the conclusion of the sub-questions in Section 7.1. Section 7.2 answers the main research question "To what extent do the factors of comfort, safety and motion sickness influence the decision among train passengers in selecting ACs as their transportation mode?". Section 7.3 describes the discussion which resulted from this study. Section 7.4 describes the scientific contribution this study has. The limitations are described in Section 7.5, Lastly, the recommendations for future research are described in Section 7.6.

7.1 Sub-questions insights

This section describes the conclusions of the following three sub-questions; I) '*What factors influence individuals' to decide on utilizing trains or cars?*', II) '*What are the weights assigned to the three factors as determined through a Stated Choice Experiment?*' and lastly, III) '*Under what hypothetical scenarios would this shift affect real-world road and rail conditions?*'.

7.1.1 Conceptualization

This subsection describes the conclusion of the following first sub-questions '*What factors influence individuals' to decide on utilizing trains or cars?'*.

The concept of ACs has been a prominent topic in the technology sector since the 1980s. numerous developments have occurred in this field since then, to the extent that multiple paths in the development of ACs have been developed. The Dutch Institute for Mobility Policy (KiM) has identified four paths for ACs, which are distinguished by their varying degrees of sharing and automation. When conducting research on a yet-to-be-implemented technology, the level of practical realization needs to be considered. It is evident that semi-fully ACs are likely to be adopted quicker than fully ACs. Furthermore, comparing a fully AC to a train trip is akin to an asymptote scenario. An asymptote scenario is the situation where two things, two transportation modes in this study, are fundamentally different and never become equivalent in a comparison (Hanley et al., 1998). In the case of a train trip, action must be taken before control can be relinquished, which is fundamentally different from a fully AC capable of self-driving right from its point of origin.

In addition to the aspect of realization, it is important to consider ownership. To understand why train passengers do not shift to regular cars but may shift to ACs, it is important to ensure equality in ownership. A regular car and a private AC are two entirely distinct transportation modes but have the same level of ownership. Consequently, the definition and scope of AC in this research are formed by the degree of automation and ownership. Therefore, the definition of the AC scope is private ACs with SAE level 4 automation, where control over the steering wheel must be relinquished on highways, with the stipulation of control in urban areas.

Train passengers have selected the train as a transportation mode. However, to determine the rationale behind travellers' preference for either trains or regular cars, it is important to delineate the factors for this choice, which is done through a literature review. The analysis revealed that these factors can be categorized into two distinct groups: characteristics of the transportation modes, and the characteristics of travellers, that influence the choice of a transportation mode.

The most important characteristics of the transportation modes encompass proximity, also referred to as 'walkability', travel costs, and travel time in the transportation mode. Meanwhile, the most important characteristics of travellers encompass age, gender, employment, ownership of a driving license of a car, and income levels. Following an expert interview with R. Happee, it was determined to incorporate the degree of environmental awareness as a traveller's characteristic, along with CO_2 emissions as a transportation mode characteristic, into the conceptual model in order to measure the impact of this factor.

In addition to the aforementioned decision factors, this study encompasses the three factors by which an AC distinguishes itself from a regular car: safety, motion sickness and comfort. The object of this study is to measure the impact of the three factors.

7.1.2 The impact of safety, motion sickness and comfort

This subsection describes the conclusion of the following second sub-questions '*What are the weights assigned to the three factors as determined through a Stated Choice Experiment?'*

An SCE was used to quantify the impact of the decision factors. An SCE is the preferred method for gaining insight into individuals' decisions when choosing between two different transportation modes. All inputs derived from the conceptual model have been incorporated into the SCE survey design as attributes. In order to isolate and quantify the influence of the factors safety, motion sickness, and comfort, all other characteristics of the two transportation modes have been fixed. These fixed attribute levels have been established based on the characteristics of the two transportation modes for a trip between Rotterdam and Amsterdam. This approach allows respondents to make choices that resemble real-life scenarios, enabling an accurate assessment of the pure effects of safety, motion sickness and comfort. The results table is added in Table 30 for clarification.

Variable	β	Sign.
(Intercept)	-3.480	.001*
Safety_8and4	-1.331	.034*
Safety_8and6	.308	.498
Safety_8and8	1.250	.003*
motionsick_car_worse	-.373	.457
motionsick_car_equal_to_train	1.181	.006*
Comfort_both_good	.401	.373
Comfort_car_better	2.255	.000*
often_traintravel	-.969	.000*
auto_parts	.337	.000*
Age	.027	.001*
class	.824	.000*
neareststation	.395	.001*
levelmotionsickness	-.131	.268

Table 30 - MNL parameter estimates summary

Following the completion of the survey and subsequent dataset analysis, comfort emerged as the most significant factor, displaying the highest beta coefficient of 2.255. This implies that the utility for AC increases with this coefficient. The train has a utility score of 0, which indicates that a high positive coefficient results in a greater likelihood of choosing AC over the train. Safety follows with a coefficient of 1.250, and motion sickness has a coefficient 1.181. Notably, when the safety perception of an AC was significantly lower than that of a train, it resulted in the largest negative coefficient of -1.331.

Additionally, travel frequency emerged as a highly influential factor in mode selection. Individuals who travel more frequently are less inclined to choose an AC. This trend is likely due to the proximity of frequent passengers to a train station due to residential self-selection, making train travel a more convenient option for them.

7.1.3 Hypothesized scenarios

This subsection describes the conclusion of the following last sub-questions '*What is the real-world applicability of the Stated Choice Experiment results when exposed to hypothetical what-if scenarios?*'.

Parameters can potentially present a skewed representation of the actual probability because they are unstandardized. It may appear from the parameters that a particular group is likely to have a large probability to shift, but if this group constitutes a relatively small portion of the whole population, the actual probability to shift may turn out to be low. The actual probability to shift can be assessed with a what-if scenario, where assumptions are made to fill in the passengers' characteristics. These are drawn from the NVP dataset of travellers commuting between Rotterdam and Amsterdam. It was decided to design three what-if scenarios to measure the study's robustness in order to conduct triangulation.

The first what-if scenario focuses on the distribution of proximity to train stations in Rotterdam and Amsterdam. A minimum probability to shift of 3% is anticipated when an AC has a low safety perception score, and a maximum probability to shift of 56% when the AC comfort surpasses the train comfort. The second what-if scenario focuses on the distribution of motion sickness rates. Here again, a minimum probability to shift of 3% is expected under the same safety perception conditions, and a maximum probability to shift of 51%, additionally under the same comfort conditions. Lastly, the third what-if scenario focuses on travel class. This what-if scenario showed the same minimum and maximum probabilities to shift.

It shows that the AC has minimal to no influence on first-class train passengers, but a significant impact on second-class train passengers. This because first-class carriages already offer a higher level of comfort compared to second-class carriages. The comfort level is determined by independent comfort factors, which are included in this study. However, the comfort level within first-class is also influenced by dependent factors, which are considered dependent because they are influenced by other passengers. Although, these dependent factors were not included in the study, they might potentially explain why the impact of AC on first-class travel is relatively low.

7.2 Conclusion

To address the central question of this study – Does a shift happen? – the answer is affirmative. This study shows that there is a relatively high probability that there will be a shift from train travel to AC travel as the preferred transportation mode. Additionally, this study shows that there is a probability to shift, even a small probability in the worst-case AC scenario where the safety perception train passengers have for the AC is considerably lower than the safety perception train passengers have for the train.

In instances where the comfort level of AC surpasses that of the train, there is a high probability that a shift might occurs, encompassing a probability of more than 50%. Despite the nature of making methodological decisions and thereby leaving other aspects out of the study scope, this conclusion remains robust, supported by several factors. The AC definition is standardized among the survey respondents, the SCE design underwent expert validation, and the actual probability of a shift is explored by multiple what-if scenarios. Consequently, it can be confidently asserted that the direction of the probability of a shift is indeed accurate and valid, though the magnitude of the probability of a shift may naturally fluctuate, occasionally lower than the initial expectations. The probability of a shift is still significant and if this shift occurs, it will have substantial implications for both road and rail transport. This will be further discussed in Section 7.3.

Furthermore, the fixed attributes were not assigned weights in the MNL model as they remained constant. However, the hierarchy of their influence can be derived from the existing literature. This ranking was then compared to the ranking of the most influential factors by the survey respondents. The comparison revealed that comfort remained the most significant factor, followed by travel time and safety. This highlights the importance of including the fixed attributes in this study, as they play a large role in the modal choice, in addition to the three key factors. Nevertheless, it reaffirms that comfort remains the most influential factor.

To reflect on the outcome, surprisingly, comfort emerged as the most influential factor in this study, contrary to the authors' initial expectations, which leaned towards motion sickness or safety as the most influential factor. The author’s expectation can be explained by the frequent studies of motion sickness and safety in the context of AC developments (Almanee et al., 2021; Iskander et al., 2019; Karjanto et al., 2018; Schartmüller et al., 2020; Zou et al., 2022). However, the consistent focus on these two factors can be attributes to NS’s customer requirements pyramid. In this pyramid, safety and convenience, which includes addressing motion sickness, are considered dissatisfiers (Boes, 2007; Govers & van Hagen, 2019). This means that if a mode of transportation does not meet the criteria of the dissatisfiers, it will lead to dissatisfaction and reluctance to it (Vos & van Hagen, 2015). Consequently, it becomes crucial to thoroughly investigate these aspects. Therefore, the emphasis on investigating a satisfier, such as comfort, is relatively lower. Interestingly, this pyramid explains also why comfort emerged as the most significant factor. Comfort is considered a satisfier and has the potential to exceed travellers expectations, thus encouraging its use.

In other words, safety and convenience are crucial factors to consider when choosing a mode of transportation. This also elucidates why there is only a 3% probability of a shift when safety is significantly comprised for an AC. If both safety and convenience are equalized, comfort becomes the decisive factor, as it acts as a satisfier. Consequently, comfort emerges as the primary driver of the potential shift from train usage to AC. This explains why comfort displays the largest beta coefficient.

7.3 Discussion

This study shows that comfort has the most significant impact on the probability of a shift towards AC travel. When the comfort level of both transportation modes is equally good and there is no distinction in the extent of comfort, there is already a probability of one-eight that train passengers might shift. However, when the comfort level of AC surpasses that of the train, there is a probability that more than half of the passengers might shift to AC. But what exactly constitutes ‘better comfort’, and what are the implications of such a large probability of a shift?

If manufacturers of AC place a strong focus on comfort, it would entail incorporating features such as a foldable steering wheel, a pull-out table with wireless charging, high-speeds 5G internet for enhanced workspace comfort, reclining seats with adjustable sides and personalized armrests for seating comfort, and a dedicated climate control zone for each seat, minimal noise pollution, and advanced air purification systems for environmental comfort.

7.3.1 Impact on the public transport sector

If these features are incorporated into ACs, and as a result, there is a probability of a shift. A probability exceeding 50% implies that over half of the train passengers are likely to consider using ACs instead of the train. The probability represents the extent of the likelihood of a shift occurring. However, it should be acknowledged that this is a predictive probability, and the actual shift depends on factors beyond just the comfort features installed in an AC.

Nevertheless, suppose the probability of a shift of 50% would result in an actual shift of half the train users, it would mean a 50% reduction in train usage. In the current situation, NS is experiencing financial losses, similar to previous years ((NOS, 2023; NS, 2022.). A 50% decrease in train passengers would lead to a larger revenue decrease. Moreover, the reduced utilization of trains may necessitate schedule adjustments, potentially leading to a decline in employment within NS, ProRail and other train-related organisations (Besinovic et al., 2020). Furthermore, it could result in infrastructure investment postponements, as the demand for expanding or improving the rail network diminishes (Nash, 2009). The conclusion can be drawn that a decline in train usage will have large negative consequences for the public transportation sector, which is supported by the negative figures from all the COVID-19 impact studies (Kroeze, 2020).

These figures illustrate that a 90% decrease in train passengers leads to a substantial loss of €4.7 billion. To put it in perspective, a 50% drop in train passengers could result in a significant additional loss of €2.5 billion for NS. These financial challenges could be further worsened by the upcoming year’s price increases, including a 7% rise in train ticket prices, following last year’s 5.5% price increase (Booij, 2022; van Kuijeren, 2023). These higher fares are likely to discourage more individuals from choosing train travel (Blainey et al., 2012). The upcoming year’s price increase is a very recent adjustment and therefore not factored in this study. However, it will certainly influence passenger’s travel behaviour. Consequently, these price increases may result in a larger portion of passengers choosing AC over train usage, as evidenced by numerous news articles reporting passenger dissatisfaction regarding the rising fares and their inclination to explore other travel options (Bremmer, 2023; van Gurp, 2023).

7.3.2 Increased road Density

An even more significant consequence of this shift is the rise in car usage on Dutch highways. As mentioned in Chapter 1, the Netherlands faces a significant shortage of highway capacity due to the high number of cars. Without the influence of AC, traffic congestion is projected to double by 2040 compared to 2018 (Klein & Kersten, 2022). In addition, Chapter 1 discussed that there is a high probability that the Dutch highway will be gridlocked in 2040. As resulted from this study, if half of train passengers shift to road travel, this number will be substantially higher. Besides the increased congestion, the rising car density on the Dutch highway network induces numerous negative consequences.

Highways will become more congested more frequently, even outside peak hours and during holiday periods. This will lead to longer travel times, more stress for drivers, and economic losses resulting from wasted time (Bull et al., 2003). Furthermore, the increased number of cars will contribute to higher CO_2 emissions (de Bruyn & de Vries, 2020). This is attributed to the fact that despite ACs being more sustainable than fuel-based cars, it is still less sustainable than travelling by train, leading to increased emissions (Taiebat et al., 2018).

Another consequence is the heightened risk of traffic accidents (Duivenvoorden, 2010). When more cars share the same roads, hazardous situations occur more frequently. It is often overlooked that, even though, the AC removes human error, the human factor also stops many potential accidents by intervening (Bengler, 2023). Moreover, the infrastructure will be worn out faster, not only road- but also tunnel and bridge infrastructure (Sanchez-Robles, 1998). This results in higher maintenance costs and more frequent reparations and renovations, resulting in higher societal costs which can therefore not be spent on other societal challenges (Bleijenberg, 2021). A final consequence is that more cars on the road will increase pressure on expansion investments, which in turn puts pressure on natural areas. This can result in disruptions to ecosystems (McKinsey & Company, 2021).

All these consequences could potentially results from the introduction of ACs on Dutch highways. However, the question rises; how soon will this occur? According to the European Union, SAE level 4 cars are expected to be legally accepted to be on the European highways between 2026 and 2030 (Pillath, 2016). If the developments of ACs run parallel to the European legislation, the gridlock of the Dutch highways could occur even sooner than 2040. However, this only occurs if the technological developments keep pace. The technological problem of Tesla's FSD have already been described in Section 3.1.2. A recent situation has emerged in Austin, United States, where 125 automated taxis are in operation. These driverless cars caused a traffic congestion because, as stated by the company Cruise "there were too many people and vehicles on the road." (Chang, 2023). This highlights that before ACs are allowed to drive on the European highways, the AC still has several advancements to undergo.

7.3.2 Policy recommendations

In summary, the introduction of ACs will probably have several negative consequences. AC companies are private enterprises, whereas the public transport sector is predominantly comprised of public entities (Hamadneh et al., 2022). This fundamental difference makes it challenging to stop the advent of ACs. Based on this study, two possible interventions have been devised of the government could possibly do to reduce a shift. An intervention inevitably entails limitations in terms of time, budgetary resources, and capacity, which have been taken into account. (Chambers et al., 2013).

The first potential intervention that the Dutch government could implement to counter the shift is balanced investments. In order to achieve favourable outcomes from a policy intervention, it is advantageous to spread the investments, also referred to as balanced investments (Kindig et al., 2003). Therefore, the first policy intervention is a modest enhancement of all three factors – safety, motion sickness and comfort. The perception of safety on a train differs from that of an AC. Elevating safety perception could involve increasing security personnel presence on trains (Coppola & Silvestri, 2020). To alleviate motion sickness, AI algorithms could be devised to detect the need for braking more rapidly, initiating braking earlier in scenarios such as track changes or station approaches (Persson et al., 2012). For comfort-related investments, refer to the second policy intervention. In conclusion, achieving beneficial outcomes from a policy intervention involves spreading investments, entailing improvements in safety, motion sickness, and comfort in the train.

Additionally, one potential intervention that the Dutch government could implement to counter a shift could be focused investments. In addition to balanced investments, focused investments can also lead to favourable outcomes (Zellweger, 2007). Focused investments refer to an investment approach that prioritizes investing in the most affecting factor to mitigate the consequences of an issue. Therefore, the second policy intervention focuses on exclusively enhancing train comfort. As this study indicates, AC travel has minimal impact on first-class travel, as first-class travel offers superior comfort compared to second-class travel (Thompson, 2021). One reasonable recommendation is to configure the entire train similarly to a first-class wagon. However, this approach does not eliminate discomfort stemming from overcrowding. Insights from the interview with S. Nordhoff and the survey feedback highlight the importance of the feeling of privacy for travellers (Nordhoff, 2023). This can be replicated on a train by introducing designated 'private cubicles', similar to office privacy pods, where passengers can engage in activities such as making phone calls, watching movies without headphones, exercising and other activities that require privacy (ZoneZ, 2023).

It should be noted that these are potential interventions that the Dutch government could implement to mitigate a shift. However, the primary finding from this study is the high probability of train passengers shifting to AC, primarily driving by a high level of comfort in ACs.

7.4 Reflection on the scientific relevance

Scientific relevance encompasses scientific contribution and a reflection on this study's methodology and results. In this subsection, the scientific relevance is presented in two components; methodology and results.

7.4.1 Reflection on the methodology

In this study, a different methodology is applied, an SCE with fixed attribute levels. This subsection reflects on this methodology and considers its scientific contribution.

Scientific contribution
In traditional SCEs, multiple attribute levels are typically varied in the choice scenarios to present multiple situations to respondents (Fayyaz et al., 2021; Hensher, 1994). This approach is useful because it helps in understanding how different attributes affect the choices people make.

However, a new approach was introduced in this study in Section 2.7.1. Instead of varying all attribute levels, certain attribute levels were kept constant across all SCEs, also called "fixed attribute levels". These attributes, derived from the literature review, were considered already well researched and understood. What makes the addition of fixed attributes so innovative is that this approach emphasises maintaining realism in choice situations. It takes into account that some attributes are more or less constant in reality and do not vary from scenario to scenario. This creates choice situations that more closely resemble what people encounter in everyday life. In addition, the addition of fixed attributes minimises hypothetical biases as much as possible. This is the phenomenon where respondents' answers may differ from their actual choices due to the hypothetical nature of scenarios (Hensher, 2010). This is further explained in Sections 7.2.1 and 7.5.

Lastly, limiting the variation in attribute levels helps keep the survey manageable for both researchers and respondents. Fewer varying attribute levels results in fewer scenarios which respondents need to answer, and researchers need to analyse. This makes it more manageable for both groups, while it allows for more attributes to be included in the SCE and results in more comprehensive results and conclusions. This is crucial to maintain a sufficient number of respondents and to ensure a high response rate so that the results are representative of the target population (Van Essen, 2023). The dropout rate is 25%, as shown in Section 5.1.1. On average, this is 33%, which means that it did indeed lead to a higher response rate of people who opened the survey (Rico-Mena et al., 2023; Shaikh, 2022).

Reflection
Using fixed attribute levels also has limitations that need to be recognised. Firstly, maintaining fixed attribute levels limits the possibility of obtaining generalisable results from the relevant fixed attributes. Consequently, broad conclusions cannot be drawn about these fixed attributes and their influence using

solely the SCE results. This limitation arises from the fact that a MNL model is designed to work with variable attribute levels (Holmes & Adamowicz, 2003). MNL is a statistical model used to analyse choice processes where individuals have to choose between alternatives. The model takes into account the probability of each alternative being chosen, given the characteristics of the choice conditions (El-Habil, 2012; Fagerland & Hosmer, 2012; Simon, 1955). Keeping attribute levels fixed means that these attributes have the same values in all choice scenarios. Since they do not vary, there is nothing to model with beta coefficients in the MNL model. The model cannot draw information from attributes that show no variation across choices. Since fixed attribute levels have no variability, estimates of beta coefficients for these attributes would effectively be zero, meaning they have no impact on choice because they are always the same (Hess & Train, 2017).

To still draw a conclusion about these fixed attributes, a question was put in the survey to rank all the attributes from greatest impact on the decision for the alternatives to smallest impact on the choice for the alternatives. This was then compared with the existing literature in Section 6.6. Consequently, although no numerical conclusions can be drawn about these attributes, their relative impact on the choice of transportation mode is assessed.

Second, individuals' transportation behaviour is shaped by various factors, such as personal preferences, environmental conditions, and socioeconomic factors (Van Vugt et al., 1996; Wiig & Smith, 2009). By fixing attribute levels, only the varying factors can be targeted and important influences may be overlooked. In other words, gaining insight into the influence of these specific attributes may result in that the complexity of transportation behaviour may not be fully understood (Beirão & Sarsfield Cabral, 2007; Clifton & Handy, 2003). In this study, the emergence of this situation was minimized by choosing a corridor where the fixed attribute levels are close together. In Section 4.1.1, three routes were compared with each other at the same distance. The Delta, the difference in time and costs, is ample smallest for the chosen corridor from Section 2.7.2, Rotterdam-Amsterdam. In other words, by choosing a corridor where the actual values of the fixed attribute levels closely resemble each other, the new methodological approach can still be employed, while minimizing the risk of not fully understanding the workings of transportation behaviour.

7.4.2 Reflection on the results

The results from this study are discussed with respect to the sane topics; scientific contribution and reflection.

Scientific contribution

This study has a scientific contribution on multiple fronts. Firstly, this study addresses an unexplored area by examining the impact of AC on train usage, a topic that has not been previously researched. This study provides novel insights into the mobility patterns in the Netherlands. With the increasing interest in the usage of AC, it is important to understand how it influences individuals' modality choices. This is evidenced by the many negative consequences the AC arrival brings mentioned in Section 7.3. Consequently, this research lays the groundwork for further research into the role of ACs in modal shifts.

Secondly, this study conducts an unexamined comparison between road and rail transportation modes in terms of safety. Normally, cars and trains have different safety definitions, making it challenging to assess safety as a factor in researching travel mode choices. In this study, safety is introduced as a perceptual aspect, forming an innovative approach for future researchers to incorporate safety as a factor in the examination of modal shifts.

Thirdly, the conclusion of this study, that there is a high probability that a shift towards AC might occurs and that comfort is the pivotal driver, enhances the conception of the impact of ACs. Understanding this impact helps in the strategic planning of future mobility systems. Furthermore, this study introduces a novel, unexplored mobility scenario that needs to be considered in the conceptualization of future transportation policy interventions.

Reflection

The results highlight that traveller behaviour is influenced by many factors, including personal preferences and the characteristics of transport modes (Van Vugt et al., 1996; Wiig & Smith, 2009). By holding attribute levels constant, understanding the full impact of variable attributes may be limited, as already discussed in the reflection of the methodology. Therefore, it is important to acknowledge that there is more variability in transportation behaviour than can be represented by these results. As described in the methodology reflection, conclusions about the fixed attributes were drawn by comparing the results with the existing literature, as detailed in Section 6.6.

Secondly, the fact that comfort emerges as the most influential factor highlights the importance of providing travellers with a comfortable travel experience. The reason why comfort is the most influential factor is explained in Section 7.2 through NS' customer desire pyramid, where comfort is a satisfier (Boes, 2007; Govers & van Hagen, 2019). This implies that comfort has the potential to exceed travellers' expectations. This finding carries important policy implications for train development. It highlights that investments in comfort components and a pleasant travel experience are crucial to mitigate a shift towards ACs, and positioning trains as stronger competitors to ACs. In Section 7.3.2, options have been presented on how this could potentially be incorporated into Dutch government policy.

Lastly, as mentioned in Sections 4.2.4 and 6.5.2, this study primarily focused on the independent aspects of comfort, such as interior characteristics of the transportation modes. Especially in shared transportation modes, like trains, dependent aspects of comfort, such as the presence of other travellers, also play a significant role in travellers' overall comfort experience (Beirão & Sarsfield Cabral, 2007; Mims et al., 2023; Nahrin & Rahman, 2012). This study did not delve into the these dependent factors, including crowdedness, heat, smell, and the availability of seating, resulted from the presence of other travellers (Austin & Brunner, 2004; Frank, 2000; Tirachini et al., 2013). The conclusion that comfort is of great importance can but further substantiated by expanding the study to encompass aspects like the presence of other travellers during their journey. This would provide researchers deeper insights into the factors influence mode choice. This suggestion for future research is discussed in more detail in Section 7.6.

7.4.3 Reflection on gender bias

A potential limitation to consider is the presence of sample group bias within the respondents' group. In this study, two-thirds of the total sample is male due to distribution constraints, as discussed in section 3.2. However, men generally exhibit a higher level of interest in technology compared to women (Robinson & McIlwee, 1991). This sample size difference in gender could potentially influence the extent of the shift towards AC.

To address this concern, a sensitivity analysis was conducted with only female respondents. The results of this analysis have been included in Appendix P. These results show that there are slight numerical variations in the results. However, the directions, the significance levels and the predominant influencing factors remain consistent with the results when both genders are included.

Consequently, it can be defended that despite the disparity in gender distribution in the sample group, the findings of this study remained broadly applicable and are not constrained by this gender imbalance. Therefore, it can be concluded that the outcomes of this study are generalizable across both genders, mitigating the potential limitation caused by sample group bias.

7.5 Limitations

This study has a few limitations, which will be elaborated in this section. First, when conducting the SCE, respondents may exhibit a hypothetical bias. This means that for scenarios that are not yet tangible in reality, respondents give answers based on what they would hypothetically choose, but this does not necessarily align with their real-world preferences (Hensher, 2010). This study shows that a large proportion of train passengers are willing to shift to AC under specific circumstances. However, the extent of this shift might be much smaller in reality. This difference could arise because respondents may think that showing they want to shift is the socially desirable answer (Z. Li & Hensher, 2013). To mitigate the occurrence of this bias, a realistic scenario with actual attribute levels was provided to the respondents (Ready et al., 2010). Nonetheless, in future research, this bias can be further addressed by allowing train passengers to experience the scenarios within a physically AC. This experience provides train passengers with a tangible understanding of the actual conditions, enabling a more accurate assessment of their preferences and behaviours regarding modal choices.

A second limitation of this study refers to its focus on exclusively privately owned ACs classified as SAE level 4. As a result, the findings derived from this study are not applicable to other forms of ACs, such as fully ACs, SAE level 5, or shared AC (hereafter; SAC). In addition, as this study focuses on private ACs that require an upfront purchase, it is assumed that any shift, if it occurs, is unlikely to be a one-time event. However, the study's structure restricts the capacity to make definitive conclusions on this matter. Yet, there is a substantial difference between a one-tine shift and a sustained, permanent shift, especially in terms of the implications for the road and rail sectors, as detailed in Section 7.3. The generalizability of this study to these forms of AC, and the extent of the shift require further research, as elaborated in Section 7.6.

7.6 Future research recommendations

The first recommendation for future research is the examination of fully ACs, SAE level 5. While this study focused on semi-fully AC, SAE level 4, the dynamics of modal shift, or even the presence thereof, may substantially differ when examining fully AC operating at SAE level 5. Exploring this form of AC gives insight into the anticipated integration on the highway.

Additionally, future research must be conducted on the impact of SAC. SAC usage has commonalities with train travel, more than the semi-fully AC from this study. Both train travel and SAC usage are forms of public transportation and shared mobility. Furthermore, neither mode requires individual storage facilities, such as parking spaces. These unique characteristics can lead to different model choices. To examine this, further research is needed to analyse the preferences and choices associated with SAC in relation to train travel. Since this study focuses on private ACs, the assumption is made that if a shift occurs, it is not a one-time event because a purchase of the mode of transport is acquired. In the case of SACs, there is no need to purchase a means of transport, and research can be conduct to explore the nature of the shift, whether it will be a one-time occurrence, temporary, permanent or seasonal. Once this is known, more insight can be provided into the expected impact of the advent of ACs.

Another recommendation for future research is the study of the dependent variables of comfort. Another recommendation for future research is to investigate the dependent variables related to comfort. As mentioned in Section 6.5.2, the dependent variables of comfort, which include factors influence by the presence of fellow passengers such as crowding, heat, smell, and seat availability, are expected to influence the probability of a shift. Currently, only the independent variables have been considered, and they do not vary with the presence of few or many train passengers. However, it is anticipated that these factors might influence people's modal choice. To confirm or contradict this, future research should be conducted.

Other recommendations for future research include conducting a repeated SCE. In the current study, the SCE was conducted only once. To strengthen the reliability of the findings and gain a more comprehensive understanding of the modal choices, it is advisable to conduct the SCE in future research. Additionally, it is recommended that the SCE is replicated outside the Netherlands to enhance the robustness and broaden the applicability of the findings. Additionally, the SCE could also be expanded to include other potentially confounding attributes, such as reliability and parking facilities. These attributes depend on a multitude of variables, making them potentially confounders if introduced into this study due to time and scope limitations. Confounding variables are variables influenced by factors not examined in the study. In future research, all the factors that actually explain the effect of the confounding variable must be identified. A more focused examination of these attributes in a new SCE could give more insights in all the aspects that influence a decision between train and AC travel.

Additionally, a future research recommendation is to research the dependent aspects of comfort. Aa mentioned in Section 7.4, there are dependent aspects of comfort that were not examined in this study. The reason for exclusively examining the independent aspects of comfort was to prevent comfort from becoming a confounding variable. This occurs when comfort is influenced by factors not considered in the research. However, in future research, both independent variables, such as the interior of the transportation modes, and dependent variables, such as the presence of other travellers, can be incorporated into the study. This will enable researchers to gain deeper insight into the various aspects of comfort and their significance. When all aspects of comfort are included in future research, it will no longer pose a risk of becoming a confounding variable because there will be no unmeasured (third) variables. Nevertheless, it is essential to thoroughly investigate all aspects of comfort to ensure that there are no unaccounted variables in the study.

Lastly, a future research recommendation is to not constrain the fixed attributed within the SCE. This study did not show the extent to which these fixed attributes exert influence on choice behaviour, as they remained fixed throughout the SCE. Future research should consider varying these attributes and be examined alongside safety, motion sickness and comfort. This approach will give a more precise understanding of the influence of these latter three factors and their impact on modal choice.

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Appendix A- Summary interview Riender Happee

Riender Happee is an expert in human interaction and automated driving, and was therefore asked to be interviewed. The main goal of the interview was to identify the attributes. the requirements for the attributes where that they are key factors that are crucial in the decision for choosing an automated vehicle, and that the attributes are the factors in how the automated car differs from the regular car are noticeable for a passenger. The highlights from the interview:

- *Comfort* stands out as a primary factor. Vehicles must provide physical comfort and enable passengers to engage in secondary tasks.
- With regard to comfort, private space and the flexibility to talk or be quiet are important, along with the perception and awareness of travel time.
- *Motion sickness* is a big concern regarding the acceptance of automated driving. The potential to resolve motion sickness through groundbreaking research. Lean into the curve mechanisms, similar to trains, contribute to lower sickness levels.
- The expectations are that sustainability will not be a driver for acceptance, but to conclude that, further research is required.
- Trust and Safety is important. Feeling safe and having trust in the technology are paramount. Establishing the *perception of safety* is essential.

The most important factors for choosing an automated vehicle include feeling safe and trusting the technology, addressing motion sickness, and ensuring overall comfort.

Appendix B – Automated Car Scenarios

Automation

Due to the variations in the definition of ‘automation’, the Society of Automative Engineers (hereafter; SAE) has distinguished between six levels (On-Road Automated Driving (ORAD) committee, 2015). These levels are globally recognised and provide the current standard for measuring the degree of automation. The six automation levels are attached in Table B.1.

Level	Designation	Features	
		Human driver monitors driving environment	
0	No Automation	• Blind spot warning • Lane departure warning	• Automatic emergency braking
1	Drivers Assistance	• Lane centering OR	• Adaptive cruise control
2	Partial Automation	• Lane centering AND	• Adaptive cruise control
		Automatic system monitors driving environment	
3	Conditional Automation	• Traffic jam chauffeur	
4	High Automation	• Local driverless taxi	• Pedals/steering wheel may be installed
5	Full Automation	• Local driverless taxi •	• System can drive everywhere under all conditions

Table B.1 - SAE automation levels (On-Road Automated Driving (ORAD) committee, 2021)

Sharing

In addition to automation, the degree of sharing also comes into play. A private car sits idle for most of the day, implying inefficient capacity utilization. This inefficient use of capacity underlies the sharing economy. Platforms are being developed to enable the sharing of e.g., cars. Currently, a distinction can be made between private and sharing. The latter can be further distinguished into car sharing or car-ride sharing.

As a result, Tillema et al. worked with knowledge institutions and specialists to outline four scenarios. These scenarios are added in Figure B.1.

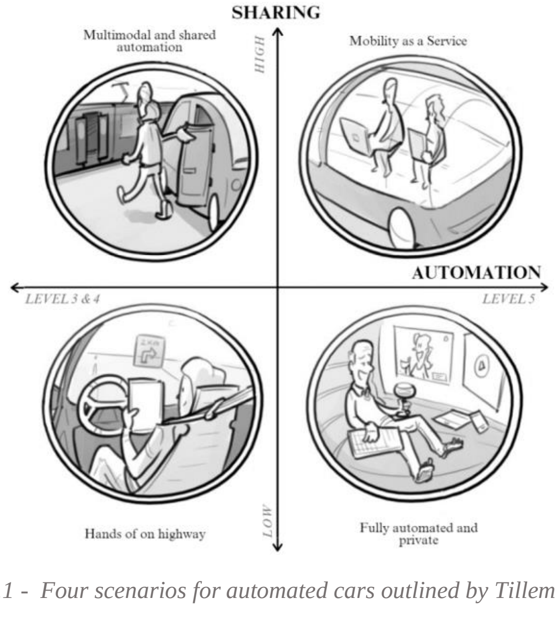


Figure B.1 - Four scenarios for automated cars outlined by Tillema et al. (2017)

MaaS

MaaS integrates various transportation services into a single online platform, offering personalized door-to-door travel solutions and trip planning (Durand et al., 2018). However, the support for its adoption is limited, primarily attracting highly mobile individuals with higher economic status, income and education (Zijlstra et al., 2020). Additionally, privacy concerns, lack of availability in suburban areas, and attachments to personal vehicles hinder MaaS adoption (Agbe & Shiomi, 2021; Maas, 2022). In conclusion, the success of MaaS relies on government intervention and public transportation support, which are currently lacking (Beneder et al., 2022).

MaSA

This scenario envisions widespread public transport usage and shared rides with high automation levels. Currently, travel assistants like 9292.nl and Google Maps already exist, just as subsidies for public transport, and frequent services. Due to the combination of the need for widespread public transportation usage and shared rides, but with semi-full AC, SAE level 3/4, this scenario is not achievable in the short term due to the desire of privately owned vehicles (Agbe & Shiomi, 2021; Taede Tillema et al., 2015).

FAP

The use of fully automated AC, SAE level 5, increases trust and control issues for potential drivers, compared to the use of SAE level 4 AC. Namely, challenges include reacting to spontaneous traffic situations and traffic’s inherent unpredictability (Parekh et al., 2022). Therefore, the adoption of this scenario will be lengthier than the HOH scenario (Agbe & Shiomi, 2021; Kyriakidis et al., 2019; McKinsey, 2023).

HOH

This scenario involves SAE level 4 automation, which means that drivers are still responsible for driving the car off the highway, while the car operates autonomously on the highway. However, governmental intervention is crucial for ensuring safety and issuing certification (Hancock et al., 2019). Recent incidents involving Tesla’s Full Self-Driving (hereafter; FSD) system highlights the importance of transparency and governmental oversight (van Wingerden, 2023). Recent studies indicate that this scenario is the most feasible in short term because it eliminates the primary challenge of FAP and SAE level 5 automation where in urban areas there are numerous external human factors active in traffic (Agbe & Shiomi, 2021; Kyriakidis et al., 2019; McKinsey, 2023).

Appendix C – PRISMA method execution

Literature search
The search for articles for a literature review has multiple phases. First, the keywords need to be determined. Thereafter it is necessary to see how many results come from the search terms. Next, the papers are selected based on certain criteria. Lastly, there will be a brief discussion on excluded papers.

Keywords
The use of the search terms started globally and generically. Many hits came out of the first search terms 'Travel behaviour' AND 'rail' AND 'road'. Therefore, the search terms were more and more specified until the title included all relevant keywords. Even though the number of hits were still very big, it was decided to proceed to scanning the titles and to check the titles with the inclusion and exclusion criteria.

The table is in chronological order from top to bottom. In the top row are the first search terms for general information gathering about the subject. In the bottom row are the final search terms for detailed research on the subject.

The search terms for a literature review of decision factors for the current travel behaviour are added in Table 1.

Search terms	**Database**	**Hits**
'travel behaviour' AND 'rail' AND 'road'	ScienceDirect	4.201
'travel behaviour' AND 'train' AND 'road'	ScienceDirect	3.550
'travel behaviour' AND 'train' AND 'car' AND 'modal shift'	ScienceDirect	
'travel behaviour' AND 'train' AND 'car' AND 'modal shift' AND 'factors'	ScienceDirect	1.658
'travel behaviour' AND 'train' AND 'car' AND 'modal shift' AND 'factors' AND 'preferences'	ScienceDirect	1.205

Table 1 – Inclusion and exclusion criteria

Inclusion and exclusion criteria
The titles were selected on several inclusion and exclusion criteria. These are criteria that are used to determine whether to include or exclude an article. There is the possibility that these criteria must be refined or re-defined later in the process.

The language of the report is English. However, Dutch papers are also readable, so the language of a paper may also be Dutch. In addition, preference will be given to peer-reviewed articles. For the time being, this will be covered by the criteria, until it turns out that this is not enough and non-peer-reviewed articles can also be used.

Criteria	**Inclusion**	**Exclusion**
Period	≥ 2015	≤ 2014
Language	English or Dutch	Non-English or non-Dutch
Resource medium	Peer-reviewed scientific articles	Blogs, forums and patents
Database	ScienceDirect	Other
Transportation subtopic	Rail, Train	Busses, Trams, Metros, Shared Mobilities

Table 2 – Inclusion and exclusion criteria

Discussion
There is a possibility of unintendedly excluding very defined papers that suit the topic. Some articles will research a smart transportation project, where only the name of the project is mentioned. These articles will be one of the search results.

Literature findings
Table 3 includes the literature findings, followed by the comparison of the papers in Table 4. An extended literature review is added to clarify the tick boxes in Table 4.

Title	**Author**
Factors Influencing to Travel Behaviour on Transport Mode Choice	(Madhuwanthi et al., 2016)
Factors that affect travel behaviour in developing cities: A methodological review	(Mwale et al., 2022)
Residential self-selection and travel behaviour: what are the effects of attitudes, reasons for location choice and the built environment?	(Ettema & Nieuwenhuis, 2017)
Activity based travel demand modelling of Thiruvananthapuram urban area.	(Lekshmi et al., 2016)
Factors affecting car ownership and mode choice in rail transit-supported suburbs of a large Chinese city.	(Shen et al., 2016)
Preference heterogeneity in mode choice based on a nationwide survey with a focus on urban rail.	(Zheng et al., 2016)
Urban form, transit supply, and travel behaviour: Evidence from Mexico's 100 largest cities.	(Guerra et al., 2018)
Factors influencing travel behaviour and their potential solution: a review of current literatures	(Shariff & Shah, 2008)
How do public transport users adjust their travel behaviour if public transport ceases? A qualitative study	(Nguyen-Phuoc et al., 2018)
The demand for public buses in sub-Saharan African cities: Case studies from Maputo and Nairobi	(Tembe et al., 2019)

Table 3 – Article titles

	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[9]**	**[10]**
Passenger characteristics										
• Gender	X	X	X	X	X	X	X			X
• Age	X	X	X	X	X	X	X			X
• Income	X	X	X	X	X		X	X		X
• Education level		X	X				X			
• Vehicle ownership	X		X	X					X	X
• Household size	X	X	X		X		X		x	
• Possession of driver license	X		X	X		X			X	X
• Residential density	X					X	X	X		X
• Social status		X		X						
Trip characteristics										
• Trip purpose	X							X	X	X
• Trip frequency		X								
• Subsidy					X					
• Time of day	X			X				X		X
• Availability								X		
• Single-occupancy	X									X
Transport mode characteristics										
• Waiting time	X	X				X		X		X
• Time of trip					X	X			X	
• Walkability			X	X		X	X	X	X	X
• Costs	X	X		X	X	X		X	X	X
• Parking availability	X	X	X							X
• Transferring						X				
• Reliability	X	X				X			X	X
• Comfort	X	X			X	X				X
• Safety	X	X			X					X
• sustainability			X				X	X		

Table 4 – Literature comparison

In recent years, several research studies have shed light on the factors influencing the choice of transportation mode, aiming to reduce road congestion and promote sustainable travel options. These studies have explored various variables, divided into personal factors and travel behaviour factors, to understand the underlying motivations behind transportation mode choices.

One such study conducted by Madhuwanthi et al. (2015) focused on the identification of the factors that influence the decision for a transportation mode in order to reduce road congestion and private vehicle use. Their research shows that the traveller's mode choice is related to three variables, I) travellers' characteristics, II) the trip travellers choose, and III) the attributes of a transport mode travellers choose. They divided the results into personal factors and travel behaviour factors. The personal factors with the greatest impact on the choice of transport mode are *income* and *age*. The travel behaviour factors with the greatest impact are *waiting time, comfort* and *safety* (Madhuwanthi et al., 2016).

Building upon this research, Mwale et al. conducted a literature review in 2022 to further explore the factors influencing travel behaviour, specifically in developing cities. Their study highlighted that the most commonly used methods to measure these factors were Stated Choice Experiments using a Multinominal Logit model (MNL) and Structural Equation Models (SEM). The MNL method was favoured due to its ease of use and availability of software. *Ownership of a car* and *trip frequency* emerged as the most influential factors in choosing a transportation mode. Furthermore, Mwale identified additional factors affecting car ownership, such as *income*, *education level*, *household size*, and *walking distance*. However, one limitation of this study was the exclusion of technological developments like sensors and GPS, which could have impacted the influence of certain factors (Mwale et al., 2022).

In 2017, Ettema and Niewenhuis conducted research on transportation mode choice and challenged the assumption of self-selection. Their findings indicated that train-oriented areas had a positive influence on building a car-friendly environment, and vice versa. The study further revealed that *owning a car* was the strongest preference, followed by *age*, while *household size* had little influence on train choice (Ettema & Nieuwenhuis, 2017).

Another study by Lekshimi et al. in 2016 focused on the factors impacting transportation mode choice in the Thiruvavanthapuram area of India, a region known for its wealth and tourism. The researchers examined the overarching theme of "costs" and found that young people and those with lower incomes were more likely to choose the train over a car, especially during off-peak hours. However, it should be noted that the cost-quality distribution of public transport and the car network in India differs from that of the Netherlands, limiting the direct applicability of these findings (Lekshmi et al., 2016).

Shen et al. (2016) conducted a study on rail transport choices in rapidly growing cities with expanding rail networks. Consistent with previous research, car ownership was identified as the primary influencing factor, linked to income and social status. The study also highlighted the increasing popularity of trains in crowded areas with shorter distances to train stations, with cost and comfort also playing significant roles in mode choice (Shen et al., 2016).

Zheng et al. (2016) investigated factors influencing rail transport choice, categorizing them into service quality and character attributes of transport modes and socio-demographic attributes. The study revealed that walking distance to the train station had the most substantial impact, followed by cost and the presence of a laptop station. For cars, the cost of petrol and parking costs were the major factors. Interestingly, the distance from the train station or parking location to the destination had little influence on the mode choice for both cars and trains (Zheng et al., 2016).

In 2018, Guerre et al. explored mode choice in crowded areas and found that individuals were more likely to use trains in densely populated regions with well-developed public transport networks. Conversely, a higher income was associated with a greater likelihood of choosing a car (Guerra et al., 2018).

Shariff and Shah (2008) investigated why people choose to drive, ultimately arriving at policies to reduce congestion. The results of their study indicate that in developed countries, public transport is better, and the need for getting a driving licence is much lower. They also show that rising fuel prices result in more train use (Shariff & Shah, 2008).

Appendix D – Proximity to train stations

For each postcode area, the distance to the nearest station for both Rotterdam and Amsterdam was analysed.

Rotterdam	
Postal code area	**Distance**
Charlois	4.7
Delfshaven	2.9
Feijenoord	1.2
Hillegersberg-Schiebroek	1.7
Hoek van Holland	8.1
Kralingen-Crooswijk	2.2
Nieuw Mathenesse	2.2
Overschie	3.7
Rivium	2.3
Rotterdam centrum	1.4
Rotterdam Noord	0.9
Rotterdam-Noord-West	2.3
Spaanse Polder	1.4
Waalhaven-Eemhaven	3.3
Average =	2.735714

Amsterdam	
Postal code area	**Distance**
Zuidas	0.6
Indische Buurt West	0.6
Bijlmer Centrum	0.8
Burgwallen-Oude Zijde	0.8
Nieuwmarkt/Lastage	0.9
De Kolenkit	1
Buitenveldert-Oost	1
Westlandgracht	1.1
Amstel III/Bullewijk	1.2
Frankendael	1.2
De Weteringschans	1.2
Grachtengordel-Zuid	1.3
Haarlemmerbuurt	1.5
Grachtengordel-West	1.6
Zuid Pijp	1.7
Nieuwe Pijp	1.8
Sloterdijk	1.9
Erasmuspark	2
Westindische Buurt	2.1
Jordaan	2.2
Oude Pijp	2.2
Museumkwartier	2.4
Helmersbuurt	2.4
Staatsliedenbuurt	2.4
Houthavens	2.5
Gein	2.6
Overtoomse Sluis	2.7
Driemond	3.2
Nellestein	3.7
Eendracht	3.9
Geuzenveld	4.2
Buikslotermeer	4.6
De Punt	4.8
Kadoelen	5.8
gemiddelde	2.173529

2.735714 + 2.173529 = 4.909243/2 = 2.4546215

Roudend to 2.5 km (2,500 metres).

Appendix E - Identification of comfort elements

Ten individuals were asked to write down their ideas of comfort in various modes of transportation. The responses have been added in Table E.1.

Respondent #	Answer	Element
1	“I think of a comfortable chair, because if I sit in it for a while, I want to sit comfortably.”	Seating
2	“I don't want it to get hot or stuffy in the car, if I take the train as an example.”	Environmental
3	“As long as I can work normally I don't mind anything. If I have to stand, it's very annoying because then I can't use my laptop.”	Workspace
4	“When I think of comfort, I think of a well-regulated temperature and good air circulation, so that the environment remains pleasant throughout the journey.”	Environmental
5	"When I think of comfort, I imagine very soft cushions or maybe some back support because I have some back problems sometimes. I really want to relax if I need to sit in the train for a very long time."	Seating
6	“By comfort I simply mean that I can sit restfully.”	Seating
7	“By comfort I mean that I can do whatever I want at that moment. If I want to sleep, that's possible, or if I want to work, that's possible. For example, that there is a table near my chair.”	Workspace
8	"Yes, comfort for me is that I can work and stuff."	Workspace
9	"Oh I think hygiene is very important so that it is clean and that there is fresh air. I also want it not to be so sweaty and sticky."	Environmental
10	"I don't do much on the train so I don't need that much, but if I have to stand for a long time my legs hurt, so I understand comfort as good seats, or seats at all."	Seating

Table E.1 – Comfort element identification

Subsequently, the three components of comfort were selected. A second group of 23 individuals was asked what people understand by comfort. The results have been added in graph E.1.

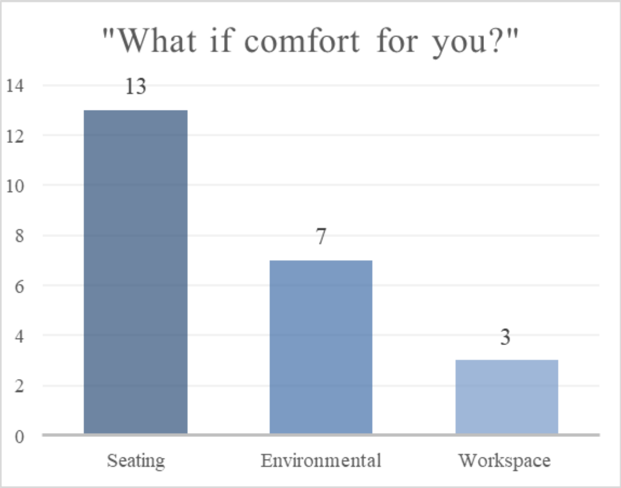


Figure E.1 – Comfort selection graph

None of the three elements had been chosen by anyone, so it was decided to keep all three elements.

Appendix F – Calculations fixed attributes

Distance from origin to transport mode
The distance from the origin to the transportation means is an attribute which significantly influences the choice of transport. The distance to a station was calculated by averaging the distance to the nearest station for every postal code. For Amsterdam, this is an average distance of 2.203 and for Rotterdam it is an average distance of 2.709. The combined city average of 2.456 has been rounded to 2,500 meters for respondent clarity. The estimated distance to the private automated car is assumed for 50 meters, accounting for varying parking locations, including door fronts, car parks, and garages. Distances are provided in meters in the survey, not minutes, due to diverse modes of travel in order to prevent bias and ensure accurate respondent input.

Time in main transport
Travel time plays a crucial role in influencing traveller's modal choices. To assess travel time, the route was put into Google Maps, and both the train and car travel time can be derived from it. The 2,500 metres for the train and the 50 metres for the car is yellowed from the route because the travel time is determined based on sitting in the main transport. The travel time in the train is 40 minutes. The travel time in the car is 60 minutes outside rush hour, and 1 hour and 45 minutes during rush hour. Respondents can decide whether they travel in rush hour of not (Van Essen, 2023).

Price
The price for the automated car is similar to the price for an electric car because too little information is known about depreciation costs and maintenance costs. The calculation is based on that of the NS travel comparator, which based its price calculation on NIBUD data (NIBUD, 2023; NS, 2023).

Fuel costs are 77.4 km*€0.084, maintenance and repair costs are 77.4 km*€0.046 and depreciation costs are 77.4 km*€0.080 = €16.25, assuming the postcodes with the highest population density in both cities (CYBO, 2022).

The exclusion of the price structure aimed to avoid overcomplication for respondents. Given their limited attention span during a survey, it was more prudent to allocate their attention to the core scenarios. In addition, the absence of the price build-up forces respondents to rely on their general perception of costs, which is important to get a realistic reflection of their decision (Van Essen, 2023).

Distance from transport mode to destination
The distance between the transportation mode and the destination minimally affects the decision. Consequently, the effect of this attribute will not be measured in this study. Nevertheless, by excluding the last-mile factor, respondents are provided room for subjective interpretation, which could impact their decision. In order to illustrate the entire route, an attribute level of 400 meters is included. Notably, this level remains consistent for both transport modes due to the non-assessment of its impact.

CO_2 emission
The attribute level design session with Van Essen concluded that respondents gain more clarity from comparisons than grams of CO_2 emissions per kilometre (Van Essen, 2023). As a result, the decision was made to base the attribute levels on comparisons. While Dutch trains operate on 100% wind energy, CO_2 emissions arise from energy infrastructure production, leading to residual emissions. On average, Dutch trains emit 40 times fewer CO_2 emissions than gasoline cars, considering the dominance of gasoline cars in the Netherlands (CBS, 2021), en 5 times fewer emissions than an electric car (Rodenboog, 2020). In the case of automated cars, their energy-driven systems contribute to emissions that are 1.5 times higher than those of electric cars.

Appendix G – Test group

In this section, respondents are presented with six dilemma's in order to establish the most optimal survey design. The dilemmas cover SAE level 4, scenario layout, safety perception attribute levels, safety perception scale, altered attribute layout, and the choice between phone and laptop to fill in the survey.

Dilemma 1 – Which definition is more clear to you?

Option A - An SAE level 4 automated car is meant to be driven on fixed routes such as the highway and not in built-in areas. Nordhoff states that however, the driver is not fully obligated to switch off the automation system upon exiting the highway (Nordhoff, 2023).

Option B - Upon entering the built-in areas, the automated system must be deactivated, requiring the driver to take control again over the wheel. This regulation is rigid, allowing no room for flexibility within this vehicle category.

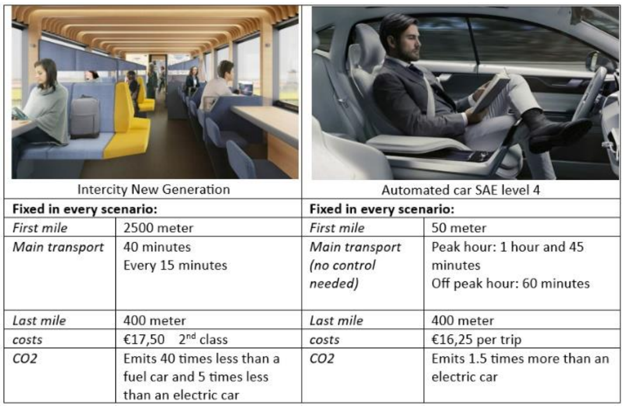
Option A represents the actual definition, yet, putting this in the explanation video risks confusing respondents. To address this, both options were presented to the test group. Answers to this dilemma are:

> "I don't understand why you don't necessarily have to deactivate? I thought level 4 only drove on highways anyway."
> "Okay, but then with option A, how do you know when to change anyway?"
> "Option A is correct, but I think it can cause ambiguity for the entire audience."

Based on the responses, it was decided to choose for a consistent definition, rather than the strictly accurate one. This decision was aimed to prevent any potential confusion in the answers of the respondents.

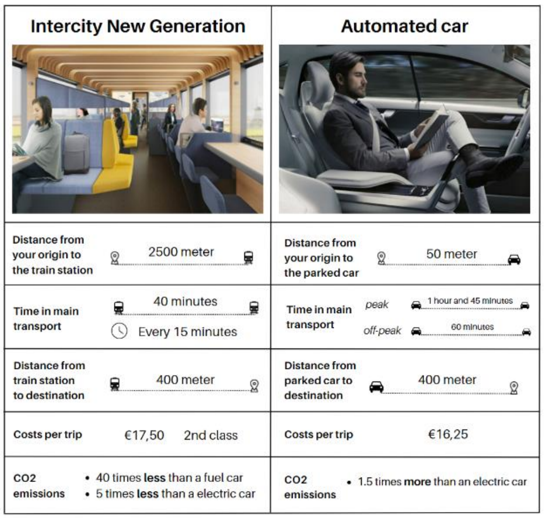
Dilemma 2 – Which of these two layouts is more attractive for use in a survey?

Option A - Table



Intercity New Generation		Automated car SAE level 4	
Fixed in every scenario:		**Fixed in every scenario:**	
First mile	2500 meter	*First mile*	50 meter
Main transport	40 minutes Every 15 minutes	*Main transport (no control needed)*	Peak hour: 1 hour and 45 minutes Off peak hour: 60 minutes
Last mile	400 meter	*Last mile*	400 meter
costs	€17,50 2nd class	*costs*	€16,25 per trip
CO2	Emits 40 times less than a fuel car and 5 times less than an electric car	*CO2*	Emits 1.5 times more than an electric car

Option B - Figure



Intercity New Generation		Automated car	
Distance from your origin to the train station	2500 meter	Distance from your origin to the parked car	50 meter
Time in main transport	40 minutes Every 15 minutes	Time in main transport	*peak* 1 hour and 45 minutes *off-peak* 60 minutes
Distance from train station to destination	400 meter	Distance from parked car to destination	400 meter
Costs per trip	€17,50 2nd class	Costs per trip	€16,25
CO2 emissions	• 40 times **less** than a fuel car • 5 times **less** than a electric car	CO2 emissions	• 1.5 times **more** than an electric car

The first dilemma is to whether the scenarios should be incorporated in the survey as a table or as a figure. Among the responses were:

> "Option B seems more professional, which makes me want to put more effort into the survey."
> "It may be a little harder to read, but it looks a lot neater."

Every respondent selected option B, and therefore it was chosen for in the survey.

Dilemma 3 – Which of the two safety perception attribute levels do you think is better?

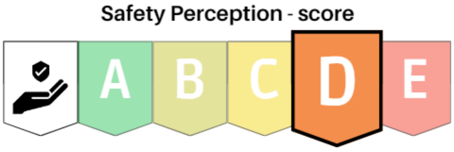
Option A – Comparison *Option B - Score*

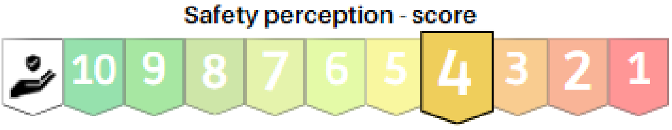
Van Essen recommended avoiding the phrase 'so many times more unsafe' in the safety perception attribute level (Van Essen, 2023). To assess this, respondents were asked about their preference for a score or a comparison. The responses received were as follows:

> “Safety is important, and if one of the options is less safe than the other, you could very much steer people in a certain direction."
> “I think my preference would be a score, but it depends on what scale is used.”
> “I don't know much about transport safety, I wouldn't really know what it means if one of them is less safe than the other."

Dilemma 4 – Which of the two safety perception scales would you choose?

Option A – A to E *Option B – 10 to 1*



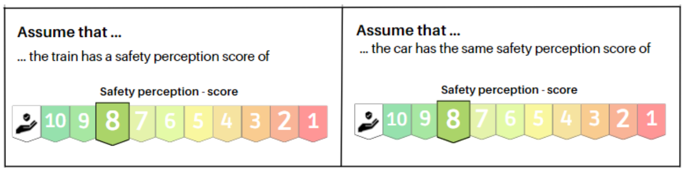


To address the feedback on dilemma 2 on the scoring attribute level, two options were considered: one using grades (A to E) and one using numbers (10 to 1). Responses were as follows:

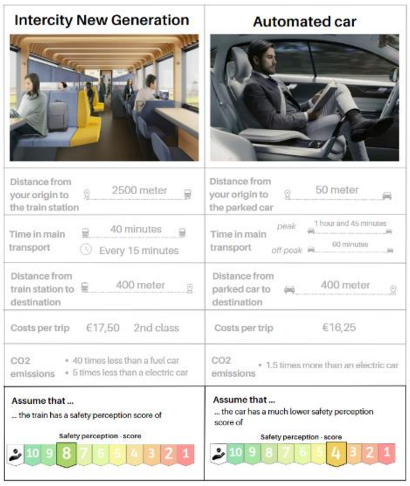
> “The score of 10 to 1 has more options, making it easier to make a choice.”
> “In the Netherlands, we always use 1 to 10 anyway, so then option B makes much more sense for us to fill in."

Dilemma 5 – Would you choose only the changed attribute level or the whole set*?*

Option A – Only the change attribute *Option B – The whole set*



Assume that ... ... the train has a safety perception score of Safety perception - score 10 9 8 7 6 5 4 3 2 1	**Assume that ...** ... the car has the same safety perception score of Safety perception - score 10 9 8 7 6 5 4 3 2 1



Intercity New Generation		Automated car	
Distance from your origin to the train station	2500 meter	Distance from your origin to the parked car	50 meter
Time in main transport	40 minutes Every 15 minutes	Time in main transport	peak 1 hour and 45 minutes off-peak 60 minutes
Distance from train station to destination	400 meter	Distance from parked car to destination	400 meter
Costs per trip	€17,50 2nd class	Costs per trip	€16,25
CO2 emissions	• 40 times less than a fuel car • 5 times less than a electric car	CO2 emissions	• 1.5 times more than an electric car
Assume that ... ... the train has a safety perception score of Safety perception - score 10 9 8 7 6 5 4 3 2 1		**Assume that ...** ... the car has a much lower safety perception score of Safety perception - score 10 9 8 7 6 5 4 3 2 1	

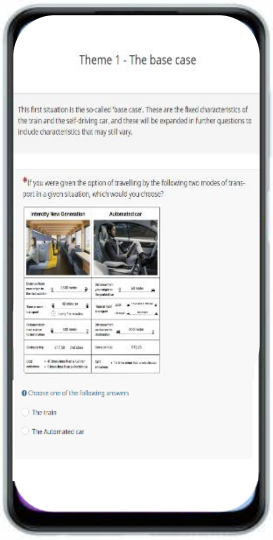
In order to establish the most optimal layout for the scenario questions, the test group was asked, when the last attribute level changes, it is preferable to only display the changed level, or reshow the complete set of attribute levels. responses to this dilemma were:

> “I think I would get irritated if I re-read everything and it turns out to be the same. Then I would also skip reading the last one, even though it has changed."
> “I find this difficult, I would find it too much reading, but it could also be that it makes me so focused on just that last part that I might forget the other parts.”

Based on these comments, option A was chosen, but textually with each question it was raised that the other attributes should also be included in the choice.

Dilemma 5 – Should the survey be made for phone or laptop?

Option A – Phone



Theme 1 - The base case

This first situation is the so-called 'base case'. These are the fixed characteristics of the train and the self-driving car, and these will be expanded in further questions to include characteristics that may still vary.

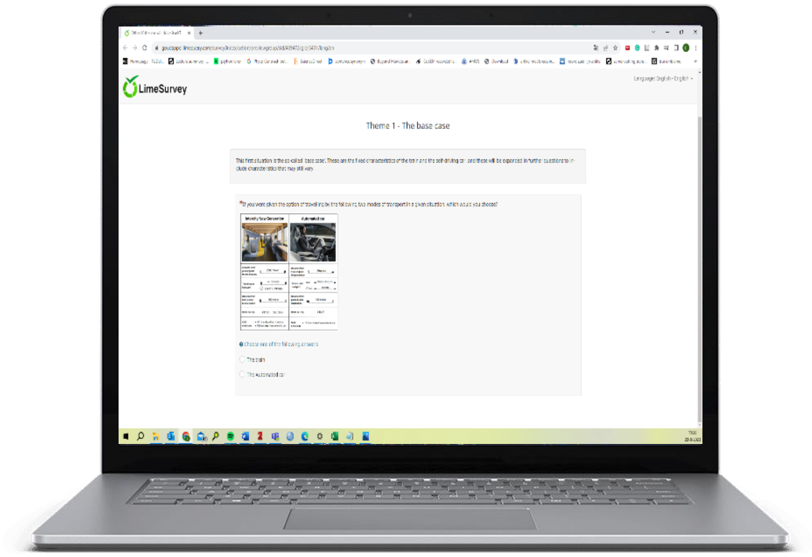
*If you were given the option of travelling by the following two modes of transport in a given situation, which would you choose?

Choose one of the following answers

○ The train

○ The Automated car

Option B – Laptop



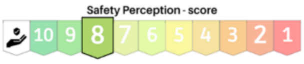
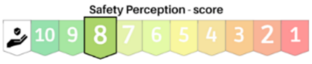
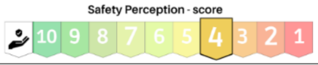
Theme 1 - The base case

Because of a limitation of LimeSurvey, a decision must be made whether the survey should be tailored for laptops or for phones. Responses to this dilemma include:

> “I believe that a larger number of people use their phones while on the train. If that aligns with your target audience, adjusting the survey for the phone could enhance accessibility for train passengers.”
> “It varies. Are you planning to distribute the survey through e-Mail, LinkedIn, WhatsApp etc.? It is essential to consider the communication methods that people typically use on each platform.”
> “I find that using a smartphone might be slightly simpler and more user-friendly.”

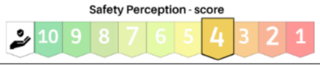
Based on the comments, it was decided to adjust the survey on the phone.

Appendix H.1 - Final survey design, attributes and attribute levels

Attribute	**Train**	**(Automated) Car**
Distance from origin to transport mode	• 2500 meter	• 50 meter
Time in main transport	• 40 minutes • Every 15 minutes	• Peak: 1 hour and 45 minutes • Off peak: 60 minutes
Price	• €17.50 2nd class	• €16.25
Distance from transport mode to destination	• 400 meter	• 400 meter
CO_2 emission	• 40 times less than a fuel car • 5 times less than an electric car	• 1.5 times more than an electric car
Safety	• 	•  •  • 
Motion sickness	<u>Level 1:</u> • As an occupant on a train, your experience of motion sickness is similar to any average train ride.	<u>Level 1</u>: • As an occupant of an automated car, your motion sickness experience is equivalent to that of a passengers in a regular car. <u>Level 2</u>: • Due to a pioneering technology, the motion sickness in an automated car is mitigated. Hence, as an occupant of an automated car, you experience less motion sickness, and your experience is equivalent to that of a train passenger.
Comfort - Seating	<u>Level 1:</u> • There are multiple vents present, equipped with a filtering system. • Sensors are utilized to measure and automatically regulate the temperature. • The wagons' walls are equipped with sound insulation.	<u>Level 1</u>: • There is a ventilation system is present, allowing passengers to adjust the direction of airflow to their preferences. • The temperature is automatically adjusted based on current weather conditions. • The interior is made of sound-absorbing materials that reduce noise pollution. <u>Level 2</u>: • An air purification system actively detects and eliminates the harmful pollutants. • Passengers can set their preferred climate zone for each individual seat. • The car's floor, walls and roof are equipped with sound insulation, complemented by designed tires aimed at minimizing noise pollution.
Comfort - Workspace	<u>Level 1:</u> • The train seats are spaced far apart, allowing enough	<u>Level 1</u>: • When the self-driving system is engaged, the seat automatically slides back.

	room for a big to fit between them. - On both sides there are wide arm supports. - The seats are wide and have soft cushioning.	- Solid and adjustable armrests are located on both sides. - The seat is spacious and deep. *Level 2*: - During the ride, the seat can be fully reclined and flattened. - The arm rest have reclining pads adapted to the passenger's comfort. - The seat has adjustable sides, enabling customization for a wider seating space.
Comfort - Environment	*Level 1:* - There are multiple vents present, equipped with a filtering system. - Sensors are utilized to measure and automatically regulate the temperature. - The wagons' walls are equipped with sound insulation.	*Level 1*: - There is a ventilation system is present, allowing passengers to adjust the direction of airflow to their preferences. - The temperature is automatically adjusted based on current weather conditions. - The interior is made of sound-absorbing materials that reduce noise pollution. *Level 2*: - An air purification system actively detects and eliminates the harmful pollutants. - Passengers can set their preferred climate zone for each individual seat. - The car's floor, walls and roof are equipped with sound insulation, complemented by designed tires aimed at minimizing noise pollution.

Appendix H.2 - Final survey design, attributes and attribute levels in Dutch

Attribuut	**Trein**	**Zelfrijdende auto**
Afstand vanaf uw vertrekpunt naar treinstation	• 2500 meter	• 50 meter
Tijd in het hoofd transport	• 40 minuten • Elke 15 minuten	• In de spits: 1 uur en 45 minuten • Buiten de spits: 60 minuten
Prijs	• €17,50 2e klas	• €16,25
Afstand van het transport naar uw eindbestemming	• 400 meter	• 400 meter
CO$_2$ uitstoot	• 40 keer meer uitstoot dan een brandstof auto • 5 keer meer uitstoot dan een elektrsiche auto	• 1.5 keer meer uitstoot dan een reguliere auto.
Veiligheid	• 	•  •  • 
Wagenziekte	*Level 1:* • Als passagier in een trein ervaart u wagenziekte als bij een gemiddelde treinrit.	*Level 1*: • Als inzittende van een zelfrijdende auto is uw ervaring met bewegingsziekte gelijk aan die van een passagier in een reguliere auto. *Level 2*: • Dankzij een baanbrekende technologie wordt de bewegingsziekte in een zelfrijdende auto verminderd. Zo ervaart u als bewoner van een zelfrijdende auto minder wagenziekte en is uw ervaring vergelijkbaar met die van een treinreiziger.
Comfort - zitplaats	*Level 1:* • Er zijn meerdere ventilatieopeningen aanwezig, voorzien van een filtersysteem. • Er wordt gebruik gemaakt van sensoren om de temperatuur te meten en automatisch te regelen. • De wanden van de wagons zijn voorzien van geluidsisolatie.	*Level 1*: • Er is een ventilatiesysteem aanwezig, waardoor passagiers de richting van de luchtstroom naar eigen voorkeur kunnen aanpassen. • De temperatuur wordt automatisch aangepast op basis van de huidige weersomstandigheden. • Het interieur is gemaakt van geluidsabsorberende materialen die geluidsoverlast verminderen. *Level 2*: • Een luchtzuiveringssysteem detecteert en verwijdert actief de schadelijke verontreinigende stoffen. • Passagiers kunnen voor elke individuele stoel hun voorkeursklimaatzone instellen. • De vloer, wanden en het dak van de auto zijn voorzien van geluidsisolatie, aangevuld met speciaal ontworpen banden die gericht zijn op het minimaliseren van geluidsoverlast.
Comfort - Werkplek	*Level 1:* • De treinstoelen staan ver uit elkaar, waardoor er	*Level 1*:

	voldoende ruimte is voor een grote tussenruimte. • Aan beide zijden bevinden zich brede armsteunen. • De stoelen zijn breed en voorzien van zachte kussens.	• Wanneer het zelfrijdende systeem wordt ingeschakeld, schuift de stoel automatisch naar achteren. • Aan beide zijden bevinden zich stevige en verstelbare armleuningen. • De zit is ruim en diep. *Level 2*: • Tijdens de rit kan de stoel volledig naar achteren en plat worden gezet. • De armleuningen zijn voorzien van verstelbare kussens die zijn aangepast aan het comfort van de passagier. • De stoel heeft verstelbare zijkanten, waardoor maatwerk voor een grotere zitruimte mogelijk is.
Comfort - Omgeving	*Level 1:* • Er zijn meerdere ventilatieopeningen aanwezig, voorzien van een filtersysteem. • Er wordt gebruik gemaakt van sensoren om de temperatuur te meten en automatisch te regelen. • De wanden van de wagons zijn voorzien van geluidsisolatie.	*Level 1*: • Er is een ventilatiesysteem aanwezig, waardoor passagiers de richting van de luchtstroom naar eigen voorkeur kunnen aanpassen. • De temperatuur wordt automatisch aangepast op basis van de huidige weersomstandigheden. • Het interieur is gemaakt van geluidsabsorberende materialen die geluidsoverlast verminderen. *Level 2*: • Een luchtzuiveringssysteem detecteert en verwijdert actief de schadelijke verontreinigende stoffen. • Passagiers kunnen voor elke individuele stoel hun voorkeursklimaatzone instellen. • De vloer, wanden en het dak van de auto zijn voorzien van geluidsisolatie, aangevuld met speciaal ontworpen banden die gericht zijn op het minimaliseren van geluidsoverlast.

Appendix I – Coding scheme

This appendix included in Table H.1 the coding scheme for one individual.

Scen.	Scenario name	Choice (0=train 1=car)	Safety				MS			Comfort			Characteristics														
			Base	8 and 4	8 and 6	8 and 8	Base	Car worse	Equal	Base	Both good	Car better	age	gender	empl.	inc.	MS level	envir. aw.	driv. lic.	driv. exp.	own car	type	auto parts	near. stat.	trav. freq.	NS bc	class
1	Basecase	0	1	0	0	0	1	0	0	1	0	0	35	1	2	5	3	2	1	2	1	1	2	2	2	2	2
2	Safety_8and4	0	0	1	0	0	1	0	0	1	0	0	35	1	2	5	3	2	1	2	1	1	2	2	2	2	2
3	Safety_8and6	0	0	0	1	0	1	0	0	1	0	0	35	1	2	5	3	2	1	2	1	1	2	2	2	2	2
4	Safety_8and8	0	0	0	0	1	1	0	0	1	0	0	35	1	2	5	3	2	1	2	1	1	2	2	2	2	2
5	Ms_car	0	1	0	0	0	0	1	0	1	0	0	35	1	2	5	3	2	1	2	1	1	2	2	2	2	2
6	Ms_train	1	1	0	0	0	0	0	1	1	0	0	35	1	2	5	3	2	1	2	1	1	2	2	2	2	2
7	Comfort_equal	0	1	0	0	0	1	0	0	0	1	0	35	1	2	5	3	2	1	2	1	1	2	2	2	2	2
8	Comfort_ car_better	1	1	0	0	0	1	0	0	0	0	1	35	1	2	5	3	2	1	2	1	1	2	2	2	2	2

Table H.1 – Coding scheme

Appendix J – Iterative MNL steps

Step 1 – Adding all variables

Parameter Estimates

Choice (0=train 1=car)[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
1	Intercept	-5.604	1.302	18.520	1	.000			
	Safety_8and4	-1.498	.689	4.729	1	.030	4.473	1.159	17.256
	Safety_8and6	.759	.444	2.920	1	.087	.468	.196	1.118
	Safety_8and8	1.667	.428	15.191	1	.000	.189	.082	.437
	motionsick_car_worse	-.251	.503	.250	1	.617	1.286	.480	3.445
	motionsick_car_equal_to_train	1.473	.429	11.795	1	.001	.229	.099	.531
	Comfort_both_good	.414	.458	.818	1	.366	.661	.269	1.622
	Comfort_car_better	2.451	.432	32.148	1	.000	.086	.037	.201
	often_traintravel	.851	.161	27.929	1	.000	.427	.311	.586
	auto_parts	.280	.087	10.420	1	.001	.756	.638	.896
	Age	.054	.016	11.444	1	.001	.948	.919	.978
	class	.597	.196	9.299	1	.002	.551	.375	.808
	stationnearest	.418	.126	11.099	1	.001	.658	.515	.842
	levelmotionsicknessx	-.124	.119	1.090	1	.296	1.132	.897	1.429
	NS_bc	-.031	.051	.357	1	.550	1.031	.933	1.140
	Driving_experience	-1.040	.353	8.666	1	.003	2.830	1.416	5.657
	environmental_awareness	-.109	.185	.345	1	.557	1.115	.776	1.601
	Income	.229	.122	3.533	1	.060	.795	.627	1.010
	Employment	-.390	.277	1.975	1	.160	1.477	.857	2.544
	Gender	-.397	.294	1.820	1	.177	1.487	.836	2.645
	typeofcar	-.194	.245	.627	1	.429	1.214	.751	1.962
	own_car	**0[b]**	.	.	0	.	.	.	.
	Driving_license	**0[b]**	.	.	0	.	.	.	.
	motionsick_base	**0[b]**	.	.	0	.	.	.	.
	Comfort_base	**0[b]**	.	.	0	.	.	.	.
	Safety_base	**0[b]**	.	.	0	.	.	.	.

a. The reference category is: 0.

b. This parameter is set to zero because it is redundant.

First exclude:

- driving_license
- own_car
- safety_base → reference group
- motionsick_base → reference group
- comfort_base → reference group

These factors are all redundant and so they are removed from the model.

Step 2 – Adjusted model

Parameter Estimates

Choice (0=train 1=car)[a]		B	Std. Error	Wald	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
							Lower Bound	Upper Bound
1	Intercept	-5.604	1.302	18.520	.000			
	Safety_8and4	-1.498	.689	4.729	.030	4.473	1.159	17.256
	Safety_8and6	.759	.444	2.920	.087	.468	.196	1.118
	Safety_8and8	1.667	.428	15.191	.000	.189	.082	.437
	motionsick_car_worse	-.251	.503	.250	.617	1.286	.480	3.445
	motionsick_car_equal_to_train	1.473	.429	11.795	.001	.229	.099	31
	Comfort_both_good	.414	.458	.818	.366	.661	.269	1.622
	Comfort_car_better	2.451	.432	32.148	.000	.086	.037	.201
	often_traintravel	.851	.161	27.929	.000	.427	.311	.586
	auto_parts	.280	.087	10.420	.001	.756	.638	.896
	Age	.054	.016	11.444	.001	.948	.919	.978
	class	.597	.196	9.299	.002	.551	.375	.808
	stationnearest	.418	.126	11.099	.001	.658	.515	.842
	levelmotionsicknessx	-.124	.119	1.090	.296	1.132	.897	1.429
	NS_bc	-.031	.051	.357	**.550**	1.031	.933	1.140
	Driving_experience	-1.040	.353	8.666	.003	2.830	1.416	5.657
	environmental_awareness	-.109	.185	.345	**.557**	1.115	.776	1.601
	Income	.229	.122	3.533	.060	.795	.627	1.010
	Employment	-.390	.277	1.975	.160	1.477	.857	2.544
	Gender	-.397	.294	1.820	.177	1.487	.836	2.645
	typeofcar	-.194	.245	.627	**.429**	1.214	.751	1.962

a. The reference category is: 0.

Highest significance levels:

- NS_bc
- Environmental_awareness
- Typeofcar
- Df kolom weggehaald want overal is dat 1

‘Safety8and8’ is kept in the model because it is relevant to the study, even if significant.

Step 3 – Adjusted model 2.0

Parameter Estimates

							95% Confidence Interval for Exp(B)	
Choice (0=train 1=car)[a]		B	Std. Error	Wald	Sig.	Exp(B)	Lower Bound	Upper Bound
1	Intercept	-6.379	1.115	32.740	.000			
	Safety_8and4	-1.498	.689	4.728	.030	4.472	1.159	17.249
	Safety_8and6	.758	.444	2.917	.088	.469	.196	1.118
	Safety_8and8	1.663	.427	15.154	.000	.190	.082	.438
	motionsick_car_worse	-.251	.503	.250	.617	1.286	.480	3.444
	motionsick_car_equal_to_train	1.470	.429	11.769	.001	.230	.099	.532
	Comfort_both_good	.414	.458	.817	.366	.661	.270	1.622
	Comfort_car_better	2.444	.432	32.034	.000	.087	.037	.202
	often_traintravel	.861	.156	30.343	.000	.423	.311	.574
	auto_parts	.251	.083	9.218	.002	.778	.662	.915
	Age	.051	.016	10.664	.001	.950	.922	.980
	class	.602	.194	9.597	.002	.547	.374	.801
	stationnearest	.427	.126	11.505	.001	.653	.510	.835
	levelmotionsicknessx	-.118	.118	1.002	.317	1.125	.893	1.418
	Driving_experience	-.958	.344	7.748	.005	2.607	1.328	5.120
	Income	.217	.118	3.384	.066	.805	.639	1.014
	Employment	-.335	.273	1.505	**.220**	1.398	.819	2.386
	Gender	-.354	.276	1.649	**.199**	1.425	.830	2.447

a. The reference category is: 0.

Variables with higher significance levels than in step 2:

- Gender
- Employment

Stap 4 – Adjusted model 3.0

Parameter Estimates

							95% Confidence Interval for Exp(B)	
Choice (0=train 1=car)[a]		B	Std. Error	Wald	Sig.	Exp(B)	Lower Bound	Upper Bound
1	Intercept	-5.627	.918	37.575	.000			
	Safety_8and4	-1.505	.690	4.753	.029	4.503	1.164	17.415
	Safety_8and6	.761	.445	2.928	.087	.467	.196	1.117
	Safety_8and8	1.666	.428	15.165	.000	.189	.082	.437
	motionsick_car_worse	-.253	.504	.251	.616	1.287	.479	3.457
	motionsick_car_equal_to_train	1.474	.429	11.786	.001	.229	.099	.531
	Comfort_both_good	.416	.459	.821	.365	.660	.268	1.622
	Comfort_car_better	2.467	.432	32.651	.000	.085	.036	.198
	motionsickness_level	.258	.131	3.865	.049	.773	.597	.999
	nearest_station	-.382	.118	10.581	.001	1.466	1.164	1.845
	often_traintravel	.794	.149	28.223	.000	.452	.337	.606
	auto_parts	.261	.081	10.388	.001	.770	.657	.903
	Age	.042	.014	9.502	.002	.959	.933	.985
	Income	.245	.104	5.569	.018	.782	.638	.959
	Driving_experience	**-.844**	.339	6.180	.013	2.325	1.195	4.520
	class	.551	.189	8.486	.004	.577	.398	.835

a. The reference category is: 0.

Exclude variable

- Driving_experience → is negative number, which does not make sense. Because according tot his model, the longer people drive the faster they choose the train
- The modal fit, -2 Log Likelihood, is bette rif driving experience is not included in the model.

Stap 5 - Adjusted model 4.0

Parameter Estimates

Choice (0=train 1=car)[a]		B	Std. Error	Wald	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
							Lower Bound	Upper Bound
1	Intercept	-3.538	.856	58.389	.000			
	Safety_8and4	-1.495	.688	4.718	.030	4.462	1.157	17.199
	Safety_8and6	.751	.442	2.891	.089	.472	.198	1.122
	Safety_8and8	1.642	.425	14.951	.000	.194	.084	.445
	motionsick_car_worse	-.250	.502	.249	.618	1.284	.481	3.433
	motionsick_car_equal_to_train	1.453	.426	11.620	.001	.234	.101	.539
	Comfort_both_good	.411	.456	.812	.368	.663	.271	1.621
	Comfort_car_better	2.432	.428	32.227	.000	.088	.038	.203
	motionsickness_level	.288	.129	5.012	.255	.750	.583	.965
	nearest_station	-.308	.112	7.525	.006	1.361	1.092	1.696
	often_traintravel	.835	.148	31.810	.000	.434	.325	.580
	auto_parts	.316	.078	16.540	.000	.729	.626	.849
	Age	.016	.009	3.449	.063	.984	.967	1.001
	Income	-.135	.092	2.148	**.143**	.874	.730	1.046
	class	.572	.190	9.104	.003	.564	.389	.818

Exclude the following variable:

- Income → switches from positive to negative and is not significant
- The modal fit is better without the inclusion of this variable.

Final model

Choice (0 = train 1 = AC)[a] - Parameter estimates							
Variable	**β**	**ε**	**Wald**	**Significance**	**Exp(β)**	**95% confidence interval for Exp(β)**	
						LB	**UB**
(Intercept)	**-3.480**	1.004	12.006	.001*			
Safety_8and4	**-1.331**	.627	4.505	.034*	.264	.077	.903
Safety_8and6	**.308**	.455	.459	.498	1.361	.558	3.318
Safety_8and8	**1.250**	.426	8.613	.003*	3.491	1.515	8.045
motionsick_car_worse	**-.373**	.501	.553	.457	.689	.258	1.840
motionsick_car_equal_to_train	**1.181**	.427	7.655	.006*	3.259	1.411	7.526
Comfort_both_good	**.401**	.450	.793	.373	1.493	.618	3.610
Comfort_car_better	**2.255**	.427	27.932	.000*	9.534	4.132	22.000
often_traintravel	**-.969**	.152	40.378	.000*	.380	.282	.512
auto_parts	**.337**	.080	17.564	.000*	1.401	1.197	1.640
Age	**.027**	.008	11.666	.001*	1.027	1.012	1.043
class	**.824**	.198	17.283	.000*	2.280	1.546	3.363
neareststation	**.395**	.117	11.403	.001*	1.484	1.180	1.866
levelmotionsickness	**-.131**	.118	1.229	.268	.877	.696	1.106

Appendix K – Postal code levels

In appendix:

Rotterdam	
Distance/postal code	**level**
3.3	2
2.2	1
1.9	1
1.4	1
0.9	1
1.9	1
4.0	2
2.3	1
1.6	1
2.2	1
8.1	4
Average =	2.709091

Amsterdam	
Distance/postal code	**level**
1.2	1
1.7	1
1.2	1
0.9	1
0.7	1
1.1	1
2.2	1
1.6	1
1.8	1
1.2	1
0.6	1
0.7	1
1.3	1
3.7	2
5.8	3
1	1
1	1
1.3	1
1.8	1
2.2	1
2.7	1
2.6	2
2.8	2
2.4	1
2.3	1
2.3	1
2.5	2
2.1	1
2	1
3.2	2
4.8	2
4.6	2
gemiddelde	2.103125

Appendix L - Nearest station partial shifts

impact nearest station (1 = 0 to 2.5 km)				Origin (1)		Total impact	
	Utility	**Exp**	**p**	**Rdam**	**Adam**		
Utrain	**0**	**1**					
Basecase	-2.166	0.115	10%	64%	74%	**8%**	**8%**
Safety_8and4	-3.497	0.030	3%	64%	74%	**2%**	**2%**
Safety_8and6	-1.858	0.156	13%	64%	74%	**10%**	**10%**
Safety_8and8	-0.916	0.400	29%	64%	74%	**21%**	**21%**
motionsick_car_worse	-2.539	0.079	7%	64%	74%	**5%**	**5%**
motionsick_equal	-0.985	0.373	27%	64%	74%	**20%**	**20%**
Comfort_both_good	-1.765	0.171	15%	64%	74%	**11%**	**11%**
Comfort_car_better	0.089	1.093	52%	64%	74%	**38%**	**39%**

impact nearest station (2 = 2.5 to 5 km)				Origin (2)		Total impact	
	Utility	**Exp**	**p**	**Rdam**	**Adam**		
Utrain	0	1					
Basecase	-1.771	0.170	15%	29%	24%	**3%**	**3%**
Safety_8and4	-3.102	0.045	4%	29%	24%	**1%**	**1%**
Safety_8and6	-1.463	0.232	19%	29%	24%	**3%**	**4%**
Safety_8and8	-0.521	0.594	37%	29%	24%	**7%**	**8%**
motionsick_car_worse	-2.144	0.117	10%	29%	24%	**2%**	**2%**
motionsick_equal	-0.590	0.554	36%	29%	24%	**6%**	**8%**
Comfort_both_good	-1.370	0.254	20%	29%	24%	**4%**	**4%**
Comfort_car_better	0.484	1.623	62%	29%	24%	**11%**	**14%**

impact nearest station (3 = 5 to 7.5 km)				Origin (3)		Total impact	
	Utility	**Exp**	**p**	**Rdam**	**Adam**		
Utrain	0	1					
Basecase	-1.376	0.253	20%	0%	3%	**0%**	**1%**
Safety_8and4	-2.707	0.067	6%	0%	3%	**0%**	**0%**
Safety_8and6	-1.068	0.344	26%	0%	3%	**0%**	**1%**
Safety_8and8	-0.126	0.882	47%	0%	3%	**0%**	**1%**
motionsick_car_worse	-1.749	0.174	15%	0%	3%	**0%**	**0%**
motionsick_equal	-0.195	0.823	45%	0%	3%	**0%**	**1%**
Comfort_both_good	-0.975	0.377	27%	0%	3%	**0%**	**1%**
Comfort_car_better	0.879	2.408	71%	0%	3%	**0%**	**2%**

impact nearest station (4 = 7.5 to 10 km)				Origin (4)		Total impact	
	Utility	**Exp**	**p**	**Rdam**	**Adam**		
Utrain	0	1					
Basecase	-0.981	0.375	27%	7%	0%	**2%**	**0%**
Safety_8and4	-2.312	0.099	9%	7%	0%	**1%**	**0%**
Safety_8and6	-0.673	0.510	34%	7%	0%	**3%**	**0%**
Safety_8and8	0.269	1.309	57%	7%	0%	**5%**	**0%**
motionsick_car_worse	-1.354	0.258	21%	7%	0%	**2%**	**0%**
motionsick_equal	0.200	1.221	55%	7%	0%	**5%**	**0%**
Comfort_both_good	-0.580	0.560	36%	7%	0%	**3%**	**0%**
Comfort_car_better	1.274	3.575	78%	7%	0%	**7%**	**0%**

impact nearest station (5 = 10 km or more)				**Origin (5)**		**Total impact**	
	Utility	**Exp**	**p**	**Rdam**	**Adam**		
Utrain	0	1		73%	75%		
Basecase	-0.586	0.557	36%	0%	0%	**0%**	**0%**
Safety_8and4	-1.917	0.147	13%	0%	0%	**0%**	**0%**
Safety_8and6	-0.278	0.757	43%	0%	0%	**0%**	**0%**
Safety_8and8	0.664	1.943	66%	0%	0%	**0%**	**0%**
motionsick_car_worse	-0.959	0.383	28%	0%	0%	**0%**	**0%**
motionsick_equal	0.595	1.813	64%	0%	0%	**0%**	**0%**
Comfort_both_good	-0.185	0.831	45%	0%	0%	**0%**	**0%**
Comfort_car_better	1.669	5.307	84%	0%	0%	**0%**	**0%**

Therefore, depending on their distance to the train station, 3% of train passengers in the entire population of Rotterdam and Amsterdam would potentially shift to automated cars, if the safety perception for the train is high and for the AC is low. If the safety perception for an AC increases to medium, the potential shift of the population increases to 15%. If the safety perception for an AC increases to the same level of the train, the potential shift of the population increases further to 30%. Next, if the experience of motion sickness in an AC is the same as in a regular car, the potential shift of the population is 7%. If the experience of motion sickness in an AC increases to that of the motion sickness experience in a train, the potential shift of the population is 29%. Lastly, if the level of comfort in an AC is alright, the potential shift of the population is 16%. If the level of comfort in an AC exceeds the level of comfort in the train, the potential shift is 55%.

Total probability that people will shift on the R-A route	
Scenario	**%**
Base case	12
Safety_8and4	3
Safety_8and6	15
Safety_8and8	30
Motionsick_car_worse	7
Motionsick_equal	29
Comfort_both_good	16
Comfort_car_better	55

Appendix M - Motion sickness partial shifts

impact level of motion sickness (1)				**Origin (1)**	**Total impact on R-A route**
	Utility	**exp**	**p**		
Utrain	0	1			
Basecase	-2.035	0.131	12%	16%	**2%**
Safety_8and4	-3.366	0.035	3%	16%	**1%**
Safety_8and6	-1.727	0.178	15%	16%	**2%**
Safety_8and8	-0.785	0.456	31%	16%	**5%**
motionsick_car_worse	-2.408	0.090	8%	16%	**1%**
motionsick_equal	-0.854	0.426	30%	16%	**5%**
Comfort_both_good	-1.634	0.195	16%	16%	**3%**
Comfort_car_better	0.220	1.246	55%	16%	**9%**

impact level of motion sickness (2)				**Origin (2)**	**Total impact on R-A route**
	Utility	**exp**	**p**		
Utrain	0	1			
Basecase	-2.166	0.115	10%	29%	**3%**
Safety_8and4	-3.497	0.030	3%	29%	**1%**
Safety_8and6	-1.858	0.156	13%	29%	**4%**
Safety_8and8	-0.916	0.400	29%	29%	**8%**
motionsick_car_worse	-2.539	0.079	7%	29%	**2%**
motionsick_equal	-0.985	0.373	27%	29%	**8%**
Comfort_both_good	-1.765	0.171	15%	29%	**4%**
Comfort_car_better	0.089	1.093	52%	29%	**15%**

impact level of motion sickness (3)				**Origin (3)**	**Total impact on R-A route**
	Utility	**exp**	**p**		
Utrain	0	1			
Basecase	-2.297	0.101	9%	26%	**2%**
Safety_8and4	-3.628	0.027	3%	26%	**1%**
Safety_8and6	-1.989	0.137	12%	26%	**3%**
Safety_8and8	-1.047	0.351	26%	26%	**7%**
motionsick_car_worse	-2.670	0.069	6%	26%	**2%**
motionsick_equal	-1.116	0.328	25%	26%	**7%**
Comfort_both_good	-1.896	0.150	13%	26%	**3%**
Comfort_car_better	0.089	1.093	52%	26%	**14%**

impact level of motion sickness (4)				**Origin (4)**	**Total impact On R-A route**
	Utility	**exp**	**p**		
Utrain	0	1			
Basecase	-2.428	0.088	8%	16%	**1%**
Safety_8and4	-3.759	0.023	2%	16%	**0%**
Safety_8and6	-2.120	0.120	11%	16%	**2%**
Safety_8and8	-1.178	0.308	24%	16%	**4%**
motionsick_car_worse	-2.801	0.061	6%	16%	**1%**
motionsick_equal	-1.247	0.287	22%	16%	**4%**
Comfort_both_good	-2.027	0.132	12%	16%	**2%**
Comfort_car_better	-0.173	0.841	46%	16%	**7%**

impact level of motion sickness (5)				**Origin (5)**	**Total impact on R-A route**
	Utility	**exp**	**p**		
Utrain	0	1			
Basecase	-2.559	0.077	7%	13%	**1%**
Safety_8and4	-3.890	0.020	2%	13%	**0%**
Safety_8and6	-2.251	0.105	10%	13%	**1%**
Safety_8and8	-1.309	0.270	21%	13%	**3%**
motionsick_car_worse	-2.932	0.053	5%	13%	**1%**
motionsick_equal	-1.378	0.252	20%	13%	**3%**
Comfort_both_good	-2.158	0.116	10%	13%	**1%**
Comfort_car_better	-0.304	0.738	42%	13%	**6%**

Appendix N – Train travel class partial shifts

Impact of class (1)				**Origin (1)**	**Total impact on R-A route**
	Utility	**exp**	**p**		
Utrain	0	1			
Basecase	-2.990	0.050	5%	20%	**1%**
Safety_8and4	-4.321	0.013	1%	20%	**0%**
Safety_8and6	-2.682	0.068	6%	20%	**1%**
Safety_8and8	-1.740	0.176	15%	20%	**3%**
motionsick_car_worse	-3.363	0.035	3%	20%	**1%**
motionsick_equal	-1.809	0.164	14%	20%	**3%**
Comfort_both_good	-2.589	0.075	7%	20%	**1%**
Comfort_car_better	-0.735	0.480	32%	20%	**6%**

Impact of class (2)				**Origin (2)**	**Total impact on R-A route**
	Utility	**exp**	**p**		
Utrain	0	1			
Basecase	-2.166	0.115	10%	80%	**8%**
Safety_8and4	-3.497	0.030	3%	80%	**2%**
Safety_8and6	-1.858	0.156	13%	80%	**11%**
Safety_8and8	-0.916	0.400	29%	80%	**23%**
motionsick_car_worse	-2.539	0.079	7%	80%	**6%**
motionsick_equal	-0.985	0.373	27%	80%	**22%**
Comfort_both_good	-1.765	0.171	15%	80%	**12%**
Comfort_car_better	0.089	1.093	52%	80%	**42%**

Appendix O – Factor ranking

Rank	1	2	3	4	5	6	r1	r2	r3	r4	r5	r6	tot	rank
comfort	77	45	22	10	13	2	77	90	66	40	65	12	350	**1**
duurzaamheid	21	26	23	26	49	25	21	52	69	104	245	150	641	**5**
tijd	34	45	33	32	26	1	34	90	99	128	130	6	487	**2**
kosten	13	28	43	32	32	20	13	56	129	128	160	120	606	**4**
veiligheid	21	16	42	45	28	15	21	32	126	180	140	90	589	**3**
wagenziekte	3	7	6	23	22	105	3	14	18	92	110	630	867	**6**

Appendix P – gender sensitivity analysis

Male and female

Choice (0 = **train** 1 = **AC)**[a] **- Parameter estimates**

						95% confidence interval for Exp(β)	
Variable	**β**	**ε**	**Wald**	**Significance**	**Exp(β)**	**LB**	**UB**
(Intercept)	**-3.480**	1.004	12.006	.001*			
Safety_8and4	**-1.331**	.627	4.505	.034*	.264	.077	.903
Safety_8and6	**.308**	.455	.459	.498	1.361	.558	3.318
Safety_8and8	**1.250**	.426	8.613	.003*	3.491	1.515	8.045
motionsick_car_worse	**-.373**	.501	.553	.457	.689	.258	1.840
motionsick_car_equal_to_train	**1.181**	.427	7.655	.006*	3.259	1.411	7.526
Comfort_both_good	**.401**	.450	.793	.373	1.493	.618	3.610
Comfort_car_better	**2.255**	.427	27.932	.000*	9.534	4.132	22.000
often_traintravel	**-.969**	.152	40.378	.000*	.380	.282	.512
auto_parts	**.337**	.080	17.564	.000*	1.401	1.197	1.640
Age	**.027**	.008	11.666	.001*	1.027	1.012	1.043
class	**.824**	.198	17.283	.000*	2.280	1.546	3.363
neareststation	**.395**	.117	11.403	.001*	1.484	1.180	1.866
levelmotionsickness	**-.131**	.118	1.229	.268	.877	.696	1.106

Female

Choice (0 = **train** 1 = **AC)**[a] **- Parameter estimates**

						95% confidence interval for Exp(β)	
Variable	**β**	**ε**	**Wald**	**Significance**	**Exp(β)**	**LB**	**UB**
(Intercept)	**-7.693**	3.045	6.381	.012			
Safety_8and4	**-1.453**	.869	2.796	.045	.264	.077	.903
Safety_8and6	**1.955**	1.296	2.275	.131	1.361	.558	3.318
Safety_8and8	**3.911**	1.288	9.217	.002	3.491	1.515	8.045
motionsick_car_worse	**.907**	1.392	.425	.515	.689	.258	1.840
motionsick_car_equal_to_train	**3.614**	1.279	7.980	.005	3.259	1.411	7.526
Comfort_both_good	**.907**	1.392	.425	.515	1.493	.618	3.610
Comfort_car_better	**5.164**	1.355	14.521	.000	9.534	4.132	22.000
often_traintravel	**-.061**	.019	9.804	.002	.380	.282	.512
auto_parts	**.579**	.218	7.064	.008	1.401	1.197	1.640
Age	**.414**	.414	4.863	.027	1.027	1.012	1.043
class	**1.049**	1.229	.729	.039	2.280	1.546	3.363
neareststation	**.635**	.274	5.391	.020	1.484	1.180	1.866
levelmotionsickness	**-.777**	.253	9.440	.002	.877	.696	1.106