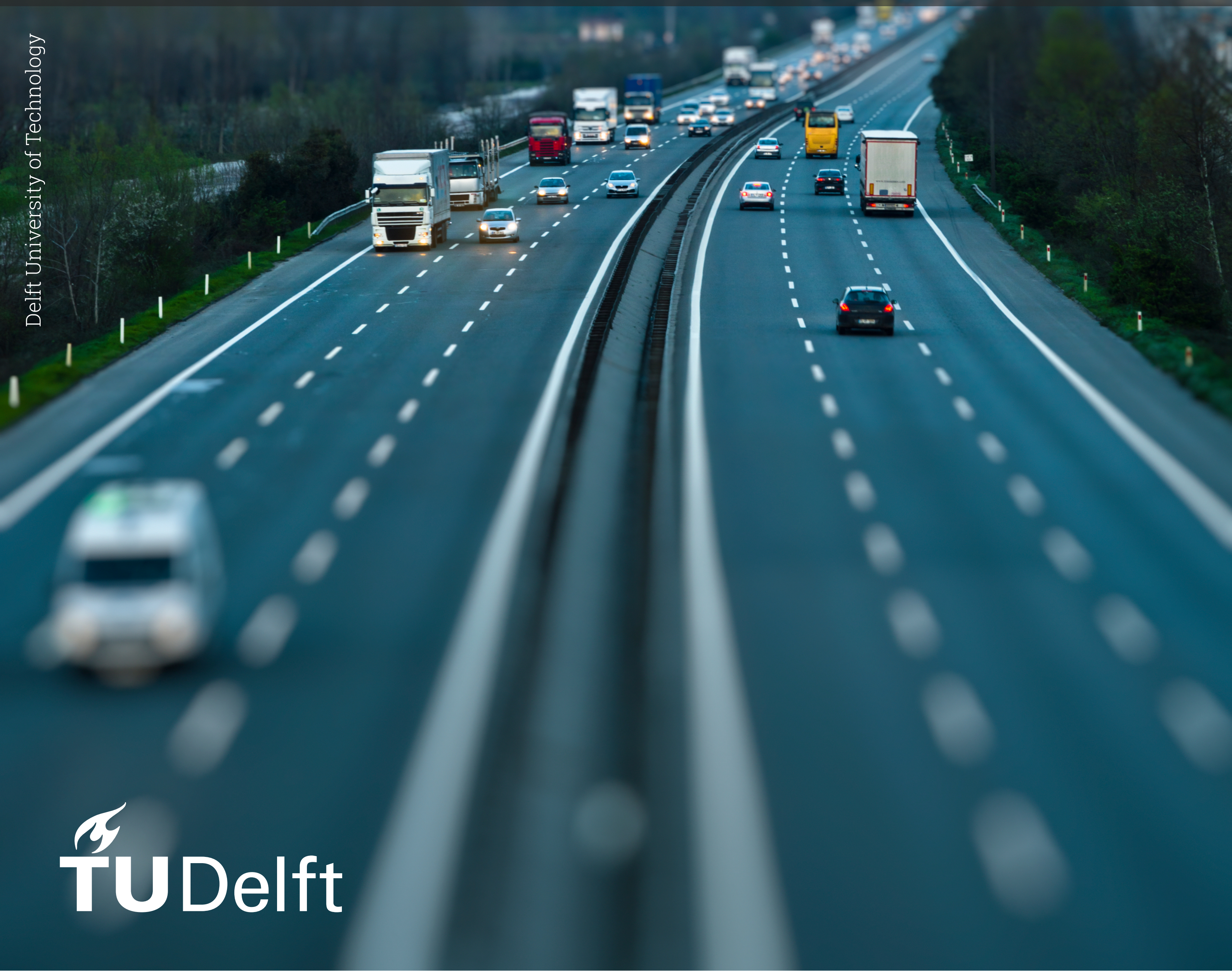
Company car induced travel behavior

The influence of company cars on employee travel behavior over time and implications for sustainable transportation policies in the Netherlands.

Master Thesis

L. Honée



Delft University of Technology

TU Delft

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by

L. Honée

Student Name	Student Number
Lucas Honée	4676548

Thesis committee:	
First supervisor:	Dr.ir. M. Kroesen
Second supervisor:	Dr. O. Oviedo-Trespalacios
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Faculty:	Faculty of Technology Policy and Management, Delft

Preface

This thesis focuses on the impact of company car availability on travel behavior, specifically examining how access to a company car influences shifts in individual mobility patterns over time.

When I began searching for a topic for my thesis, I initially struggled to find a direction. At that time, I did not feel a strong passion for a particular subject, but I knew that throughout my bachelor's and master's studies, I had developed a growing interest in courses that use quantitative methods to analyze behaviors and shape policy recommendations. This interest naturally led me to the Transport and Logistics department at TPM, as I had thoroughly enjoyed the Travel Behavior Research course.

It was through a conversation with Maarten Kroesen that I was first introduced to the idea of researching company cars using the Latent Transition Analysis. After several discussions, this topic evolved into the subject of this thesis. I would like to extend my sincere gratitude to him for these discussions and for his invaluable support throughout this research. I also want to express my thanks to Oscar Oviedo-Trespalacios for guiding this research, always offering a critical perspective, and providing valuable feedback.

Their guidance encouraged me to think more deeply about various aspects of the research, and I truly appreciated their flexibility and willingness to think along during the challenging moments in the planning. Their support has greatly contributed to the quality of this work, and for that, I am deeply grateful.

L. Honée
Delft, October 2024

Summary

The urgent need to transform urban mobility systems towards sustainability is a key focus in environmental and transportation policy discussions. Transport accounts for more than a quarter of the EU's greenhouse gas emissions and the share is expected to grow as demand increases. In the Netherlands alone, passenger transport is responsible for 45-50% of the entire mobility sector's emissions. This situation underscores the critical role of sustainable transportation in mitigating climate change and calls for significant policy interventions to promote greener transport alternatives, such as public transport, cycling, and electric vehicles. One of the primary motives for travel in the Netherlands is commuting. As such, reducing the ecological footprint of work-related travel offers an opportunity to significantly lower transport emissions. The Dutch Ministry of Infrastructure and Water Management has proposed a mobility vision for 2050, focusing on greener cars, active travel (such as walking and cycling), and increased public transport use. These policies align with the EU's broader goals of reducing greenhouse gas emissions and creating a sustainable transport system.

Despite these efforts, there remain policies that unintentionally counteract sustainability goals. One of the most notable examples is the provision of company cars, which are highly attractive due to various tax and financial benefits offered to both employers and employees. A company car allows an employee to use a vehicle for private and professional purposes at a lower cost, with additional perks such as fuel cards. The cost advantages for employees lead to increased car ownership and higher car usage, often at the expense of more sustainable modes of transport. Employees are likely to choose larger, more polluting vehicles due to the favorable tax system, and the presence of company cars tends to promote unimodal, car-centered travel behavior. Studies show that company cars lead to higher mileage and increased emissions, while also displacing more sustainable, multimodal transport options.

The contradiction between the sustainability goals outlined by governments and the ongoing appeal of company cars highlights a significant misalignment between policy and practice. Although company cars are linked to higher emissions and reduced use of sustainable transport modes, they continue to be offered as fringe benefits due to the financial incentives they provide. This paradox reveals a critical gap in understanding how current policies may inadvertently undermine efforts to promote sustainable mobility.

The main objective of this research is to fill the gap in understanding how company cars influence individual travel behavior over time. Specifically, the research aims to examine whether gaining access to a company car leads individuals to adopt more car-oriented travel patterns and whether this comes at the expense of multimodal or sustainable travel options such as cycling and public transport. Furthermore, the research will investigate how company cars might reinforce exclusive car use or prevent transitions toward more sustainable modes of transport.

The main research question that this thesis seeks to address is:

"In what way does company car availability affect the travel behavior of individuals with similar travel patterns over time, and what are its implications for designing sustainable transport policies?"

This research will explore how company cars influence the transitions between different travel patterns over time, providing insights into the broader implications of company car policies. The aim is to inform policymakers on the extent to which these vehicles impact travel behavior, and how future policies can better align with sustainability goals.

This research started with an extensive literature to explore the findings of previous studies. The review focused on examining how company cars influence travel behavior and highlighted key findings from previous research. It was clear that company cars contribute to increased vehicle ownership, more frequent car use, and higher emissions. Employees often use company cars not only for commuting but also for personal trips, which leads to an overall rise in car usage. This expanded car use, coupled

with the associated environmental impact, indicates that company cars may unintentionally promote unsustainable travel patterns.

The availability of company cars reduces the likelihood of individuals adopting sustainable, multimodal transport behaviors, reinforcing car-centric travel and discouraging the use of greener alternatives like public transport and cycling. Once car-oriented habits are established, they become difficult to reverse, creating long-term car dependency. Life events, such as gaining access to a company car, often trigger these changes, making a shift back to sustainable modes challenging. The literature also highlights the limited research on how travel patterns evolve in response to company car access, particularly using Latent Class and Latent Transition Analysis (LCA and LTA). While some studies have used clustering methods to explore company car usage, the need for longitudinal studies to assess the impact of company cars on mobility dynamics remains significant. Overall, company cars promote long-term car dependency, discourage sustainable transport, and create lasting habits, but more research is needed to understand how these patterns evolve.

The methodology employs two main techniques: Latent Class Analysis (LCA) and Latent Transition Analysis (LTA), chosen for their effectiveness in studying travel behavior patterns and transitions, especially in the context of company car use.

LCA is a probabilistic clustering method that identifies subgroups based on shared response patterns, making it useful for understanding different mobility styles. It offers advantages over traditional clustering techniques by using probability distributions and incorporating socio-demographic covariates, allowing for a deeper analysis of the factors influencing class membership.

LTA builds on LCA by examining how these mobility patterns change over time. This Markov model tracks transitions between latent classes, such as shifts in travel behavior due to changes like gaining access to a company car, making it particularly suited for longitudinal studies that capture the dynamic impact of life events on mobility.

For this quantitative research, a comprehensive dataset from the Dutch Mobility Panel (MPN) was used as input for the LCA and LTA models. The MPN is an initiative from the Dutch Ministry of Infrastructure and Water Management, established in 2013. It gathers detailed travel behavior data from individuals aged 12 and older in around 2000 households each year. Respondents record their travel over three days, including details such as distances traveled and modes of transport used. Alongside travel data, socio-demographic information is collected, which makes this dataset highly valuable for mobility research. The MPN's primary goal is to track shifts in mobility patterns over time, providing insights that can inform public policy.

The sample for this research draws from the first seven waves of the MPN, spanning 2013 to 2019. While the full dataset includes around 35,000 respondents, many participated in multiple waves. After accounting for this, the unique sample size was reduced to 12,778 respondents from 6,769 households. To focus on mobility behavior changes, only individuals who participated in consecutive waves were considered, resulting in a final sample of 8,183 respondents across various wave pairs. Chi-square tests were used to assess the sample's representativeness by comparing socio-demographic characteristics with Dutch population data from the CBS. The tests examined variables such as gender, age, education, occupational status, and income. Results showed that the sample was not fully representative in some areas. There were significant deviations in age, gender, education, and income, with an overrepresentation of older individuals and those with mid-to-low education levels. Gender was also skewed, with men slightly underrepresented. However, the sample aligned more closely with the population in terms of occupational status, an important factor given the study's focus on commuting patterns and travel behavior. This suggests that despite some demographic deviations, the sample still offers relevant insights into mobility trends, particularly about work-related travel. In the overall sample, two key subgroups were analyzed to gain deeper insights into company car usage and mobility patterns: main users of company cars and non-main users with access to a company car. These subgroups showed distinct differences from the general population. Main users of company cars are predominantly male (72.6%) and middle-aged, with most between 30 and 60 years old. They are heavily reliant on car travel, averaging 6 car trips over three days. Main users typically have higher incomes, with many earning more than twice the national average, and their households often include couples with children. These households also tend to own more cars than the average Dutch household.

Non-main users with access to a company car have a more balanced gender distribution and are slightly younger. While they have access to a company car, they rely less on it, preferring a more diverse travel mix that includes public transport and biking. Their income levels are also relatively high, though slightly lower than those of the main users.

In addition to the sample representativeness tests, a correlation analysis was conducted to explore whether life events, such as starting a new job, relocating, or having a child, are related to changes in company car ownership. The analysis used Pearson Chi-square tests and the Phi Cramer's V statistics to assess the strength and significance of these correlations. The results indicated that certain life events, such as starting a new job or moving to a new residence, were significantly correlated with changes in company car ownership. However, the strength of these associations was weak, with none of the correlation coefficients exceeding 0.05. This suggests that while life events can influence company car ownership, they do not strongly explain travel behavior changes.

The operationalization of variables was a critical step in setting up the LTA model. Key variables were operationalized as follows. The main indicators of mobility behavior were the number of trips made by different modes of transport (car, public transport, bicycle, and walking) and the distance traveled using each mode. While the MPN collects data on both trips and trip segments, the analysis focuses on full trips because distance data is only available for trips, not for individual segments. This decision helps provide a more comprehensive understanding of overall travel patterns, despite the risk of underreporting multi-modal travel behavior. The company car variable was central in the study and operationalized into three categories: (1) households without a company car, (2) households with a company car but where the respondent is not the main user, and (3) households where the respondent is the main user of a company car. This distinction allows for a more nuanced analysis of how company car ownership and access impact travel behavior.

Several latent class models were tested to determine the best fit for the data. Models with 1 to 12 classes were considered, but the 7-class model was ultimately selected as the optimal solution based on the Bayesian Information Criterion (BIC) and interpretability. The 7-class model strikes a balance between capturing the complexity of travel behavior and maintaining manageable class sizes for analysis.

The seven clusters identified are:

- Strict Car Users (26%): Predominantly middle-aged men who rely almost exclusively on cars for travel. They tend to be higher-income individuals, many of whom have access to company cars. This group shows the highest distances traveled by car and minimal use of other transport modes.
- Bicycle Users (17.8%): A group characterized by high levels of cycling, with very low car usage. This cluster is mostly composed of younger individuals, particularly females, and includes many students and people with lower income levels. Cycling is their primary mode of transport.
- Mixed Car and Bicycle Users (16.6%): This group uses both cars and bicycles frequently. They tend to be middle-aged, employed individuals with higher-than-average incomes. Their travel behavior reflects a balanced mix of car and bike use.
- Low Mobility (12.2%): This group has very low mobility across all modes of transport. It consists largely of older individuals, many of whom are retired or unemployed. The group may be somewhat overrepresented due to biases such as atypical travel days (e.g., weekends).
- Mixed Car and Foot Travellers (11.6%): These individuals travel frequently on foot, complemented by moderate car use. The cluster includes a significant proportion of older individuals, often retirees, who prefer walking for shorter trips.
- Public Transport Users (9.9%): A younger, predominantly student-based group that relies heavily on public transportation. This group tends to have lower incomes and fewer cars in their households.
- Mixed Car and Public Transport Users (6%): This group uses both cars and public transport, typically for longer trips. It consists of younger professionals who have higher education levels and incomes. Many in this group are transitioning towards more car use while maintaining some reliance on public transport.

Using the structural LCA model, several 7-state Latent Transition Models (LTA) were estimated to analyze travel behavior dynamics, with a specific focus on the effect of company car ownership. Two main types of models were used: standard logit and transition logit models. Both types were estimated using LatentGOLD.

The standard logit model estimates direct effects between variables, offering transition probabilities without considering interactions with initial class membership. In contrast, the transition logit model accounts for these interactions, capturing more complex relationships but at the cost of increased computational complexity and lower convergence likelihood.

Generally speaking, the transition logit model provides a more detailed view of how initial travel profiles affect mobility changes, however, this model has insignificant results. Therefore we chose to interpret the outcomes of the standard logit model.

The outcomes of the Latent Transition Analysis (LTA) provide key insights into the effects of company car ownership on travel behavior, highlighting distinct outcomes for main users, non-main users, and the general population. The findings reveal that the availability of a company car significantly influences travel patterns, particularly by increasing car dependency, with important differences between main and non-main users.

For the main users of company cars, the analysis shows a pronounced shift towards car-centric travel behaviors. Main users are much more likely to remain in or transition into strictly car-dependent profiles, reinforcing their reliance on cars. The results indicate that those who start in a car-dominant profile, such as the "strict car" (SC) group, are highly likely to stay within this cluster. The presence of a company car further amplifies this inertia, making it more difficult for main users to move away from car-intensive travel. Moreover, even individuals who previously engaged in sustainable travel modes, such as cycling or public transport, are significantly affected by the availability of a company car. These groups, once committed to more sustainable practices, now show a notable reduction in the probability of remaining in their original profiles. Many main users transition from these sustainable modes to more car-dependent patterns, signaling a clear disruption in their travel behavior.

For nonmain users, a company car in a household promotes a shift toward car-dependent travel, particularly for members who previously used mixed-modal travel patterns, such as combining car and bike or car and walking. This shift reduces the stability of more sustainable travel behaviors, making car-exclusive mobility more likely. Interestingly, non-primary users of company cars tend to maintain their unimodal sustainable modes, such as public transport or cycling, whereas primary users show a stronger tendency to become more reliant on car use in each cluster. Overall, company car availability reinforces car dependency and decreases the likelihood of adopting or maintaining sustainable transportation options.

Another key finding is that the transition logit model for company cars proved insignificant, as shown by the Wald statistic. This indicates that the effects of company car ownership are independent of a person's initial mobility profile. In other words, the presence of a company car affects individuals similarly, regardless of whether they start as cyclists, public transport users, or mixed-mode travelers. The shift toward car dependency is consistent across different starting points, suggesting that company car availability exerts a broad influence on travel behavior, independent of initial cluster membership.

The outcomes have various policy implications that are related to the reduction of company car benefits using targeted policy interventions. While eliminating company cars in favor of public transport may be an unrealistic goal in the near term, making company cars less appealing while incentivizing sustainable transportation modes is a more feasible approach. This ensures that only those who truly need a company car for work-related travel maintain access while promoting environmentally friendly alternatives.

One potential reform involves the tax system, particularly the "bijtelling" tax. Currently, employees only pay a fraction of the cost of the vehicle for personal use, which encourages the selection of larger, more luxurious, and more polluting cars. By increasing the "bijtelling" for larger and higher-emission vehicles, a progressive tax structure could be introduced, making smaller, cleaner vehicles more attractive by comparison. Companies can also take responsibility by enforcing emission caps on their fleets and promoting electric or hybrid vehicles as default options. Another key issue is the excessive private use of company cars, often enabled by untaxed fuel cards that reduce the cost of driving. Introducing taxes on fuel provided for private use or taxing private kilometers driven by company cars could discourage excessive personal driving. Additionally, companies could limit or eliminate fuel cards for private use or impose restrictions on the amount of private driving allowed, thus reducing unnecessary driving and encouraging more sustainable habits.

A more sustainable approach could involve companies offering shared vehicle pools for work-related purposes instead of providing individual cars to employees. This reduces the overall number of vehicles needed and limits private use, lowering both emissions from driving and the environmental impact of manufacturing vehicles. Promoting alternative, sustainable modes of transport is crucial. Expanding programs like the National Bicycle Plan and offering more financial incentives for long-distance commuters to use e-bikes could encourage a shift away from cars. Partnering with companies to provide free or discounted public transport passes would also make public transport a more appealing option for employees. Additionally, offering relocation assistance to employees moving closer to their workplaces could reduce car dependency by cutting commuting distances. Corporate responsibility plays a significant role in shaping travel behaviors. Companies should set internal goals to reduce fleet emissions and ensure that company cars are only provided when necessary for work purposes. By prioritizing sustainability in their policies, businesses can influence the broader travel patterns of their employees and help reduce the environmental impact of company cars.

In summary, reforming company car policies and implementing measures to encourage alternative transportation modes can significantly reduce car dependency. By reshaping financial incentives, promoting sustainable options, and fostering corporate responsibility, it is possible to reduce the negative environmental impact of company cars and move toward greener mobility practices.

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1 Introduction

The transformation of urban mobility paradigms towards sustainability is a critical issue in contemporary environmental and transportation discussions and policy-making (Ministerie van Infrastructuur en Waterstaat, 2024). According to the EEA (2024) transport currently accounts for more than a quarter of the EU's greenhouse emissions. This share becomes bigger and bigger as years pass by while demand grows, and other sectors reduce emissions. Within the Netherlands, passenger transport accounts for 45% to 50% of the complete mobility sector's emissions figure (Planbureau voor de Leefomgeving, 2022). This means that the mobility sector will have to adapt and focus on making passenger transport more sustainable by offering greener alternatives and incentivizing users to use these through inventive policies.

Moreover, for Dutch citizens transport to and from work remains one of the main motives to travel, this indicates that this might be an area where ecological footprint could be reduced (Centraal Bureau voor de Statistiek, 2024d). In response to these environmental challenges, the European Union has identified some key actions to be fulfilled to boost the adoption of green vehicles, public transport rail use, and more active multi-modal transportation means such as cycling or walking. The Dutch Ministry of Infrastructure and Watermanagement has a report on their mobility vision for 2050 that underlines the pressing need for a more sustainable mobility system in which greener cars and public transport travel thrive (Ministerie van Infrastructuur en Waterstaat, 2023).

In addition, most Dutch citizens are aware that climate change poses a significant problem, worry about its effects, and believe that the government should focus on creating sustainable policies, but they do not always act accordingly. (TNO, 2022). Despite their recognition of this problem, it does not automatically lead to more sustainable behavior (CBS, 2021). Mouter et al. (2018) labeled this general notion of misalignment between citizens' private and public needs and choices as the consumer-citizen duality. The fact that citizens do not always necessarily act according to their political beliefs underlines the need for effective government policy measures that shape citizens' behavior in a desired way for society. Therefore, the overarching goals as stated in the mobility vision of the Ministry can only be reached by combining effective policy measures with technological advancements to ensure a transition in a more sustainable society.

Naturally, the government is contemplating how to shape society's path toward sustainability through its policies. The 2050 mobility vision report shows that the Ministry is willing to allocate its efforts in such a way that the mobility system is aligned with commuter opportunities by addressing mobility issues in the way it fits workers' and companies' needs. For example, government initiatives such as the 'bicycle scheme', make it financially attractive for employees to commute by bicycle, benefiting both employees and employers through tax advantages (Belastingdienst, 2024; Nationale Fietsprojecten, 2024). Additionally, the government has ambitious plans to promote public transport use as this is currently one of the most sustainable modes of transport for longer distances (Rijksoverheid, 2024).

However, despite many good government efforts in the mobility sector, there are still policies that may inadvertently hinder the transition to sustainable mobility. One such policy is the provision of company cars, which remains highly attractive due to favorable (tax) benefits for both commuters and companies ((Debesteleasedeal.nl, 2020; Ministerie van Algemene Zaken, 2022; Rabobank, 2024). The concept of a 'company car' refers to the definition of Cornelis et al. (2007): *"A vehicle whose initial cost is supported by the employer which is awarded to an employee for his personal, professional and/or private trips, and which can be used by the employee without the authorization of his employer"*.

Companies offer company cars as part of secondary employment benefits, allowing employees to lease vehicles for business purposes or use a company car provided by the employer. This arrangement allows employees to effectively "own" a car at a relatively low cost (YoungCapital, 2024). When employees use this car for more than 500 kilometers per year for private purposes, it is considered additional taxable income; however, this often remains financially advantageous. In such cases, employees pay so-called 'bijtelling' which is an addition to account for taxes on this "extra income". This is a percentage of the vehicle's catalog value, which is lower, and thus more favorable, for sustainable vehicles. Normally, employees might have had to take out a personal loan for the same type of car, but since the employer covers the costs, this is unnecessary. The fact that they only pay a percentage also leads to people choosing bigger cars as they are enabled to pay just a fraction of the price (May et al., 2019). Another advantage for the employee is that, unlike a personal car loan, the additional tax (bijtelling) does not affect the maximum mortgage value when purchasing a house. In the current tight housing market, this is an attractive aspect for many people, providing an advantage in securing housing (Hypotheek.nl, 2024).

Moreover, companies often provide a fuel card with the company car, whereby the employer covers the most usage costs, including fuel (Nijland & Dijst, 2015; Overheid.nl, 2022). Initially, it seems reasonable that the actual costs of a company car—such as parking fees and fuel—are untaxed, provided the car is used for business purposes. In practice, however, a company car falls under secondary employment benefits and the fuel card serves as an extra perk for the employee (YoungCapital, 2024). This means that private use is often also paid for with the fuel card, and these reimbursements remain untaxed (Overheid.nl, 2022; Sigma Personeel, 2024). Ultimately, this leads to employees incurring fewer personal expenses. They generally find this attractive because it increases their disposable income. Employers also have an incentive to offer these vehicles as this leads to tax benefits (Nijland & Dijst, 2015). According to Gutiérrez-i-Puigarnau and Van Ommeren (2011) including a company car with a fuel card as an employment benefit is often used as a gimmick to attract ambitious staff. This means it is also interesting from an employer's point of view to participate in the company car playing field.

In 2024 car ownership still is a growing phenomenon within the Netherlands and about 12,5% of all Dutch cars are registered in the name of the company (CBS, 2024). Even though the current share of company cars (12,5%) does not seem to be a lot, the share of company cars within new car fleets in the Netherlands accounts for 45% and is one of the highest among OECD countries (Frenkel et al., 2014). This is not surprising to see considering the employee benefits, and the anticipated effects of these negatively show their presence.

Notably, company cars have been associated with greater use instead of more environmentally benign transportation modes (Frenkel et al., 2014). The same research also indicates that, next to increased use, the availability of company cars raises the likelihood of individuals choosing the car as their sole mode of transportation. Both findings suggest that company cars do not only emit more but also promote more unimodal travel behavior, thereby displacing multimodal transport options, which are generally considered more sustainable.

In addition, research from Wadud et al. (2022) has found that company cars are also often associated with higher mileage. These findings are not novel as there have been others that came to the same conclusion (Albert et al., 2014; Frenkel et al., 2014; Metzler et al., 2019) Seeing this, we can conclude that displaying figures related to company cars in terms of cars might give a distorted view of reality on the matter. The share of pollution and mileage which originates from company cars is likely to be higher than the figure of 12,5%. The latter hypothesis that company cars are more polluting than privately owned vehicles is thereby underlined by research from Metzler et al. (2019). Those results show that the abandonment of company car benefits in the use-case country Germany, is very likely to make a significant contribution to the mitigation of CO2 emissions as company cars would cause up to twice as many emissions due to their increased usage.

Even though academic research indicates that company cars are often associated with negative environmental effects and might replace sustainable multimodal practices, there are still quite some tax rules in place that are beneficial to company car users (Debesteleasedeal.nl, 2020; Hypotheek.nl, 2024; Ministerie van Algemene Zaken, 2022; Nijland & Dijst, 2015; Overheid.nl, 2022; Rabobank, 2024; YoungCapital, 2024). The latter will indirectly stimulate the greater adoption of company cars. Apart from the fact that this is intuitively a logical consequence, academic research also confirms that fiscal policy has effects on travel behavior such as car use (Potter et al., 1999; Shiftan et al., 2012). These researchers have shown that fiscal policy can reduce car use and even encourage sustainable behavior. Even though all sorts of mobility policies have been shown to be effective in reducing ecological footprint, there are still domains such as company car policies that have detrimental effects on sustainable efforts. The fact that these counteracting policies are still in place highlights the societal need for further research within this field.

Returning to Mouter et al. (2018) concept of consumer-citizen duality; the case of company cars seems to be a prime example. Derived from the country its numbers we could state that the attitude and behavior of Dutch citizens regarding their choices for company cars seem to be contrary to their willingness to allocate and their societal inclination for sustainability and climate. However, the question is if they are the ones at fault. Looking at broader governmental ambitions to create a more durable world for the generations to come, there seems to be quite a misalignment of means and ends, as company car policies continue to exist. The intricate dynamics of company cars not only encapsulate the consumer-citizen duality as highlighted by Mouter et al. (2018) but can also be seen as a component within the broader societal context in reconciling economic incentives with environmental sustainability.

Despite evidence that company cars disproportionately contribute to greenhouse gas emissions and possibly replace other transport options, they remain popular due to favorable tax incentives and depreciation policies. This paradox underscores a critical gap in policy and practice, where the pursuit of sustainability is not being achieved optimally. The societal relevance of this field of research lies in the potential to inform and shape policies that bridge the gap between current practice and ambitious goals for a sustainable future.

It is known that travel behavior is a complex interplay of individual choices, influenced by various factors including personal preferences, societal norms, and organizational policies. This research seeks to untangle these intricacies by researching the effect of company car policies on travel behavior. The focus on the use of company cars is timely and societally relevant, as studies show that they represent a significant aspect of corporate influence on transportation trends and are hence not contributing to environmental sustainability goals (Albert et al., 2014; Caputo et al., 2023; De Wilde et al., 2023; Frenkel et al., 2014; Shiftan et al., 2012; Wadud et al., 2022).

1.1. Deeper into the company car case

The effects related to company-car policies have been an area of interest in various studies. Various researchers have found that company-car policies have been related to increased personal use and therefore impose negative environmental effects (De Witte & Macharis, 2010; Gutiérrez-i-Puigarnau & Van Ommeren, 2011).

Research of Metzler et al. (2019) investigated the effect of company car fringe benefits on car use and the negative effects related to this. The outcomes of this research show that company car benefits lead to increased car ownership and increased use, which is also related to negative environmental effects. Furthermore, Shiftan et al. (2012) have investigated the effects of company-car taxation policies on changes in travel behavior. They conducted a stated preference research and outcomes show that if people had to use privately owned cars, many would make fewer trips and that 40% would even consider other transport modes. Even though the author implies that the use of panel data would assist in creating meaningful insights into company car phenomena, they were not able to rely on longitudinal revealed preference data. Busch-Geertsema et al. (2021) have also focused on employee mobility fringe benefits by investigating the effect of company mobility benefits to employees on their mode choices. They found that the (financial) encouragement related to and the provision of public transport tickets to employees, led to an increase in public transport use. De Wilde et al. (2023) used a discrete choice experiment to investigate the choice-variability of car-dependent employees to gain insight into the viability of alternatives. Even though the study confirms the polluting nature of company cars, it merely focuses on the effectiveness of the provision of car-minded alternatives such as hybrid cars and electric vehicles. It does not account for potential underlying causes of car-minded travel behavior.

There have also been several quantitative studies that have examined the impact of mobility policies on travel behavior using revealed preference data. Researchers have employed various methodologies to explore how these policies influence decisions related to car purchases and travel behaviors but the main limitation remains that there is no insight into how this changes over time. Notably, Tsairi et al. (2023) performed quantitative research on the effect of vehicle reimbursement policies on vehicle ownership and usage among workers. Using cross-sectional data gathered by hosting a survey among Israeli public sector workers, they found that reimbursement policies play a significant role in car purchase decision processes. In addition to this, company cars have been found to lead to increased car usage. Others have also focused on the effects of commuting benefits on mode ownership and use. Quantitative research using the Dutch National Time Use Survey found that employer-provided benefits possibly lead to mode ownership and induced travel with the respective mode (Nijland & Dijst, 2015). Using revealed preference of Israeli knowledge workers, Frenkel et al. (2014) investigated the linkage between travel behaviour and car-related job perks. Their cross-sectional study confirms that car-related fringe benefits are related to unsustainable travel patterns. These results are expressed in mileage and use intensity. Even though this provides a general overview of the output related to company car users, it does not provide insight into the division over types of travelers.

A limitation of the preceding studies is that either stated preference or cross-sectional data was used. Even though both methods are fit for research they lack the explanatory power of revealed behavior over time. In addition, these researches mainly focused on the negative effects of policies on company car use in terms of ownership and environmental damage instead of investigating changes in the behavioral aspect of traveler mode choices. There is a lot of research that shows the negative effects that are linked to company cars and their users. Even though stated preference research implies that company cars also detract people from using other more sustainable modes, research on this specific topic using revealed preference data has not been performed yet. Specifically, there is a notable gap in the literature regarding how access to a company car influences individual travel patterns and potentially leads to mode switching over time. Results of these studies indicate that people state that there are scenarios in which they would consider alternative modes, however, this remains a stated choice experiment. While the environmental and ownership impacts are well-documented, the understanding of how travel behavior shifts in response to acquiring a company car remains under-explored. The potential of the company car to detract from the use of other modes is particularly interesting to confirm, as this effect could have an even larger negative environmental impact than it appears, by drawing people away from more environmentally friendly modes of transport. Therefore, this research aims to examine the dynamic changes in travel mode choices when individuals gain access to a company car, thereby providing new insights into the behavioral adaptations that occur.

Even though the studies above investigate the effect of policies in a quantitative way, their contributions are mostly directed at confirming the effect of use and ownership; they do not provide insights into the division of mobility styles among respondents and how these change. Another drawback of the aforementioned quantitative studies is that they cannot confirm time precedence due to their reliance solely on cross-sectional data. Travel behavior is perceived as an inert phenomenon within the research community. Consequently, researchers have focused on identifying the factors capable of influencing changes in travel behavior.

A popular theory for assessing behavioral change is the mobility biographies framework from Müggenburg et al. (2015). This assumes that people reconsider their behavior as important changes in their lives occur. This framework has also been used by mobility researchers to determine modality type choices, and have found that people reconsider their mode choices as so-called 'life-events' happen (Van der Waerden et al., 2003). Examples of key life events within this framework are residential relocation or employment transitions. A panel study conducted by Kroesen and van Cranenburgh (2016) investigated the use of Markov models in determining how and why people change their travel patterns over time. An interesting finding of this study is that car users are the most consistent mode users. They recommend considering the role of key life events as predictors for behavioral change. The latter analysis has been performed before, and revealed that the effect of exogenous life events on transitioning probabilities strongly influences respondents revealed travel behavior over time (Kroesen, 2014; Kroesen & Handy, 2014). This reinforces the notion of the mobility biography framework, that pivotal life changes present a 'window of opportunity' for a behavioral shift (Müggenburg et al., 2015). Research of Gutiérrez-i-Puigarnau and Van Ommeren (2011) using panel data from the Dutch Central Bank confirms that gaining access to a company car can be used as a predictor for car ownership and use. Even though this study monitors change over time it does not provide any additional insight into how changes between mobility styles are affected by gaining access to a company car; the study merely focuses on change of ownership and (private) use in the implied car-minded mobility segment.

From previous longitudinal studies, we can conclude that there has been some research on changes in travel behavior over time, however, present studies have been focusing on more 'traditional' significant life events such as residential relocation, change of jobs, or the birth of a child. There does not seem to be much previous research that investigates the effect of more 'practical life changes', such as gaining access to a company car, on travel behavior.

1.2. Knowledge gaps

The intersection of societal relevance and the scientific gap in the context of urban mobility and company car policies underlines a critical area for investigation. The necessity to navigate towards more sustainable urban mobility paradigms is underscored by the escalating environmental and transportation challenges confronting society. The Ministerie van Infrastructuur en Waterstaat (2024) and the EEA (2024) have highlighted the substantial contribution of transport to greenhouse gas emissions within the EU, a concern that is exacerbated by the growing reliance on passenger vehicles in the Netherlands, contributing to 45% to 50% of the mobility sector's emissions (Planbureau voor de Leefomgeving, 2022). With transportation accounting for a substantial share of the EU's greenhouse gas emissions, and the mobility sector identified as a pivotal area for sustainable transformation, the persistence of company car usage presents a paradox in efforts towards sustainability.

Company cars, representing a considerable share of new car fleets in the Netherlands and associated with higher vehicle usage and emissions, stand at the intersection of corporate policy and individual mobility choices (Frenkel et al., 2014; Wadud et al., 2022). The persistence of incentivizing policies, despite their environmental implications, points to a misalignment between policy objectives and actual travel behavioral outcomes as people are still inclined to use these vehicles because of the low marginal cost of use. Because of current policies, this marginal cost of use is very low and we expect people to adopt exclusive car patterns. This underscores the need for a better understanding of how company cars change the travel patterns of their users.

Despite the acknowledged adverse effect of company car policies, the literature reveals a significant knowledge gap in understanding the specific dynamics of change in travel behavior related to company cars, a gap this research aims to fill. The most predominant gap is the lack of knowledge on how gaining and having access to a company car makes people reconsider their mobility styles. Previous studies over the years have shown the direct negative effects of company car use, but there is something bigger lurking. The benefits that are associated with company cars could make those who are offered one reconsider their current mobility styles. Previous research shows negative environmental effects linked to company car use but the main comparison is often made with current car users. There is little insight into how company cars might make people gravitate towards even more exclusive car use or even draw away from more sustainable modes such as public transport, cycling, or walking. This motivates research to focus on changes in travel patterns over time.

Even though there have been many who have researched the dynamics of travel behavior by looking at travel patterns, few have focused on the influence of company car policies. While those who have looked into this topic have established the association between company cars and increased vehicle use, ownership, and emissions, there is a notable lack of research that shows how patterns evolve over time. This presses the need for the employment of longitudinal methodologies to unravel the causality of change in mobility patterns and thus deeper implications of these relationships. In current research, there is a lack of investigation on how the revealed travel patterns of individuals evolve as a result of company car policy. The current body of knowledge predominantly relies on cross-sectional data, which falls short in capturing the temporal variations and the potential for mobility style changes over time, especially in response to the concept of 'practical life changes'. As cross-sectional data cannot generate deeper insights into the change in travel patterns of variables over time, longitudinal research is needed. Some examine the variability of travel patterns over time, and this has shown that longitudinal research is fit to establish causality. However, these have not been focused on company car policies in particular. This whilst the employment of longitudinal methods has been a proven method to better understand the causality and the direction of changes over time.

In conclusion, the main knowledge gap in scientific literature is that despite the wide acknowledgment of the many negative environmental impacts of company cars, there remains an absence of insight into how company cars specifically influence individuals' mode choices and how this might change their travel patterns over time away from more sustainable modes. The potential for the availability of a company car, to trigger shifts away from more sustainable mobility patterns over time, underscores the need for longitudinal research to explore these transitions in the context of company car policies.

1.2.1. Research objectives

The previous section shows there is a knowledge gap in the literature. This research aims to fill this gap. Hence, the main objective of this research is to examine how gaining access to a company car affects individuals' mode choices and underlying travel patterns over time. These insights can be used to determine whether company car policies lead individuals to adopt an exclusive car-using pattern thereby possibly replacing more sustainable mobility practices. These insights will add to the comprehension of company car policies and what adverse effects they lead to. Another objective of this research is to provide insights that can help shape policies aimed at reducing the negative environmental impacts of mobility, specifically those of company car policies, and to provide guidelines for a better sustainable transport policy instrument.

1.3. Research questions

This chapter provides an overview of the research questions of this thesis which are based on the research objectives.

1.3.1. Main research question

The knowledge gaps and the research contribution led to the formulation of a comprehensive research question:

In what way does company car availability affect the travel behavior of individuals with similar travel patterns over time and what are its implications for designing sustainable transport policies?

The question above aims to explore the multifaceted impact of company cars on travel behavior, delving into the socio-demographic, economic, and policy-driven factors that possibly shape these behaviors.

In addition to identifying the direct impact of company cars on travel behavior, this research will also explore the broader implications of these findings. For instance, understanding how company car policies influence individuals' decisions to use other modes like public transport or engage in other sustainable travel behaviors is crucial. This aspect of the research is particularly relevant in the context of increasing environmental concerns and the need for more sustainable urban planning. By identifying the likelihood of transitioning to car-minded traveling styles, this research can provide valuable insights for companies and policymakers.

1.3.2. Sub-questions

To address the primary research question, a set of sub-questions must be answered. The formulation of sub-questions is designed to systematically address all aspects of the main research question.

1. ***What latent travel patterns can there be identified among individuals in the Netherlands?***

   This sub-question arises from the theoretical notion that there exist latent sub-groups within the population with underlying mobility styles. The theoretical notion behind this is that the mobility styles of these groups are linked to certain attitudes, motivations, and characteristics of individuals with a similar response pattern. This means that there also is a possibility to determine the effect of certain exogenous variables on the chance of being associated with a certain mobility style. This question aims to map the heterogeneous subgroups that exist in the population and label them according to their associated travel patterns. In addition, this question aims to find the exogenous variables that can be used as predictors to determine the chance that individuals fit into a certain mobility type.

2. ***How does company car access affect household members' travel patterns over time?***

   The third sub-question is likewise aimed at the longitudinal aspect of behavioral change. It intends to gain insight into if and possibly how the presence of a company car in a household affects the travel behavior of non-main user individuals living in this household. Previous research has shown that partners within the same household influence each others' travel patterns over time (Kroesen, 2015). We consider all persons within a household to be subject to the objective characteristics of that household. If company car access is to be used as a determinant for the travel pattern of its main user, one could say that this possibly affects the travel behavior of other residents within this household.

3. ***How does company car access affect main users' travel patterns over time?***

   Focusing on the temporal aspect of behavior changes, the second sub-question investigates whether and how the introduction of a company car into an individual's life influences their mobility choices. Specifically, it aims to understand the dynamics of transitioning from one travel behavior pattern to another considering the role of the main user of a company car in this process. The term "main user" inherently implies that these individuals are the ones most frequently exposed to this vehicle. Hence, we expect to observe the greatest effect here.

1.4. Methods

This section provides a brief outline of the research design, data collection, and analytical techniques employed to investigate the impact of company car access on travel behaviors.

To answer the first question, a quantitative method is required that is able to group individuals based on their revealed behavioral patterns. The chosen statistical method is a Latent Class Analysis (LCA), which is known for its potential to give researchers insights into the mobility styles within the population. The LCA is a probabilistic clustering method that enables us to find the optimal amount of heterogeneous sub-groups in the population with similar response patterns. This leads to a nuanced understanding of how (exogenous) factors influence the travel choices of different segments of respondents (Macharis & Witte, 2012). In the interest of this method, a literature review is needed to gain an understanding of the method and the role of using exogenous variables as predictors for cluster membership. Another aspect of answering the first sub-question is a descriptive analysis. This presents a composition of the sample and its characteristics. To obtain results from the LCA a comprehensive set of data is needed. The dataset needs to contain the revealed travel patterns of respondents. In addition, the dataset needs to contain certain socio-demographic information about respondents and the characteristics of their households to monitor their access to a company car.

As the second and third questions tend to focus more on the dynamics of one's travel behavior, a quantitative method is needed that assesses change over time. Specifically, these questions are aimed at understanding individuals' transitions from one travel behavior pattern to another. For this we propose to combine the Latent Class models of two consecutive time steps into a single framework, this relatively new method is known as the Latent Transition Analysis (LTA). The LTA has been employed before in explorations of the longitudinal effects on travel behavior (De Haas et al., 2018; Haustein & Kroesen, 2022; Kalter et al., 2020; Kroesen, 2014, 2015; Kroesen & Handy, 2014; Zhang et al., 2024). The method constitutes a person-centered approach that uses panel data, this enables researchers to gain deeper insights into changes in behavioral patterns over time (Bartolucci et al., 2012; Kroesen, 2014). As this method essentially represents a combination of two latent class models, the same data requirements apply. This method does however require that the data required for a LCA is available in twofold so that the difference in behavioral patterns over time can be monitored.

The Mobility Panel Netherlands (MPN) dataset is well-suited for this research. The MPN provides insights into the factors that play a role in changes in the travel behavior of Dutch residents (Ministerie van Infrastructuur en Waterstaat, 2022). Insights from the MPN are typically used by the Dutch Ministry of Infrastructure and Water Management to respond to changes in mobility and to improve transport models. Initiated in July 2013, the MPN collects data from respondents aged 12 and older from approximately 2,000 households who record their travel behavior over three days in a travel diary. By providing annual datasets that include household, personal, and travel diary information the MPN is a valuable resource for understanding travel behavior changes over time. This makes it ideal for both the LCA and LTA methodologies. Thus, leveraging this dataset aligns perfectly with the objectives of this research.

1.5. Research contribution

This research aims to bridge the societal relevance of sustainable urban mobility with the identified scientific gap which shows a lack of insight into the revealed effects of company car policies on travelers' mobility patterns over time. This will be brought into practice by performing longitudinal research that captures the change in travel behavior as a result of having access to a company car. This research aims to find out if having access to a company car strengthens exclusive car use and/or detracts travelers from other (sustainable) modes. Therefore we propose a longitudinal quantitative study that examines how access to company cars affects travel behavior over time. By investigating whether the observed patterns are a direct result of company car access or reflect deeper, pre-existing mobility preferences, this study seeks to provide a nuanced understanding of the interplay between company car policies, individual mobility styles, and sustainable urban transportation goals. It aims to gain insights into the factors that determine whether people transition towards more car-oriented mobility styles. These insights are not only valuable for companies in re-aligning their policies with sustainability goals but also offer guidance for policymakers and urban planners in crafting effective sustainable mobility strategies that prevent these undesirable transitions (Ministerie van Infrastructuur en Waterstaat, 2022, 2024).

In addition, this thesis aims to contribute to the existing work on using the mobility biographies approach as an underlying theory for travel behavioral research. Specifically by assessing the effects of a 'softer life event' on potential change in mobility behavior.

1.6. Reading guide

The first chapter of this research focuses on the background information on the topic of interest and reflects on gaps within the literature that are the cause of this research. It highlights the main research question and divides this into the sub-questions used throughout this research. The second chapter of this thesis is a literature review that compiles findings of previous studies on company cars, the concept of multimodality, changes in travel behavior, and latent mobility patterns. The third chapter introduces the methodologies of this research. The concepts of Latent Class Analysis (LCA) and Latent Transition Analysis (LTA) are introduced and their conceptual models are presented. The fourth chapter of the research dives into the characteristics of the sample and provides information on the model specifications. As the LCA is a component of the LTA model, this section also presents the outcomes of the cluster analysis. The fifth chapter presents the results of multiple Latent Transition Models that have been estimated in Latent GOLD. This chapter shows detailed model output and discusses findings. The sixth and final chapter reflects on the findings in the discussion section, here, limitations are discussed. After this the conclusion reflects on the reseach theme and question and provides practical policy implications based on the findings with suggestions for further research.

2
Literature review

This chapter will discuss the (initial) literature review of previous mobility research. This chapter reviews a series of studies that have focused on the relationship between company cars and travel behavior. The literature review was also used to investigate how others have used panel data in research and how the use of Latent Class and Latent Transition Analysis have been applied before to explore mobility topics. Furthermore, the literature review explored the domain of multimodality.

2.1. Approach and criteria

The pursuit of this research topic began with an extensive literature search utilizing Scopus. The selection of literature was guided by criteria prioritizing English language papers, primarily from the last 25 years to ensure contemporary relevance. However, this rule was relaxed for seminal papers with high citation counts, acknowledging their ongoing influence in the field. Further paper selection was conducted based on title and abstract screening for relevance.

Additionally, the snowballing technique was employed, where references within papers were explored for further relevant literature, ensuring a comprehensive understanding of the topic. The table below shows a list of the search words used to identify previous research on the topic. The choice of certain keywords has been developed through the review itself.

2.2. Previous studies

2.2.1. Company car research

Throughout the literature review, several key insights were gained on the topic of company cars and travel fringe benefits in general. Studies like those by Ye et al. (2007), and Xianyu (2013) highlighted the complexities of travel behavior, including the interplay of mode choice and increased car use for purposes such as 'so-called trip chaining' (combining commuting with personal trips). These studies show that individuals might be inclined to use their travel benefits in ways not originally intended by their employers. Even though these studies addressed the role of company cars and their effect on (increased) usage during personal trips, the implications of these studies mostly focus on ineffective taxation policies and not on the effects of mode encouraging subsidies (Shiftan et al., 2012). There is a case where Busch-Geertsema et al. (2021) performed research on the effects of free public transport for employees. This research monitored the transitions of travelers after the introduction of free transport. Their result suggests that people only abandon their cars if they feel like they can fall back on reliable alternatives. They propose this could be improved by both making alternative modes more attractive, but also by restricting company car subsidies at the same time. It seems to be the case that there are few explorations within the specific field of research related to company car policies and their influence on traveler mobility styles. This stresses the need for research into this topic as unimodal car transport continues to dominate at the expense of more sustainable modes in European countries (Holotová et al., 2022).

Research of Metzler et al. (2019) has shown that company cars also lead to increased transport demand and vehicle ownership, which is associated with higher emissions. Similarly, Tsairi et al. (2023) found that transport-related benefits can lead to higher vehicle ownership and use. Their study also shows that the nature of transportation policies about employee benefits is contrary to governmental ambitions to limit environmental impact. The latter ties in nicely with the societal relevance of this topic. Alike, Nijland and Dijst (2015) studied commuting benefits in the Netherlands, they suggested that employer-provided benefits, like company cars, could significantly impact the number of cars in a household and hence increase car travel. However, this study does not provide any insight into the effects on underlying mobility styles. The finding that company cars lead to increased use is also endorsed by multiple studies that show that the provision of company cars is positively and significantly related to mileage (Albert et al., 2014; De Wilde et al., 2023; Frenkel et al., 2014; Shiftan et al., 2012).

Overall, we can conclude that the subject of company car research is not a topic that has been researched a lot. Despite its significance in influencing travel behavior and its potential implications for transportation policy, there remains a gap.

2.2.2. Multimodality

Research into multimodality also presents insights to be used for the investigation of company car effects. Apart from the findings in section 2.2.1 that highlight that company cars are related to higher use in terms of distance, it is important to note that car use on itself decreases the usage of other (more sustainable) modes (Faber et al., 2022). This finding is also confirmed by the research of Frenkel et al. (2014), which shows that the availability of company cars leads to a higher probability of choosing a car as the only mode. This suggests that company cars lead to behavior that replaces the usage of sustainable (multimodal) transport. Unimodal travel patterns have been found to be less sustainable in general (Faber et al., 2022). Moreover, an increase in the degree of multimodality seems to be leading to less car dependence inferring more sustainable travel behaviour and this underlines the societal need to move away from unimodal transport. Heinen (2018) found that the more multimodal individuals were, the more likely they intended they were to decrease their car use. Nevertheless, this research was performed using cross-sectional data making it difficult to establish causality.

2.2.3. Change in travel behavior

Determining and explaining modality-type choices seems to be a subject of interest that has been tried to be explained by assessing the effects of key life course events. Research performed by Janke et al. (2021) has focused on explaining changes in travel behavior, by seeing certain big life events as windows of opportunity in which individuals may reconsider their current mobility styles as Van der Waerden et al. (2003) and Müggenburg et al. (2015) put it. According to them, the theoretical notion has to do with habits and routines. They name external conditions, such as employer mode support, as potential life events. Again, this research supports the argument that unimodal users are more inert, meaning that they are more likely to stick with their sole mode. In addition, they report that the increase in car availability led to a decrease in multimodality, this is also found by other researchers (Klinger, 2017; Scheiner et al., 2016). Even though research of Scheiner et al. (2016) was not performed with the specific type of subsidized car ownership in mind, it supports the idea that its availability can lead to unsustainable and inert mobility styles.

Another theoretical approach of factors determining travel behavior is proposed by the research of Kroesen and van Cranenburgh (2016). They also support the notion that inertia of travel behavior leads to certain mobility styles, but note that it can also be determined by choice instead of only originating from habit. They also propose further research that predicts latent travel patterns or transition probabilities between groups considering the mobility biographies approach of Müggenburg et al. (2015). To create transition probabilities between groups over time, longitudinal data is essential.

2.2.4. Latent mobility patterns

Research of Macharis and Witte (2012) used a clustering method to investigate the types of company car users. Their findings emphasize the need for different policy approaches tailored to specific target groups. Apart from their research, search results suggest there has not been much research on this specific topic using panel methodology. This gap was further echoed in the works of Tejaswi and Prasad (2023) and Vidal and Lersch (2021), who emphasized the influence of socio-demographic factors on travel behavior and the need for panel data to capture both change and persistence of respondents, reinforcing the findings of Kitamura (1990). This research poses a discussion on the advantages of panel data in transportation research. It underscores panel data its potential in capturing temporal variations in travel behavior, a feature notably absent in many existing studies on company cars using cross-sectional data.

The application of panel data in travel behavior research in general on the other hand has been performed before. Findings of De Haas et al. (2018) state that there is quite some research that focuses on theory related to the mobility styles/biographies, but that this does not account for interactions between past travel behavior and the effects of certain exogenous variables. Research of Kroesen (2014) has explored the use of longitudinal data in a mobility context in a relatively new manner, by using a Latent Transition Analysis that focused on its qualitative explanatory power for travel behavior patterns over time. The research reports on the use of a model in which life events are incorporated to see their influence on the transition probabilities between revealed behavioral patterns. In this instance, examples of life events are the relocation of respondents or the change of jobs.

The use of panel data to investigate (transitions in) travel pattern effects and the identification of determining variables through LTA is also endorsed by others (Kroesen & Handy, 2014). At this time the transition of respondents between clusters over time had not been a widely researched topic. Kroesen (2014) mentions sample size and event frequency as important drawbacks of the method as the method is based on observations, reinforcing the findings of others (Collins & Wugalter, 1992; Velicer et al., 1996). Newer and more complete data may provide valuable insights. In addition, the probabilistic LTA method proves to be promising compared to competitors, like conditional change models, as it can reveal more complex substitution and complementary patterns when exogenous variables change (Kroesen & Handy, 2014). Another point of interest of previous LTA research on car use and ownership, in general, is the exploration of attitude-behavior transitions (Haustein & Kroesen, 2022; Kalter et al., 2020).

Results of Kalter et al. (2020) suggest that attitudes towards car use and ownership are reasonably stable. Again, this reinforces that travel behavior is stable, especially for the unimodal car user. This research does however also report that there is a window of opportunity where (mainly younger) respondents may be inclined to change their mobility profiles to be more car-oriented based on certain life-events. The latter is also partly in line with the findings of research of Haustein and Kroesen (2022), as they identify one of the clusters within their research to be more susceptible to transitioning into being car-minded. Another interesting finding related to this so-called window of opportunity can be derived from research of Faber et al. (2022) as they propose the idea that multimodal travelers are more sensitive to exogenous variation and therefore those will use the car more when car-favoring weather conditions arise. Even though this research has focused on weather events such as rain, a comparison could be made to the proposed research in which we consider company car availability to be an exogenous variable affecting travel behavior. The effect found by Faber et al. (2022) does however not occur the other way around as car-minded travelers have been found to be unlikely to deviate from their travel patterns if conditions arise that are more favorable for other modes. This reinforces the findings of Kroesen and Handy (2014) on the inert nature of travel behavior. Likewise, Kalter et al. (2020) report on findings that indicate that once individuals adopt car-focused ways of getting around, they are not likely to shift away from this mobility style by themselves. Therefore, it seems to be important to prevent the more sustainable multimodal travelers from transitioning into car-oriented travelers.

2.2.5. Summary of prior studies

This literature review has yielded several key insights into the intricate dynamics of travel behavior with regard to company cars. Previous research indicates that company cars are strongly related to increased transport demand and vehicle use and ownership, leading to negative environmental impacts. At the same time, we see that unimodal car transport continues to predominate to the detriment of more sustainable multimodal transport in European countries. Notably, the availability of company cars discourages the use of more sustainable, multimodal transport options, underscoring the societal imperative to transition away from unimodal transport. However, research does not show if the increase in car use is caused by the company car. It could also be the case that the typical company car driver has an intensive car usage mobility style. Previous research on company cars does not report on this, because it uses cross-sectional data which makes it difficult to establish causality between factors. In light of these findings, it is clear that understanding the nuances of travel behavior, particularly in the context of company car access, is crucial.

Past research uses life events to model mobility style change over time. Even though travel behavior is found to be inert, key life events represent opportunities for individuals to reconsider their mobility styles. There is a pressing need for research that goes beyond cross-sectional studies to explore how transitioning to company car use affects travel patterns over time. This involves examining whether the observed travel behaviors are a direct result of having access to a company car or if they reflect underlying preferences independent of this access.

To address these questions, it is essential to employ longitudinal studies that can capture the evolution of travel behaviors and the impact of life events on mobility styles, such as gaining access to a company car. Such research could offer invaluable insights into preventing the transition towards car-oriented mobility styles, thereby supporting the development of policies aimed at promoting more sustainable travel behaviors.

In conclusion, while cross-sectional studies have highlighted the impact of company cars on increased car use and reduced use of public transport and bicycles, there remains a gap in understanding whether this behavior results from the availability of company cars or pre-existing travel patterns of company car users. To accurately determine the effect of company cars on travel behavior, we must focus on finding out more about the chance that individuals transition to company car usage and assess the likelihood of them adopting an exclusive car-use pattern. This approach is critical for developing strategies to prevent the entrenchment of car-oriented mobility styles, emphasizing the importance of longitudinal research in capturing these dynamics. In addition, it is important to consider that the effects of company car availability may be amplified or weakened depending on socio-demographics. Therefore, it is crucial to investigate the role of covariates in predicting travel behavior so that the inclusion of certain variables can be argued for.

3
Methodology

This chapter presents the methodological approach of this research. Since multiple approaches are used, general information will be provided for each approach. As there are numerous approaches linked to the sub-question, these will be discussed below:

- **Data Operationalisation:** Sub-question 1, 2, and 3;
- **Descriptive Analysis:** Sub-question 1, 2, and 3;
- **Latent Class Analysis:** Sub-question 1;
- **Latent Transition Analysis:** Sub-question 2 and 3;
- **Interpretation and inference:** Main research question

3.1. Literature findings

The literature review found that even though previous cross-sectional studies have effectively highlighted the relationship between company cars and increased car use, they fall short of establishing causality. In addition to this, there is little to no research that has focused on transitions of travel behavior. The inherent limitations of cross-sectional data underscore the need for longitudinal quantitative methods to accurately assess the impact of company car availability on travel behavior. Longitudinal studies are particularly well-suited to capture the evolution of travel behaviors over time and the influence of key life events, such as gaining access to a company car. By employing these methods, researchers can better determine whether the observed increase in car use is directly caused by company car access or if it reflects pre-existing mobility preferences. Furthermore, considering socio-demographic covariates in these studies is essential to understand the full spectrum of influences on travel behavior. This approach is crucial for developing effective policies to promote sustainable travel behaviors and prevent the entrenchment of car-oriented mobility styles.

3.2. Data operationalisation

For this research, the data from the Dutch Mobility Panel is used (Ministerie van Infrastructuur en Waterstaat, 2022). The panel started in 2013 by collecting data on travel behavior.

Even though the KiM offers access to the datasets from 2013 through 2021, this research only considers the first seven waves of the MPN. The reason for this is related to the comparative characteristic of the LTA method and the fact that the world was struck by the pandemic at the beginning of 2020. We hypothesize that the intelligent lockdowns during the COVID-19 pandemic had a significant impact on the travel behavior of the Dutch population. The latter is confirmed by research that shows that during this period activities changed and there was a strong inclination towards car use instead of public transport (De Haas et al., 2020).De Haas et al. (2020) also exacerbated a longitudinal approach using data from the MPN and found significant differences between the waves. Since the main focus of this research is aimed at gaining an understanding of if and how travel behavior changes as a result of gaining access to a company car, the aim is to minimize interference of third variables. In such a manner the wave selection choice is justified. Combining the observations from waves 1 through 7, the final panel consists of about 6700 households representing approximately 12700 respondents.

The Dutch Mobility Panel does not monitor travel behavior in such a way that it can directly be transposed into the statistical software used to conduct the LCA and LTA. Therefore, the travel behavior and socio-demographic variables will need to be rearranged to fit the method. A more in-depth data operationalisation including design choices will be discussed in the methodology of the Latent Class and Latent Transition Model.

3.3. Descriptive analysis

As the first seven waves of the Dutch mobility panel consist of approximately 6700 unique households and 12700 respondents, descriptive statistics are provided to assess the representativeness of the sample.

3.3.1. Sample representativeness

In research, establishing the representativeness of the sample is essential to ensure the validity of the findings. To this end, the Chi-Square test serves as a statistical tool to compare the distribution of socio-demographic characteristics between the sample and the population. The sample of the final wave combination will be compared to publicly available data of the Dutch population (Centraal Bureau voor de Statistiek, 2024a).

The application of the Chi-Square test allows us to determine if the differences in frequencies of these characteristics between our sample and the population are statistically significant. By conducting this test, we can identify potential biases in sample selection. It helps to determine if the conclusions drawn from this sample can reasonably be generalized to the population.

The formula for the Chi-square test is as follows:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{3.1}$$

Equation 3.1: Chi-square test

- χ^2 = Chi-square value
- O_i = Observed frequency
- E_i = Expected frequency

3.4. Latent Class Analysis

The Latent Class Analysis (LCA), or Latent Class Clustering Analysis (LCCA), is a probabilistic clustering method that can provide researchers with the optimal amount of distinct mobility styles within a sample (Araghi et al., 2017). The method is defined as a technique that models a discrete latent or unobservable variable using multiple discrete observed variables as indicators (Araghi et al., 2017). According to Magidson and Vermunt (2002a), the fundamental assumption underlying a Latent Class model is one of local independence. This states that persons who belong to the same cluster, have the same probability of scoring similar response patterns on the (observed) indicators. The method assigns cases to clusters based on the shared variance of their indicators, which adds to homogeneity within groups. At the same time, the method tries to maximize the heterogeneity between the subgroups (Muthén, 2004; Nylund et al., 2007). The LCA assigns respondents into subgroups that correspond to the highest posterior membership probability given their observed response patterns (Magidson & Vermunt, 2002a). These subgroups create a new category of a categorical latent variable, where individuals share characteristics (Muthén, 2004; Vermunt & Magidson, 2004).

The concept of the latent class categorical variables is that it accounts for the similarity in response patterns in such a way that it explains away the correlation between indicators. In literature, this is referred to as the local independence assumption (Araghi et al., 2017; Molin et al., 2016). The goal of Latent Class Analysis is to identify the smallest number of latent classes that can accurately describe the relationships among a set of observed categorical variables (Muthen & Muthen, 2000). If the latter is obtained, the LCA allows for a more nuanced understanding of factors influencing (travel) behavior and has been widely applied as categorical data analysis which is used to identify subgroups in groups of respondents (Vermunt & Magidson, 2004).

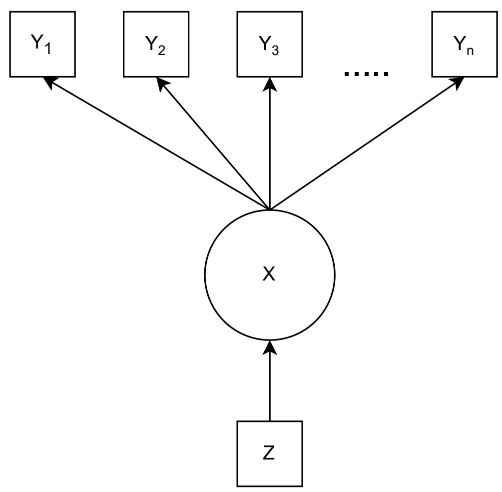

Figure 3.1: General conceptualization of the Latent Class Model

Figure 3.1 represents a general conceptualization of the LCA model with n indicators, latent variable X, and the covariates z. This figure clearly shows how exogenous variables might provide explanatory power for class membership (Muthen & Muthen, 2000). The figure also visualizes that the indicators are dependent on class membership. This can be explained under the theoretical notion that there is an underlying variable that can account for similarities in the measured response patterns or indicators (Araghi et al., 2017; Molin et al., 2016; Weller et al., 2020).

3.4.1. Advantages compared to traditional clustering

Since the start of the 21st century, the Latent Class Analysis has been recognized to be a model-based alternative to the more traditional clustering techniques such as K-means. The LCA offers various advantages over traditional clustering techniques, which will be discussed below.

Model-based implies that the LCA method uses a statistical model based on probability distributions (Magidson & Vermunt, 2002b). This means that cases are assigned a probability of belonging to a cluster. This is one of the key differences from this method compared to the more traditional cluster techniques, where cases are assigned deterministically (Magidson & Vermunt, 2002a).

Even though both traditional and model-based clustering techniques use a maximum log-likelihood method for parameter estimation based on certain criteria, model-based techniques assign cases less random, making it a more robust method (Magidson & Vermunt, 2002b).

The Latent Class Analysis assigns cases based on similarity in response patterns, whilst the K-means algorithm assigns them based on the Euclidean distances between, initially randomly assigned, cases and clusters. This also means that the (unsupervised) deterministic way of assigning clusters is more prone to misclassification bias (Araghi et al., 2017; Magidson & Vermunt, 2002a; Molin et al., 2016).

The difference in cluster allocation presents additional benefits in favor of the Latent Class Analysis. As the method assigns cases based on similarity in response pattern, it does not require Euclidian distances. This means it can account for nominal variables, where distances between answers are hard to define, as well as the use of different scale types at the same time without any prior standardization(Magidson & Vermunt, 2002b).

Magidson and Vermunt (2002b) report on more advantages over the K-means approach. The LCA can assist researchers in determining the optimal amount of clusters in the sample. There are several statistical measures available to test this, such as the Bayesian Information Criterion (BIC) and the Bivariate Residuals (BVR) (Araghi et al., 2017; Magidson & Vermunt, 2002a, 2002b; Schreiber & Pekarik, 2014).

A final advantage of the LCA over traditional clustering techniques is the possibility to include covariates. The K-means needs an additional discriminant analysis to describe differences among clusters based on exogenous variables. The LCA method allows the classification and cluster description to be estimated simultaneously (Magidson & Vermunt, 2002a; Schreiber & Pekarik, 2014).

3.4.2. Limitations of Latent Class Analysis

Even though the Latent Class Analysis has many benefits, the method also has various limitations. One of those limitations is that because the method assigns individuals to classes in a probabilistic manner, the exact class distribution cannot be determined (Weller et al., 2020).

Another potential drawback of the method is the so-called 'naming fallacy'. This refers to researchers naming classes in a way that the label does not provide an accurate description of their characteristics (Weller et al., 2020). A final limitation of the LCA is that it is not able to handle dynamics of latent variables that change systematically over time (Velicer et al., 1996)

3.5. Latent Transition Analysis

The Latent Transition Analysis (LTA) is a Markov model that complements the LCA, in such a way that it enables researchers to investigate the dynamics of latent variables(Velicer et al., 1996). The LTA is a method that is fit to test theoretical models about the patterns of change over time. It is a type of latent variable model that is used for the analysis of longitudinal data (Bartolucci et al., 2012). In this case, it could be used to assess the time-lagged effects of the introduction of the company car variable on the latent classes to see how it changes the transitioning probabilities. The main complementary characteristic of the Latent Transition Analysis is that the latent process that represents individual characteristics follows a Markov-chain (Bartolucci et al., 2012). This is a mathematical system that models the sequence of events, where the probability of an event depends on the previous state of the event. This means that the method is designed to handle and explain first-order autocorrelation in longitudinal data (Inc., 2013). Evidently, the LTM is related to the LCA as it represents both current and future latent states or memberships, this is visualized in Figure 3.2. The main objective of the Latent Transition Analysis is to map the probability of transitioning between classes (Muthen & Muthen, 2000). This method has been used by various researchers to study its application in a mobility context (De Haas et al., 2018; Haustein & Kroesen, 2022; Kalter et al., 2020; Kroesen, 2014, 2015; Kroesen & Handy, 2014; Zhang et al., 2024).

Vermunt et al. (2008) describe the execution of an LTA in the Latent Gold software package. The LTA model consists of five types of variables: response variables (measured indicators), time-constant explanatory variables (e.g. socio-demographics), time-varying explanatory variables (e.g. company car ownership), and time-constant and time-varying discrete latent variables (LCA models at different moments in time) (Vermunt et al., 2008). The latter leads to the following general conceptual model of the Latent Transition Analysis of a consecutive wave pair.

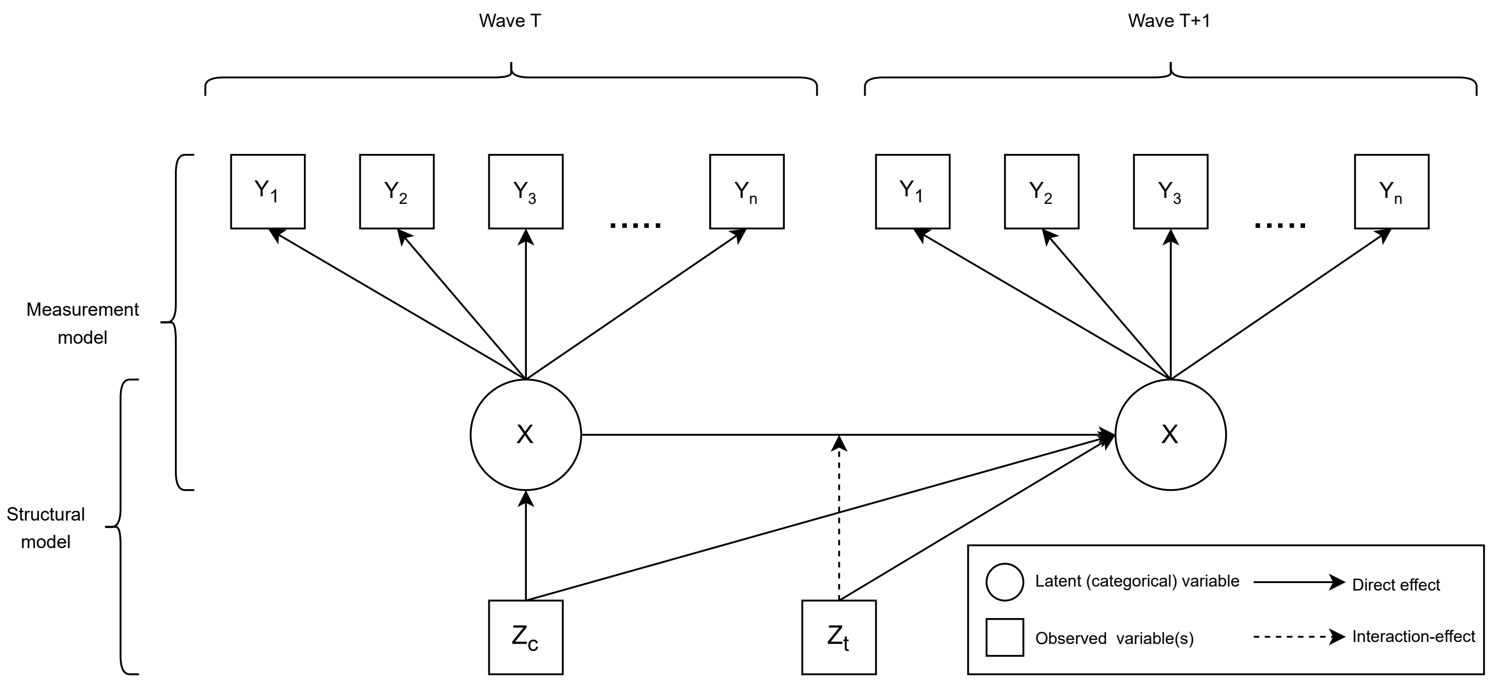

Figure 3.2: General conceptualization of the Latent Transition Model

As shown in Figure 3.2, the Latent Transition Model captures both direct and indirect effects. A direct, or main, effect refers to the influence of one variable on another without the interference of additional variables. For example, gender, a time-constant explanatory variable, may have a direct effect on the categorical variable X. Similarly, a direct effect might be observed from a time-varying explanatory variable, such as company car ownership, on variable X. This effect reflects changes in class membership at Wave T+1, independent of any initial state membership.

The model also enables us to explore interaction effects, where the influence of one variable is considered in the context of another. For instance, the impact of company car ownership on variable X might vary based on the initial state of X at T-1. A significant interaction effect indicates that the influence of an explanatory variable could be either amplified or diminished, depending on the initial class membership.

In the Latent Gold software package, there are two ways to estimate a Latent Transition Model, either by using standard or transition logit parameterization. The standard logit parameterization refers to a model where only direct effects between the variables are computed. When using the transition logit, an additional parameter is estimated to capture interaction effects.

3.5.1. Advantages and limitations of the Latent Transition Analysis

One of the main advantages of the LTA is its potential to include time-constant and time-varying covariates. This helps to explain the differences in the initial class memberships and the transitions of individuals over time (Di Mari et al., 2016). But this also means that the method is fit to evaluate the contribution of certain measures to the different latent classes (Velicer et al., 1996). This enables us to gain insights into how the company car variable potentially has more effect on certain types of travelers.

One of the major drawbacks of the Latent Transition Analysis is that it requires a large sample size (Velicer et al., 1996). Each possible transition can be seen as a cross table that contains the possible response patterns. Because of this, there is a possibility that many of the cells in this contingency table will be empty, underlining the need for large sample sizes (Collins & Wugalter, 1992; Velicer et al., 1996). This drawback becomes even more apparent when the transition logit parameterization is used, the reason being that the model estimates additional parameters to monitor the interaction effects. This does not only requires more time and computing time but possibly leads to estimation problems as it is likely to require even bigger sample sizes to yield significant results.

3.6. Interpretation and synthesis

The results of both the Latent Class Analysis and the Latent Transition Analysis will be interpreted to find out how the mobility styles of subgroups in the sample might be affected by the company car variable. Based on these outcomes, a synthesis aimed at improving policy design will be performed.

3.7. Inference

Finally, the conclusions of this quantitative research will be drawn and translated into recommendations. This section will also go deeper into the limitations of this study and the discussion of the results.

4
Model specification

The following chapter will discuss all aspects needed for the operationalization of the LTA model. This includes the respondent selection, sample composition, and the operationalization of variables.

4.1. The Dutch Mobility Panel

The Dutch Mobility Panel (MPN) is an initiative from the Dutch Ministry of Infrastructure and Water Management that has been active since July 2013 (Ministerie van Infrastructuur en Waterstaat, 2022). The MPN is a yearly questionnaire that asks persons aged 12 years and older from about 2000 households to report their mobility behavior in a travel diary over a period of three days.

The goal of the Dutch Mobility Panel is to gain insight into changes in mobility and to use this to shape policy that is better fit to handle these changes. The Ministry uses the outcomes of the models made using the data from the MPN to decide upon mobility policies.

The travel diary used in the Mobility Panel asks the respondent to report their travel behavior during a period of three days. This is quite detailed, as the panel asks respondents to fill in all of the trips they make, including distances, main modes of transport, and more. In addition to this, the panel asks respondents to fill in information such as person and household socio-demographics or underlying preferences. This means the dataset is quite extensive and therefore fit to use in detailed mobility research. Seeing that the mobility panel is a yearly initiative that collects data since 2013, the data of multiple waves is available. The Kennisinstituut voor Mobiliteit collects and handles the dataset for the Ministry and has published the datasets from 2013 through 2021.

However, there is a slight limitation to the dataset. The MPN collects both trip as trip-segment data. A trip is defined as a movement from location A to B and has a main mode of transport. A trip can consist of multiple trip segments that each have a main mode of transport. For example: a trip may originate from a respondent's house located in Rotterdam to his or her office that is located in Amsterdam. If the respondent travels by train, this will be the main mode of transport for the trip. In this case, a trip segment could be the transportation on foot from the house to the train station, a segment by train between the stations, and a final segment from the Amsterdam station to the office by bike. Trips contain information about the distances traveled, whilst trip segments do not. The latter can be seen as a drawback of the dataset, as distances traveled per segment would contribute to a deeper understanding of travel behavior when used in quantitative analysis. Ultimately this will result in a modelling choice that needs to be made that fits the objectives of this research as well as possible.

4.2. Respondent selection

As stated before in section 1.4 the first seven waves of the Dutch Mobility Panel are used for this research. The MPN asks respondents aged 12 years and over to keep a record of their mobility behavior over three days.

The table below provides an overview of the number of respondents participating in each wave. Respondents may participate in multiple waves, this allows us to investigate potential changes in their behavior patterns over time. It is important to note that respondents are not obliged to participate in multiple or consecutive waves. This limitation will be dealt with in the following section.

Research year	Sample size
2013	3996
2014	5582
2015	3983
2016	4446
2017	5586
2018	6382
2019	5753
Total	**35228**

Table 4.1: Sample sizes of MPN waves

Even though the amount of respondents over all seven waves comes down to about 35.000, there are 12.778 unique respondents originating from 6769 households. This indicates that there are quite some respondents who have participated in multiple waves of the mobility panel. Another important note to this statistic is that this number of respondents only includes participants who are 18 years or older. Even though the Dutch Mobility panel gathers data from participants aged 12 years and older, this research only uses the diaries of adults. The reason for this is that the research aims to find out more about travel behavior using revealed preference. As respondents under 18 are not of legal age to use the car, this excludes them from using this mode. Including them in the research would lead to a potential bias in the results.

4.2.1. Wave-pooling

As the proposed Latent Transition Analysis investigates behavioral change over time, wave pairs need to be constructed. The chosen approach is to select consecutive wave pairs. Even though some respondents might have participated in multiple waves, we only use the data from those who have participated in consecutive years. This is done to ensure that the time between waves, and thus the time between potential behavioral change, is constant for all cases. If there is a larger period in between cases, the monitored change of travel behavior might be subject to more external influences that potentially explain away effects. This could lead to a bias in the results, hence the choice for the use of consecutive wave pairs.

The amount of respondents that have participated in two or more consecutive wave pairs comes down to 8183. The table below presents the sample sizes of consecutive wave pairs.

Wave pair	Sample size	Change in CC ownership
2013 - 2014	2562	102
2014 - 2015	3318	148
2015 - 2016	2518	150
2016 - 2017	2823	142
2017 - 2018	4466	208
2018 - 2019	5043	278
Total	**20730**	**1028**

Table 4.2: Sample sizes of MPN wave pairs and possible company car transitions

As table 4.2 shows, the maximum amount of wave pairs and thus possible transitions is 20730. As mentioned in subsection 3.5.1 a major drawback of the LTA is that it requires a large sample size. The maximum amount of possible transitions as shown in table 4.2 should be able to overcome this limitation. However, we cannot use all of these transitions as this would lead to biased results. The reason for this is that respondents are allowed to participate in multiple waves of the mobility panel. This means that a unique respondent that participates in multiple consecutive waves, generates multiple consecutive wave pairs by doing so. If one would use all of the available wave pairs, it would be as if those have been unique observations of different subjects while they are not. This violates the assumption that observations are independent of each other as multiple observations of one respondent are correlated to each other, creating bias. Therefore, the maximum amount of transitions used for the model cannot exceed the amount of unique participants with consecutive wave pairs.

This means that for respondents with multiple consecutive wave pairs, one pair needs to be selected to be used in the LTA. To ensure that no bias arises from this selection process, a random selection following a normal distribution was used to select the wave pair to be used in the LTA. As this research specifically focuses on the effects of company car ownership, additional explanatory power is nested in the wave pairs where respondents have reported gaining or losing access to a company car. Therefore the wave selection process prioritized the selection of wave pairs where this event, either gaining access to or losing access to, took place. The definition and operationalization of a company car transitioning wave pair will be discussed in section 4.5.2.

In the unique cases that this event was reported multiple times for one respondent, the same random selection process was used to select the wave pair used for the analysis. This resulted in the final consecutive wave-pair sample sizes.

Wave pair	Selected sample	Change in CC ownership
2013 - 2014	1143	79
2014 - 2015	1321	104
2015 - 2016	752	114
2016 - 2017	868	95
2017 - 2018	1739	139
2018 - 2019	2360	194
Total	**8183**	**725**

Table 4.3: Selected wave pair distribution that includes most company car transitions

Table 4.4 shows the proportion of selected cases originating from each year including the selection ratio. The table shows that there is some variety in the proportion of selected cases in each year. More specifically, the cases originating from ’17-’18 and ’18-’19 have a higher proportion within the sample. A potential reason for this observation is the fact that the initial sample of, both non- and CC transitioning, wave pairs is larger compared to the other years.

Wave pair	Initial sample	Selected sample	Selection ratio	Proportion of sample
Selection process of non-CC transitioning wave pairs				
2013-2014	2460	1064	43.25%	14.27%
2014-2015	3170	1217	38.39%	16.32%
2015-2016	2368	638	26.94%	8.55%
2016-2017	2681	773	28.84%	10.37%
2017-2018	4258	1600	37.57%	21.45%
2018-2019	4765	2166	45.45%	29.04%
Total	**19702**	**7458**		**100.00%**
Selection process of CC transitioning wave pairs				
2013-2014	102	79	77.45%	10.90%
2014-2015	148	104	70.27%	14.34%
2015-2016	150	114	76.00%	15.72%
2016-2017	142	95	66.90%	13.10%
2017-2018	208	139	66.83%	19.17%
2018-2019	278	194	69.78%	26.76%
Total	**1028**	**725**		**100.00%**

Note: some values may not add up to 100% due to rounding.

Table 4.4: Sample distribution of (non-)CC transitioning wave pairs after the random-selection process

If we consider the selection ratio of the initial samples of wave pairs we see that these percentages range between 26.94% - 45.45% and 66.83% - 77.45% for the non-CC and CC transitioning wave pairs respectively. As the selection of a wave pair is made at random following a uniform distribution, we would expect a low deviation between these percentages. A potential explanation for the observed deviations could be that some wave pairs may have had more ’competition’ with other potential wave pairs during selection. With this, we mean that respondents participating in the wave pairs ’15-’16(selection rate 26.94%) and ’16-’17 (selection rate 28.84%) may have been inclined to participate in more waves or could have a more similar participation pattern.

The deviation in selection rates of company car transitioning wave pairs seems to be lower than the one from non-transitioning pairs. This can be explained by the fact that individuals having multiple CC transitions is an event that is less likely to be observed, leading to fewer 'competing' wave pairs during the selection process. This leads to less disparity between selection rates.

The figure below shows histograms for the selected cases and their corresponding years.

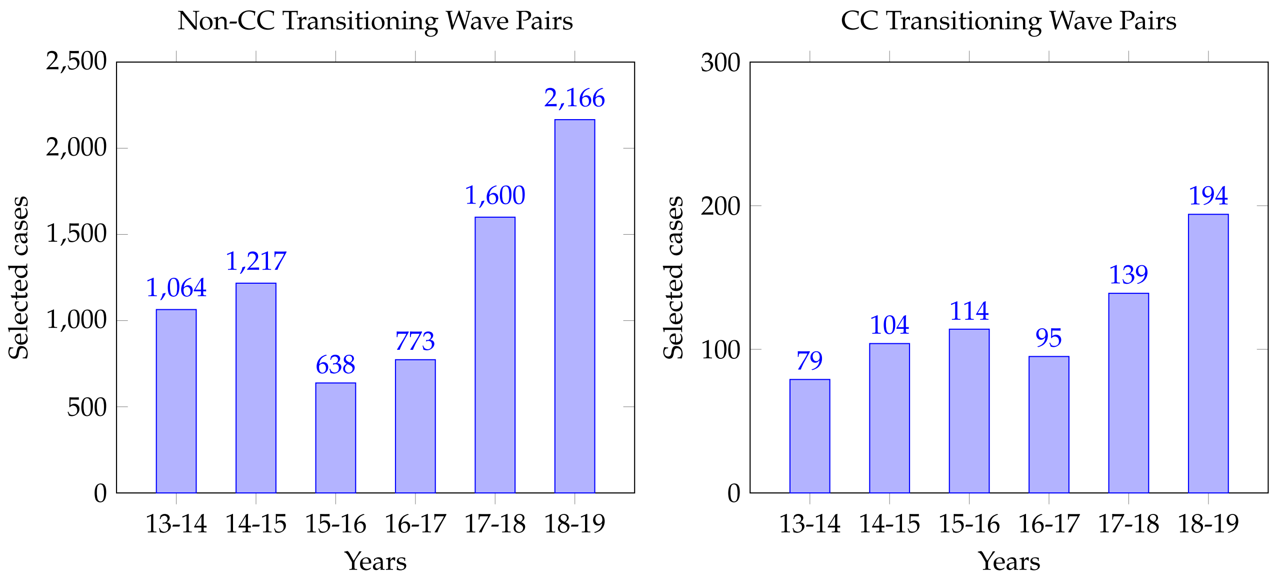

Figure 4.1: Distribution of the selected non-CC and CC transitioning wave-pairs per year

A notable observation from this plot is that the share of company car transitioning wave pairs is quite high between 2015 and 2016 (waves 3 and 4) compared to other years. The proportion of company cars transitioning wave pairs of the total sample used is shown in table 4.5.

Year	CC cases	Total sample	Proportion CC cases (%)
2013-2014	79	1143	6.91%
2014-2015	104	1321	7.87%
2015-2016	114	752	15.16%
2016-2017	95	868	10.94%
2017-2018	139	1739	7.99%
2018-2019	194	2360	8.22%

Table 4.5: Proportion of CC cases in the sample (per year)

Both figure 4.1 and table 4.5 show that the wave pair '15-'16 has a noticeably higher proportion of company car cases. Also, wave pairs '16-'17 have a slightly higher share of company cases. This observation is extraordinary as the selection rates of these years do not differ significantly from others. A possible reason for these observations could be that respondents have gained more access to company cars during the years these waves took place.

4.3. Sample composition

This section provides an overview of the sample that corresponds to the selected wave pairs. It provides the descriptive statistics of the individuals participating in these waves. The statistics discussed in this section are linked to the self-reported characteristics of participants taken from the first time step of their corresponding wave pair. It should be emphasized that the MPN asks respondents to report their movements during three days as this explains the order of magnitude of the mean values of trips per mode.

The sample composition must represent the Dutch population as well as possible because this enables us to generalize the findings of this research. As mentioned in section 3.3.1, the sample statistics are compared to that of the Dutch population according to the CBS (Centraal Bureau voor de Statistiek, 2024a). As the current selection represents a pooled sample, the weighted CBS statistics will be used to assess the sample representativeness with the Chi-square test. An elaborate discussion on the Chi-square values is presented in Appendix A.

The main findings of the representativeness tests using Chi-square, point out that the gathered sample is not representative of the Dutch population. The Chi-square tests show significant p-values for most covariates that have been assessed. These tests have been performed for the covariates of gender, age, educational level, occupational status, and income. Surprisingly, the sample is representative of the Dutch population considering the occupational status covariate. These findings have some implications and nuances for the results of this research.

First, the test in Appendix A shows that the differences between the sample and the population are great enough for statistical significance. This is quite a notable finding as at first glance at the sample distribution one would not expect this outcome. Looking at the sample distribution we see that the division of categories for the variables gender, age, educational level, and occupational status are very similar to those of the Dutch population (CBS, 2022; Centraal Bureau voor de Statistiek, 2019, 2022, 2023, 2024e). This can be explained by the nature of the Chi-square test where it becomes more likely to find statistically significant differences between observed and expected values as sample sizes increase.

Second, the fact that the sample occupational status is representative of the population might be more valuable for this research than in other instances. One of the reasons for this is that company cars are inherently connected to commuting and therefore employment. More important is that commuting makes up a great deal of travel activity as it is one of the most prominent purposes of travel. (Centraal Bureau voor de Statistiek, 2024d). Because commuting is such a big driver for transport we would expect that a representative sample based on occupational is needed to gain insights into underlying travel patterns without creating a bias. To exemplify the value of this finding; we know that car use is the most popular mode for commuters. If the share of employed people had been strongly overrepresented in the sample, the outcomes of a cluster analysis would reflect this and vice versa. So even though at first glance the sample representativeness seems to fall short, the distribution of occupational status is likely to give a good reflection of travel behavior in the population.

Because the sample size in this research is quite large and the distribution within the sample does not show great differences for most categories, we conclude that the sample is comparable to the Dutch population. In addition to this, we anticipated that the effect of the sample, which is representative based on occupational status, on the outcomes of clustering of travel behavior in such a way that it creates no to little bias. Of course, the statistical significance of the representativeness tests will be taken into account in a nuanced way before generalizing results to the population especially when other covariates are discussed.

Variable	**Level**	**N= 8183**
Trips by car	Mean (SD)	4.4 (4.5)
Trips by public transport	Mean (SD)	1.5 (4.3)
Trips by bicycle	Mean (SD)	2.5 (3.6)
Trips by walking	Mean (SD)	1.5 (2.6)
Distance travelled by car	Mean (SD)	75.4 (116.9)
Distance travelled by public transport	Mean (SD)	64.1 (281.2)
Distance travelled by bicycle	Mean (SD)	8.4 (17.5)
Distance travelled by walking	Mean (SD)	1.9 (8.1)
Gender	Male	46.3%
	Female	53.7%
Age	12-17	8.7%
	18-24	8.9%
	25-29	6.7%
	30-39	16.3%
	40-49	15.9%
	50-59	18.4%
	60-69	14.1%
	70-79	9.1%
	80+	1.8%
Educational level	Low	32.5%
	Mid	36%
	High	30%
	Unknown	1.4%
Occupational status	No job	36.9%
	Employed	60.2%
	Unknown	2.9%
Income	Minimum	3.9%
	Below average	14.7%
	Average	20%
	1-2 times average	29.3%
	2 times average	7.4%
	> 2 times average	10%
	Unknown	14.8%
Household composition	Single	19.2%
	Couple	29.1%
	Couple with kids and/or others	43.4%
	Single parent with kids (and others)	6.6%
	Other	1.6%
No. of cars in household	Mean (SD)	1.3 (0.8)
Company car	No company car in household	89.4%
	CC in household not main user	7%
	CC in household and main user	3.6%

Note: some values may not add up to 100% due to rounding.

Table 4.6: Descriptive statistics of the sample composition

4.3.1. Sample composition of company car users

This research examines the travel behavior of company car users over time, making it important to understand the characteristics of the average company car user. Consequently, this section provides a more in-depth analysis of the composition of this specific sub-sample. Analyzing a subsample within a larger sample offers valuable insights, even though this does not always allows for a direct comparison to the overall population. By focusing on a specific group, such as individuals with access to a company car, it becomes possible to identify sociodemographic characteristics that distinguish this group from others within the sample. This approach can reveal patterns or differences that may remain obscured in a broader analysis. While the findings may not be fully generalizable to the entire population, they provide important internal comparisons and insights into the composition and behaviors of specific subgroups. Within the sample, we can identify two types of company car users: those who are the primary users and those who, while not the main users, have access to a company car through another member of their household. Both of these groups have been analyzed.

Main users

Looking at the sample distribution of main users of company cars we see some notable differences with the total sample. Non-surprisingly, we find that the trips by car drastically increases to a mean use of 6.0 trips over three days. We also see that the mean trips taken, using other modes has dropped. The latter finding indicates that in the sample, main users of company cars are likely to have a very exclusive car-oriented mobility pattern. This is confirmed by the distances travelled per mode, here we see a great increase in kilometers travelled by car, this figure has doubled. We also see a strong decrease in the distances travelled for other modes.

An examination of the socio-demographic variables reveals that the primary users of company cars are predominantly male (72.6%), a figure notably higher than the overall sample, where men represent just 46.3%. This percentage in the full sample is slightly below the national population distribution, suggesting that the percentage of males in the sample of main users may reflect a slight underestimation. Nonetheless, these findings suggest that men are either more inclined to become company car users or are more frequently in positions where such fringe benefits are offered.

In terms of age, most primary company car users fall within the 30 to 60 age range, aligning with expectations that this is the prime working age group. Since company cars are inherently tied to occupational status, it is unsurprising that the majority of main users are employed.

Income levels among company car users do not differ substantially from the overall sample. There is however one notable observation that can be made and that is that the shares of main users earning average or less is lower than sample average. Among main users of company cars the income levels are higher. The most striking observation is that the share of individuals earning more than 2 times the average income is twice that of the overall sample. This suggests that company car benefits are more frequently offered to individuals after reaching 1-2 times the average income threshold.

Finally, in terms of household composition, there are significant differences compared to the overall sample. The proportion of main users living in households as couples with children or others is considerably higher. This may indicate that the perceived utility of a company car increases for individuals in such household compositions, potentially driven by family responsibilities associated with these living arrangements.

We also see that the mean number of cars in a household is bigger than in the overall sample. This finding is according to expectation as company cars have been found to be related to an increased car ownership (Metzler et al., 2019).

Variable	Level	N= 310
Trips by car	Mean (SD)	6.0 (4.6)
Trips by public transport	Mean (SD)	0.5 (2.5)
Trips by bicycle	Mean (SD)	0.9 (2.1)
Trips by walking	Mean (SD)	0.8 (1.7)
Distance travelled by car	Mean (SD)	151.9 (175.0)
Distance travelled by public transport	Mean (SD)	21.4 (175.0)
Distance travelled by bicycle	Mean (SD)	2.7 (7.8)
Distance travelled by walking	Mean (SD)	1.5 (4.4)
Gender	Male	72.6%
	Female	27.4%
Age	12-17	0.3%
	18-24	6.5%
	25-29	8.4%
	30-39	26.8%
	40-49	31.0%
	50-59	22.9%
	60-69	3.9%
	70-79	0%
	80+	0.3%
Educational level	Low	12.9%
	Mid	34.5%
	High	46.8%
	Unknown	5.8%
Occupational status	No job	3.9%
	Employed	89.7%
	Unknown	6.5%
Income	Minimum	1.3%
	Below average	2.9%
	Average	15.5%
	1-2 times average	31.0%
	2 times average	13.2%
	> 2 times average	19.0%
	Unknown	17.1%
Household composition	Single	11.3%
	Couple	21.6%
	Couple with kids and/or others	64.8%
	Single parent with kids (and others)	1.6%
	Other	0.6%
No. of cars in household	Mean (SD)	2.0 (0.7)

Note: some values may not add up to 100% due to rounding.

Table 4.7: Descriptive statistics of the non-main users of company cars

Non main users
From the sub sample distribution that focuses on the individuals that are not main users of company cars we can tell that the mode use does not differ that much from the sample distribution. We see that use frequencies are more or less the same. The first notable distance is that the distances travelled by these individuals slightly differs, they shows longer travel by car and public transport.

The gender distribution also shows a slight difference as the proportion of women in this subsample is a little bigger than in the overall statistic. In the main user subsample, we saw that predominantly men are main users of these vehicles. Therefore, a possible explanation for the observation could be that women are often the partners or living together with men that are main users of company cars. However, there is just a slight deviation from the overall sample, thus this explanation should be taken into account with caution.

For the variables related to educational level and occupational status, we see small to no difference with the overall sample distribution. The bigger and potentially more meaningful differences of this subsample can be found under income levels and household composition. Alike the main user subsample, the non main users are more often associated with income levels starting at the 1-2 times average level compared to the overall sample.

In addition to this, by far most non main user household compositions are couples with kids and/others (75.3%). This figure is even higher than for main users. This can be explained by the nature of this variable level: if someone is not the main user of a company car but does have one in the household, evidently there is some other adult in the household that does have one.

As one would expect, the mean number of cars in households of non main users is also higher than the overall sample. The mean of 1.9 cars indicates that in these households, there probably is one additional (privately owned) car.

Variable	Level	N= 559
Trips by car	Mean (SD)	4.5 (4.9)
Trips by public transport	Mean (SD)	2.0 (5.0)
Trips by bicycle	Mean (SD)	2.1 (3.2)
Trips by walking	Mean (SD)	0.9 (3.2)
Distance travelled by car	Mean (SD)	91.5 (148.8)
Distance travelled by public transport	Mean (SD)	74.6 (241.3)
Distance travelled by bicycle	Mean (SD)	8.4 (16.0)
Distance travelled by walking	Mean (SD)	1.4 (7.4)
Gender	Male	40.1%
	Female	59.9%
Age	12-17	17.5%
	18-24	16.6%
	25-29	7.3%
	30-39	19.0%
	40-49	17.4%
	50-59	15.6%
	60-69	4.5%
	70-79	2.1%
	80+	0%
Educational level	Low	32.2%
	Mid	33.6%
	High	29.5%
	Unknown	4.7%
Occupational status	No job	33.3%
	Employed	59.6%
	Unknown	7.2%
Income	Minimum	1.1%
	Below average	3.8%
	Average	14.3%
	1-2 times average	32.6%
	2 times average	13.8%
	> 2 times average	15.9%
	Unknown	18.6%
Household composition	Single	4.8%
	Couple	8.4%
	Couple with kids and/or others	75.3%
	Single parent with kids (and others)	1.1%
	Other	0.4%
No. of cars in household	Mean (SD)	1.9 (0.7)

Note: some values may not add up to 100% due to rounding.

Table 4.8: Descriptive statistics of the non-main users of company cars

4.4. Correlation analysis for life events

The exploration of potential correlations between company car accessibility and certain life events, such as securing a new job or relocating residences, poses interesting opportunities for mobility research. The logic behind this focus lies in the possibility that such life events may substantially influence the acquisition and/or usage of company cars. If these events demonstrate a strong correlation with company car ownership, they might serve as third variables that explain away the direct impact of company car ownership on travel behavior.

Understanding this relationship is important because it could elucidate to what extent external factors, like job changes or residential relocation, dictate transportation choices. Following the theory of the mobility biographies framework, correlated life events could be the driving factors creating the 'window of opportunity' for behavioral change instead of company car ownership (Müggenburg et al., 2015). Insight into these correlations contributes to a correct conceptualization of the models that allow for controlling for these potential effects.

Various life events are being monitored in the Dutch mobility panel. There are various categories in which these events could be placed, the most important ones recognized would be the events that are either job or housing and household-related events as these might be relevant for this research. Therefore, the correlation between the categorized list, as shown below, and company car accessibility and ownership has been assessed.

Job-Related Events

- **Event 1**: I have obtained a new/another job
- **Event 2**: I have started working
- **Event 3**: I have stopped working (e.g., due to dismissal, retirement, or disability)
- **Event 4**: I have reduced my working hours
- **Event 5**: I have started my own business

Household-Related Events

- **Event 6**: A child has been born into my household
- **Event 7**: I have divorced or broken up my relationship
- **Event 8**: I have moved or moved into student housing

The relationship between these variables has been assessed by correlation analysis in SPSS. Information on life events is not available for all respondents. To overcome potential bias, the sample size has been reduced to 7501 by deleting all of these cases before performing the correlation analysis. The correlation analysis has been performed with the information that corresponds to the second wave of the pair that will be used in the Latent Transition Analysis. This is done because it allows for an investigation of the cases where a change in company car ownership has taken place in addition to the ownership variable.

Correlation of company car ownership and life events

The company car ownership and event variables are both nominal variables, therefore a Pearson Chi-square test and the Phi & Cramer's V are used to test for significance and strength of association between the variables. It is important to note that when dealing with bigger sample sizes, the Chi-square statistic becomes less reliable to measure associations between variables as it is more likely to detect associations in small differences. The Phi and Cramer's V coefficients take sample size into account and account for this drawback. In addition, the Chi-square statistic does not provide insight into the strength of the association, therefore the Phi and Cramer's V are used to monitor the strength of association (Prematunga, 2012).

From the Chi-square statistics of the correlation tests between company car availability and life events, it becomes apparent that there are significant associations for events 1, 2, 5, and 8 (at significance level $p < 0.05$). More detailed output can be found in AppendixB.

Despite significant associations, Cramer's V shows that the strength of these associations is extremely low as none of the correlation coefficients exceeds 0.05. We suppose that in this case the significance of association may be caused by the sample size as explained before. Based on the results of the correlation analysis, we conclude that just some of the eight life events considered exhibit statistically significant association but those have a really weak correlation with the company car ownership variable and therefore do not need to be factored into the interpretation of this research's findings.

Correlation of change in company car ownership and life events

In addition to the correlation analysis of the company car ownership variable with life events, the correlation between a change in company car ownership is also monitored. This is done because a change in ownership of a company car can be seen as a soft-life event. It is also plausible to assume that gaining access to a company car goes hand in hand with certain other changes in life; for example a job change to a company that offers these fringe benefits.

The outcomes of the analysis show that only events 1, 5, and 8 show a statistically significant association with change in company car ownership. The Phi-coefficient shows that there is a very weak association between the events and the change in CC ownership variable. The life events in question are changes in jobs, starting an own business, and residential relocation. At first glance, these events sound plausible to be related to a change in company car ownership, but the effects are not that strong. In the sample, the biggest association between a change in company car ownership and a life event is in the scenario that one obtains a new job. However, this association is quite weak with a coefficient of just 0.069. This finding is quite interesting as the literature suggests that company cars are often used to attract motivated staff (Gutiérrez-i-Puigarnau & Van Ommeren, 2011). This suggests that the considered statistically significant life events do not have a strong association with change in company car ownership. This is beneficial for this research as it shows that the outcomes of this research are not found as a result of a spurious effect, where another change in the life of respondents explains away the behavior change.

The correlation analysis also shows that for the sample there apparently are no particular moments in one's career or household events that they strongly gravitate towards a company car. This seems a bit contradictory as the literature suggests that companies use fringe benefits to attract staff. The finding is also counterintuitive as you would expect that change in company car ownership is inherently connected to a job-related event. It is also possible that certain job-related life events, such as receiving a promotion that qualifies respondents for a company car, were not captured in this questionnaire. Nonetheless, we must conclude that only some of the events show a statistically significant association, but the effects are weak and none of these stands out as more compelling than the others.

4.5. Operationalisation of variables

This section will discuss the operationalization of the variables used in the LCA and LTA model. It will also substantiate the choice for certain modeling choices.

4.5.1. Indicators

The Dutch Mobility Panel asks its respondents to keep a travel diary of all of their movements. This way mobility data is collected through location-based diaries. It is important to note that we cannot be sure of the completeness of this diary, as participants might forget to or do not report their trips on purpose.

Within the travel diary we can distinguish the concepts of trips and trip segments:

- **Trips**: A trip is defined as a movement from one location to another with a specific purpose, such as commuting to work, going to school, or shopping.
- **Trip Segments**: A trip may consist of multiple segments if different modes of transport are used. For example, a trip to work might involve driving to a train station, taking the train, and then walking to the office.

Both trips and trip segments can be used as indicators for the LCA and LTA models. It is worth mentioning that there are some benefits and limitations to both concepts.

As stated above, trips are defined as a movement from one location to another. In the MPN datasets, participants are asked to report the *main* mode of transport. This means that only one mode is attributed to a trip. Suppose a person reports to have used public transport as the main mode of a trip, it is very likely that this person also used another mode to get to the bus, tram, or train station. Using the trip format, these movements are left out of scope. Even though we know this might be the case it still leads to a certain bias where multimodal travelers underreport their behavior.

On the other hand, there are trip segments that represent shares of a trip. Respondents are also asked to fill in the main mode of transport of these trip segments. As respondents are allowed to fill in as many trip segments as they want, this way of observing overcomes the potential 'underreporting bias' that trips suffer from.

From the above the trip segments seem to be most fit to use for this research. However, there is a limitation to the Dutch Mobility Panel. The MPN datasets do not contain the distance traveled for trip segments, it only includes distances for trips made.

This means that there is a trade-off to be made by choosing either trips or trip segments as indicators. Even though, using trips as indicators would lead to an "underreporting bias", we consider there to be additional explanatory value in the distances traveled by respondents. If we were to leave this out of scope we abandon the possibility to provide more context to the behavioral profiles that are being constructed by the LCA. This means that critical insights into the overall travel behavior and the relationship between distance and mode choice are lost. Therefore, despite the potential for underreporting, the choice of trips over trip segments as indicators provides a more comprehensive understanding of travel patterns, making it a valuable component of our analysis.

4.5.2. Exogenous variables

There are various exogenous variables, or covariates, to be included in the LCA and LTA as predictors for class membership and transitional probabilities. This section will explain how these covariates have been specified.

Distances travelled by mode

As mentioned in section 4.5.1, the distances traveled per mode are assumed to provide additional explanatory power to the analysis. As we are interested in mode choice in general and not mode choice per distance category we propose to include the distances traveled by mode as inactive covariates. The reason is that this way, these variables are not part of the model but do provide additional insight into the classes.

Gender
The MPN dataset offers two options to respondents to report their gender.

- Male
- Female

Age
The age of respondents participating in the MPN is categorized into the following levels:

- 12-17
- 18-24
- 25-29
- 30-39
- 40-49
- 50-59
- 60-69
- 70-79
- 80+

Educational level
In the MPN dataset, educational level is measured differently throughout the years. As part of making the dataset operational, the measured levels of education are recoded into the following three levels as defined by Centraal Bureau voor de Statistiek (2019).

- Low
- Mid
- High
- (Unknown)

Occupational status
Occupational status is measured on three different levels.

- No job
- Employed
- Unknown

No. of cars in household
The number of cars in a household is measured by a mean value.

Income level
Income level has 7 categories. The amounts in euros involved with these labels changed throughout the years. Even though the absolute amount of money has evolved throughout the years, the value labels have remained the same. As the amount of money related to the labels is constructed based on economic parameters, we assume that the value labels represent a weighted distribution of income in their respective years. The latter enables us to consider the levels to be regarded as standardized values. Therefore the categories are as follows:

- Minimum
- Below average
- Average
- 1-2x average
- 2x average
- More than 2x average
- Unknown or not willing to report

Household composition
In the Dutch Mobility Panel, participants can report their household composition in various ways: single, couple, couple with children, couple with children and others, couple with others, single parent and children, single parent and others, and other composition. For the sake of reducing model complexity and improving interpretability, these categories have been recoded into the following five categories:

- Single
- Couple
- Couple with children and/or others
- Single parent with children or children with others
- Other

Year of participation
The final set of respondents is a pooled sample with travel diary data originating from different years. There might be differences in travel patterns throughout the years, this variable allows us to see how big the variations in these years are.

Company car availability
The Dutch Mobility Panel does not only ask participants to report information about their travel activities but also their vehicle characteristics. This allows us to see whether vehicles in households are company cars. Both cars purchased and leased by the company are considered to be company cars. The MPN also asks participants to disclose which persons in households are the main users of vehicles. We assume that all persons in a household have access to the same vehicles in a household. This means that company car presence in households can also be considered as a person-level variable. This enables us to create a categorical variable that measures company car availability with the following three levels:

- No company car in household
- Company car in household, not main user
- Company car in household and main user

4.6. Measurement model

As shown in Figure'3.2, the Latent Class Analyses of two consecutive time steps are assumed to be the measurement models for the LTA. Therefore we must determine what this model looks like. This includes determining and defining the optimal amount of clusters in the sample. This section will elaborate on the statistical criteria used for determining the best-fitting LCA model (without covariates). Next, the covariates are added to obtain a final model. The estimates of this model will be presented and its classes will be described based on their distinguishable characteristics.

4.6.1. Determining the optimal amount of classes

As mentioned before, one of the main benefits of the Latent Class Analysis is that the method offers various statistical criteria to assess model fit. According to Magidson and Vermunt (2004) there are various ways to assess model fit using statistical criteria.

- **Likelihood ratio chi-square statistic (L^2):**

  This is the most used approach that assesses in what way the maximum likelihood estimates for expected cell frequencies differ from the observed frequencies. Using this method, a model fit is obtained if the value of L^2 is low enough to be caused by chance. This can be assessed by using a confidence interval of 5%. As the frequencies of mode use, are handled as indicators there is no finite amount of response patterns. Consequently, this leads to a lot of possible combinations of response patterns, which in turn leads to a lot of observed frequencies being zero. This creates a certain sparsity in the data which hinders us in using this measure as a statistical test to assess model fit (Magidson & Vermunt, 2004).

- **Bayesion Information Criterion:**

  Magidson and Vermunt (2004) propose alternative approaches when dealing with sparsity. These approaches can account for model fit and parsimony at the same time. This means that it monitors the trade-off between an increase in log likelihood and the increasing number of parameters being estimated by the model. The most used statistic is the Bayesian Information Criterion (BIC), which uses the following formula.

  $$\mathrm{BIC}_{LL} = -2LL + \ln(N)M \tag{4.1}$$

  Where N is the number of respondents and M is the number of parameters.

  As the formula shows, the value of the BIC is penalized by the amount of parameters. Hence, lower outcomes are preferred when using this statistic.

  When dealing with more complex models the BIC statistic tends to keep declining even though classes are being added. This means that the statistic might not be able to determine whether the best model fit has been achieved, as it indicates that a great number of classes should be used.

- **Baseline L^2 comparisons:** A third method to assess model fit is to use the L^2 of a non-fitting H_0 (1-Class) model as the baseline of association amongst the data. This allows us to compare L^2 of other models to this baseline to see how much those have reduced. The reduction percentages present the total association explained by the model (Magidson & Vermunt, 2004). This measure is typically used as a complementary mode to the previously named more statistically precise methods.

Even though the presence of statistical tests is one of the main benefits of the LCA, the criteria proposed by Magidson and Vermunt (2004) have some limitations considering the characteristics of this research.

In addition to the previously named statistical tests, the Bivariate Residuals (BVRs) of the indicators can also be used to determine a model fit. The BVRs indicate how much association there is left between the indicators after accounting for the LC-variables (Vermunt & Magidson, 2013). The bivariate residuals are Chi-square distributed at one degree of freedom, this corresponds to a threshold value of 3.84 at a 5 significance level. Hence, lower values of BVRs are preferred, as this indicates the is no residual between the indicators.

Another measure to take into account is the cluster size. Even though statistical tests might indicate that additional classes should be added, including more classes with really small sizes only provides insight into a very small group within the sample. Therefore, we aim to construct a model where all classes are bigger than 5%.

Other factors to take into account whilst determining model fit have to do with the interpretability of results and beneficiality to research goals. It is important to take into account that the next step of this research methodology is to construct a transition probability matrix by performing an LTA. The size of this matrix is determined by the number of classes between which respondents can switch. This means that the expansion of the LCA model will lead to an exponential growth in the output of the structural model when classes are added. Ultimately, this may make the results of the LTA more difficult to interpret. Therefore, there is a slight preference to create a fitting LCA model with the least amount of classes which still encapsulates the behavior of interest.

Finally, the interpretability of results is a key component to determining the model fit. The fact that the method allows researchers to label subgroups in the sample based on their behavioral patterns is also one of the main benefits of the research. Accordingly, adding additional classes as a contribution to the interpretation of the result is also used as a measure to determine the amount of clusters in the measurement model.

4.6.2. Initial estimations

Table 4.9 shows the output of various latent class models that have been estimated without covariates.

Model	Log-likelihood	L^2	P-value	BIC (LL)	Size of smallest class	Total BVR	L^2 Baseline comparison
1-Class	-102075.23	103634.92	0.00	204186.49	100.00%	4724.54	0.00%
2-Class	-81878.87	63242.21	0.00	163838.83	15.94%	2479.11	19.79%
3-Class	-72238.62	43961.70	0.00	144603.37	15.89%	590.18	29.23%
4-Class	-68323.08	36130.62	0.00	136817.34	15.82%	256.74	33.07%
5-Class	-65465.43	30415.33	0.00	131147.09	12.85%	163.04	35.87%
6-Class	-63746.96	26978.39	0.00	127755.20	11.75%	186.08	37.55%
7-Class	-62519.18	24522.83	0.00	125344.70	6.38%	206.94	38.75%
8-Class	-61530.94	22546.34	0.00	123413.26	5.02%	176.17	39.72%
9-Class	-60558.82	20602.11	0.00	121514.08	5.00%	128.83	40.67%
10-Class	-59772.67	19029.81	0.00	119986.83	4.96%	74.92	41.44%
11-Class	-59326.74	18137.95	0.00	119125.18	1.89%	50.02	41.88%
12-Class	-58875.27	17235.00	0.00	118278.81	3.59%	77.09	42.32%

Table 4.9: Model fit statistics of the latent class models

The table above shows that the p-values of the models are all below the threshold of 0.05. This means that using the maximum likelihood chi-square test as a measure to denote a model fit would lead to a bad model fit. The reason for this is that a value of $p < 0.05$ means that we cannot reject the null hypothesis (H_0) and must accept the alternative hypothesis (H_1). This hypothesis states that the observed values matrix differs significantly from the expected values matrix in the population.

The model output for the BIC and AIC have been estimated by the models as well. As expected the values of both statistics keep declining when adding classes, this might be caused by the complexity of the model. Therefore these statistics are not decisive for the assessment of model fit.

4.6.3. Model choice considerations

As shown in Table 4.9, the model fit statistics do not indicate a single superior model. This section explains the considerations taken to determine the final amount of classes.

For models with 8 or more classes, the sizes of the smallest classes become quite small. Although the 8- and 9-class models meet the threshold set in section **??**, we excluded models with 8 or more classes.

Measurement models with this many classes result in a substantially large transition probability matrix in LTA, complicating the interpretation of results. Thus, only 1- through 7-class models were considered.

Table 4.9 shows that BIC values consistently decline with the addition of more classes. Similarly, the L^2-baseline statistic decreases, but the incremental explanatory value gained by adding classes diminishes. This suggests that models with more classes provide a better fit.

The total BVR for models with 4 or fewer classes is relatively high, leading us to disregard these models. The total BVR assessment also reveals that the 5-class model has the lowest summed residual associations among the remaining models.

Given the conflicting results from statistical measures, we examined the 5-, 6-, and 7-class models in more detail to identify potential interpretation benefits of models. The smallest cluster sizes of these models satisfy the 5% threshold. A comprehensive description of these models is provided in Appendix C

Careful consideration has led to the selection of a 7-class model, which holds several advantages over other models. The 7-class model has a lower BIC value and a higher L^2-baseline comparison, indicating greater explanatory power despite increased complexity.

A detailed investigation reveals that the residuals in the 7-class model are primarily centered around public transport and bike indicators. This may be due to the use of trip data, where only the main mode of transport is reported, potentially leading to an under-reporting bias for bicycles among multimodal travelers who primarily use public transport. This theoretical notion could explain the residuals between these indicators.

Although the 7-class model has the highest total BVR among the three models, it is more focused on a single indicator pair, while other models show relatively high residuals across multiple pairs. Additionally, the 7-class model introduces an extra class partially oriented towards car use. This could be beneficial for later stages of this research, as it aligns with the hypothesis that individuals familiar with car use are more likely to adopt car-oriented travel styles and stick with them. This assumption is supported by findings from Kalter et al. (2020), who noted that car users tend to remain consistent with this mode and that providing company car benefits increases its utility. Therefore, the additional class in the 7-class model could offer valuable insights, particularly concerning the impact of company cars on exclusive car use.

The model below has been chosen as the final (measurement) model with the following classes:

- Cluster 1: Strict car users (SC)
- Cluster 2: Bike users (B)
- Cluster 3: Mixed car and bike users (CB)
- Cluster 4: Low mobility (LM)
- Cluster 5: Mixed car and foot travelers (CF)
- Cluster 6: Public transport users (PT)
- Cluster 7: Mixed car and PT users (CPT))

		1	2	3	4	5	6	7	Overall
Profile label		SC	B	CB	LM	CF	PT	CPT	
Cluster Size (%) N=8183		26.0	17.6	16.8	12.0	11.8	9.5	6.4	
Indicators									
Trips by car	Mean	8.3	0.8	6.6	0.8	4.1	0.6	5.4	4.4
Trips by PT	Mean	0.0	0.0	0.0	0.0	0.0	11.3	7.3	1.5
Trips by bike	Mean	0.0	7.0	4.2	0.0	1.5	2.9	1.5	2.5
Trips on foot	Mean	0.6	0.9	0.6	0.3	6.3	1.8	1.3	1.5

Note: some values may not add up to 100% due to rounding.

Table 4.10: Output of the 7-class LCA model without covariates

4.7. Structural LC-model

The structural LCA model contains the (in)active covariates as named in section 4.5.2. This leads to the following latent class models that will be used in the LTA.

		1	2	3	4	5	6	7	Overall
Profile label		SC	B	CB	LM	CF	PT	CPT	
Cluster size (%) N=8113		26.0	17.8	16.6	12.2	11.6	9.9	6.0	
Indicators									
Trips by car	Mean	8.3	0.8	6.7	0.9	4.0	0.7	5.4	4.4
Trips by PT	Mean	0.0	0.0	0.0	0.0	0.0	11.0	7.3	1.5
Trips by bike	Mean	0.0	7.0	4.2	0.0	1.6	3.1	1.0	2.5
Trips on foot	Mean	0.6	0.9	0.6	0.3	6.4	1.8	1.3	1.5
Inactive covariates									
Distance by car (km)	Mean	144.0	16.4	106.9	21.1	66.2	15.8	92.2	75.4
Distance by PT (km)	Mean	0.1	0.0	0.2	0.0	0.3	457.0	305.0	63.5
Distance by bike (km)	Mean	0.0	25.0	12.3	0.3	5.0	10.5	4.1	8.4
Distance on foot (km)	Mean	0.8	1.3	1.0	0.4	7.3	3.2	2.0	1.9
Active covariates									
Gender (%)	Male	52	43	45	48	41	46	41	46
	Female	48	57	55	52	59	54	59	54
Age (%)	12-17	1	28	7	4	2	13	8	9
	18-24	5	8	4	9	3	29	18	9
	25-29	8	5	6	6	5	11	9	7
	30-39	21	11	16	16	18	14	16	16
	40-49	20	13	18	16	15	8	12	16
	50-59	22	14	21	20	18	11	15	18
	60-69	13	13	16	15	22	8	12	14
	70-79	8	7	11	10	15	6	8	9
	80+	2	1	1	3	3	1	1	2
Educational level (%)	Low	23	46	30	42	33	32	24	33
	Mid	43	28	36	37	37	30	35	36
	High	33	25	34	17	29	36	40	30
	Unknown	1	1	1	3	1	2	0	1
Occupational status (%)	No job	24	50	32	43	41	43	37	37
	Employed	74	46	67	52	54	53	63	60
	Unknown	2	4	2	5	4	4	0	3
No. of cars in household (#)	Mean	1.58	1.06	1.44	1.17	1.17	0.79	1.39	1.28
Income (%)	Minimum	2	5	1	4	3	11	4	4
	Below average	12	15	12	22	17	15	12	15
	Average	21	20	20	18	24	20	15	20
	1-2 times average	32	30	30	25	29	27	30	29
	2 times average	9	7	10	5	5	6	9	7
	> 2 times average	11	10	12	6	7	10	17	10
	Unknown	14	14	15	20	15	11	13	15
Household composition (%)	Single	18	17	14	17	22	34	23	19
	Couple	32	23	34	32	37	18	24	29
	Couple w/ kids and/or others	44	50	46	41	35	39	47	44
	Single parent with kids (and others)	6	9	6	8	5	8	6	7
	Other	1	1	0	2	1	1	0	1
Year of participation (%)	2013	16	12	15	12	13	15	15	14
	2014	16	17	17	12	14	17	20	16
	2015	10	10	9	8	8	10	10	9
	2016	11	9	10	8	10	11	12	10
	2017	22	20	23	20	25	21	16	21
	2018	25	32	27	40	29	27	27	29
Company car (%)	No company car in household	86	91	88	91	93	91	87	89
	CC in household not main user	7	8	7	5	4	9	10	7
	CC in household and main user	6	1	4	4	3	0	4	4

Note: some values may not add up to 100% due to rounding.

Table 4.11: Profile output of the 7-class LCA model with covariates

In the results, we see that the division of clusters has remained more or less the same. This is in line with the expectation as the conceptual modes assume that covariates precede the causal chain of events and thus do not influence the latent categorical variable.

The changes that can be seen are slight differences in cluster sizes (0.2% - 0.4%) and means of mode use (0.2- 0.5). This is caused by the fact that active covariates are part of the classification in the model. The distance covariates merely provide insights into the mean kilometers traveled in each class. Inactive covariates are not part of the model which means they do not offer predictive value, they do however contribute to the interpretability of the differences between clusters by giving additional insight into behavior.

A more in-depth output of the 7-class model can be found in Appendix D.2.

The p-values related to the Wald statistic of the indicators, clusters, and covariates are all below the threshold of 0.05. For the indicators, this means that they are significantly affected by the latent variable in the population (Kroesen, 2019). For clusters, this means that classes significantly differ between clusters, and for covariates, this means that they significantly predict cluster membership. For more details see Table D.3.

The bivariate residuals of the model have slightly changed. Some residuals of the indicators have decreased to the <3.84 thresholds whilst others have become larger. The most notable change is between the PT and bike indicators, the size of the remaining association between these indicators is attributed to the operationalization of variables as whole trips as discussed in section 4.5.1. For more details see Table D.4.

4.7.1. Profiles of the travel patterns

From table 4.11 we can infer additional insights that contribute to a better understanding of the previously identified clusters. Below, figure 4.2 shows a visual representation of the clusters that have been found using the Latent Class Analysis. In addition to examining the travel behavior characteristics of these clusters, this section will also discuss the interpretation of their associated socio-demographic variables.

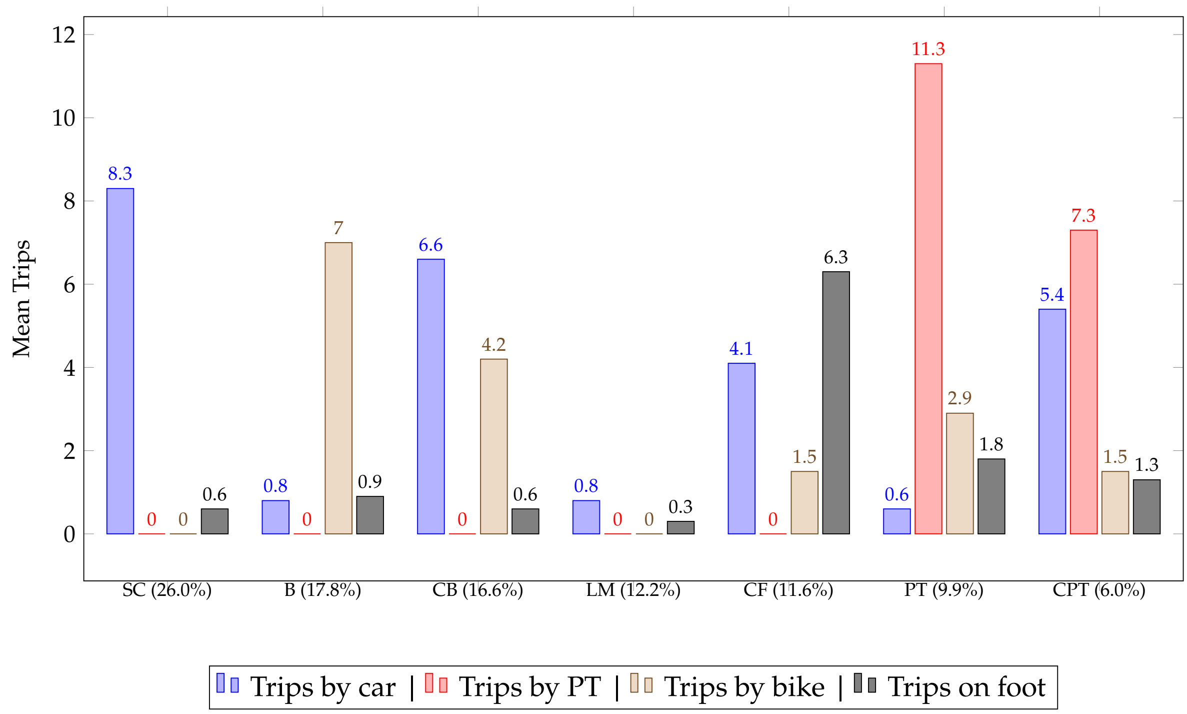

Figure 4.2: Mean trips per mode for each mobility cluster

Strict car users

The first class consists of stricter car users and accounts for 26% of the sample. These travelers report no to almost no travel activity with the use of other modes. The inactive covariates also indicate that people who belong to this group are the most intensive car travelers in terms of distances traveled. This is evident as these people also report more frequent usage.

This profile is the only one that consists of more males (52%) than females (48%). Also compared to the sample distribution (46% male), this cluster contains predominantly more men. Another interesting observation is that the respondents within this group are mostly middle-aged and tend to have at least a middle education or higher. The latter also explains the fact that this group has significantly higher levels of employment and tends to have average to high income. It is also noteworthy that this group has above-average levels of company car availability which goes hand in hand with a higher amount of cars in the household.

Combining the travel patterns with the exogenous variables considers these middle-aged males highly car-dependent. The intensity of car use over a shorter period emphasizes the dependence on personal vehicles possibly for work activities. Especially the higher presence of company car availability and higher main user membership suggest that this travel pattern might be related to commuting practices. The higher economic stability and exclusive mode frequency hint that car convenience has also become a necessity.

Bike users

The second class consists of active cyclists and accounts for 17.8% of the sample. These travelers report a high frequency of trips by bike (7.0 trips on average) and almost none by car (0.8 trips on average) or public transportation (0.0 trips on average). They also report a considerable distance traveled by bike (25.0 km on average) within the three days, while car and public transportation distances remain minimal (16.4 km and 0.0 km respectively). The fact that the mean distance traveled by car is this number, shows that these respondents are occasional car users for shorter trips.

This profile has a higher proportion of females (57%) compared to males (43%). This is interesting as it contrasts with the overall sample distribution where males constitute 46% and 54% females. Respondents within this group tend to span across various age groups with a notable presence in the younger demographic (28% aged 12-17 and 8% aged 18-24). Especially the age category 12-17 is extremely high compared to the population. This cluster also has a substantial proportion of individuals with low educational levels (46%) and a notable percentage of individuals without a job (50%). This might be explained by the fact that a substantial portion of this cluster is quite young and is still in education which would explain the absence of the employed compared to the sample. Respondents in this clusters also have company cars in their households, however almost a really small proportion of these people are the main users of these vehicles. The dearth of main users is not only in the absolute sense but also relatively compared to the sample.

Combining the travel patterns with the exogenous variables, we could consider these individuals as predominantly young and female, highly reliant on cycling for their daily mobility needs. The high frequency and long distances traveled by bike within a short period suggest that these individuals likely reside in areas with good cycling infrastructure or in urban regions where biking is a convenient mode of transportation. The fact that unemployment of individuals within this class is relatively high, is in line with the finding that there are few main users of company cars. This does however not necessarily have to impact the availability as other members within the household might cause these effects. The significant presence of younger (female) individuals and those without a job indicates that these travelers might be students or young adults who either choose or need to rely on biking. The combination of high bike usage and minimal reliance on other modes of transportation reflects both the convenience and necessity of biking in their daily lives.

Mixed car and bike users

The third class consists of mixed car and bike users and accounts for 16.6% of the sample. These travelers report a high frequency of trips by car (6.7 trips on average) and a moderate or somewhat considerable number of trips by bike (4.2 trips on average), while public transportation usage and walking remain minimal (0.0 and 0.6 trips on average respectively). They also cover moderate distances by car (106.9 km on average) and significant distances by bike (12.3 km on average) within the three days.

This profile has a balanced gender distribution with 45% males and 55% females. The age distribution shows a significant presence of middle-aged individuals, with 16% aged 30-39, 18% aged 40-49, and 21% aged 50-59. Educational levels within this group are varied but do not deviate significantly from the overall sample. Notably, the employment rate within this group is slightly higher than the sample average: 32% of the individuals do not have a job, while 67% are employed.

Income levels for this cluster are distributed across different brackets. A noteworthy observation here is that incomes within this class tend to be on the higher side. There are lower proportions of minimum and below-average incomes and higher proportions of incomes that are 1-2 times average (30%), 2 times average (10%), and > 2 times average (12%). This suggests that members of this class are predominantly wealthier.

Household composition indicates that members of this class are mainly couples with or without kids and/or others. Especially the proportion of 'regular' couples (34%) is higher within this class compared to the sample (29%). The preference for car usage is also reflected in the relatively high average number of cars in households (1.44 cars on average).

Combining the travel patterns with the exogenous variables, we could consider these individuals as balanced users of both cars and bikes for their daily mobility needs. The significant frequency and distances traveled by both modes suggest that they likely reside in suburban areas or regions where car travel is necessary for longer commutes and/or errands, while biking is used for shorter, local trips. The couple-oriented household composition and presence of employed, middle-aged individuals indicate that this group might include working professionals who manage their daily activities with a mix of car and bike travel.

Income distribution reveals a tendency towards average to above-average earnings, suggesting that these individuals can afford car ownership and maintenance while also valuing the cost-effective and health benefits of biking. Their educational levels and employment status indicate a relatively stable socio-economic background, supporting their ability to use multiple transportation modes. The household composition with a high percentage of couples suggests that car travel is practical for family mobility, complemented by biking for shorter trips.

In summary, this class's travel behavior is characterized by a balanced use of cars and bikes, supported by their socio-demographic characteristics that include a balanced gender distribution, a significant presence of middle-aged working professionals, and varied educational levels. The combination of car and bike usage reflects a pragmatic approach to transportation, leveraging the strengths of both modes to meet their diverse travel needs. This cluster likely includes working professionals and families who use cars for longer commutes and biking for local, shorter trips, reflecting a versatile and adaptive travel behavior.

Low mobility

The fourth class consists of low mobility users and accounts for 12.2% of the sample. These travelers report very low frequencies of trips by all modes, with an average of 0.9 trips by car, 0.0 trips by public transportation, 0.0 trips by bike, and 0.3 trips on foot over the three days. The distances traveled are also minimal, with 21.1 km by car, 0.0 km by public transportation, 0.3 km by bike, and 0.4 km on foot. This indicates that members of this group only travel occasionally by car.

This profile has a slightly higher proportion of females (52%) compared to males (48%), these are slight deviations from the sample. The age distribution reveals a significant presence of older individuals, particularly those aged 50-59 (20%), 60-69 (15%), and 70-79 (10%), which is higher compared to the overall sample. This suggests that the low mobility might be related to age and possibly health-related constraints.

Educational levels within this group show a higher proportion of individuals with low education (42%), which is a notable deviation from the overall sample. This finding could be explained by the fact that educational levels have risen in the past decades and therefore supports the finding that this class has a higher share of elderly. The employment rate is also significantly lower, with 43% of individuals not having a job and 52% being employed, compared to the overall sample where 60% are employed. This indicates that many in this group might be retirees or those not actively engaged in the workforce due to a lack of education.

Income levels for this cluster are generally lower, with 22% below average income and higher proportions of individuals with minimum income (4%) and below average income (22%). Only 6% earn more than

2 times the average income, which is lower compared to the overall sample. This suggests economic constraints may also influence their low mobility. These income levels are also accordingly to the lower educational levels and higher unemployment rates.

Household composition indicates a mix, but with a notable proportion of single individuals (17%) and couples (32%), while the proportion of couples with kids is slightly lower (41%). This could imply that household responsibilities requiring frequent travel are less prevalent in this group. The number of cars in households is also lower, with an average of 1.17 cars per household.

Combining the travel patterns with the exogenous variables, we could consider these individuals as having limited mobility due to a combination of age, economic constraints, and possibly health issues. The significant presence of older individuals, lower employment rates, and higher proportions of individuals with low educational levels suggest that this group might include retirees, unemployed individuals, or those with limited economic means. Their lower income levels further support the idea that economic constraints significantly impact their mobility, making them more dependent on local and limited travel.

However, it is important to interpret these findings with nuance. The low mobility group is susceptible to bias, as people may deviate from their usual travel patterns and report their behavior on 'atypical' days. Such days might include weekend travel or instances of reporting during sick days. While deviations from 'typical' patterns can occur in any cluster, we believe it is more likely that people in atypical situations simply refrain from traveling, rather than temporarily adopting a completely different mobility style. This leads us to believe there is a higher likelihood of overestimating the number of people in this group. Additionally, this group is also linked to a limitation of the MPN questionnaire, which relies on the self-reporting of travel behavior. There may be cases where respondents, perhaps unintentionally, fail to accurately record their movements during the survey period.

In summary, based on the outcomes of the LCA this class's travel behavior is characterized by very low mobility, supported by their socio-demographic characteristics that include a higher proportion of older individuals, lower educational levels, and lower income levels. The combination of minimal travel and lower economic activity reflects a constrained lifestyle, likely driven by age, health, and economic factors. This cluster likely includes retirees, economically constrained individuals, and those who travel infrequently, reflecting a limited and localized travel behavior. However, there is a possibility that the exogenous variables provide a distorted view of who truly belongs to this group, as it is inherently affected by bias. The size of this group is likely overestimated, so the results should be interpreted with caution and nuance.

Mixed car and foot travelers

The fifth class consists of mixed car and foot travelers and accounts for 11.6% of the sample. These travelers report a moderate frequency of trips by car (4.0 trips on average) and a significant number of trips on foot (6.4 trips on average), while public transportation and biking usage remain minimal (0.0 and 1.6 trips on average, respectively). They cover moderate distances by car (66.2 km on average) and significant distances on foot (7.3 km on average) within the three days.

This profile has a slightly higher proportion of females (59%) and a lower proportion of males (41%) compared to the sample. The age distribution shows a significant presence of older individuals, particularly those aged 60-69 (22%) and 70-79 (15%), which is higher compared to the overall sample. This suggests that walking might be preferred due to the convenience and health benefits it offers to older adults. However, this might also be caused by the fact that the elderly may find public transport hard to use or are not mobile enough to use a bicycle.

Educational levels within this group are varied, with a notable proportion of individuals having low to mid-level education (33% and 37%, respectively) which is not a significant difference from the sample. The employment rate is slightly lower than the sample average, with 41% of individuals not having a job and 54% being employed. This indicates that many in this group might be retirees.

Income levels for this cluster are distributed across different brackets, with a higher proportion of individuals below average income (17%) and a lower proportion earning more than 2 times the average income (7%). This suggests a moderate economic status, where cost-effective modes of transport such as walking may become more favorable. The moderate economic status is also in line with the finding that this group predominantly consists of the elderly.

Household composition indicates a higher proportion of single individuals (22%) and couples (37%) compared to the overall sample, with fewer couples with kids (35%). This composition is in line with the age of respondents and could mean that potential family members have already passed or kids have left the house. A larger share of single or couple without kids households in combination with lower employment could also imply that there might be fewer household responsibilities that require frequent car travel (commuting or family activities), allowing for more walking trips. The number of cars in households is average, with 1.17 cars per household, which aligns with their moderate use of cars.

Combining the travel patterns with the exogenous variables, we could consider these individuals as balanced users of both cars and walking for their daily mobility needs. The significant frequency and distances traveled on foot suggest that they likely reside in areas where walking is practical and safe, possibly in urban or suburban regions with good pedestrian infrastructure. The presence of older individuals and those with lower to mid-level education indicates a preference for walking due to its cost-effectiveness and potential health benefits of active modes.

Income distribution reveals a tendency towards average to below-average earnings, suggesting that these individuals appreciate the cost savings associated with walking or are more inclined to travel according to income. The employment status and household composition further support the idea that this group includes retirees, part-time workers, and individuals with fewer household responsibilities, making walking a viable and preferred mode of transport.

In summary, this class's travel behavior is characterized by a balanced use of cars and walking, supported by their socio-demographic characteristics that include a higher proportion of older individuals, varied educational levels, and moderate-income levels. The combination of car and foot travel reflects a practical approach to transportation, leveraging the benefits of walking for health and cost savings while using cars for longer commutes. This cluster likely includes retirees, part-time workers, and individuals who value the convenience and health benefits of walking, reflecting a flexible and adaptive travel behavior.

Public transport users

The sixth class consists of public transportation users and accounts for 9.9% of the sample. These travelers report a high frequency of trips by public transportation (11.0 trips on average) and minimal usage of other modes, with 0.7 trips by car, 3.1 trips by bike, and 1.8 trips on foot on average over the three days. They also cover substantial distances by public transportation (457.0 km on average), while distances traveled by car (15.8 km), bike (10.5 km), and on foot (3.2 km) remain moderate to relatively low.

This profile has a balanced gender distribution with 46% males and 54% females. The age distribution reveals a significant presence of younger individuals, particularly those aged 18-24 (29%), which is notably higher compared to the overall sample. This suggests that younger adults, likely students or young professionals, are predominant in this group.

Educational levels within this group are varied but show a higher proportion of individuals with mid to high-level education (30% and 36%, respectively). The employment rate is slightly lower than the sample average, with 43% of individuals not having a job and 53% being employed. This indicates that many in this group might be students or individuals in transitional job phases.

Income levels for this cluster are generally lower, with a higher proportion of individuals with minimum income (11%) and below average income (15%). Only a small fraction earn more than 2 times the average income (10%). This suggests that economic constraints may influence their preference for public transportation, which is often more affordable than owning and maintaining a car. This also leads to extremely low values for the main users of company cars.

Household composition indicates a higher proportion of single individuals (34%) and a lower proportion of couples (with kids) (18% & 39% respectively). This composition implies fewer family-related travel responsibilities and a more individually oriented approach, allowing for a greater reliance on public transportation. The number of cars in households is notably lower, with an average of 0.79 cars per household, indicating a reduced dependence on personal vehicles. This is also in line with the findings of lower incomes.

Combining the travel patterns with the exogenous variables, we could consider these individuals as primary users of public transportation for their daily mobility needs. The significant frequency and distances traveled by public transportation suggest that they likely reside in areas with well-developed public transport networks, such as urban regions. The presence of younger individuals and those with mid to high-level education indicates that this group might include students who are likely to be constrained by financial means and/or incentivized by traveling policies in the Netherlands. On the other hand, this cluster also fits a profile for young professionals who find public transportation convenient and cost-effective.

Income distribution reveals a tendency towards lower earnings, suggesting that these individuals appreciate the affordability of public transportation. The employment status and household composition further support the idea that this group includes students, young professionals, and single individuals who prefer public transport due to its economic benefits and convenience.

In summary, this class's travel behavior is characterized by a predominant use of public transportation, supported by their socio-demographic characteristics that include a significant presence of younger individuals, varied educational levels, and lower income levels. The combination of high public transport usage and minimal reliance on personal vehicles reflects a practical and economically driven approach to transportation. This cluster likely includes students, young professionals, and single individuals who rely on public transportation for its affordability and efficiency, reflecting a cost-conscious and transit-oriented travel behavior.

Mixed car and PT users users

The seventh class consists of public transportation and bike users and accounts for 6% of the sample. These travelers report a high frequency of trips by public transportation (7.3 trips on average) and a moderate number of trips by bike (1.0 trips on average), while car usage remains moderate to high (5.4 trips on average) and walking is minimal (1.3 trips on average). They cover significant distances by public transportation (305.0 km on average) and moderate distances by car (92.2 km on average), with relatively low distances traveled by bike (4.1 km) and on foot (2.0 km) within the three days.

This profile has a higher proportion of females (59%) compared to males (41%). The age distribution shows a notable presence of younger individuals, particularly those aged 18-24 (18%), which is higher compared to the overall sample. This suggests that younger adults, likely students or young professionals, are predominant in this group.

Educational levels within this group show a higher proportion of individuals with high education (40%), which deviates from the overall sample. The employment rate is also relatively high, with 63% of individuals being employed and 37% not having a job. This indicates that many in this group might be employed, young professionals, or students.

Income levels for this cluster are diverse, but there is a notable proportion of individuals with incomes that are 1-2 times the average (30%) and those earning more than 2 times the average (17%), which is higher compared to the overall sample. This suggests a relatively higher economic status within this group.

Household composition indicates a significant proportion of couples with kids and/or others (47%), which is higher than the sample average. There is also a noticeable proportion of single individuals (23%). This composition implies a mix of family responsibilities and individual lifestyles, supporting varied travel needs. The number of cars in households is relatively high, with an average of 1.39 cars per household, indicating some dependence on personal vehicles alongside public transportation and biking.

Combining the travel patterns with the exogenous variables, we could consider these individuals as balanced users of public transportation and biking, supplemented by moderate car usage. The significant frequency and distances traveled by public transportation suggest that they likely reside in urban areas with well-developed transit networks. The presence of younger individuals and those with high education levels indicates that this group might include young professionals and students who find public transportation and biking convenient and efficient.

Income distribution reveals a tendency towards higher earnings, suggesting that these individuals can afford both personal vehicle ownership and public transportation costs. The employment status and household composition further support the idea that this group includes employed young professionals and families who balance their travel needs with a mix of public transportation, biking, and car usage.

This class shares several similarities with the sixth class, as both are oriented towards high levels of public transportation use. This finding is evident as Appendix C shows that the PT-oriented cluster of the six-class model splits into two types of (younger) PT travelers in the 7 class model. The main difference between the sixth and seventh classes is that they also show a preference for car use. Additionally, this group has higher educational and income levels. The seventh class predominantly consists of households with more individuals, whereas the sixth class has a higher proportion of single households. These findings suggest that the seventh class comprises young urban professionals who are starting families and may have previously fit the profile of the sixth class. Respondents within the seventh class have possibly retained their previous preference or habitual travel with the PT and have added car travel to their mobility styles. Based on this hypothesis, we would expect higher transitional probabilities in the LTA, indicating a shift from the sixth to the seventh class.

In summary, this class's travel behavior is characterized by a balanced use of public transportation and biking, supported by their socio-demographic characteristics that include a higher proportion of younger individuals, higher education levels, and varied income levels. The combination of public transport, biking, and moderate car usage reflects a practical and adaptable approach to transportation. This cluster likely includes students, young professionals, and starting families who use public transportation and biking for their convenience and efficiency, complemented by car travel, reflecting a versatile and multi-modal travel behavior.

5 Results

This chapter will show the results of the Latent Class Analysis, focusing on the transitional probabilities between the latent travel profiles. The chapter will also assess the effect of covariates, especially company car ownership, on these probabilities.

5.1. Latent Transition Models

The Latent Transition Model is estimated in LatentGOLD 6.0. The model uses the same indicators and covariates as the Latent Class model.

The Latent Transition Model can explain first-order autocorrelation in longitudinal data. Autocorrelation refers to the concept that a person's behavior at a certain time point is dependent on their previous behavior. Therefore we postulate that the probability of resuming previous behavior is higher than the probability of altering it, again reinforcing the notion that travel behavior is an inert phenomenon.

Latent Transition Models in LatentGOLD can be estimated using either standard logit or transition logit parameters. The conceptual difference between these two methods is outlined in Section 3.5. Standard logit models focus exclusively on direct effects between variables, whereas transition logit models also capture interaction effects. The practical implications of this distinction are important: by comparing the effectiveness of both methods, we can evaluate whether interaction effects are relevant in the context of company cars. This comparison allows us to determine if the effects are independent of initial cluster membership or if initial membership influences the strength of the effects related to company cars.

The Latent Transition Model, or Markov model in LatentGOLD, differs from a traditional latent class model by providing the transition probability parameters that account for this first-order autocorrelation (Inc., 2013). The dynamic latent categories within this model are called states. As we defined 7 meaningful clusters in the LCA, there should be the same amount of states respondents could transition between. Therefore we assume there are seven previous states and seven future states. This means that there will be 49 transition probabilities to be computed by the LTA model.

As previously discussed, there is a specific interest in the cases where respondents' access to company cars has changed between the consecutive wave pairs. These observations enable us to see the effect of transitioning behavior between the latent travel profiles. Even though the number of transitions containing a change in company car ownership (725) is quite reasonable there might arise some problems during the model estimation.

The first potential problem is related to the size of the transitional probabilities matrix. By allowing the model to compute 49 transitional probabilities, we also allow a lot of possible response patterns. This increases the amount of combinations that are rarely observed or are not observed at all. This could lead to unreliable outcomes and may lead to the model not reaching convergence. This is potentially even more problematic as we are dealing with data scarcity.

A second problem with an estimation of this size is that the model including covariates could have a hard time computing all of the transitional probabilities. Seeing that there are covariates in the model with a significant amount of variable levels, this drastically increases the load on the model. Therefore, the first model estimations must show whether the use of transition logits is viable.

5.2. 7-state model with covariates (standard logit)

As expected, the model with covariates does not converge in LatentGOLD due to complexity. Especially the covariates with a lot of variable levels strain the estimations as these drastically increase the number of possible response patterns. To overcome this, the same estimation has been performed using standard logits.

5.2.1. Model statistics and fit

The profile output of the Latent Class Model is shown in table E.12. This reflects the Latent Class Model at the second point in time. In section 3.5 the assumption is made that the measurement model at the second time point is similar to the initial measurement model.

		1	2	3	4	5	6	7	Overall
Profile label		SC	B	CB	LM	CF	PT	CPT	
Cluster Size (% N=8183)		25.5	17.6	16.7	13.9	11.4	8.8	6.2	
Indicators									
Trips by car	Mean	8.1	0.8	6.6	0.9	4.2	0.6	5.5	4.3
Trips by PT	Mean	0.0	0.0	0.0	0.0	0.0	11.4	7.2	1.4
Trips by bike	Mean	0.0	6.9	4.2	0.1	1.4	2.8	1.2	2.4
Trips on foot	Mean	0.5	0.9	0.6	0.3	6.2	1.4	1.7	1.4

Note: some values may not add up to 100% due to rounding.

Table 5.1: Profile output of the 7-state LTA model (standard logit) with covariates

From the table above we can tell that the cluster size slightly differs from those as displayed in table 4.11. The most substantial difference is the increase of the "Low Mobility" class. Indicator levels of these classes have remained more or less the same, confirming the assumption made in section 3.5.

Model	**Log-likelihood**	**L^2**	**P-value**	**BIC (LL)**	**Total BVR**
7-state standard logit with covariates	-118717.51	232458.37	0.00	239849.64	2862.65

Table 5.2: Model fit statistics of the 7-state model (standard logit) with covariates

The model fit statistics are shown in table 5.2. This table shows that the log-likelihood of the model is quite high, this can be explained by the fact that the model is very complex, automatically leading to a high LL. In addition to this, the p-values also do not denote a good fitting model as these are lower than the 0.05 threshold. The BIC(LL) statistic is also listed as this will provide additional information about the fit when comparing this model with other models. The total BVR of this model is very high, which denotes a bad-fitting model. However, some nuances have to be made when using this statistic to asses this model its fit.

Indicators	Trips by car	Trips by PT	Trips by bike	Trips on foot
Trips by car	.			
Trips by PT	13.0	.		
Trips by bike	12.8	321.3	.	
Trips on foot	12.3	1.2	98.3	.
Longitudinal				
BVR-time	4.2	5.5	8.8	2.1
BVR-lag1	832.6	607.9	918.6	923.6
BVR-lag2	0.0	0.0	0.0	0.0

Table 5.3: Bivariate Residuals of the 7-state model (standard logit) with covariates

Table 5.3 shows the output of the bivariate residuals of the 7-state standard logit model with covariates. The output section of the BVRs is a bit more detailed for Markov models estimated in LatentGOLD. In addition to the standard BVRs, the output also provides information for the associations of the longitudinal model. These statistics are specifically meant to show whether the model correctly captures the time trend, and the first- and second-order autocorrelation of the indicators (Vermunt & Magidson, 2013).

Similar to the BVRs of the Latent Class Model of the first time step, most of the remaining associations between the indicators are relatively low. Only the bivariate residual of bicycle and public transport use is quite high, just as shown in table C.6. Earlier we explained that this reflects the bias in the operationalization of indicators where we fail to capture the multimodal behavior that is often observed for public transport travelers. This is also an effect that was observed in the measurement model.

BVR-time measures the model's ability to capture the overall time trend in the data (Nagelkerke, 2018; Vermunt & Magidson, 2013). When BVR-time values are low, it indicates that the model accurately reflects changes over time, effectively capturing the trend of the data. This is achieved by treating the time variable as a nominal covariate in the model, allowing it to account for time-related variations. Conversely, high BVR-time values suggest that the model struggles to represent the time trend adequately, implying that significant aspects of temporal variation remain unexplained. The model output shows that the BVR time is relatively low for all indicators, which indicates that the model can account for the variations over time and represents time trends in a good way.

The BVR-lag variables, on the other hand, focus on the first- and second-order autocorrelations, which is the relationship between responses at consecutive time points (t and t-1). For categorical variables, this metric is calculated by cross-tabulating the responses at these adjacent time points and then adjusting the estimated frequencies to match the observed ones. This means that high BVR-lag1 and BVR-lag2 values indicate that there is a substantial remaining association between consecutive time points that the model does not account for, highlighting that the model fails to fully capture the immediate temporal dependencies. As this research uses only count indicators, this statistic is not useful in assessing model fit. The fact that we are using count variables also explains the extremely high values of the BVR-lag1 statistic as the calculations are made as if the indicators are categorical variables. BVR-lag2 only has zero values because we only look at changes between two time points, making the second-order autocorrelation irrelevant.

As there are no other models estimated at this time, no comparison can be made for the basic model statistics such as the log-likelihood and BIC values. On the other hand, the (longitudinal) BVR statistics show similar output as the measurement model and also indicate that the Latent Transition Model can explain changes in behavior over time in a good way.

5.2.2. Transition probability matrix

Using only standard logits during estimation means that there are only transitional parameters estimated between state changes and only standard effects for the covariates. This leads to the following transition matrix.

		Wave 2						
		SC	B	CB	LM	CF	PT	CPT
Wave 1	SC	58.7	3.7	14.8	12.5	4.5	1.3	4.4
	B	6.0	51.5	15.3	10.3	6.0	8.7	2.1
	CB	22.1	17.2	43.1	3.7	5.1	3.8	5.1
	LM	15.4	9.1	4.1	58.9	4.9	5.5	2.0
	CF	13.0	10.4	8.7	7.9	48.7	4.8	6.5
	PT	8.4	19.4	7.7	12.8	6.7	33.7	11.3
	CPT	20.0	7.6	14.8	6.5	10.6	13.1	27.4

Table 5.4: Transition probability matrix of the 7-state LTA model (standard logit) with covariates

The matrix shows that the transitional probabilities are highest over the diagonal. This is something we would expect to see as travel behavior is inert. Therefore it would be evident to find that the chance of remaining in a previous cluster is higher than transitioning into another.

In addition to the high probabilities that are found on the diagonal, other remarkable observations can be made. The matrix shows that the low mobility and strict cars are the classes with the highest probability of remaining the same over time. Gender coefficients also show that being a man leads to a higher probability of transitioning into either the strict-car ((0.13):(-0.11)-(0.13)) or a low-mobility profile ((0.09):(-0.11)-(0.13)). Visit Appendix E for more detailed parameter output.

The matrix also shows that the highest transitional probabilities of moving classes are centered around the strict car class. Respondents in the CB-cluster have a 22.1% chance of transitioning into a strict car-using class and the CPT-cluster has a 20% chance to do so. This implies that this class is not only able to accommodate the preferences of a high number of already car-using travelers but that its characteristics also seem to be persuasive for other types of travelers.

It is also worth mentioning that there are also relatively high probabilities found for respondents moving to the bike-using class. There is a 19.4% probability for PT-using respondents to transition into bike-minded travelers and a 17.2% chance for those coming from a car and bike-using mobility style. This supports the notion that multimodal travelers are more open to changing their travel behavior than unimodal travelers.

This phenomenon is observed as the more unimodal mobility styles (SC, B, LM) show high probabilities of sticking within their class. Even though the PT class is modeled as unimodal, as explained in section 4.5.1, we acknowledge this creates a bias as this mode is often associated with multimodal behavior. This is also supported by the bivariate residuals of the measurement model, hence we consider it to be a 'multimodal' class. Contrary to the unimodal, multimodal clusters have lower probabilities on the diagonal, indicating that they are more prone to changing their travel behavior over time.

As the multimodal is more inclined to change, it is interesting to see what mobility styles these travelers adopt. The most interesting effects can be observed in the car and bike using class, where the probability of staying (43.1%) is quite low. This class shows high transitioning probabilities of moving to the strict car (2.1%) or the bike using (17.2%) classes. Both inert classes seem to compete with each other for the CB-oriented travelers. This between-class competitiveness is not observed in this way for other transitioning travelers. The transitioning probabilities away from the car and foot traveling class are highest for strict car use, but we should mention that it is quite evenly spread over the classes. Moving PT-oriented travelers are most likely to end up in the bike using class. Finally, the movers from the CPT class seem to be mostly interested in a strict car using profile.

From the transition probability matrix, we can also conclude that all profiles that are already familiar with using the car, are most likely to transition into the strict car-using profile if they reconsider their mobility style. This shows that travelers who start using a car at any point in time then have a higher probability of ending up in a strict car-using profile at some later stage of their lives.

5.2.3. Parameter output

	Wave 2								
	SC	**B**	**CB**	**LM**	**CF**	**PT**	**CPT**	**Wald**	**P value**
Model for clusters	**0.67**	**0.29**	**0.23**	-0.06	**-0.09**	**-0.30**	**-0.75**	1116.3	0.00
Transition parameters									
Constant	-0.16	**0.49**	-0.06	**0.40**	**-0.44**	0.15	**-0.39**	21.5	0.00
SC	**1.82**	**-1.12**	**0.59**	**0.47**	-0.23	**-1.58**	0.05	4067.8	0.00
B	**-1.06**	**1.62**	**0.23**	-0.03	**-0.27**	**0.49**	**-0.98**		
CB	**0.41**	**0.36**	**1.35**	**-1.08**	**-0.45**	**-0.55**	-0.04		
LM	0.17	-0.11	**-0.91**	**2.02**	-0.29	-0.01	**-0.87**		
CF	**-0.28**	**-0.29**	**-0.40**	**-0.39**	**1.82**	**-0.49**	0.03		
PT	**-1.02**	**0.31**	**-0.77**	-0.13	**-0.52**	**1.67**	**0.46**		
CPT	-0.05	**-0.78**	-0.08	**-0.85**	-0.06	**0.47**	**1.35**		
Covariates									
Gender									
Male	**0.07**	-0.02	-0.04	**0.13**	-0.07	-0.05	-0.02	20.8	0.00
Female	**-0.07**	0.02	0.04	**-0.13**	0.07	0.05	0.02		
Age									
12-17	**-1.57**	**1.29**	-0.19	-0.46	**-1.33**	**1.47**	**0.80**	364.1	0.00
18-24	-0.09	**-0.31**	**-0.28**	-0.12	**-0.57**	**0.98**	**0.37**		
25-29	0.10	**-0.34**	-0.16	**0.39**	-0.16	**0.31**	-0.13		
30-39	**0.30**	-0.20	0.07	-0.06	0.03	-0.20	0.06		
40-49	**0.27**	-0.11	0.16	**0.30**	0.11	**-0.39**	**-0.35**		
50-59	0.15	0.11	0.01	0.00	**0.28**	**-0.32**	-0.24		
60-69	0.15	-0.06	**0.20**	-0.14	**0.35**	**-0.47**	-0.03		
70-79	**0.33**	-0.01	**0.25**	-0.24	**0.52**	**-0.96**	0.10		
80+	0.35	-0.38	-0.08	0.31	**0.79**	-0.42	-0.58		
Educational level									
Low	**0.08**	0.03	**-0.24**	**0.28**	0.11	-0.11	-0.16	65.3	0.00
Mid	0.04	-0.04	-0.10	-0.06	-0.02	**0.22**	-0.03		
High	-0.03	-0.03	0.11	**-0.44**	0.12	0.09	0.18		
Unknown	-0.10	0.05	0.24	0.22	-0.21	-0.20	0.01		
Occupational status									
No job	-0.15	0.09	-0.03	**0.17**	**0.20**	-0.09	-0.18	57.5	0.00
Employed	**0.21**	0.05	0.15	**-0.31**	-0.10	-0.16	0.16		
Unknown	-0.06	-0.14	-0.12	0.14	-0.10	0.25	0.02		
No. of cars									
#	**0.55**	**-0.38**	**0.24**	**0.21**	-0.01	**-0.75**	0.14	281.7	0.00
Income									
Minimum	**-0.42**	0.22	0.08	0.24	0.03	-0.20	0.05	75.0	0.00
Below average	0.05	-0.04	0.01	**0.26**	0.19	**-0.33**	-0.14		
Average	**0.18**	-0.05	0.03	0.04	0.10	-0.07	-0.23		
1-2 times average	0.01	-0.13	0.04	-0.08	-0.06	0.05	0.16		
2 times average	0.07	-0.06	-0.02	-0.26	-0.09	0.26	0.09		
> 2 times average	0.03	-0.06	-0.13	**-0.37**	-0.27	**0.55**	0.24		
Unknown	0.08	0.13	-0.02	0.16	0.09	**-0.26**	-0.18		
Household composition									
Single	-0.04	-0.18	-0.10	-0.17	0.07	**0.32**	0.09	43.9	0.01
Couple	-0.01	0.00	0.07	-0.09	0.11	-0.01	-0.07		
Couple w/ kids and/or others	**-0.24**	0.19	0.02	-0.11	0.22	0.17	-0.23		
Single parent with kids (and others)	0.19	0.10	0.18	0.10	**-0.44**	-0.03	-0.11		
Other	0.10	-0.11	-0.16	0.27	0.03	-0.45	0.32		
Company car									
No CC in household	**-0.14**	0.21	0.09	**-0.24**	0.04	0.19	-0.15	24.7	0.02
CC in household not main user	-0.13	0.24	-0.21	**-0.27**	-0.03	0.40	0.00		
CC in household and main user	**0.27**	-0.46	0.12	**0.51**	0.00	-0.59	0.15		
Year									
2013	0.00	0.00	0.00	0.00	0.00	0.00	0.00	67.6	0.00
2014	-0.07	**0.20**	-0.01	0.10	-0.15	0.18	**-0.25**		
2015	-0.13	0.06	0.02	-0.03	-0.19	0.09	0.17		
2016	**0.25**	**-0.20**	0.15	0.12	-0.18	**-0.32**	0.18		
2017	0.12	-0.03	0.03	**-0.31**	**0.27**	-0.16	0.09		
2018	**-0.16**	0.05	0.00	0.06	0.01	0.15	-0.12		
2019	-0.01	-0.08	**-0.19**	0.07	**0.24**	0.05	-0.07		

Table 5.5: Parameter output of the 7-state LTA model (standard logit) with covariates

This section shows the parameter output of the 7-state LTA model with covariates (standard logit) and reflects on the meaning of the estimates. The transitional probabilities are calculated (by Latent GOLD) using the regression parameters of the estimated model, these parameters are shown in table 5.5. The transitional coefficients are the highest for remaining in the initial cluster, also these are all found to be statistically significant. This means that initial cluster membership is found to be a significant predictor for class membership.

In general, we could say that the parameter output holds some interesting results for all classes, as it reveals which variables are affecting the increase or decrease of transitional probabilities. The most obvious effects of covariates on transition probabilities will be discussed per class below. Hereafter, the effect of the company car variable will be discussed individually as this is the main point of interest of this research.

Strict car users
According to the results of the Latent Class Analysis, we would expect employment, gender, number of cars in a household, and income to be determinants for the strict car-using class. Looking at the parameters in table E.5, we observe that gender indeed yields a significant parameter that increases the probability of transitioning into the SC-class. The same goes for occupational status, the coefficient for being employed ((0.21): (-0.31) - (0.21)) is highest for this class. Moreover, this is the only level within the occupational status variable where a positive coefficient is observed. There is a high coefficient for the number of cars in a household as a predictor for strict car cluster membership. As this variable is computed as a numerical variable, the cluster membership is heavily affected by this variable. We also found that average incomes are associated with relatively high coefficients. It is remarkable to see that these coefficients do not seem to stay at the higher end as income goes up.

Bike users
Transitioning parameters for the bike using class show high coefficients for really young individuals (12-17), this is in line with the findings of the LCA. Contrary to the LCA findings, we see that the coefficient for gender is not on the higher end, whilst we would expect to see that being a female would lead to higher chances of transitioning into a bike-oriented travel style. Also being a lower-income individual yields high coefficients for moving to this class. Factors like low occupational status and a household composition that includes kids or others enlarge the probability of transitioning into this class. The combination of these factors confirms the findings of the LCA, where younger, mostly female individuals are members of these classes. These parameters show that these are the individuals who are mostly drawn to transitioning into this class.

Mixed car and bike users
For transitioning into a mixed car and bicycle using mobility style, an older age segment seems to be a determining factor. Especially people who are aged between 60 and 80 have a higher probability of transitioning in such a mobility style. In addition to this, having a job plays a determining role in these transition probabilities. This does not necessarily mean that a high income goes with this, as these coefficients are positive for incomes ranging between the minimum to 1-2 times average levels. Being a single parent with kids and/or others also has a high coefficient which implies that this household composition makes it likely or attractive to transition into this mobility style.

Low mobility
Earlier we found that the low-mobility class consists of people who are considered to have limited mobility due to combinations of age and economic constraints. Higher ages are also associated with low employment rates and reduced mobility. Given the age class of these respondents, these are variables that are unlikely to change in the future, which explains the inertia in this class. The parameters of the 7-state model confirm this assumption as the statistically significant coefficient of unemployment on transitioning to the low mobility class is one of the highest. The same goes for the income parameters. The LCA shows that the low-mobility class has a higher share of low-income respondents. The transition model coefficients of 'minimum' (not significant) and 'below average' (significant) are the highest for the low mobility group, indicating that low income is a predictor for low mobility cluster membership. Surprisingly, the coefficients of older age segments are negative, indicating that these do not increase the probability of transitioning into the low mobility class. Only after becoming 80 years or older, age

has a strengthening effect on transitioning into a low-mobility class. It is however important to note that there is a fair share of high coefficients on the unknown levels of the variables educational level, occupational status, and income. This means that respondents of whom there is sometimes no data available on these categories are likely to shift to this mobility style. We cannot establish if these answers are not known or if these respondents were not willing to fill in these answers of the MPN, hence this disables us to properly identify the factors that impact these individuals.

Mixed car and foot travelers

Being a male enlarges the probability of transitioning into this cluster. Other notable significant coefficients can be found under age categories. The coefficients clearly show to increase as people become older, which means that the probability of transitioning into this cluster becomes bigger as people grow older. This is also in line with the observations of occupational status as having no job increases transition probabilities. In the LCA we established that there might be a proportion of retirees within the CF profile. This assumption can be strengthened by the coefficients of occupational status, as having no job increases transition probabilities.

Public transport users

The lower age segment shows high positive and statistically significant coefficients for transitioning into this mobility style. This is in line with expectation as youngsters in the Netherlands gain access to a free subscription to the public transport if they are enrolled in an educational institution. This also explains the loading of the coefficients on mid educational level. This level denotes that at least the high school diploma has been obtained, after which many start their studies. Contrary to these findings, we also see high loading for greater income levels that are not particularly linked to any of the aforementioned characteristics. This indicates that higher incomes play a role in transitioning into this cluster and that low to middle incomes stay away from transitioning. This might be an indication that people with lower incomes think travel by public transport is too expensive. We also find that single households have higher chances of moving to this class, and interestingly the same goes for couples with kids and/or others.

Mixed car and public transport users

The most notable coefficient for this profile and its transitional probabilities is the higher educational level and employment. This goes hand in hand with incomes in the higher segments. The other factors do not seem to offer too much additional explanatory value concerning interpretation as coefficients are either quite moderate or have a high loading on factors such as 'other types of households'

Observed company car effects

The main theme of this research is to find out the effect of company cars on transitioning between different mobility styles. The parameter output of the 7-state model (standard logit) has some interesting results that should be mentioned.

For the no company car in the household category, we find that the highest coefficients are found under the bicycle and PT classes. This indicates that when a person does not have access to a company car within the household, he or she is more likely to transition into one of these mobility styles. Other slightly lower positive coefficients are found for the mixed car-bike and mixed car-foot traveler classes.

If persons have access to company cars but are not the main users they are most likely to shift to a public transport or bike-oriented mobility style. In some situations, this might be explained by the assumption that they are not able to use the company car as a result of the main user having it. Especially the coefficient for transitioning into a public transport-minded mobility style is high.

The most notable effects are found under the coefficients of main users of company cars. Being a main user increases the probability of transitioning into various profiles. The most peculiar effect is that the highest coefficient is found under those transitioning into the low mobility profile. This has the highest coefficient meaning that the transition probability increases the most as a result of being a main user. This is not particularly in line with expectations, hence a more detailed investigation of this observation is necessary. Further, we find that being a main user also contributes to a moderate increase in the transition probability into a more strict car-using profile. Finally there also seem to be slight increased effects on the probability of transitioning into the mixed car-bicycle and car-PT clusters.

These findings highlight the impact of company car access on mobility behavior. For individuals without company cars, sustainable mode profiles like cycling and public transport seem to be more attractive. Non-primary users of company cars are also inclined towards public transport, possibly reflecting practical constraints on vehicle use. However, the most surprising insight is the significant transition to low mobility among main users of company cars, challenging assumptions about their mobility patterns and suggesting areas for deeper investigation. To monitor more detailed effects of company car ownership, a Latent Transition Model with transition logits should be estimated. This allows for a deeper investigation of the effects that are conditional on initial cluster membership.

5.3. 7-state model with the company car covariate

The previous section has shown that it would be valuable to estimate a model from which more insights on the company car variable can be gained. Therefore, a 7-state model using only the company car covariate is estimated. To assess the value of the model for transitions in which transition logits are used, a comparison will be made between this model and the model that uses standard logits.

5.3.1. Profile output

The profile output of these models does not show great differences compared to the profile output of the 7-state standard logit model with covariates. Specifics for these profile outputs can be found in tables 5.6 and 5.7 below.

		1	2	3	4	5	6	7	Overall
Profile label		SC	B	CB	LM	CF	PT	CPT	
Cluster Size (% N=8183)		25.7	17.6	16.2	13.7	11.4	9.3	6.0	
Indicators									
Trips by car	Mean	8.2	0.8	6.6	0.9	4.2	0.6	5.4	4.3
Trips by PT	Mean	0.0	0.0	0.0	0.0	0.0	11.5	7.2	1.5
Trips by bike	Mean	0.0	6.9	4.2	0.1	1.4	2.8	1.2	2.4
Trips on foot	Mean	0.5	0.9	0.6	0.3	6.2	1.4	1.9	1.4

Note: some values may not add up to 100% due to rounding.

Table 5.6: Profile output of the 7-state LTA model (standard logit) with company car covariate

		1	2	3	4	5	6	7	Overall
Profile label		SC	B	CB	LM	CF	PT	CPT	
Cluster Size (% N=8183)		25.8	17.5	16.2	13.7	11.5	9.3	6.0	
Indicators									
Trips by car	Mean	8.2	0.8	6.6	0.9	4.2	0.6	5.4	4.3
Trips by PT	Mean	0.0	0.0	0.0	0.0	0.0	11.5	7.2	1.5
Trips by bike	Mean	0.0	6.9	4.2	0.1	1.4	2.9	1.1	2.4
Trips on foot	Mean	0.5	0.9	0.6	0.3	6.2	1.3	1.9	1.4

Note: some values may not add up to 100% due to rounding.

Table 5.7: Profile output of the 7-state LTA model (transition logit) with company car covariate

There are slight deviations in mean trips for some clusters but apart from that, the outcomes of this model are comparable to the 7-state LTA model (standard logit) with all covariates. This implies that the results are in a similar way coherent with the structural model defined in section 4.7.

5.3.2. Model statistics and fit

The general statistics of both models as shown in table 5.8 do not point towards a superior model. We would expect that the standard logit model would provide a better fitting model as this method only estimates direct effects and therefore estimates fewer parameters. We see that the log-likelihood of the transition logit model is slightly lower, thus better fitting, but this is offset by an increase in parameters. This explains why the BIC(LL) of this model is slightly larger, which is not desirable.

Model	Log-likelihood	L^2	P-value	BIC (LL)	Total BVR
7-state standard logit with company car	-119270.16	111554.38	0.00	239333.19	575.26
7-state transition logit with company car	-119230.79	111475.64	0.00	239903.15	575.53

Table 5.8: Model fit statistics of the 7-state LTA model (standard logit) with the company car covariate

5.3.3. Transition probability matrices

In this section, the transition probability matrices of both models are compared to each other. As one would expect, the transitional probability matrices show no big differences concerning the sizes of transition probabilities. Only the statistical significance levels of the matrices differ when using the different types of parameters. We observe that the transition logit model has more significant probabilities compared to the standard logit model. The transition logit model estimates more parameters and therefore is better in handling complexity. This characteristic is also the main drawback of the method concerning model convergence and runtime. In this case, the additional parameters are used to find more statistically significant effects which is desirable.

Standard logit

		Wave 2						
		SC	B	CB	LM	CF	PT	CPT
Wave 1	SC	65.4	2.0	14.2	10.4	4.0	0.6	3.4
	B	3.9	58.7	11.5	8.8	4.7	10.5	1.9
	CB	22.9	16.0	45.0	3.4	4.9	2.8	5.0
	LM	13.1	8.0	3.4	64.9	4.9	4.0	1.8
	CF	12.2	8.2	8.7	7.6	54.6	2.8	5.9
	PT	4.8	17.2	5.3	9.0	3.6	50.3	9.9
	CPT	18.9	6.4	14.1	5.8	10.7	13.3	30.8

Table 5.9: Transition probability matrix of the 7-state LTA model (standard logit) with the company car covariate

Transition logit

		Wave 2						
		SC	B	CB	LM	CF	PT	CPT
Wave 1	SC	65.5	2.0	14.2	10.3	4.0	0.5	3.5
	B	4.3	58.8	11.6	8.2	4.8	10.5	1.8
	CB	22.8	16.0	45.1	3.4	4.9	2.8	5.0
	LM	13.2	7.8	3.5	65.0	4.9	4.0	1.6
	CF	11.9	8.0	9.0	7.3	55.1	2.8	5.9
	PT	5.2	17.1	5.8	8.6	3.9	50.0	9.5
	CPT	19.2	6.3	13.9	5.9	10.8	13.2	30.7

Table 5.10: Estimated values transition probability matrix of the 7-state LTA model (standard logit) with the company car covariate

In these matrices, we do however observe different transitional probabilities compared to those found in the (standard logit) model that includes all covariates. We assume that the covariates offer additional explanatory power and therefore contribute to a better fitting model, thus a more valid transition probabilities matrix. Therefore we also assume that these transition probabilities provide somewhat of a limited view of the actual effects.

5.3.4. Company car effects

General model statistics do not show superiority in model fit for either one of the estimation methods. The parameter output of both models does however provide additional means to assess the fit of models. The parameter outputs are given below in tables 5.11 and 5.12.

	Wave 2								
	SC	**B**	**CB**	**LM**	**CF**	**PT**	**CPT**	**Wald**	**P value**
Model for clusters	**0.67**	**0.30**	**0.22**	-0.05	**-0.09**	**-0.31**	**-0.75**	1099.23	0.00
Transition parameters									
Constant	**0.79**	-0.08	**0.32**	**0.37**	**-0.32**	**-0.85**	**-0.24**	135.95	0.00
SC	**2.02**	**-1.23**	**0.71**	**0.50**	-0.16	**-1.86**	0.02	5330.67	0.00
B	**-1.23**	**1.79**	0.11	-0.07	**-0.36**	**0.74**	**-0.99**		
CB	**0.49**	**0.38**	**1.39**	**-1.07**	**-0.43**	**-0.69**	-0.08		
LM	0.16	-0.10	**-0.96**	**2.09**	-0.20	-0.12	**-0.88**		
CF	**-0.21**	**-0.34**	**-0.31**	**-0.35**	**1.94**	**-0.74**	0.02		
PT	**-1.18**	**0.39**	**-0.84**	-0.21	**-0.81**	**2.14**	**0.52**		
CPT	-0.05	**-0.88**	-0.11	**-0.90**	0.01	**0.52**	**1.40**		
Covariates									
Company car								52.20	0.00
No CC in HH	**-0.36**	0.33	-0.06	-0.25	0.20	0.42	-0.28		
CC in HH no main user	-0.20	0.32	-0.24	-0.27	-0.14	0.49	0.03		
CC in HH and main user	**0.56**	-0.66	0.30	0.52	-0.06	-0.92	0.25		

Table 5.11: Parameter output of 7-state LTA model (standard logit) with the company car covariate

	Wave 2								
	SC	**B**	**CB**	**LM**	**CF**	**PT**	**CPT**	**Wald**	**P value**
Transition parameters									
Constant	**0.67**	**0.29**	**0.23**	-0.05	**-0.09**	**-0.31**	**-0.75**	1098.03	0.00
SC	**0.00**	**-5.54**	**-1.85**	**-2.02**	**-3.25**	**-6.37**	**-3.24**	798.03	0.00
B	**-1.76**	**0.00**	**-1.21**	**-1.96**	**-2.47**	**-3.39**	**-4.43**		
CB	**-0.45**	**-1.17**	**0.00**	**-2.17**	**-3.45**	**-2.69**	**-1.91**		
LM	**-1.57**	**-3.75**	**-2.52**	**0.00**	-4.65	-6.31	-4.59		
CF	**-1.51**	-3.42	**-1.45**	-3.00	**0.00**	**-2.61**	**-1.94**		
PT	**-1.40**	-1.78	**-1.26**	**-0.99**	**-1.73**	**0.00**	-2.80		
CPT	**-0.58**	-3.32	-1.73	**-1.64**	-4.04	-2.73	**0.00**		
Covariates									
Company car								92.55	0.25
SC									
No CC in HH	**0.00**	2.12	**0.37**	0.21	0.51	1.63	0.33		
CC in HH no main user	**0.00**	1.82	-0.24	-0.44	-0.92	1.60	0.41		
CC in HH and main user	**0.00**	-3.94	-0.13	0.23	0.41	-3.23	-0.74		
B									
No CC in HH	**-1.22**	**0.00**	-0.48	0.00	-0.02	1.69	0.90		
CC in HH no main user	-0.36	**0.00**	-0.36	-0.17	-0.64	1.62	1.35		
CC in HH and main user	**1.57**	**0.00**	0.84	0.17	0.65	-3.31	-2.26		
CB									
No CC in HH	-0.26	0.11	**0.00**	-0.49	1.20	-0.14	-0.36		
CC in HH no main user	-0.13	0.75	**0.00**	0.25	1.98	0.79	0.14		
CC in HH and main user	0.39	-0.86	**0.00**	0.24	-3.19	-0.65	0.23		
LM									
No CC in HH	-0.06	1.66	-0.52	**0.00**	2.16	3.64	0.81		
CC in HH no main user	0.38	1.85	0.04	**0.00**	-3.49	-2.14	-3.19		
CC in HH and main user	-0.32	-3.50	0.47	**0.00**	1.33	-1.50	2.38		
CF									
No CC in HH	-0.03	1.52	-0.42	0.97	**0.00**	-0.44	-0.34		
CC in HH no main user	-1.38	1.41	-0.04	-3.66	**0.00**	-0.27	0.08		
CC in HH and main user	**1.41**	-2.93	0.47	2.70	**0.00**	0.71	0.26		
PT									
No CC in HH	-1.09	0.75	**-1.06**	-0.87	-1.01	**0.00**	1.16		
CC in HH no main user	-1.43	-0.01	-1.15	-0.43	**-1.37**	**0.00**	1.04		
CC in HH and main user	2.52	-0.75	**2.20**	1.31	**2.38**	**0.00**	-2.20		
CPT									
No CC in HH	0.14	1.77	1.06	-0.01	3.16	1.99	0.00		
CC in HH no main user	-0.40	1.98	0.35	-0.10	-1.91	1.59	**0.00**		
CC in HH and main user	0.25	-3.75	-1.40	0.11	-1.25	-3.58	**0.00**		

Table 5.12: Parameter output of the 7-state LTA model (transition logit) with the company car covariate

The parameter output of both the standard and transition logit models do show some differences. As shown in table 5.11, the standard-logit model only estimates coefficients for the company car variable that do not account for initial cluster membership. The transition-logit model estimates coefficients for all variable levels of each initial state, as shown in table 5.12. The parameter outputs of these two models have few implications.

The Wald statistic for the transition-logit model is 0.25, which exceeds the 5% significance level. Therefore we must conclude that this model is not fit to use when assessing the effect of a company car variable on travel behavior. Furthermore, as a result of this insignificance, we must conclude that the relationship between the company car variable and the transition probabilities in this model cannot be generalized to the broader population, indicating no significant interaction effect.

In contrast, the p-value of the Wald statistic for the standard logit model is below the 5% threshold, allowing us to generalize those findings to the population. As the standard-logit model only estimates direct transition coefficients, it is not possible to see which specific interaction effects (between initial cluster membership and the company car variable) are statistically significant and which are not. However, this model does have significant p-values for the Wald statistic of the transition parameters and the company car covariate. This statistic indicates that in the population at least one of the variables in the set of estimated parameters is significantly different from zero. In more simple terms this means that there is a significant effect for at least one of the parameters and that there is a relation between the company car variable in the population.

The fact that the standard logit parameters can be generalized while the transition logit parameters cannot is noteworthy. As explained in Section 3.5, these methods differ in their focus on direct versus interaction effects. The practical implication of this result is that, because only the direct effects (standard logit) can be generalized, the impact of the company car ownership variable is independent of initial cluster membership. This suggests that the effects of being a main or non-main user are neither amplified nor diminished by the respondent's initial cluster at the earlier time step.

Because the estimate indicates that there is a relation between the company car variable in the population, the estimated values under each variable level of the transition probabilities from the standard-logit model are presented in table 5.13. The effects of the company car variable levels on transition probabilities to specific classes will be discussed in detail in the following subsections.

Standard logit

		Wave 2						
		SC	B	CB	LM	CF	PT	CPT
No CC in HH	SC	64.6	2.1	14.7	10.4	4.2	0.6	3.4
	B	3.5	59.8	11.2	8.2	4.8	10.7	1.7
	CB	22.0	16.5	45.5	3.4	5.0	2.9	4.8
	LM	12.8	8.2	3.5	64.6	5.1	4.1	1.7
	CF	11.4	8.3	8.7	7.3	56.0	2.8	5.6
	PT	4.4	17.6	5.2	8.5	3.6	51.5	9.3
	CPT	18.3	6.7	14.4	5.7	11.1	13.7	30.1
CC in HH no main user	SC	69.7	1.9	11.3	9.5	2.8	0.6	4.3
	B	4.2	60.4	9.5	8.2	3.5	11.7	2.4
	CB	26.6	16.9	39.3	3.4	3.8	3.2	6.8
	LM	14.9	8.2	2.9	63.6	3.7	4.4	2.4
	CF	15.4	9.5	8.3	8.3	46.3	3.5	8.7
	PT	4.8	16.6	4.1	7.9	2.5	52.3	11.9
	CPT	19.6	6.1	11.0	5.2	7.3	13.5	37.4
CC in HH and main user	SC	75.1	0.4	9.8	10.5	1.5	0.1	2.7
	B	11.8	29.9	21.7	24.0	5.0	3.8	3.9
	CB	37.5	4.2	44.6	5.0	2.7	0.5	5.6
	LM	17.0	1.6	2.7	74.5	2.1	0.6	1.6
	CF	25.2	2.7	11.0	13.9	38.3	0.7	8.3
	PT	14.5	8.7	9.9	24.4	3.8	18.0	20.8
	CPT	31.7	1.7	14.3	8.6	6.0	2.5	35.2

Table 5.13: Transition probability matrix of the 7-state LTA model (transition logit) per company car level

No company car in household
The transitional probabilities towards a strict car (SC) profile remain more or less the same as in the general transition probability matrix (Table E.9 for this variable level. We observe that there are slightly lower probabilities of transitioning into a car-oriented class and there is a slight increase in the probabilities of transitioning into more active mode-oriented classes.

Apart from the differences in transition probabilities as a result of this variable level, there are various takeaways to be made from this probability matrix. Just as in the transition probability matrix of the model with covariates, there are high values on the diagonal. Mobility inertia is highest for the strict-car (SC) and the low-mobility (LM) classes. We also observe the 'competition' between the strict-car (SC) and bike (B) classes for travelers who were previously in the mixed-car-bike (CB) cluster. The probability of moving towards a strict car class is a bit higher for these travelers.

The mixed car-PT travelers have a significantly lower probability of remaining in their class (30.1%) than other profiles. The transition probabilities of people that originate from this cluster are not centered around a specific other profile. These people have the highest chance of transitioning into the strict car profile but also have slightly lower probabilities of changing to mixed car-bike or more exclusive PT profiles.

A general observation from this matrix is that initial state profiles that are associated with car use have the highest probability of moving to strict car use. The same was found for the probabilities in the model (standard-logit) including all covariates. Again, this means that when people get used to some levels of car use, they have a higher chance of transitioning into a strict-car-oriented mobility style at some point in the future.

Company car in household, not main user
For those who have a company car in their household but are not the main users, more interesting effects are observed. Research of Kroesen (2015) found that partners affect each other mobility choices over time. Hence we would expect to monitor a similar effect for those living together in general. Therefore one would think that there would be a change for the classes that are already familiar with car travel in a direction that leads to more car use. Interestingly, the probability of remaining in an initial cluster lowers by about 5% for both the mixed car-bike and mixed car-foot traveler classes. Simultaneously, the chance of transitioning into a strictly oriented class increases by approximately this percentage.

The competition between SC and B for CB travelers seems to be more oriented in favor of the strict car class. This means that whenever one has access to a company car within the household, he or she is more inclined to transition towards a strict car-using class than before.

Interestingly, the mixed car-PT class does not show a significant increase in the probability of moving towards the strict-car class. We do observe that travelers within this class show more inert behavior as the probability of staying increases by 7.3%. This is mostly at the cost of the mixed CB and CF classes and not so much for others.

From the above, we can conclude that having a company car in a household leads to more car-oriented travel. This statement is supported by three types of observations. Having a company car in a household makes it more attractive for people to transition towards a strict-using car class. It also makes it more attractive for people to transition into a partially car-oriented car class instead of a non-car-using class. Finally, it leads to a higher inclination to stick with partially car-oriented classes.

Furthermore, we observe that the transition probabilities towards the bike (B) cluster remain more or less the same. This means that the chance does not become lower nor higher to transition into this class. However, this also confirms that movers who could have been inclined to transition into bike users do not end up here but somewhere else. Therefore, the fact that the probabilities do not change that much in absolute sense underexposes the bigger gap between the bike class with its competing classes.

Company car in household and main user

For people who are main users of company cars, we would expect to see a structural increase in car-oriented travel, thus increasing transition probabilities towards these classes.

Strict car users

The matrix shows that specifically, the transitioning probabilities towards the strict car using class are high compared to the ones from other variable levels. There is a 75.1% probability that initial state strict car users remain within this cluster. We also observe that the probability of moving from the bike class to a strict (11.8%) car has almost tripled. The probability that one transitions from a CB to an SC profile is also extremely high (37.5%) considering that the chance of staying within this class is just 44.6%. Strikingly the increase in transition probability coming from a low mobility class towards a strict car is quite small, especially compared to the increase of other classes. The probability of moving towards a strict car-using profile increases by about 10% for the CF, PT, and CPT classes compared to people who have a company car in their household but are not main users. People who have been strict car users have not shown high transition probabilities to other classes in general. After the introduction of the main user variable, this becomes even more extreme. Overall, we can conclude that being a main user of a company car strongly increases the chance of staying in or transitioning towards a strict car using a profile. The (already high) probability of staying within this profile without a company car increases by about 10% when someone becomes the main user of such a vehicle, and the probability increases by factors ranging between 1.3 and 3.8 times depending on initial cluster membership. Another interesting general observation is that for class movers, the probability of going to a strict car is almost always the highest.

Bicycle users

The probability of transitioning into a bike-oriented mobility style becomes quite slim for those being the main users of company cars. This result is quite interesting as the probability of staying has remained almost unaltered when the company car is introduced into the household (not the main user). After people become main users, the probability strongly decreases from 59.8% and 60.4% to 29.9%. The transitioning probabilities of moving to a bike-centered mobility profile become extremely small for all classes. Only those coming from the PT class have a slight chance of going to the bicycle class.

Mixed car bike users

The most notable observation of the mixed car-bike class is that the probability of staying in this partially car-oriented class is also higher for those who are main users of company cars, compared to people who only have them in their households. This can be explained by the fact that the probability of transitioning from CB to B has strongly declined. From this, we conclude that being a main user of a company car makes people stop considering changing to a bike-oriented mobility style and would only consider moving to a strict car using class. Before we saw that the SC and B classes were competing for initial state CB respondents, now the share that initially transitioned to the bike clustered has shifted to the strict car class. This indicates that being a main user of a company car can be quite decisive for those who think about changing between strict car and bike profiles.

Low mobility users

The low mobility cluster also reveals interesting transition patterns. We see that initially, low-mobility travelers are now slightly more inclined to move to a strict car using a profile. More interestingly their inertia to stick with their class has grown by about 10% to 74.5%. Let alone, this probability is quite high, more interesting is that the fact that people are the main users of company cars increases their probability of staying within the low mobility cluster. This means that there are people who are the main users of company cars that almost do not use their cars at all. Those who were previously bike users have quite a high probability of transitioning to the low-mobility group after gaining access to a company car as main users. Where this probability was about 8.2% for both of the other variable levels, it increases to 24% for main users. The same observation can be made for the people who were initially in the public transport cluster. Previously, these respondents had an 8.5% and 7.9% probability for no CC and only a CC in their household, when the main user-ship is introduced this becomes 24.4%. This means that people who come from profiles that were not associated with very little to no car use, now have high probabilities to transition into a profile where travel becomes very limited. A logical explanation for this remains unknown as this is completely in contrast with the expectation. This highlights the need for the inclusion of socio-demographic variables as this behavior could potentially be explained away by other factors that are introduced along the company car variable, such as changes in working conditions.

Mixed car and foot travellers
The matrix shows that the transitioning probabilities towards a mixed car and foot traveling profile are quite slim. Compared to other stayers, the chances for this profile are quite moderate (38.3%). These probabilities were also lower for those having access to a company car within their households compared to those who had not, but when the main ownership is introduced, they become even smaller. Further, we see no significant differences in the probabilities of transitioning into this cluster. For people that originate from this cluster there, we observe the increased inclination to transition into the strict car-using profile.

Public transport users
For this cluster what strikes me the most are the extremely low transitioning probabilities towards this cluster. Most of the probabilities are between 0% and 1%, and the chance of staying has also decreased drastically. This means that the introduction of the main user company car variable has a serious impact on those traveling by public transport. We see that the chance of staying within the cluster is just a measly 18%, where it was around 50% for other variable levels. We see that people become more inclined to combine their pubic transport travel behavior with car use, as the transition probabilities of the CPT-cluster doubles to 20.8%. As talked about earlier, there is also a serious probability that these people transition into a low mobility profile and a moderate probability of moving to the strict car-using profile. The main implication has to be that the transition probabilities towards this class become extremely small as a result of the introduction of the company car variable.

Mixed car and public transport users
For the mixed car and public transport transition probabilities, the most interesting observation is that there is an increase in those coming from the public transport cluster. From this we can conclude that there is a small share of public transport users that see feasibility in combining these modes, thus transitioning into the mixed profile. Under the same notion, the higher probability of staying within this cluster can be explained. For other variable levels, there was a small probability for users to transition to a public transport profile. However, as we established in the PT section the chances of transitioning into this profile have become close to zero percent. Likely, the CPT respondents who were previously considering a PT mobility style are now pushed towards staying as a result of the main user company car variable.

6 Conclusions

The final chapter provides a discussion of the outcomes of this research. This section includes a summary of the findings, the implications of this research, and a comparison with previous findings in the literature. In addition to this, the limitations of this research will be presented and suggestions for future research are presented. Finally, the conclusion and recommendations section will reflect upon the research questions to see in what way the outcomes of the research fill the identified knowledge gap. The conclusion will also discuss the significance of the findings and their implications for the field of research. Finally, it will consider the broader societal implications of this research and provide recommendations based on the drawn conclusions.

6.1. Discussion

This chapter provides a discussion of the research outcomes, including a summary of findings, their implications, and a comparison with existing literature. Additionally, limitations and suggestions for future research will be presented, concluding with recommendations based on the research's contribution to the field.

Given the increasing environmental concerns related to car usage, this study addresses the pressing question of how company cars influence travel behavior. By applying Latent Class and Latent Transition Analysis, we were able to capture nuanced shifts in mobility patterns. A selection of respondents from the Dutch Mobility Panel has been pooled into a sample that supported this quantitative research.

6.1.1. The sample analyses

The sample has been analyzed to see if it is representative of the Dutch population. Comparisons were made using data from the Centraal Bureau voor de Statistiek (CBS, 2024a) to ensure alignment with the population. Representativeness was assessed using the Chi-square test to compare sample statistics for key covariates such as gender, age, educational level, occupational status, and income against national benchmarks. Despite efforts to maintain representativeness, the Chi-square tests showed significant differences for most covariates, indicating that the sample is not fully representative of the Dutch population. However, the sample was found to be representative in terms of occupational status.

The lack of representativeness on key variables like gender and age raises potential concerns about generalizing the results to the broader population. Still, the finding that occupational status is representative holds particular significance for this research, given the strong connection between employment and the provision of company cars. We found that commuting is one of the major drivers of travel behavior, and car use is the dominant mode for commuters in the Netherlands (Centraal Bureau voor de Statistiek, 2024d). Therefore, we think that having a sample that accurately reflects the occupational status of the population is essential to understanding travel patterns.

Even though, the sample shows statistical differences in covariates like gender and education level, the percentual differences with the population are quite small. The chosen statistic to measure representativeness also greatly magnifies small differences for large sample sizes. Given the similarities with population distributions in most categories, we think that the results still provide valuable insights into travel behavior. However, generalizations to the broader population should be made cautiously, considering the significance of representativeness tests.

The specific examination of company car users within the sample has also been assessed, to understand the socio-demographic characteristics of this subgroup. The analysis focused on two types of company car users: main users and non-main users, each showing distinct travel patterns.

As one would expect, the main users of company cars exhibit a pronounced car-oriented mobility pattern. On average, they report making six car trips over the three days, with a notable reduction in trips made by other modes such as public transport or cycling. The mode use and distance traveled by car for this group are significantly higher than for the overall sample. This is in line with findings of previous research (Albert et al., 2014; Frenkel et al., 2014; Metzler et al., 2019; Wadud et al., 2022). The strong car dependency and unimodal travel behavior are in line with findings of Frenkel et al. (2014), which found that the likeliness of adopting a car exclusive car pattern is higher for company car users.

In terms of socio-demographic characteristics, the main users are predominantly male (72.6%), a much higher proportion than the overall sample, which consists of 46.3% men. This suggests that men are more likely to be in positions where company cars are offered as fringe benefits, or they may be more inclined to use company cars. Most main users are between the ages of 30 and 60, aligning with the prime working age group. Since company cars are closely tied to employment, it is unsurprising that the vast majority of main users are employed. Income distribution shows that company car users generally earn higher wages than the overall sample, with twice as many earning more than double the average income. This suggests company car benefits are more common in higher income brackets. Main users are often part of households with couples and children, where a company car provides greater utility. These households also have a higher number of cars, consistent with research linking company car ownership to increased overall car ownership.

Non-main users—those who have access to a company car but are not the primary users—show travel patterns similar to the overall sample. While their mode usage frequencies remain close to average, they do report slightly longer distances traveled by car and public transport.

In terms of gender distribution, this group shows a slightly higher proportion of women compared to the main user group, which may suggest that women are often partners or household members of primary company car users. This aligns with the finding that most non-main users live in households with couples and children, indicating that the presence of a company car in the household is closely tied to family dynamics. Like main users, non-main users also report higher income levels compared to the overall sample, with a notable portion earning between one and two times the average income. The average number of cars in these households is slightly lower than that of main users but still higher than the overall sample, confirming that access to a company car is associated with higher car ownership.

6.1.2. The Latent Class Analyses

The Latent Class Analysis served as a structural model for the Latent Transition Analysis in this research. The optimal Latent Class Model (LCM) selected for this study revealed seven distinct travel behavior classes. Model selection was guided by statistical indicators to balance fit and interpretability. Ultimately, a seven-class solution was determined to best represent the variability in travel behavior within the dataset.

Each class reflects a specific travel profile, characterized by different combinations of transportation modes and frequencies of use, alongside clear socio-demographic distinctions. Below is a detailed description of the seven classes:

- **Strict Car Users (SC)**: This class, comprising individuals who rely almost exclusively on car travel, represents the most car-dependent group. Members of this class make very few, if any, trips using other modes of transport. Socio-demographically, this class is dominated by higher-income individuals and households with multiple cars. Men and people in mid-life stages (30-50 years) are overrepresented. Employment status is another defining characteristic, with employed individuals being the primary members of this class, reflecting a demographic with significant commuting needs, often for work. Unsurprisingly, this cluster shows the highest share of main company car users.
- **Bicycle Users (B)**: The bicycle users class primarily consists of individuals who use bicycles as their main mode of transportation, with little to no reliance on cars or public transport. This group is characterized by younger individuals, particularly those aged 18-35, and includes a higher proportion of women compared to some of the other classes. People in this class tend to have moderate incomes and their mobility choices suggest they live in environments that are fit for bike use. Additionally, students are well-represented in this class, reflecting the suitability of cycling for shorter trips.
- **Car and Bicycle Users (CB)**: This group represents a multimodal travel behavior where individuals frequently use both cars and bicycles depending on trip requirements. This class tends to include older adults (45-60 years), often from suburban or semi-urban areas. Members of this class typically belong to higher-income households, where car ownership is common. We suppose that people belonging to this class have a balance between car and bicycle use based on the distances between their destinations. They might reside in rural areas where cars are necessary for commuting but cycling is practical and enjoyable for more local trips.
- **Low Mobility (LM)**: The low-mobility class consists of individuals who make very few trips overall, regardless of the mode. Socio-demographically, this class includes a large proportion of elderly individuals (65+), retirees, and people with limited incomes. Household size tends to be smaller, often single-person households, and these individuals tend to live in less urbanized regions where accessibility and the necessity to travel are lower. Low mobility could be attributed to age, health constraints, or economic reasons. An alternative explanation for the low mobility within this group could be that the monitored period of three days is atypical days for these travelers, which means that their reported travel does not reflect their underlying behavior. We think this group is most prone to this bias and therefore we should consider the characteristics of this group in a nuanced way.
- **Car and Foot Travelers (CF)**: Individuals in this class combine car use with walking, reflecting a bimodal travel pattern. They tend to drive for longer trips but rely on walking for shorter journeys, such as running errands. Socio-demographically, this class skews towards older adults (50+), who may be semi-retired or employed part-time. The observation that walking is popular and practical implies that they live in places where this is safe, such as urban or suburban areas. Income levels in this class are more moderate compared to the strict car users.

- **Public Transport Users (PT)**: The public transport users class consists primarily of individuals who rely on buses, trains, trams, or metro systems for their daily transportation needs. This group has a significant representation of younger individuals (18-35), students, and individuals with lower incomes. Compared to the sample, we find high levels of being nonmain users of company cars. This is in line with the findings of the sample analysis, therefore we assume this cluster is appealing to some non-main-user company car owners. Public transport users are typically concentrated in urban areas where access to comprehensive transit systems is available. Household composition includes both single-person households and couples, with limited car ownership. These individuals often live in densely populated areas, where owning a car may be unnecessary or financially impractical.
- **Car and Public Transport Users (CPT)**: The car and public transport users are characterized by their multimodal travel pattern, regularly combining car use with public transport. Members of this class are often working professionals, aged 30-50, who live in suburban or peri-urban areas where public transport is accessible but not sufficient for all journeys. Higher-income individuals and households with children are common in this group. These individuals use cars for certain segments of their commute but rely on public transport for the remainder, particularly for trips into city centers where parking may be limited or expensive. This cluster has a relatively high share of nonmain users and a high share of women. This shows similarities to the non-main user subsample, and this leads us to believe that this mobility style is appealing to those people.

6.1.3. The Latent Transition Analysis

Multiple Latent Transition Models have been estimated using LatentGOLD. The 7-state model with covariates could only be estimated using the standard logit parameterization, transition logit leads to convergence problems. This means that only direct effects could be monitored using this model.

The results of this model point out that there is a high probability that travelers remain in their initial clusters, this is in line with general findings of previous mobility studies that proved inertia in travel behavior. The probabilities of sticking with initial cluster membership are highest for the strict car (SC). This is in line with the findings of Heinen (2018) who pointed out that inertia is bigger for car-dependent travel styles. Notably, the low mobility (LM) group has a high probability of remaining in this cluster. This finding challenges the hypothesis of the 'atypical days' bias of this group. In discussing the LCA outcomes, we observed that the low mobility group may include respondents who, by chance, had to report during atypical days, potentially misrepresenting their usual travel behavior. The fact that the probability matrix shows a high probability of staying shows that there is a large share within the LM cluster that shows consistent behavior.

The results of this model also allowed us to gain insights into which covariates are linked to transition probabilities to certain clusters. Those transitioning into the Strict Car (SC) cluster are characterized by individuals who are more likely to be male, employed, and living in households with multiple cars. The number of cars in the household is a particularly strong predictor of membership in this cluster, and while average income is associated with high coefficients for this group, these do not necessarily increase further as income rises. Bike (B) transitioners tend to be younger, particularly those aged 12-17, with lower incomes and lower employment rates. Women and individuals in lower-income households with children or others are also more likely to transition into this cluster, suggesting that younger, less economically advantaged individuals are drawn to bike-oriented travel styles. The Mixed Car and Bike (CB) cluster is more common among older individuals, particularly those aged 60-80, and people who are employed but with incomes ranging from minimum to slightly above average. Household composition also plays a role, with single parents or individuals with others in their household being more likely to adopt this mobility style. The Low Mobility (LM) cluster is associated with higher ages and lower incomes. Interestingly, the coefficients for age are negative until individuals reach the age of 80, indicating that advanced age alone does not necessarily lead to low mobility. The low-income group is a more significant predictor of membership in the low-mobility cluster. Those transitioning into a mixed car and by foot mobility style have a higher chance to do so if they become older. Employment levels are generally lower as people start belonging to the older age segments, therefore it is no surprise that being unemployed increases the chance of transitioning to this cluster. This goes hand in hand with income levels. Intuitively this could be explained by the fact that people have less disposable income available to spend on travel. The Public Transport (PT) cluster has strong positive coefficients for younger age groups and mid-level educational attainment, therefore we think that people who are younger and potentially benefit from free public transport subscriptions while studying have a high probability of transitioning into this style. Higher-income levels also show a positive association with transitioning into this group, suggesting that lower-income individuals may avoid public transport due to high perceived costs. Especially being a younger individual aged below 24 seems to contribute to transitioning into the Mixed Car Public Transport cluster. Even though high incomes and employment status are not intuitively connected to this characteristic, these socio-demographic variables also increase the probability of transitioning into this cluster.

More importantly, the LTA models offered valuable insights into how company car ownership within a household influenced transition probabilities between classes. Both the 7-state model (standard logit) with covariates and the 7-state model (standard logit) including only the company car variable shed light on behavioral changes over time related to company car ownership.

The outcomes of the LTA found that the presence of a company car in a household significantly shifts travel behavior towards car-oriented patterns. This confirms the findings from Frenkel et al. (2014) and Metzler et al. (2019), which highlight that company cars lead to increased car usage and ownership. One of the most prominent findings of this research is that the 7-state model estimated with transition logit parameters yields an insignificant p-value for the Wald statistic of the company car variable. This means that there are no significant effects found that can be generalized to the population and that there is no significant interaction effect in the sample. This means that the general finding that company car ownership shifts travel behavior towards car-oriented patterns is irrespective of initial cluster membership.

In some sense, this research also supports the findings of Faber et al. (2022) that increased car availability reduces the use of more sustainable, multimodal transport options. The observed stability of non-car modes, despite the availability of a company car, further emphasizes the societal need to promote multimodal transportation to mitigate the environmental impact of car-oriented travel behaviors. Additionally, this study found that company cars reduce the likelihood of individuals adopting sustainable transport modes, such as cycling or public transport. This finding aligns with Busch-Geertsema et al. (2021), who highlighted the importance of providing alternative transport options to decrease car dependency, suggesting that company cars may be counterproductive and pull individuals away from multimodal travel behaviors. This also highlights an area for further research where the effectiveness of multiple mode-promoting measures could be benchmarked against each other. The Latent Transition Analysis has proven to be a method fit to capture the dynamics over time caused by exogenous variables. The same dynamics could be assessed for the provision of other transportation means.

The strong tendency of company car (main) users to maintain or transition into strict car-using profiles that are associated with intensive use, as found in our study, supports the findings of Tsairi et al. (2023) and Shiftan et al. (2012), who reported that company car benefits lead to increased vehicle use. Moreover, observations from this research show that both main users of and those living in households with access to company cars exhibit a reduced likelihood of transitioning to bicycle- or public transport-oriented mobility styles resonates with the conclusions drawn by Heinen (2018), who emphasized the inert nature of car-dependent travel behaviors.

The high degree of inertia in travel behaviors observed in our study reinforces the findings of Kroesen and van Cranenburgh (2016), who noted that travel behavior is relatively stable and influenced by significant life events. This study extends this understanding by showing that company car access adds to this inertia, promoting a shift towards more car-centric travel patterns. This finding is also in line with those from Kroesen and Handy (2014), who suggested that changes in travel behavior are more likely when influenced by external factors such as job changes or residential relocations.

This research shows that Haustein and Kroesen (2022) and Kroesen (2014), were right to advocate for the use of panel data to better understand the dynamics of travel behavior over time. While the research provides significant insights, outcomes also highlight the necessity for further research to address limitations related to data sparsity and the need for more comprehensive longitudinal studies. Further echoing the suggestions of Haustein and Kroesen (2022) and Kroesen (2014).

6.1.4. Research limitations

The research offers some relevant outcomes that can have policy implications for both governmental bodies and companies. There are however some limitations to this research that should be mentioned so that readers can formulate opinions and thoughts in a nuanced way.

Sample and dataset

There are various limitations associated with the sample. The most obvious limitation is that almost all of the sample representativeness tests indicate that the results cannot be directly generalized to the population. For most socio-demographic variables, the differences between the sample and population are statistically significant, with only the occupational status being generalizable. Although we recognize the limitations of the Chi-square representativeness test for larger sample sizes and observe many similarities between the sample and population distributions, generalizing the results to the broader population should be approached with caution.

However, the significance of occupational status is particularly important because we assume that the employment distribution within the sample is similar to that of the population, and employment is one of the main drivers of travel behavior. As a result, we believe that the travel behavior observed in the sample can be generalized, even though the distribution of individuals based on other covariates cannot.

On the other hand, one might question whether a fully representative sample is necessary for transition analysis. The measurement model of the LTA is based on the LCA presented in section 4.7. In the LTA, the primary focus is on transitions between the identified clusters, and as long as these transitions remain statistically significant, the outcomes of the LTA are valid for this set of clusters. The main issue with the lack of sample representativeness arises in the LCA model, where it may lead to over- or underestimation of cluster sizes and potentially overlook unobserved behaviors that could alter cluster assignments. However, since the primary objective is to investigate the effect of company car ownership—a variable closely tied to employment status—this limitation is somewhat mitigated. Only individuals who are employed can access a company car, reinforcing the importance of employment as a key variable in this analysis.

Because we cannot generalize the results based on other covariates to the population, any conclusions drawn in this study that relate to these covariates are inherently biased. Although the distribution appears similar to that of the population, it remains statistically significantly different. This is why we only briefly discuss covariates in this research. The sample size and the complexity of the model make it difficult to achieve statistical significance for the covariates, limiting the ability to make strong claims about socio-demographic variables. Consequently, the design of this study does not lend itself well to making definitive statements about covariates or socio-demographic factors.

Another limitation is related to the nature of the travel diary. For the MPN, respondents are asked to keep track of all of their movements during three days, there are three problems with this format. First, when using self-reported data we always run the risk of under-reporting and wrong estimations of distances between locations. Respondents could potentially start under-reporting as they progress through the days of intake or could forget to report trips. A common problem with this means of data collection also is that some trips can be seen as unnecessary to report by the respondent. For example, a small trip to the supermarket nearby may be considered more of a habit than a transportation. Respondents may also think it is too much of an effort to report a rather complex trip, with multiple segments. Therefore, we would expect to see that extremely short trips and more complex trips would suffer from the phenomenon of under-reporting. Considering the operationalization of the indicators in such a way that trip rates have been used to compute mode use frequencies. The risk associated with under-reporting could also lead to active overestimation of respondents in case they choose to only fill in the main mode of transport of a trip to skip the segment reporting. Second, the duration of the travel diary period introduces variability in the data. Respondents only record for three days and are allowed to record their travel behavior during weekends. From the data, it is not clear which days each respondent chooses to track. This lack of consistency means that travel patterns can differ greatly depending on whether someone logs their travel during a workweek or over the weekend. As a result, we may be comparing different types of travel behavior that arise from these 'atypical days'. Finally, the three-day reporting period used by the MPN poses limitations, as such a short timeframe is prone to sudden changes in travel behavior. External factors like sickness or extreme weather could significantly influence travel patterns during these few days, potentially misrepresenting respondents' typical behavior. Additionally, since the MPN has been collecting data in July since 2013, this period coincides with the peak holiday season for many Dutch families. This could further distort mode use and travel distances, introducing seasonal biases into the data. Although a longer observation period would likely offer more stable insights into respondents' underlying travel preferences, it would also increase the risk of under-reporting as participants could become fatigued or less diligent in tracking their movements. Despite previous research emphasizing the inertia of travel behavior, the short and potentially atypical three-day period, influenced by external and seasonal factors, may limit the accuracy and generalizability of the data collected.

Operationalisation of variables

As reflected upon in section 4.5.1, there are some clear disadvantages of using the main modes of transport related to trips to compute the indicator frequencies. This potentially leads to biased results as it automatically penalizes modes such as public transport that have been associated with multimodality in the past. This operationalization likely leads to a structural underreporting of the modes used in the segments between train, bus, or metro stations. This choice is substantiated by the fact that there is a clear advantage to this method, namely that it also allows to include the distances as inactive covariates which eases the interpretability of the latent classes. After reviewing the bivariate residuals of the final LCA model we see a high remaining association between trips by PT and bike. We assume that this effect is observed due to the bias we created by using trip data instead of trip-segment data. However, we still have to acknowledge that by using trip-data instead of trip-segment data the model will always compromise on explanatory power.

The final sample that was used to perform this quantitative research has some drawbacks that became apparent along the way and could have been prevented during data operationalization. The dataset contains a share of respondents (9%) that is aged between 12-17 years old. As the main objective of this research was to investigate the effects of company cars on travel behavior it would have been rational to have removed these individuals from the sample as these respondents are not allowed to drive cars. Now there is a proportion of the sample that cannot be subject to all variable levels of the company car variable as they cannot be main users. Reflecting on this model choice there is a slight nuance that should be made, as respondents are also able to report trips where they are passengers of modes of transport they use. This means that for the respondents aged 12-17, the model is also able to capture their frequencies traveled as passengers. Nonetheless one could question if respondents in this group have a say in mode choice when traveling by car, or that this is predetermined by their guardians. This means that in this specific instance, their mode choices may not be dependent on their own latent preferences for mobility styles but rather on those of their guardians. Previous research of Kroesen (2015) has investigated the influence of partner mode preference mode use, this field of research could potentially be extended to all members within households.

The most significant limitation of this research is the missed opportunity to utilize a delta variable that reflects changes in company car ownership. In the initial stages, wave pairs were selected based on a criterion that prioritized pairs where a change in company car ownership occurred, aiming to create a sample that captured these changes. However, a more detailed analysis revealed that while approximately 869 cases involved some form of company car ownership, only 725 cases indicated an actual change, as shown in table 4.3. The main research question had been scoped in such a way that it suggests that ownership is the most important aspect of behavioral change, this is not true Currently, the analysis only includes static company car ownership variables, meaning the research reflects the effect of having a company car (whether as the main user or not), without specifically linking these findings to ownership changes over time. While the results provide valuable insights into the effects of company car policies in terms of ownership, the absence of a delta variable prevents us from isolating the effects of ownership change over time. A more effective approach would have been to operationalize and use the data in a way that separates the baseline effect of having a company car from the effect of acquiring one, allowing for a clearer understanding of their impacts.

Covariates

There are also some limitations concerning the use of covariates during this research. First, there is a lack of covariates that provide geographical information that might explain away travel behavioral choices that respondents make. For example, respondents in rural areas may well be less attracted to active modes because this is impractical for their lifestyle. Vice versa, the travel behavior of respondents living in highly urban environments may reflect choices that are shaped by their urban environments instead of their underlying mode preferences. A contradicting theory to this argument is the theory of residential self-selection assumes that the effect of the urban environment on travel behavior is explained away by the third variable of mode preference. It supposes that people tend to move to places that fit their mobility needs, which could be translated into an argument that weakens the importance of geographical covariates as predictors for behavior.

Due to the extensive use of covariates, the model encountered estimation issues in Latent GOLD when using transition logits. As a result, we had to perform the estimations using standard logit parameters, which prevented us from assessing any interaction effects between covariates and cluster membership. This is unfortunate, as such effects may well exist in the population. For example, our analysis revealed that men tend to gravitate more toward (exclusive) car-oriented profiles. Additionally, individuals familiar with car travel are more likely to adopt even more car-centric travel styles when reconsidering their options (assuming they do not stick with their choices). Men may be even more inclined than women to transition into these strictly car-oriented profiles after already being part of a car-oriented class. However, because we could only estimate the model using standard logit parameters, we cannot confirm or rule out such interaction effects. Therefore, estimating an LTA model with covariates using transition logit would have been ideal.

Other issues related to the use of covariates arise from their absence in the Latent Transition Analysis model that only included the company car variable. This analysis, on which many conclusions are based, includes only the company car ownership variable and excludes other covariates to improve interpretability. However, it is possible that the effects observed here could be explained away if additional covariates were incorporated into the model. For example, factors like household income, number of household members, or geographic location may have significant effects on travel behavior and car ownership dynamics. We also see that these levels strongly vary based on the investigation of the main user and non-main user samples. Therefore, it would be valuable to investigate how model parameters—particularly transition probabilities—might change with the inclusion of such covariates.

Additionally, some effects currently attributed to the company car variable may stem from an increase in the number of cars in a household, a variable that is likely correlated with company car ownership and could explain away part of the observed effect. Including covariates such as household car ownership, income levels, or employment type could provide a more nuanced understanding of the factors influencing the transitions and help disentangle the specific role of company car ownership in shaping travel behavior. This expanded version emphasizes the need for covariates and introduces specific examples that could influence the model's findings.

Company car variable

There are also some structural limitations to the company car variable and, to some extent, the depth of this research. The research has not focused on the potential observation of a selection effect. The outcomes indicate that company cars lead to higher probabilities of transitioning into a car-oriented mobility style and are associated with additional movements. If we look at the intended purpose of the company car concept, most would conclude it is meant for work-related travel practices, suggesting that individuals who travel extensively for work are more likely to receive company car fringe benefits. This implies that the increased travel or transition probabilities could be more related to the nature of their job rather than their mobility preferences. Coming back to the mobility biographies framework of Müggenburg et al. (2015), this could mean that a change of behavior is not actually one resulting from company cars but one from job change, which coincidentally is accompanied by the offering of a company car. While this research does not directly account for the potential selection effect, a correlation analysis between life events and company car ownership was conducted. The results showed associations between life events such as job changes, starting a business, and residential relocations with company car ownership, however, the effects are extremely weak. Although these events logically align with the acquisition of a company car, the effects were not strong with no correlation coefficients exceeding 0.05. This suggests that the observed behavior change is not merely a result of external life events but rather closely tied to the company car itself. Nonetheless, further research should explore the selection effect in more depth, particularly to determine how other life events may influence access to and use of company cars as we still believe these are inherently connected to each other. In further research, we would propose to investigate even more job-related events such as gaining promotion. The reason for this is that we believe that fringe benefits may be offered to more senior roles within a company, which is supported by the findings that company cars are associated with higher income levels. We also see that company car users are often part of households consisting of couples with kids and others. This relation is also something that could be examined in more detail in future research.

A final limitation of this research is the relatively small number of cases where company car ownership is a share of the total sample. As noted earlier, transition logits provide greater flexibility in capturing behavioral dynamics by allowing us to observe interactions. However, this method also generates a large number of parameters due to the various possible response patterns and the inclusion of multiple covariates and their levels. The combination of company car ownership is a relatively rare event and the high complexity of potential response patterns results in data sparsity, making it challenging to achieve statistically significant results, especially when using transition logit parameterization.

6.2. Conclusion

In the introduction of this research, we explained that the transition toward sustainable mobility is a critical challenge for contemporary societies, as transportation is a significant contributor to greenhouse gas emissions. The fact that in the Netherlands, passenger transport accounts for nearly half of the emissions from the mobility sector underscores the urgent need to create greener transport alternatives and incentivize more sustainable travel behavior.

Despite growing societal awareness of climate issues and the implementation of some effective government policies to reduce emissions, we found that there are still policies in place that have detrimental effects. One key area where this gap has become evident is in the provision of company cars. While these vehicles are intended to serve work-related travel, they are often seen as attractive fringe benefits due to favorable tax treatments, fuel card options, and low marginal costs of use. These policies make company cars highly desirable for employees, leading to increased car use and a reduction in the adoption of more sustainable transportation modes such as public transport or cycling. This creates a misalignment between the policy goals of promoting sustainable mobility and the practical incentives that encourage car ownership and use.

Although various researchers have examined the negative effects of company cars, it remains unclear whether company cars contribute to individuals adopting unsustainable, car-oriented travel patterns and discourage the use of sustainable modes over time. Therefore this research aims to address this knowledge gap by examining how company car policies influence travel behavior, particularly in the context of shifts away from multimodal or sustainable travel practices. Despite substantial evidence linking company cars to higher emissions and increased travel, there has been limited focus on how these vehicles impact individual mobility patterns over time, especially when compared to more environmentally friendly alternatives. By investigating the behavioral shifts associated with gaining access to a company car, this study sheds light on the broader implications of sustainable transportation policies. In this study, the existing travel patterns within the sample were identified through Latent Class Analysis, followed by an assessment of travel behavioral dynamics using Latent Transition Analysis with Latent GOLD.

The main research question of this research is as follows: *In what way does company car availability affect travel behavior of individuals with similar travel patterns over time and what are its implications for designing sustainable transport policies*

To answer the main research question, three sub-questions have been formulated. These will be reflected upon before answering the main research question of this research. The first sub-question is as follows:

1. ***What latent travel patterns can there be identified among individuals in the Netherlands?***

The Dutch mobility panel enabled us to operationalize a dataset to gain a deeper understanding of underlying travel patterns within the Dutch population. Using self-reported frequencies of the respondent mode used from the Dutch Mobility Panel, a Latent Class Analysis has been estimated in Latent GOLD. The trips considered in this research are those by car, public transport, bike, and on foot.

After carefully comparing various LCA models, we found that a 7-class model was the best fit for the objectives of this research. This choice implies that there are seven categorical latent variables in the population from which people can be members. The seven latent travel patterns have been given profile labels based on the associated mobility characteristics. The seven classes ordered in size are as follows: 'Strict car users' ((SC), 'Bike users' (B), 'Mixed car and bike users' (CB), 'Low mobility' (LM), 'Mixed car and on foot travelers' (CF), 'Public transport users' (PT), 'Mixed car and public transport users' (CPT). The indicator levels within the seven classes are visualized in figure 6.1.

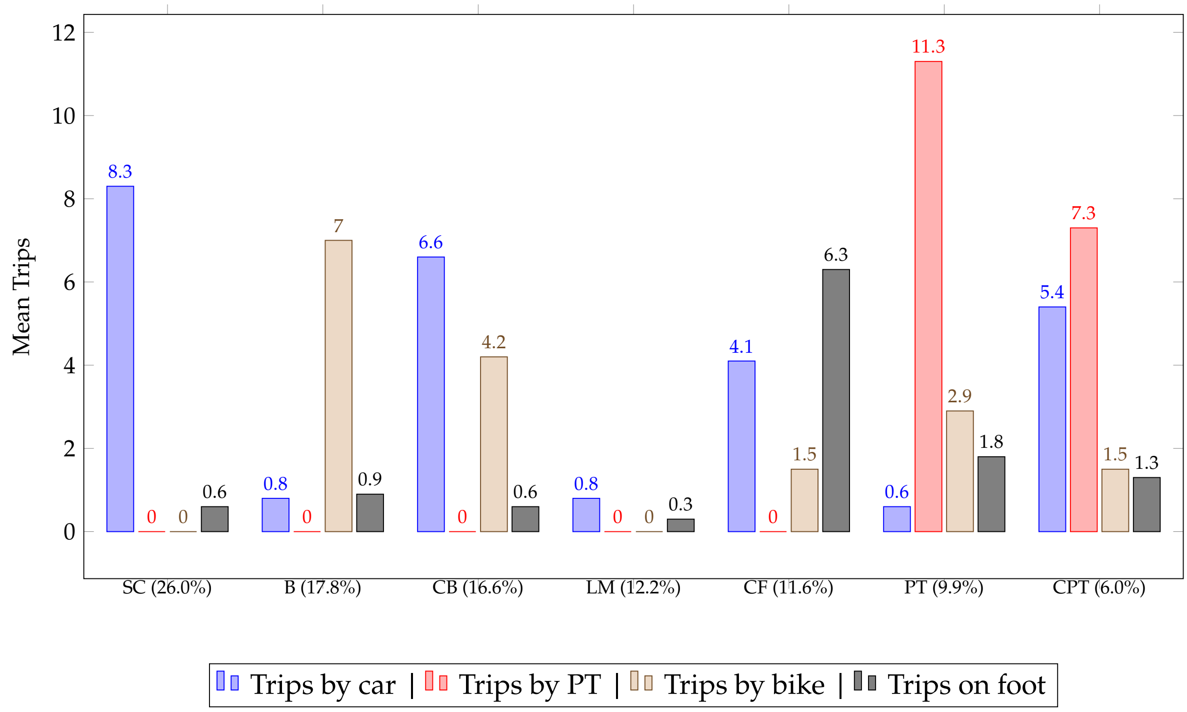

Figure 6.1: Mean trips per mode for each mobility cluster

As shown above, the analysis revealed that individuals can be categorized into seven travel profiles based on their primary modes of transportation, including car, public transport, cycling, and walking. Among these travel patterns, some classes exhibit exclusive reliance on a single mode, such as strict car users, bicycle users, and public transport users. However, the analysis also shows that car use is prevalent across most of the other classes. Whether in mixed-mode profiles or as a supplementary mode of transport, car use appears frequently. In fact, the majority of the population is associated with some level of car use, emphasizing the dominant role of the car in overall mobility patterns.

The initial classification of travel behavior formed the basis for a more dynamic analysis, allowing us to explore how travel patterns change over time. The Latent Transition Analysis (LTA) built upon these findings, offering insights into the factors influencing shifts between mobility profiles, such as the impact of external variables like company car access.

2. ***How does company car access affect household members' travel patterns over time?***

The availability of a company car in a household has notable effects on the travel behavior of its members, even for those who are not the primary users. The analysis shows that access to a company car fosters a shift toward more car-dependent travel patterns. Members of households with a company car are more likely to transition into car-exclusive mobility profiles, particularly those who were previously engaged in mixed-modal travel patterns involving cars.

This shift is reflected in the increased probability of moving from mixed mobility profiles (e.g., car-bike or car-walking combinations) to more car-centric profiles like the strict car profile. The reduction in the inertia of mixed-modal travel behavior suggests that the presence of a company car weakens the stability of more sustainable travel patterns, leading household members to adopt car-exclusive mobility.

Interestingly, this influence does not extend equally across all mobility profiles. For example, individuals in the mixed car-public transport profile have a higher probability of sticking with this mode when they have a company car in their households. Additionally, transition probabilities for exclusive bike and public transport users remain stable, suggesting that those already committed to non-car modes are less influenced by the presence of a company car in their households as long as they are not main users. This finding is notable as it suggests that, for some individuals, the presence of a company car in the household does not necessarily reduce the unimodal use of sustainable transport modes. However, it does impact those who currently use a combination of cars and sustainable modes, potentially steering them towards more exclusive car use. While a company car may not directly detract from sustainable modes, it likely has negative environmental consequences by encouraging a shift toward increased car dependency.

In summary, the presence of a company car within a household generally speaking encourages car-dependent travel behavior, particularly by reducing the stability of mixed-modal profiles and slightly promoting transitions toward exclusive car use. This dynamic highlights the broader implications of company car availability, as it diminishes the likelihood of adopting more sustainable transportation options, reinforcing car dependency within households.

3. ***How does company car access affect main users' travel patterns over time?***

The introduction of a company car for main users significantly amplifies car-oriented travel behaviors, particularly within strictly car-dependent profiles. Main users of company cars are more likely to remain in or transition into, car-intensive travel patterns, reinforcing their reliance on cars. For individuals who are already part of the strict car user profile, the inertia to remain in this group is notably strong. The probability of staying within the strict car-using class increases markedly, signaling that main users tend to deepen their commitment to car use once they gain access to a company car. This shift also extends to those in mixed-mode profiles, such as mixed car-bike or mixed car-walking, where individuals now show a higher likelihood of moving toward more exclusive car use, even if they previously balanced between modes.

What becomes clear is that company car ownership strengthens car dependency across the board, making transitions toward non-car profiles increasingly rare. Even those with more flexible travel patterns, such as those in mixed car-related profiles, are pulled toward stricter car reliance. This suggests that once a company car is introduced, it has a lasting influence on shaping the user's travel preferences, heavily favoring car use and reducing the likelihood of adopting more sustainable multi-modal practices. The convenience, cost advantages, and perceived utility of the company car play a central role in reinforcing these car-oriented behaviors.

A second important finding is that in contrast to non-main users, who largely retain their non-car mobility styles, main users experience more substantial shifts in their travel patterns, particularly those who previously engaged in sustainable, unimodal travel. These profiles, which include exclusive cyclists and public transport users, are notably affected by company car access whereas they are not if they are not main users. The availability of a company car significantly reduces the inertia within these groups, meaning that these unimodal travelers are now much more likely to transition into car-dependent profiles. Where previously there was a high probability of maintaining bicycle or public transport use, the introduction of a company car disrupts this stability, with many individuals now shifting toward car-centric travel.

This effect is particularly pronounced for public transport users, who display a notable reduction in remaining in their initial profile. Instead, they tend to move toward either mixed car-public transport use or entirely car-dependent profiles. Similarly, bicycle users who become main users of company cars show a significant reduction in the probability of staying within their initial profile, as they now face much higher chances of transitioning into car-dominant travel patterns. The pull toward car use is especially evident in these sustainable modes, highlighting how company car availability can undermine long-standing travel behaviors that were previously aligned with sustainability practices.

While the strongest influence is observed in the shift towards car use, other patterns also emerge. For low-mobility users, access to a company car does not necessarily increase travel activity. This group exhibits a high probability of remaining within the low mobility class, suggesting that for some individuals, access to a company car does not lead to increased travel or higher car use. Instead, these individuals continue with limited travel behavior, demonstrating that company car access can have a varied impact depending on the user's existing mobility profile.

Additionally, mixed car and public transport users show a more nuanced response to company car access. Unlike strict public transport users, those in the mixed car-PT profile are more likely to maintain their dual-mode usage, balancing car and public transport use. However, there is still an increased tendency for this group to transition toward stricter car use over time, suggesting that the presence of a company car subtly shifts the balance toward greater car reliance even in multimodal profiles.

In summary, company car access for main users has a dual effect: it strengthens car-oriented travel patterns across various profiles, particularly strict car users, and at the same time, it disrupts the inertia of unimodal travel patterns, detracting even sustainable travelers towards car use. This dynamic highlights the powerful influence that company cars exert on shaping travel behaviors, promoting increased car reliance at the expense of more sustainable modes of transportation.

In what way does company car availability affect the travel behavior of individuals with similar travel patterns over time and what are its implications for designing sustainable transport policies?

Based on the research findings, the availability of company cars significantly affects the travel behavior of individuals with similar travel patterns, leading to critical implications for designing sustainable transport policies which we will come to.

Firstly, this study identified seven distinct travel clusters through Latent Class Analysis (LCA), which reflect diverse mobility styles in the Dutch population, ranging from strict car users, bike users, mixed car and bike users, low mobility respondents, mixed car and by foot travelers, public transport users, and mixed car-public transport travelers. Using Latent Transition Analysis (LTA), we observed how these patterns change over time and how external factors like company car availability influence these shifts.

One of the most striking findings is the impact of company car availability on reinforcing car-oriented travel behavior, particularly for main users. Access to a company car strongly amplifies car use, especially for individuals already inclined toward car-dominant profiles. The likelihood of staying in or transitioning to strict or mixed car-use profiles increases dramatically when individuals become the main users of a company car. This phenomenon is most pronounced among strict car users, but it also affects those with more flexible, mixed-modal travel patterns. The convenience and low marginal costs associated with company cars create a reinforcing loop of car dependency, reducing the likelihood of individuals adopting more sustainable travel behaviors.

In contrast, non-main users, while still influenced by the presence of a company car, exhibit more moderate changes in their travel patterns. Non-main users primarily experience shifts within the mixed car-use categories rather than an exclusive transition to strict car profiles. Their mobility is affected less drastically, but they still show a tendency to reduce their reliance on sustainable travel modes when a company car is introduced into the household. Unlike main users, non-main users retain some inertia within their existing travel patterns, particularly in multimodal profiles that involve combinations of car and public transport or car and walking. This suggests that the influence of company car availability is stronger for those who directly control the vehicle, whereas household members experience more nuanced, secondary effects.

One of the key findings of this research is that no significant interaction effects have been found during the analyses. This means that the effects described above apply to respondents irrespective of their initial travel preferences.

A similarity between main and non-main users is that both groups show a decline in the stability of mixed or multimodal travel profiles when company cars are available. Mixed car-bike and car-walking users are particularly vulnerable to transitioning towards stricter car use, reducing the diversity of transport modes used and thus contributing to increased car dependency over time. However, the main difference lies in the intensity of this shift: main users exhibit a more significant shift towards car-exclusive profiles even from sustainable unimodal practices, while non-main users retain more mixed mobility behavior.

In conclusion, company car availability strongly promotes car-oriented travel patterns, particularly for main users, while also indirectly influencing household members. This dynamic results in a clear reduction in sustainable travel behavior, reinforcing the dominance of the car and discouraging transitions to more environmentally friendly modes of transport. As such, the findings confirm that current company car policies do not align with broader sustainability goals. The discrepancy between policy goals and practice underscores the need for a revision of current policies to mitigate the negative environmental impacts of company cars.

6.3. Policy implications

Addressing this misalignment requires specific policy interventions to reduce the attractiveness of company car benefits. While it would be ideal to eliminate company cars and shift everyone towards using public transport, this is an unrealistic goal in the near term. A more feasible approach would be to make company cars less attractive and simultaneously incentivize the use of alternative, more sustainable transportation modes. This would ensure that only those who truly need a company car for work-related travel can still have access to one. It's easy to make this argument in principle, but the data clearly shows that company cars tend to be larger, more polluting vehicles that also accumulate more kilometers than privately owned cars.

6.3.1. Reformation of policies to reduce vehicle size and emissions

The current tax system, particularly the "bijtelling" (additional taxable income), only requires employees to pay a fraction of the cost of the vehicle if they use the car for personal travel, rather than the full purchase price. This creates a strong incentive for employees to select larger, more luxurious vehicles that emit more CO2. Additionally, the system does not affect the employee's mortgage eligibility, which further increases the appeal of opting for larger vehicles. This incentivizes the use of larger, less efficient cars, with serious environmental consequences.

To address this, policymakers could consider increasing the "bijtelling" rate even more for larger and higher-emission vehicles. This would make larger, polluting vehicles less financially attractive compared to more sustainable alternatives. A progressive tax structure could be introduced, where the cost differential between sustainable vehicles (with lower tax) and polluting vehicles (with higher tax) is significant enough to influence employee choices. This would encourage employees and companies to opt for smaller, more environmentally friendly vehicles.

There is also an ethical responsibility for companies to impose stricter standards on the types of vehicles offered to their employees. Companies should consider enforcing emission caps or fleet-wide average emissions targets. Such policies would push companies to offer cleaner vehicles and ensure that, where cars are necessary, they are as sustainable as possible. Companies could also be encouraged to promote electric or hybrid vehicles by making these the default options in their fleets.

6.3.2. Addressing excessive private use and kilometers driven

One of the key findings from the research is that company cars tend to be associated with higher usage, particularly in terms of kilometers driven. This is likely due to untaxed fuel cards, which reduce the cost of driving and lead to more private travel. Currently, fuel costs for company cars are not taxed, allowing employees to increase their disposable income as they don't have to cover fuel expenses.

To curb excessive private use, the government could implement a tax on fuel provided by employers for private use. This would make it less attractive for employees to drive long distances for non-work-related purposes. Another solution could be to tax private kilometers driven by company cars, which would create an incentive for both companies and employees to reduce unnecessary personal use. This could be easily enforced through mandatory mileage tracking systems, where employers and employees record the purpose of each journey.

Moreover, companies should consider eliminating or reducing the provision of fuel cards for private use altogether. This would encourage employees to be more mindful of their driving habits, as the financial burden of private fuel costs would shift to them. Employers could also impose limits on private kilometers or reimburse employees for business-only travel, creating further disincentives for excessive private driving.

6.3.3. Shared company car solutions

From a corporate responsibility perspective, companies could reduce the environmental impact of company cars by offering shared vehicles for work-related purposes. Instead of providing each employee with a private car, a pool of shared company vehicles could be made available, limiting personal use and reducing the overall number of vehicles required. This would not only cut down on private mileage but also reduce the need to produce as many company cars, which ultimately lowers emissions associated with manufacturing and ownership.

Shared vehicle systems could be implemented within companies to encourage car-sharing between employees, particularly for work-related trips. Incentivizing ride-sharing among employees could also be a cost-effective and environmentally friendly way to address the need for company vehicles without the drawbacks of individual car ownership.

6.3.4. A growth in alternative sustainable transport modes

While limiting the attractiveness of company cars is essential, it's even more important to create an environment where other transportation modes are more appealing. The research clearly shows that people tend to stick to car-oriented travel patterns once they become accustomed to car use, making it difficult for them to switch to more sustainable modes later on. This makes it necessary to design policies that actively encourage alternative travel options.

The Dutch government has already implemented programs like the National Bicycle Plan, which offers financial incentives for employees to commute by bike. Expanding such initiatives and increasing the subsidies for e-bikes, especially for long-distance commuters, could further drive the shift away from car use. For commuters who travel longer distances, there should be more comprehensive policy tools that make public transport more affordable and accessible.

A key policy suggestion would be for the government to partner with companies to offer free or heavily discounted public transport passes to employees. By making public transportation a financially viable option, employees may reconsider the need for a company car. Additionally, companies could offer relocation assistance to employees who move closer to their workplace, reducing the overall distance employees need to commute, and thus the reliance on cars.

6.3.5. Responsibilities and ethical remarks

Beyond government intervention, companies themselves play a crucial role in shaping travel behaviors. Ethical responsibility lies with businesses to consider the long-term environmental impacts of their policies. One potential solution would be to implement internal company policies that prioritize sustainability in mobility. For example, companies could set internal goals to reduce fleet emissions by a certain percentage over the next decade or to encourage employees to use public transport where possible.

Additionally, companies could be required to provide clear justifications for offering company cars, ensuring that vehicles are only provided when necessary for work-related purposes. This would help limit the number of cars on the road and focus car use on those who genuinely need it for their job.

6.3.6. Concluding remarks

In summary, policy measures can serve as powerful levers to influence travel behavior. While current company car policies inadvertently encourage car use and hinder environmental sustainability efforts, there are clear paths to reform. Government intervention—through higher taxes on polluting vehicles, fuel taxation, and incentives for alternative modes—coupled with corporate responsibility to offer sustainable options and limit unnecessary car use, will be key in reducing the negative impact of company cars on both travel behavior and the environment. By reshaping company car policies and promoting alternatives, it is possible to move toward a more sustainable, less car-dependent future.

6.4. Areas for future research

Various areas lend themselves to be explored in future research. The recommendations for further research are given below.

6.4.1. Alternative policy effectiveness

Policy-wise, future research could focus on the effectiveness of alternative fringe benefits. To better understand which policies will be most effective in changing employee travel behavior, stated choice experiments could be conducted to assess the perceived attractiveness of various policy instruments. Such research would allow policymakers to develop targeted, data-driven solutions that align with employees' preferences and help shift behavior toward more sustainable modes of transport.

6.4.2. Investigation into the low mobility group

The research uncovered a peculiar increase in the attractiveness of the low mobility class for individuals who are not familiar with car travel but become main users of company cars. This finding suggests a complex interaction between car access and travel behavior that justifies further investigation. Future studies should delve deeper into the low mobility group to understand the underlying factors driving this behavior. The causes behind these observations remain unknown and are not so easily substantiated. Therefore additional research would prove valuable to gain deeper insights into the peculiar behavior of these individuals. This further research could include a qualitative research component that explores personal attitudes, lifestyle changes, and external influences that might contribute to low mobility despite having access to a company car.

6.4.3. Additional Analysis Using Latent Transition Analysis

Various areas within the company car scope are suitable for further research. As reflected upon, a big limitation of this research is that only the baseline variable level of company car ownership has been assessed. A future study should focus on the effect of the inclusion of a delta variable that monitors the change in ownership to see the individual effects of both variables.

The current study faced limitations due to the sparsity of data when using latent transition analysis (LTA). The method has been proven fit to assess these types of issues but it does not reach its full potential due to minimal data on company car ownership. Luckily the MPN keeps collecting data on Dutch respondents, hence the recommendation for future research is to aim at overcoming previous limitations by revisiting this subject using more waves of the MPN. The matter could be solved more quickly by employing additional data collection methods. A more extensive dataset would provide more robust insights into the dynamics of travel behavior changes over time and would allow for better examination of possible interaction effects. Enhancing the statistical power of LTA models will help in better understanding the transition probabilities and the long-term effects of company car availability on travel patterns.

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A

Sample representativeness testing

This appendix contains the representativeness tests for covariates. As result of the use of a pooled sample, the expected count values have been computed proportionally to the population means of the years 2013-2018.

A.1. Gender

The respresentativeness of the sample based on gender can be assessed in multiple ways as we are dealing with a pooled sample. These methods will be discussed in this section. Using the yearly data from Centraal Bureau voor de Statistiek (2023) and from table 4.5 the expected values could be computed. This leads to the following Chi-square values for assessing the representativeness per year.

Year	O_i **Male**	O_i **Female**	E_i **Male**	E_i **Female**	χ^2	p-value	df
2013	532	611	565.88	577.12	4.018	0.0450	1
2014	614	707	654.20	666.80	4.894	0.0270	1
2015	360	392	372.55	379.45	0.838	0.3600	1
2016	390	478	430.30	437.70	7.484	0.0062	1
2017	788	951	862.82	876.18	12.876	0.0003	1
2018	1106	1254	1171.28	1188.72	7.223	0.0072	1

Table A.1: Chi-Square Tests for gender (per year)

Regarding the representativeness per year, this table shows that only the p-value of respondents starting in 2015 exceeds the 5% confidence level. This means that for the years 2013, 2014, 2016, 2017 and 2018 there are significant differences between the observed and expected frequencies, this indicates a lack of representativeness in most of the individual years.

Gender	O_i	E_i	χ^2	p-value	df
Male	3790	4057.03	34.86	<0.0001	1
Female	4393	4125.97			

Table A.2: Chi-Square Test for gender

Therefore it is not suprising to see that the sample Chi-square value also lead to a highly significant p-value, indicating there is a difference between the observed and expected values. This shows that the sample lacks representativeness based on gender.

A.2. Age

The table below shows that the p-value that corresponds with the observed and expected counts of the age categories is highly significant. Therefore we conclude that the sample statistically differs from the population. The expected values have been computed according to data from CBS (2022).

Age	O_i	E_i	χ^2	p-value	df
12-17	713	665.61	264.37	<0.0001	8
18-24	732	809.72			
25-29	551	587.37			
30-39	1335	1121.96			
40-49	1298	1322.48			
50-59	1507	1337.70			
60-69	1153	1195.77			
70-79	748	714.35			
80+	146	428.04			

Table A.3: Chi-Square Test for age

A.3. Educational level

Using data from the CBS, the expected values of the educational levels could be computed (Centraal Bureau voor de Statistiek, 2019, 2022). These have been compared with the sample distribution using the Chi-square test and this leads to a highly significant p-value. This means that the observed sample is statistically significant from the expected values meaning that the results of cannot be generalized to the population based on this covariate.

Educational Level	O_i	E_i	χ^2	p-value	df
Low	2663	2416.53	40.9402	<0.0001	3
Mid	2949	3170.35			
High	2458	2478.55			
Unknown	113	117.57			

Table A.4: Chi-Square Test for educational Level

A.4. Occupational status

Using data from CBS we were able to compute the expected values of occupational status of the sample. As there is no data available that matches the operationalised variable of occupational status, this had to be reconstructed. The CBS defines the dutch active workforce to be aged between 15-75. The expected values are corrected for this by assuming respondents are evenly spread around their age level. In addition to this, the respondents that do not fall within these age category are therefore assumed to not be employed. This allows us to define the proportion of active labor workforce in the sample to be matched to the data of the CBS (Centraal Bureau voor de Statistiek, 2024e). The active net labor participation of the third quarters have been used as starting points as the MPN collects its data in July (Ministerie van Infrastructuur en Waterstaat, 2022). This leads to the following Chi-square values.

Occupational status	O_i	E_i	χ^2	p-value	df
No job	4925	4848.40	3.04	0.218	2
Employed	3022	3097.30			
Unknown	236	237.31			

Table A.5: Chi-Square Test for occupational Status

The chi-square value has a p-value of 0.218, this means that the sample does not differ significantly from the population. Hence we conclude that the sample is representative for the population for the variable occupational status.

A.5. Income

Using data from the Centraal Bureau voor de Statistiek (2024c) the expected values for income levels have been reconstructed. The MPN dataset only ask respondents to report their income into categorical levels. Therefore we assumed respondents to be distributed evenly over these groups allowing to use income data from the years 2013-2018 to compute the expected values (Centraal Bureau voor de Statistiek, 2024c).

Income	O_i	E_i	χ^2	p-value	df
Minimum	313	1677.13	4106.49	<0.0001	5
Below average	1189	2097.75			
Average	1624	1355.00			
1-2 times average	2378	1007.58			
2 times average	599	237.80			
> 2 times average	812	539.74			

Table A.6: Chi-Square Test for income

The Chi-square vlaue for income is extremely high, leading to a low p-value. This indicates that the observed values differ significantly from the population. This shows a lack of representativeness in the sample regarding this covariate.

A.6. Household composition

The Central Bureau of Statistics (CBS) tracks household composition in the Netherlands. However, the specific categories used in the Dutch Mobility Panel dataset differ from those employed by the CBS, making it difficult to perform a valid comparison using Chi-square tests to assess sample representativeness (Centraal Bureau voor de Statistiek, 2024b). As a result, the sample representativeness test for this covariate has been excluded from the analysis.

B
Correlation analysis

This appendix contains more detailed output of the correlation analysis of company car variables with other life events. The MPN questionaire contains various questions that asks respondents if change occured in their lives during the past year. The events that are included in the analysis are the following:

Job-Related Events

- **Event 1**: I have obtained a new/another job
- **Event 2**: I have started working
- **Event 3**: I have stopped working (e.g., due to dismissal, retirement, or disability)
- **Event 4**: I have reduced my working hours
- **Event 5**: I have started my own business

Household-Related Events

- **Event 6**: A child has been born into my household
- **Event 7**: I have divorced or broken up my relationship
- **Event 8**: I have moved or moved into student housing

B.1. Correlations with the company car ownership variable

For the company car ownership variable, correlation test have been performed in SPSS. Cross tables have been computed and the association between the variables in question have been tested using the Pearson Chi-Square statistic. Company car ownership is operationalised as a nominal variable with three-levels, therefore the Cramer's V is used as statistic to gain insight into the strength of statistically significant associations (Prematunga, 2012). The cross-tables are not presented in this case because the results show that none of the statistically significant associations between variables have a correlation coefficient that is higher than 0.05. This loading is very low, therefore additional insight into the cross tables seems unnecessary.

	Value	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	16.159	< 0.001
	Value	**Approximate Significance**
Cramer's V	0.046	<0.001
N of valid cases	7501	

Table B.1: Event 1: Association statistics of CC ownership with life events

	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square*	13.487	0.001
	Value	**Approximate Significance**
Cramer's V	0.042	0.001
N of valid cases	7501	

*Two cells (33%) have expected count less than 5.

Table B.2: Event 2: Association statistics of CC ownership with life events

	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square	4.181	0.124
	Value	**Approximate Significance**
Cramer's V	0.024	0.124
N of valid cases	7501	

Table B.3: Event 3: Association statistics of CC ownership with life events

	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square	0.067	0.967
	Value	**Approximate Significance**
Cramer's V	0.003	0.967
N of valid cases	7501	

Table B.4: Event 4: Association statistics of CC ownership with life events

	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square	8.317	0.016
	Value	**Approximate Significance**
Cramer's V	0.033	0.016
N of valid cases	7501	

Table B.5: Event 5: Association statistics of CC ownership with life events

	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square*	1.326	0.515
	Value	**Approximate Significance**
Cramer's V	0.013	0.515
N of valid cases	7501	

*Two cells (33%) have expected count less than 5.

Table B.6: Event 6: Association statistics of CC ownership with life events

	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square	2.09	0.352
	Value	**Approximate Significance**
Cramer's V	0.017	0.352
N of valid cases	7501	

Table B.7: Event 7: Association statistics of CC ownership with life events

	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square*	7.109	0.029
	Value	**Approximate Significance**
Cramer's V	0.031	0.029
N of valid cases	7501	

*Two cells (33%) have expected count less than 5.

Table B.8: Event 8: Association statistics of CC ownership with life events

B.2. Correlations with change in company car ownership variable

Change in company car ownership is operationalised as a nominal variable with two-levels, therefore the Phi is used as statistic to gain insight into the strength of statistically significant associations (Prematunga, 2012). From the analysis we see that there only is a statistically significant association between event 1, 5, and 8. The Phi coefficients of the respective events are 0.069, 0.037m and 0.047. These numbers show that the associations between the variables are quite low.

	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square	35.49	< 0.001
	Value	**Approximate Significance**
Phi	0.069	<0.001
N of valid cases	7501	

Table B.9: Event 1: Association statistics of change in CC ownership with life events

Categorie	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square	2.297	0.13
Categorie	**Value**	**Approximate Significance**
Phi	0.017	0.13
N of valid cases	7501	

Table B.10: Event 2: Association statistics of change in CC ownership with life events

Categorie	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square	3.271	0.071
Categorie	**Value**	**Approximate Significance**
Phi	0.021	0.071
N of valid cases	7501	

Table B.11: Event 3: Association statistics of change in CC ownership with life events

Categorie	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square	0.001	0.975
Categorie	**Value**	**Approximate Significance**
Phi	0	0.975
N of valid cases	7501	

Table B.12: Event 4: Association statistics of change in CC ownership with life events

Categorie	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square	10.518	0.001
Categorie	**Value**	**Approximate Significance**
Phi	0.037	0.001
N of valid cases	7501	

Table B.13: Event 5: Association statistics of change in CC ownership with life events

Categorie	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square	0.002	0.961
Categorie	**Value**	**Approximate Significance**
Phi	0.001	0.961
N of valid cases	7501	

Table B.14: Event 6: Association statistics of change in CC ownership with life events

Categorie	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square	1.004	0.307
Categorie	**Value**	**Approximate Significance**
Phi	0.012	0.307
N of valid cases	7501	

Table B.15: Event 7: Association statistics of change in CC ownership with life events

Categorie	Value	Asymptotic Significance (2-sided)
Pearson Chi-Square	16.639	<0.001
Categorie	**Value**	**Approximate Significance**
Phi	0.047	<0.001
N of valid cases	7501	

Table B.16: Event 8: Association statistics of change in CC ownership with life events

C

Initial Latent Class Models

This appendix will provide a more detailed overview of the Latent Class Models considered for the measurement model. It includes the estimations output of LatentGOLD and short description of the classes within the model. Additionally, the bivariate residuals will be discussed to see if and where association between indicators remains in models.

C.1. Model estimations

All of the Latent Class Model estimations have been performed in LatentGOLD. The indicators discussed in section 4.5.1 have been included into the model as count variables. There were no additional variables used to estimate the model. The starting values of random sets have been set to 100. The other settings of the model have been set to their default values.

C.1.1. 5-Class Latent Class Model

The profile output of the 5-class model is as follows:

		1	2	3	4	5	Sample
Cluster Size (%) N=8183		30.1	26.5	15.7	14.8	12.9	
Indicators							
Trips by car	Mean	8.9	2.2	2.4	1.4	4.2	4.4
Trips by PT	Mean	0.0	0.0	9.7	0.0	0.0	1.5
Trips by bike	Mean	0.6	6.5	2.4	0.0	1.8	2.5
Trips on foot	Mean	0.6	0.7	1.6	0.3	6.1	1.5

Table C.1: Output of the 5-class LCA model

Within this model we can distinguish 5 types of travellers.

- Cluster 1: Strict car users
- Cluster 2: Mixed car and bike users
- Cluster 3: Public transport users
- Cluster 4: Low mobility
- Cluster 5: Mixed car and foot travellers

The bivariate residuals of this model are shown in table C.2.

Indicators	Trips by car	Trips by PT	Trips by bike	Trips on foot
Trips by car	.			
Trips by PT	67.4	.		
Trips by bike	1.1	68.5	.	
Trips on foot	0.0	0.5	25.6	.

Table C.2: Bivariate Residuals of the 5-class LCA model

The BVRs of this model show that there remains some association between some indicators. Usually this implies that additional classes should be added into the model to explain away these effects, as the value of the BVRs ideally is below 3.84 (Vermunt & Magidson, 2013). In this case, however we already know from table 4.9 that the total BVRs in the model does not decline in the 6- and 7-class model. On the other hand this does not necesarrily mean that this model has the best fit for this research. This table shows that the remaining association between indicators is distributed over various indicators.

C.1.2. Output of the 6-class LCA model

The profile output of the 6-class model is as follows:

		1	2	3	4	5	6	Sample
Cluster Size (%) N=8183		26.0	17.6	16.9	15.7	12.0	11.8	
Indicators								
Trips by car	Mean	8.3	0.8	6.6	2.4	0.8	4.1	4.4
Trips by PT	Mean	0.0	0.0	0.0	9.7	0.0	0.0	1.5
Trips by bike	Mean	0.0	7.0	4.2	2.3	0.0	1.5	2.5
Trips on foot	Mean	0.6	0.9	0.6	1.6	0.3	6.3	1.5

Table C.3: Output of the 6-class LCA model output

Within this model we can distinguish 6 types of travellers.

- Cluster 1: Strict car users
- Cluster 2: Bike users
- Cluster 3: Mixed car and bike users
- Cluster 4: Public transport users
- Cluster 5: Low mobility
- Cluster 6: Mixed car and foot travellers

The main observation from the 6-class model, is that it introduces a new cluster of (strict) bike users compared to the 5-class model.

The bivariate residuals of this model are shown in table C.4.

Indicators	Trips by car	Trips by PT	Trips by bike	Trips on foot
Trips by car	.			
Trips by PT	74.7	.		
Trips by bike	3.4	67.7	.	
Trips on foot	10.1	0.4	29.7	.

Table C.4: Bivariate Residuals of the 6-class LCA model

The table above shows that the BVRs of the 6-class model are distributed over the indicator pairs in the same way. Notably the values have increased compared to the 5-class model. This means that the association between the indicators is higher in this model. This means that for assessing the fit of this model, a trade-off needs to be made between the increase in association between indicators and improved interpretability.

C.1.3. 7-Class Latent Class Model

The profile output of the 7-class model is as follows:

		1	2	3	4	5	6	7	Overall
Cluster Size (%) N=8183		26.0	17.6	16.8	12.0	11.8	9.5	6.4	
Indicators									
Trips by car	Mean	8.3	0.8	6.6	0.8	4.1	0.6	5.4	4.4
Trips by PT	Mean	0.0	0.0	0.0	0.0	0.0	11.3	7.3	1.5
Trips by bike	Mean	0.0	7.0	4.2	0.0	1.5	2.9	1.5	2.5
Trips on foot	Mean	0.6	0.9	0.6	0.3	6.3	1.8	1.3	1.5

Note: some values may not add up to 100% due to rounding.

Table C.5: Output of the 7-class LCA model

Within this model we can distinguish 7 types of travellers.

- Cluster 1: Strict car users
- Cluster 2: Bike users
- Cluster 3: Mixed car and bike users
- Cluster 4: Low mobility
- Cluster 5: Mixed car and foot travellers
- Cluster 6: Public transport users
- Cluster 7: Mixed car and PT users

By adding an additional class to the previous model, the 'Public transport user' cluster of the 6-class model splits into a more intensive public transport user, which reports higher use frequencies, and a mixed car and PT user.

The bivariate residuals of this model are shown in table C.6.

Indicators	Trips by car	Trips by PT	Trips by bike	Trips on foot
Trips by car	.			
Trips by PT	7.0	.		
Trips by bike	5.3	141.5	.	
Trips on foot	25.4	5.9	21.8	.

Table C.6: Bivariate Residuals of the 7-class LCA model

From the above we can conclude that by introducing the 7th class to the model, the BVRs have centred more around the PT and Bike indicators. This might be explained by the fact that trip-data was used to construct the model. Public transport travel is often associated with a degree of multimodality, as those users tend to travel to the station on foot or by bike. As only the main use of transport is used to report how trips have been made, this could be the explanation for the remaining residual between the indicators.

D

Complete 7-Cluster LCA results

This appendix gives a detailed overview of the 7-Cluster LCA model output.

D.1. Model statistics

Chi-squared Statistics		
Degrees of freedom (df)	7887.0	**p-value**
L-squared (L^2)	110935.1	0.00
X-squaews (χ^2)	3.4E+24	0.00
Cressie-Read	4.1E+16	0.00
BIC (based on L^2)	39942.5	
AIC (based on L^2)	95161.1	
AIC3 (based on L^2)	87274.1	
CAIC (based on L^2)	32055.5	
SABIC (based on L^2)	65005.8	
Dissimilarity Index	0.98	
Total BVR	1185.6	
Log-likelihood Statistics		
Log-likelihood (LL)	-60434.1	
Log-prior	-10.7	
Log-posterior	-60444.9	
BIC (based on LL)	122902.6	
AIC (based on LL)	121320.3	
AIC3 (based on LL)	121546.3	
CAIC (based on LL)	123128.6	
SABIC (based on LL)	122184.4	
Classification Statistics		
Classification errors	0.07	
Reduction of errors (Lambda)	0.91	
Entropy R-squared	0.91	
Standard R-squared	0.88	
Classification log-likelihood	-61856.1	
Entropy	1422.0	
CLC	123712.2	
AWE	128458.8	
ICL-BIC	125746.5	

Table D.1: Model statistics of the 7-class LCA model

D.2. Profile output

		1	2	3	4	5	6	7	Overall
Profile label		SC	B	CB	LM	CF	PT	CPT	
Cluster size (%) N=8113		26.0	17.8	16.6	12.2	11.6	9.9	6.0	
Indicators									
Trips by car	Mean	8.3	0.8	6.7	0.9	4.0	0.7	5.4	4.4
Trips by PT	Mean	0.0	0.0	0.0	0.0	0.0	11.0	7.3	1.5
Trips by bike	Mean	0.0	7.0	4.2	0.0	1.6	3.1	1.0	2.5
Trips on foot	Mean	0.6	0.9	0.6	0.3	6.4	1.8	1.3	1.5
Inactive covariates									
Distance by car (km)	Mean	144.0	16.4	106.9	21.1	66.2	15.8	92.2	75.4
Distance by PT (km)	Mean	0.1	0.0	0.2	0.0	0.3	457.0	305.0	63.5
Distance by bike (km)	Mean	0.0	25.0	12.3	0.3	5.0	10.5	4.1	8.4
Distance on foot (km)	Mean	0.8	1.3	1.0	0.4	7.3	3.2	2.0	1.9
Active covariates									
Gender (%)	Male	52	43	45	48	41	46	41	46
	Female	48	57	55	52	59	54	59	54
Age (%)	12-17	1	28	7	4	2	13	8	9
	18-24	5	8	4	9	3	29	18	9
	25-29	8	5	6	6	5	11	9	7
	30-39	21	11	16	16	18	14	16	16
	40-49	20	13	18	16	15	8	12	16
	50-59	22	14	21	20	18	11	15	18
	60-69	13	13	16	15	22	8	12	14
	70-79	8	7	11	10	15	6	8	9
	80+	2	1	1	3	3	1	1	2
Educational level (%)	Low	23	46	30	42	33	32	24	33
	Mid	43	28	36	37	37	30	35	36
	High	33	25	34	17	29	36	40	30
	Unknown	1	1	1	3	1	2	0	1
Occupational status (%)	No job	24	50	32	43	41	43	37	37
	Employed	74	46	67	52	54	53	63	60
	Unknown	2	4	2	5	4	4	0	3
No. of cars in household (#)	Mean	1.58	1.06	1.44	1.17	1.17	0.79	1.39	1.28
Income (%)	Minimum	2	5	1	4	3	11	4	4
	Below average	12	15	12	22	17	15	12	15
	Average	21	20	20	18	24	20	15	20
	1-2 times average	32	30	30	25	29	27	30	29
	2 times average	9	7	10	5	5	6	9	7
	> 2 times average	11	10	12	6	7	10	17	10
	Unknown	14	14	15	20	15	11	13	15
Household composition (%)	Single	18	17	14	17	22	34	23	19
	Couple	32	23	34	32	37	18	24	29
	Couple w/ kids and/or others	44	50	46	41	35	39	47	44
	Single parent with kids (and others)	6	9	6	8	5	8	6	7
	Other	1	1	0	2	1	1	0	1
Year of participation (%)	2013	16	12	15	12	13	15	15	14
	2014	16	17	17	12	14	17	20	16
	2015	10	10	9	8	8	10	10	9
	2016	11	9	10	8	10	11	12	10
	2017	22	20	23	20	25	21	16	21
	2018	25	32	27	40	29	27	27	29
Company car (%)	No company car in household	86	91	88	91	93	91	87	89
	CC in household not main user	7	8	7	5	4	9	10	7
	CC in household and main user	6	1	4	4	3	0	4	4

Note: some values may not add up to 100% due to rounding.

Table D.2: Profile output of the 7-class LCA-model with covariates

D.3. Parameter output

Table D.3 shows the parameter output of the 7-class model with covariates. This provides insight in the significance of the model estimations.

N=8113	1	2	3	4	5	6	7	Wald	p-value
Profile label	SC	B	CB	LM	CF	PT	CPT		
Indicators									
Trips by car	1.2	-1.14	0.97	-1.03	0.46	-1.22	0.76	5783.89	0.00
Trips by PT	-2.25	-3.03	-2.28	-4.33	-0.67	6.49	6.07	843.88	0.00
Trips by bike	-5.22	2.51	2	-2.57	1.02	1.7	0.57	3121.23	0.00
Trips on foot	-0.54	-0.17	-0.55	-1.3	1.8	0.54	0.23	10637.96	0.00
Intercepts	**Overall**								
Trips by car	0.92							2529.15	0.00
Trips by PT	-4.09							81.66	0.00
Trips by bike	-0.56							23.61	0.00
Trips on foot	0.06							10.62	0.00
Model for clusters									
Intercepts	0.09	1.2	-0.07	0.91	0.15	1.28	-3.55	48.55	0.00
Covariates									
Gender									
Male	0.13	-0.06	-0.05	0.09	-0.08	0.07	-0.11	50.06	0.00
Female	-0.13	0.06	0.05	-0.09	0.08	-0.07	0.11		
Age									
12-17	-2.12	1.74	0.3	-0.82	-1.13	1.38	0.66	930.98	0.00
18-24	-0.55	0.08	-0.85	-0.17	-0.9	1.67	0.72		
25-29	0.24	-0.27	-0.21	0.08	-0.14	0.32	-0.01		
30-39	0.47	-0.4	-0.09	0.27	0.28	-0.27	-0.26		
40-49	0.51	-0.06	0.13	0.23	0.18	-0.51	-0.48		
50-59	0.25	-0.08	0.04	0.23	0.19	-0.31	-0.32		
60-69	0.18	-0.03	0.21	-0.11	0.49	-0.58	-0.16		
70-79	0.25	-0.31	0.32	-0.21	0.43	-0.53	0.04		
80+	0.76	-0.66	0.14	0.49	0.62	-1.16	-0.19		
Educational level									
Low	-0.34	-0.08	-0.17	0.01	0.04	-0.22	0.75	121.49	0.00
Mid	-0.28	-0.05	-0.12	-0.36	-0.06	-0.23	1.09		
High	-0.47	0.07	-0.12	-0.86	-0.12	0.17	1.34		
Unknown	1.09	0.05	0.42	1.2	0.14	0.28	-3.18		
Occupational status									
No job	-0.08	-0.09	-0.06	0.17	-0.12	-0.21	0.39	69.82	0.00
Employed	0.24	-0.19	0.25	-0.2	-0.32	-0.28	0.52		
Unknown	-0.16	0.28	-0.19	0.04	0.44	0.5	-0.91		
No. of cars in household	0.9	-0.62	0.51	0	0.14	-1.22	0.3	618.5	0.00
Income									
Minimum	-0.14	0.31	-0.52	0.3	0.15	-0.13	0.03	128.82	0.00
Below average	0.08	-0.05	0.05	0.39	0.05	-0.26	-0.25		
Average	0.11	0.04	0.1	-0.14	0.1	0.09	-0.29		
1-2 times average	0.04	-0.03	0.01	-0.17	0.02	0.1	0.03		
2 times average	0.07	-0.15	0.26	-0.26	-0.2	0.1	0.18		
> 2 times average	-0.19	-0.02	-0.01	-0.43	-0.26	0.47	0.43		
Unknown	0.03	-0.1	0.1	0.32	0.14	-0.37	-0.13		
Household composition									
Single	-0.06	-0.44	-0.35	-0.62	-0.26	0.15	1.57	121.32	0.00
Couple	-0.19	-0.18	-0.03	-0.31	-0.19	-0.25	1.16		
Couple w/ kids and/or others	-0.57	0.07	-0.22	-0.2	-0.12	-0.03	1.07		
Single parent with kids (and others)	-0.05	-0.36	-0.1	-0.27	-0.25	-0.29	1.32		
Other	0.88	0.91	0.69	1.4	0.81	0.43	-5.12		
Year of participation									
2013	0.06	-0.06	0.04	-0.09	-0.02	0.05	0.03	77.93	0.00
2014	0.01	0.01	0.06	-0.17	-0.07	-0.01	0.17		
2015	-0.02	0.09	-0.12	0	-0.07	0.12	0.01		
2016	0.13	-0.09	0.11	-0.11	0.04	-0.2	0.12		
2017	0.05	-0.03	0.06	0.02	0.14	0.01	-0.26		
2018	-0.22	0.08	-0.14	0.35	-0.02	0.03	-0.07		
Company car									
No company car in household	-0.08	0.23	-0.02	-0.19	0.06	0.06	-0.07	48.53	0.00
CC in household not main user	-0.2	0.4	-0.18	-0.35	-0.39	0.77	-0.04		
CC in household and main user	0.28	-0.63	0.2	0.55	0.33	-0.83	0.11		
No. of cars in household									
	0.90	-0.62	0.51	0.00	0.14	-1.22	0.30	618.50	0.00

Table D.3: Parameter output of the 7-class LCA model with covariates

D.4. Bivariate residuals

	Trips by car	Trips by PT	Trips by bike	Trips on foot
Indicators				
Trips by car	.			
Trips by PT	2.4	.		
Trips by bike	13.9	160.4	.	
Trips on foot	27.6	2.2	18.8	.
Covariates				
Gender	19.1	12.3	64.6	57.9
Age	39.6	4.6	9.7	58.2
Educational level	69.6	6.1	17.2	21.5
Occupational status	38.6	19.3	7.7	1.2
Income	10.3	7.5	11.0	13.3
Household composition	8.4	2.1	15.4	69.2
Year of participation	11.3	0.7	8.2	4.7
Company car	30.3	0.2	2.8	11.3
No. of cars in household	21.1	1.2	65.7	218.5

Table D.4: Bivariate residuals of the 7-class LCA model with covariates

E

Latent Transition Models

This appendix provides more detailed output of the estimated Latent Transition Models used in this research.

E.1. 7-State Model with covariates (standardlogit)

E.1.1. Model statistics

		1	2	3	4	5	6	7	Overall
Profile label		SC	B	CB	LM	CF	PT	CPT	
Cluster Size (% N=8183)		25.5	17.6	16.7	13.9	11.4	8.8	6.2	
Indicators									
Trips by car	Mean	8.1	0.8	6.6	0.9	4.2	0.6	5.5	4.3
Trips by PT	Mean	0.0	0.0	0.0	0.0	0.0	11.4	7.2	1.4
Trips by bike	Mean	0.0	6.9	4.2	0.1	1.4	2.8	1.2	2.4
Trips on foot	Mean	0.5	0.9	0.6	0.3	6.2	1.4	1.7	1.4

Note: some values may not add up to 100% due to rounding.

Table E.1: Profile output of the 7-state LTA model (standard logit) with covariates

Model	**Log-likelihood**	**L^2**	**P-value**	**BIC (LL)**	**Total BVR**
7-state standard logit with covariates	-118717.51	232458.37	0.00	239849.64	2862.65

Table E.2: Model fit statistics of the 7-state LTA model (standard logit) with covariates

Indicators	Trips by car	Trips by PT	Trips by bike	Trips on foot
Trips by car	.			
Trips by PT	13.0	.		
Trips by bike	12.8	321.3	.	
Trips on foot	12.3	1.2	98.3	.
Longitudinal				
BVR-time	4.2	5.5	8.8	2.1
BVR-lag1	832.6	607.9	918.6	923.6
BVR-lag2	0.0	0.0	0.0	0.0

Table E.3: Bivariate Residuals of the 7-state LTA model (standard logit) with covariates

E.1.2. Transition probability matrix

		Wave 2						
		SC	B	CB	LM	CF	PT	CPT
Wave 1	SC	58.7	3.7	14.8	12.5	4.5	1.3	4.4
	B	6.0	51.5	15.3	10.3	6.0	8.7	2.1
	CB	22.1	17.2	43.1	3.7	5.1	3.8	5.1
	LM	15.4	9.1	4.1	58.9	4.9	5.5	2.0
	CF	13.0	10.4	8.7	7.9	48.7	4.8	6.5
	PT	8.4	19.4	7.7	12.8	6.7	33.7	11.3
	CPT	20.0	7.6	14.8	6.5	10.6	13.1	27.4

Table E.4: Transition probability matrix of the 7-state LTA model (standard logit) with covariates

E.1.3. Parameter output

	Wave 2								
	SC	B	CB	LM	CF	PT	CPT	Wald	P value
Model for clusters	**0.67**	**0.29**	**0.23**	-0.06	**-0.09**	**-0.30**	**-0.75**	1116.3	0.00
Transition parameters									
Constant	-0.16	**0.49**	-0.06	**0.40**	**-0.44**	0.15	**-0.39**	21.5	0.00
SC	**1.82**	**-1.12**	**0.59**	**0.47**	-0.23	**-1.58**	0.05	4067.8	0.00
B	**-1.06**	**1.62**	**0.23**	-0.03	**-0.27**	**0.49**	**-0.98**		
CB	**0.41**	**0.36**	**1.35**	**-1.08**	**-0.45**	**-0.55**	-0.04		
LM	0.17	-0.11	**-0.91**	**2.02**	-0.29	-0.01	**-0.87**		
CF	**-0.28**	**-0.29**	**-0.40**	**-0.39**	**1.82**	**-0.49**	0.03		
PT	**-1.02**	**0.31**	**-0.77**	-0.13	**-0.52**	**1.67**	**0.46**		
CPT	-0.05	**-0.78**	-0.08	**-0.85**	-0.06	**0.47**	**1.35**		
Covariates									
Gender									
Male	**0.07**	-0.02	-0.04	**0.13**	-0.07	-0.05	-0.02	20.8	0.00
Female	**-0.07**	0.02	0.04	**-0.13**	0.07	0.05	0.02		
Age									
12-17	**-1.57**	**1.29**	-0.19	-0.46	**-1.33**	**1.47**	**0.80**	364.1	0.00
18-24	-0.09	**-0.31**	**-0.28**	-0.12	**-0.57**	**0.98**	**0.37**		
25-29	0.10	**-0.34**	-0.16	**0.39**	-0.16	**0.31**	-0.13		
30-39	**0.30**	-0.20	0.07	-0.06	0.03	-0.20	0.06		
40-49	**0.27**	-0.11	0.16	**0.30**	0.11	**-0.39**	**-0.35**		
50-59	0.15	0.11	0.01	0.00	**0.28**	**-0.32**	-0.24		
60-69	0.15	-0.06	**0.20**	-0.14	**0.35**	**-0.47**	-0.03		
70-79	**0.33**	-0.01	**0.25**	-0.24	**0.52**	**-0.96**	0.10		
80+	0.35	-0.38	-0.08	0.31	**0.79**	-0.42	-0.58		
Educational level									
Low	**0.08**	0.03	**-0.24**	**0.28**	0.11	-0.11	-0.16	65.3	0.00
Mid	0.04	-0.04	-0.10	-0.06	-0.02	**0.22**	-0.03		
High	-0.03	-0.03	0.11	**-0.44**	0.12	0.09	0.18		
Unknown	-0.10	0.05	0.24	0.22	-0.21	-0.20	0.01		
Occupational status									
No job	-0.15	0.09	-0.03	**0.17**	**0.20**	-0.09	-0.18	57.5	0.00
Employed	**0.21**	0.05	0.15	**-0.31**	-0.10	-0.16	0.16		
Unknown	-0.06	-0.14	-0.12	0.14	-0.10	0.25	0.02		
No. of cars									
#	**0.55**	**-0.38**	**0.24**	**0.21**	-0.01	**-0.75**	0.14	281.7	0.00
Income									
Minimum	**-0.42**	0.22	0.08	0.24	0.03	-0.20	0.05	75.0	0.00
Below average	0.05	-0.04	0.01	**0.26**	0.19	**-0.33**	-0.14		
Average	**0.18**	-0.05	0.03	0.04	0.10	-0.07	-0.23		
1-2 times average	0.01	-0.13	0.04	-0.08	-0.06	0.05	0.16		
2 times average	0.07	-0.06	-0.02	-0.26	-0.09	0.26	0.09		
> 2 times average	0.03	-0.06	-0.13	**-0.37**	-0.27	**0.55**	0.24		
Unknown	0.08	0.13	-0.02	0.16	0.09	**-0.26**	-0.18		
Household composition									
Single	-0.04	-0.18	-0.10	-0.17	0.07	**0.32**	0.09	43.9	0.01
Couple	-0.01	0.00	0.07	-0.09	0.11	-0.01	-0.07		
Couple w/ kids and/or others	**-0.24**	0.19	0.02	-0.11	0.22	0.17	-0.23		
Single parent with kids (and others)	0.19	0.10	0.18	0.10	**-0.44**	-0.03	-0.11		
Other	0.10	-0.11	-0.16	0.27	0.03	-0.45	0.32		
Company car									
No CC in household	**-0.14**	0.21	0.09	**-0.24**	0.04	0.19	-0.15	24.7	0.02
CC in household not main user	-0.13	0.24	-0.21	**-0.27**	-0.03	0.40	0.00		
CC in household and main user	**0.27**	-0.46	0.12	**0.51**	0.00	-0.59	0.15		
Year									
2013	0.00	0.00	0.00	0.00	0.00	0.00	0.00	67.6	0.00
2014	-0.07	**0.20**	-0.01	0.10	-0.15	0.18	**-0.25**		
2015	-0.13	0.06	0.02	-0.03	-0.19	0.09	0.17		
2016	**0.25**	**-0.20**	0.15	0.12	-0.18	**-0.32**	0.18		
2017	0.12	-0.03	0.03	**-0.31**	**0.27**	-0.16	0.09		
2018	**-0.16**	0.05	0.00	0.06	0.01	0.15	-0.12		
2019	-0.01	-0.08	**-0.19**	0.07	**0.24**	0.05	-0.07		

Note: Significant parameters (p <0.05) are bold

Table E.5: Parameter output of the 7-state LTA model (standard logit) with covariates

E.2. 7-state model with the company car covariate (standardlogit)

E.2.1. Profile output

		1	2	3	4	5	6	7	Overall
Profile label		SC	B	CB	LM	CF	PT	CPT	
Cluster Size (% N=8183)		25.7	17.6	16.2	13.7	11.4	9.3	6.0	
Indicators									
Trips by car	Mean	8.2	0.8	6.6	0.9	4.2	0.6	5.4	4.3
Trips by PT	Mean	0.0	0.0	0.0	0.0	0.0	11.5	7.2	1.5
Trips by bike	Mean	0.0	6.9	4.2	0.1	1.4	2.8	1.2	2.4
Trips on foot	Mean	0.5	0.9	0.6	0.3	6.2	1.4	1.9	1.4

Note: some values may not add up to 100% due to rounding.

Table E.6: Profile output of the 7-state LTA model (standard logit) with company car covariate

E.2.2. Model statistics

Model	**Log-likelihood**	**L^2**	**P-value**	**BIC (LL)**	**Total BVR**
7-state standard logit with company car	-119270.16	111554.38	0.00	239333.19	575.26

Table E.7: Model fit statistics of the 7-state LTA model (standard logit) with the company car covariate

Indicators	**CarUse**	**PTUse**	**BikeUse**	**WalkUse**
CarUse	.			
PTUse	13.8	.		
BikeUse	15.2	340.7	.	
WalkUse	4.0	0.0	109.4	.
Longitudinal				
Time	3.5	0.5	7.4	2.8
Lag1	577.9	224.6	721.5	752.4
Lag2	0.0	0.0	0.0	0.0

Table E.8: Bivariate Residuals of the 7-state LTA model (standard logit) with the company car covariate

E.2.3. Transition probability matrix

Standard logit

		Wave 2						
		SC	B	CB	LM	CF	PT	CPT
Wave 1	SC	65.4	2.0	14.2	10.4	4.0	0.6	3.4
	B	3.9	58.7	11.5	8.8	4.7	10.5	1.9
	CB	22.9	16.0	45.0	3.4	4.9	2.8	5.0
	LM	13.1	8.0	3.4	64.9	4.9	4.0	1.8
	CF	12.2	8.2	8.7	7.6	54.6	2.8	5.9
	PT	4.8	17.2	5.3	9.0	3.6	50.3	9.9
	CPT	18.9	6.4	14.1	5.8	10.7	13.3	30.8

Table E.9: Transition probability matrix of the 7-state LTA model (standard logit) with the company car covariate

E.2.4. Transition probabilities per variable level

Standard logit

		Wave 2						
		SC	B	CB	LM	CF	PT	CPT
No CC in HH	SC	64.6	2.1	14.7	10.4	4.2	0.6	3.4
	B	3.5	59.8	11.2	8.2	4.8	10.7	1.7
	CB	22.0	16.5	45.5	3.4	5.0	2.9	4.8
	LM	12.8	8.2	3.5	64.6	5.1	4.1	1.7
	CF	11.4	8.3	8.7	7.3	56.0	2.8	5.6
	PT	4.4	17.6	5.2	8.5	3.6	51.5	9.3
	CPT	18.3	6.7	14.4	5.7	11.1	13.7	30.1
CC in HH no main user	SC	69.7	1.9	11.3	9.5	2.8	0.6	4.3
	B	4.2	60.4	9.5	8.2	3.5	11.7	2.4
	CB	26.6	16.9	39.3	3.4	3.8	3.2	6.8
	LM	14.9	8.2	2.9	63.6	3.7	4.4	2.4
	CF	15.4	9.5	8.3	8.3	46.3	3.5	8.7
	PT	4.8	16.6	4.1	7.9	2.5	52.3	11.9
	CPT	19.6	6.1	11.0	5.2	7.3	13.5	37.4
CC in HH and main user	SC	75.1	0.4	9.8	10.5	1.5	0.1	2.7
	B	11.8	29.9	21.7	24.0	5.0	3.8	3.9
	CB	37.5	4.2	44.6	5.0	2.7	0.5	5.6
	LM	17.0	1.6	2.7	74.5	2.1	0.6	1.6
	CF	25.2	2.7	11.0	13.9	38.3	0.7	8.3
	PT	14.5	8.7	9.9	24.4	3.8	18.0	20.8
	CPT	31.7	1.7	14.3	8.6	6.0	2.5	35.2

Note: Significant parameters ($p < 0.05$) are bold

Table E.10: Estimated values transition probability matrix of the 7-state LTA model (standard logit) with the company car covariate

E.2.5. Parameter output

	Wave 2								
	SC	**B**	**CB**	**LM**	**CF**	**PT**	**CPT**	**Wald**	**P value**
Model for clusters	**0.67**	**0.30**	**0.22**	-0.05	**-0.09**	**-0.31**	**-0.75**	1099.23	0.00
Transition parameters									
Constant	**0.79**	-0.08	**0.32**	**0.37**	**-0.32**	**-0.85**	**-0.24**	135.95	0.00
SC	**2.02**	**-1.23**	**0.71**	**0.50**	-0.16	**-1.86**	0.02	5330.67	0.00
B	**-1.23**	**1.79**	0.11	-0.07	**-0.36**	**0.74**	**-0.99**		
CB	**0.49**	**0.38**	**1.39**	**-1.07**	**-0.43**	**-0.69**	-0.08		
LM	0.16	-0.10	**-0.96**	**2.09**	-0.20	-0.12	**-0.88**		
CF	**-0.21**	**-0.34**	**-0.31**	**-0.35**	**1.94**	**-0.74**	0.02		
PT	**-1.18**	**0.39**	**-0.84**	-0.21	**-0.81**	**2.14**	**0.52**		
CPT	-0.05	**-0.88**	-0.11	**-0.90**	0.01	**0.52**	**1.40**		
Covariates									
Company car								52.20	0.00
No CC in HH	**-0.36**	0.33	-0.06	-0.25	0.20	0.42	-0.28		
CC in HH no main user	-0.20	0.32	-0.24	-0.27	-0.14	0.49	0.03		
CC in HH and main user	**0.56**	-0.66	0.30	0.52	-0.06	-0.92	0.25		

Note: Significant parameters (p <0.05) are bold

Table E.11: Parameter output of 7-state LTA model (standard logit) with the company car covariate

E.3. 7-state model with the company car covariate (transition logit)

E.3.1. Profile output

		1	2	3	4	5	6	7	Overall
Profile label		SC	B	CB	LM	CF	PT	CPT	
Cluster Size (% N=8183)		25.8	17.5	16.2	13.7	11.5	9.3	6.0	
Indicators									
Trips by car	Mean	8.2	0.8	6.6	0.9	4.2	0.6	5.4	4.3
Trips by PT	Mean	0.0	0.0	0.0	0.0	0.0	11.5	7.2	1.5
Trips by bike	Mean	0.0	6.9	4.2	0.1	1.4	2.9	1.1	2.4
Trips on foot	Mean	0.5	0.9	0.6	0.3	6.2	1.3	1.9	1.4

Note: some values may not add up to 100% due to rounding.

Table E.12: Profile output of the 7-state LTA model (transition logit) with company car covariate

E.3.2. Model statistics

Model	**Log-likelihood**	**L^2**	**P-value**	**BIC (LL)**	**Total BVR**
7-state transition logit with company car	-119230.79	111475.64	0.00	239903.15	575.53

Table E.13: Model fit statistics of the 7-state LTA model (transition logit) with the company car covariate

Indicators	**CarUse**	**PTUse**	**BikeUse**	**WalkUse**
CarUse	.			
PTUse	13.4	.		
BikeUse	16.1	343.1	.	
WalkUse	2.8	0.1	110.8	.
Longitudinal				
Time	4.2	0.7	7.6	3.2
Lag1	589.6	232.7	711.5	741.7
Lag2	0.0	0.0	0.0	0.0

Table E.14: Bivariate Residuals of the 7-state model LTA model (transition logit) with the company car covariate

E.3.3. Transition probability matrix

Transition logit

		Wave 2						
		SC	B	CB	LM	CF	PT	CPT
Wave 1	SC	65.5	2.0	14.2	10.3	4.0	0.5	3.5
	B	4.3	58.8	11.6	8.2	4.8	10.5	1.8
	CB	22.8	16.0	45.1	3.4	4.9	2.8	5.0
	LM	13.2	7.8	3.5	65.0	4.9	4.0	1.6
	CF	11.9	8.0	9.0	7.3	55.1	2.8	5.9
	PT	5.2	17.1	5.8	8.6	3.9	50.0	9.5
	CPT	19.2	6.3	13.9	5.9	10.8	13.2	30.7

Table E.15: Transition probability matrix of the 7-state LTA model (transition logit) with the company car covariate

E.3.4. Transition probabilities per variable level

Transition logit

		Wave 2						
		SC	B	CB	LM	CF	PT	CPT
No CC in HH	SC	64.4	2.1	14.7	10.5	4.2	0.6	3.5
	B	3.0	59.9	11.0	8.4	5.0	10.9	1.8
	CB	22.5	15.9	46.1	3.2	4.9	2.7	4.8
	LM	12.8	8.0	3.1	64.8	5.4	4.5	1.5
	CF	11.9	8.4	8.5	7.3	55.7	2.6	5.7
	PT	4.2	18.4	5.0	7.9	3.3	51.2	9.9
	CPT	18.8	6.2	14.7	5.5	12.1	13.8	29.0
CC in HH no main user	SC	76.0	1.9	9.4	6.5	1.2	0.6	4.5
	B	7.0	58.5	12.2	7.0	2.6	10.0	2.7
	CB	19.2	22.5	34.4	5.0	7.9	5.1	5.9
	LM	19.9	9.7	5.4	64.9	0.0	0.0	0.0
	CF	3.4	8.3	13.8	0.1	61.4	3.4	9.6
	PT	3.3	9.5	5.1	13.6	2.6	56.4	9.6
	CPT	15.9	11.0	10.4	7.3	0.1	13.4	41.9
CC in HH and main user	SC	72.3	0.0	10.0	12.1	4.2	0.0	1.4
	B	29.0	35.1	24.3	5.8	5.7	0.0	0.0
	CB	38.6	5.4	41.0	5.9	0.1	1.5	7.6
	LM	10.6	0.1	9.0	70.1	2.5	0.0	7.7
	CF	26.9	0.1	11.2	22.0	29.9	4.5	5.6
	PT	30.7	0.8	25.6	13.7	19.2	10.0	0.1
	CPT	36.4	0.0	2.2	10.9	0.3	0.1	50.2

Table E.16: Estimated values transition probability matrix of the 7-state LTA model (transition logit) with the company car covariate

E.3.5. Parameter output

	Wave 2								
	SC	**B**	**CB**	**LM**	**CF**	**PT**	**CPT**	**Wald**	**P value**
Transition parameters									
Constant	**0.67**	**0.29**	**0.23**	-0.05	**-0.09**	**-0.31**	**-0.75**	1098.03	0.00
SC	**0.00**	**-5.54**	**-1.85**	**-2.02**	**-3.25**	**-6.37**	**-3.24**	798.03	0.00
B	**-1.76**	**0.00**	**-1.21**	**-1.96**	**-2.47**	**-3.39**	**-4.43**		
CB	**-0.45**	**-1.17**	**0.00**	**-2.17**	**-3.45**	**-2.69**	**-1.91**		
LM	**-1.57**	**-3.75**	**-2.52**	**0.00**	-4.65	-6.31	-4.59		
CF	**-1.51**	-3.42	**-1.45**	-3.00	**0.00**	**-2.61**	**-1.94**		
PT	**-1.40**	-1.78	**-1.26**	**-0.99**	**-1.73**	**0.00**	-2.80		
CPT	**-0.58**	-3.32	-1.73	**-1.64**	-4.04	-2.73	**0.00**		
Covariates									
Company car								92.55	0.25
SC									
No CC in HH	**0.00**	2.12	**0.37**	0.21	0.51	1.63	0.33		
CC in HH no main user	**0.00**	1.82	-0.24	-0.44	-0.92	1.60	0.41		
CC in HH and main user	**0.00**	-3.94	-0.13	0.23	0.41	-3.23	-0.74		
B									
No CC in HH	**-1.22**	**0.00**	-0.48	0.00	-0.02	1.69	0.90		
CC in HH no main user	-0.36	**0.00**	-0.36	-0.17	-0.64	1.62	1.35		
CC in HH and main user	**1.57**	**0.00**	0.84	0.17	0.65	-3.31	-2.26		
CB									
No CC in HH	-0.26	0.11	**0.00**	-0.49	1.20	-0.14	-0.36		
CC in HH no main user	-0.13	0.75	**0.00**	0.25	1.98	0.79	0.14		
CC in HH and main user	0.39	-0.86	**0.00**	0.24	-3.19	-0.65	0.23		
LM									
No CC in HH	-0.06	1.66	-0.52	**0.00**	2.16	3.64	0.81		
CC in HH no main user	0.38	1.85	0.04	**0.00**	-3.49	-2.14	-3.19		
CC in HH and main user	-0.32	-3.50	0.47	**0.00**	1.33	-1.50	2.38		
CF									
No CC in HH	-0.03	1.52	-0.42	0.97	**0.00**	-0.44	-0.34		
CC in HH no main user	-1.38	1.41	-0.04	-3.66	**0.00**	-0.27	0.08		
CC in HH and main user	**1.41**	-2.93	0.47	2.70	**0.00**	0.71	0.26		
PT									
No CC in HH	-1.09	0.75	**-1.06**	-0.87	-1.01	**0.00**	1.16		
CC in HH no main user	-1.43	-0.01	-1.15	-0.43	**-1.37**	**0.00**	1.04		
CC in HH and main user	2.52	-0.75	**2.20**	1.31	**2.38**	**0.00**	-2.20		
CPT									
No CC in HH	0.14	1.77	1.06	-0.01	3.16	1.99	0.00		
CC in HH no main user	-0.40	1.98	0.35	-0.10	-1.91	1.59	**0.00**		
CC in HH and main user	0.25	-3.75	-1.40	0.11	-1.25	-3.58	**0.00**		

Note: Significant parameters (p <0.05) are bold

Table E.17: Parameter output of the 7-state LTA model (transition logit) with the company car covariate