Longitudinal Studies in Travel Behaviour Research

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Proefschrift

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door

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Preface

As I write this, I realize that I am six weeks away from completing my PhD. Something I could never have imagined when I was a student. In fact, during my master's I quickly came to the conclusion that a PhD would not be for me. I always pictured it as being ‘locked up’ for four years, focused only on your own research. That was the reason that when I was asked at KiM if I was interested in a PhD program, I had to think about it for a short time. My main concern was that I would be working parallel to and isolated from my colleagues for four years. Fortunately, this concern was quickly addressed. George, Arjen and Sascha, thank you for giving me the opportunity to pursue a PhD within KiM.

For me, the combination of working at KiM and following a PhD track combines the best of both worlds. By definition, the work is policy-relevant due to KiM's position within the Ministry of Infrastructure and Water Management. At the same time, the close connection with the TU Delft ensures that the work progresses just a bit further academically and also lands well within the scientific world. I am happy to see that both the TU Delft and KiM also see the value of this, given that since I started, several colleagues have taken the same path.

Sascha, thank you for the discussions we had, especially in the first two years of my PhD. I avidly used all your knowledge on conducting questionnaire- and panel research. The first time we met, during an interview for a graduate internship, you managed to get me excited about the MPN. Who would have known then that this would lead to a dissertation a few years later?

Serge, thank you for your input, confidence and creativity. Although circumstances sometimes made you less closely involved than you would have liked, I have enjoyed our discussions over the years.

Caspar, thank you for your eternal enthusiasm and always asking critical questions. During our conversations over the past few years, you always provided me with good ideas and managed to challenge me to dig a little deeper into the data. Last but not least, thank you for letting me enjoy your karaoke skills in Leuven!

Maarten, thanks for your guidance and our many discussions. Our biweekly meeting was a good motivator to give some attention to my PhD. Without these meetings it is doubtful that I was writing this preface at this very moment. In addition to substantive conversations, there was

always room for humor and beer. Both in the Netherlands, and during the conferences we visited together (What happens in Budapest...)!

I would also like to thank my committee member for taking the time to read and assess my dissertation. Thank you Ralph, Tina, Patricia, Karst and Lori. I look forward to a lively discussion during my defense.

Of course, I would also like to thank my parents, who are always there for me. Mom and dad, I know I didn't always react enthusiastically when you asked about my dissertation, but know that this was purely my frustration when things weren't going fast enough for me. No matter what, you are always there for me.

The life of an external PhD student comes with some challenges. When hours are short in the week, the free evenings have to come around to work on the dissertation. The person who has noticed this well is my girlfriend, Annelies. So that is the last person I want to thank. Sorry for the many evenings you had to sit alone on the couch because I had locked myself in the study. Thank you for always being there for me!

Mathijs de Haas
September 2022

Content

Summary

Background

Mobility is an important part of daily life. With modern mobility systems, people have access to a range of transport modes allowing them to basically reach any destination they want. Although people often have multiple options to choose from, personal mobility is dominated by motorized road transport in many countries and cities, also in the Netherlands, owing to the ease of use and high level of flexibility. This popularity poses challenges for governments to keep their countries and cities accessible, attractive, safe and liveable since motorized road transport comes with several negative effects such as increased congestion, damage to the environment, negative effects on human health due to emissions, inefficient use of space and reduced liveability of cities.

The solution to these challenges does not only lie in changing the mobility system itself. Especially in light of physical space becoming scarcer due to the increase in urbanization rates, expanding the system's capacity by expanding the infrastructure is not always possible. To face these challenges, the behaviour of users of the mobility system also has to change. This may even be a bigger challenge than changing the mobility system itself, as earlier research has shown that travellers are behaviourally inert; they do not change their travel behaviour often (Chorus & Dellaert, 2012; Gärling & Axhausen, 2003). To promote behavioural change among travellers, there is a need to understand the underlying mechanisms of changes in travel behaviour. Understanding these mechanisms allows to design and implement effective policies that are aimed to change travel behaviour.

Aim of this thesis

Although several decades of travel behaviour studies are available, most studies to date are limited by having to rely on cross-sectional data, i.e. data in which individuals are only surveyed or observed a single time. Since individuals only participate a single time, cross-sectional data do not allow studying intra-individual changes that occur over time. As a result, directions of

causation of travel behaviour change have to be assumed, rather than be inferred from the data with the risk of drawing wrong conclusions. To effectively study the mechanisms underlying travel behaviour change, one needs data on travel behaviour at different time points, including data on the factors of interest (e.g. events leading up to a travel behaviour change).

The aim of this thesis is to uncover several mechanisms behind travel behaviour change towards sustainable travel modes, based on a large-scale longitudinal travel survey; the Netherlands Mobility Panel (MPN). As this panel has been operating for several years and collects a wide range of relevant information from its respondents, it allows studying numerous aspects of travel behaviour (change). I specifically focus on topics that will support policy makers in facing the challenges regarding the mobility system that I discussed in the previous section. This thesis will help policy makers understand how travel behaviour changes and provide them with knowledge to promote travel behaviour change towards a more sustainable mobility system. I focus on four topics that are imperative to achieve this goal: the effects of life events on travel behaviour, new technologies to promote a mode shift away from car (in this case, the e-bike), the links between personal health and active travel and effects of the COVID-19 pandemic on mobility. To correctly study these topics, longitudinal data is needed, as we want to infer the direction of effects from the data rather than making assumption on this direction, with the risk of drawing wrong conclusions (e.g., we do not know whether active travel has an effect on personal health or that the effect runs from personal health to active travel). While these longitudinal data are ideally suited to study travel behaviour changes, it is crucial that the data quality is guaranteed. To address one possible cause of low data quality, I present a fifth study focused on the notion of soft-refusal, which describes the tendency of some respondents to use a strategy to lower their response burden, e.g. by claiming they did not leave their house even though they actually did.

Outline of this thesis

The general outline is as follows. The first study focuses on behavioural changes in daily mobility after major life events, such as having a baby or moving house (Chapter 2). The following study is focused on a new technology that may help in realizing a modal shift away from car (Chapter 3). In this study, the focus is on the e-bike. Next, in the third study I focus on the bi-directional effect between health and active travel (i.e. walking and cycling) (Chapter 4). The fourth study is of a more methodological nature as it addresses the issue of soft-refusal in (longitudinal) travel behaviour surveys (Chapter 5). As the COVID-pandemic occurred during the process of writing this thesis, this presented the unique opportunity to study how travel behaviour changes under the extreme conditions of a pandemic. In the fifth study I address these effects (Chapter 6). The following paragraphs summarize the results of the individual studies.

Results

Study 1: The effect of life events on daily travel patterns

Previous studies have shown that travel behaviour does not change very often, but that there may be certain moments in life when changes occur more often. Latent class- and transition models are estimated in the first study using the first three waves (2013-2015) of MPN data to reveal different travel patterns and assess the effect of life events and other exogenous variables on transitions between these travel patterns. The latent class model identified six different meaningful and distinguishable travel patterns: a strict car class, a car and bicycle class, a bicycle class, a car and walk class, a low mobility class and a public transport class.

In line with earlier studies, the transition analysis shows that travel behaviour is inert as people tend to keep the same travel pattern over time. In addition, unimodal travellers show a higher probability of remaining in the same travel pattern, compared to multimodal travellers, regardless of any life events. Furthermore, all identified travel patterns show a very low probability of transitioning towards the public transport travel pattern. To show the effect of life events on daily travel patterns, the interaction between the transitions between travel patterns and six life events are assessed (change in number of adults living in the household, birth of a child, changing jobs, stop working, starting or changing an educational programme and a residential move).

Overall, it can be concluded that changes in travel patterns occur more often after a life event, while the effects can be different dependent on the travel pattern before the life event. For instance, after a decrease in the number of adult household, public transport users show a strong increase in the probability of shifting towards a more car dependent travel pattern. People with a low mobility travel pattern on the other hand, show a higher probability of adopting a bicycle travel pattern. Similarly, after a residential move, people with a car and bicycle or car and walk travel pattern tend to change their travel pattern more often, while strict car or bicycle users are limitedly affected by this life event.

In general, unimodal travellers are less affected by life events than multimodal travellers. Since changes in travel behaviour occur more often after a life event, this may indicate that these events are ‘windows of opportunity’ for policy makers to change travel behaviour.

Study 2: The e-bike: a new technology that may promote a shift towards sustainable travel

In recent years, the popularity of the e-bike rapidly increased. Due to ability to travel at higher speeds with fewer efforts compared to the normal bicycle, it has the potential to replace a large share of car trips. However, it is unknown to what extent the e-bike indeed replaces the car. To study this, I estimated a Random Intercept Cross-Lagged Panel Model (RI-CLPM) based on five waves of the MPN (2014-2018) to assess substitution effects between travel modes on a within-person level. Furthermore, I reveal which homogenous groups are present within the e-bike population and their development over time based on a Latent Class Analysis with data from five years of the Dutch national travel survey (OViN).

Substitution effects turn out to be dependent on trip motive, as different results were found when estimating separate models for different trip motives. When only assessing commuting trips, the results show the e-bike not only substitutes the conventional bicycle, but also the car. Apparently, for commuting trips people see the e-bike not only as a replacement for the conventional bicycle but also for the car. For both leisure and shopping trips, the e-bike turns out to only be a significant substitution for the conventional bicycle.

The latent class analysis showed that we can distinguish five meaningful e-bike user groups. The first and largest class (53% of the sample) represents the traditional e-bike users, with virtually everyone in this group aged 65+. The second class (20% of the sample) represents middle-aged full-time working people. The third class (14% of the sample) represents mostly female users aged between 50 and 65 years old who are primarily homemakers or have a part-time job. The fourth class (11% of the sample) represents the younger part-time working women with children. The fifth and smallest class (1% of the sample) represents students and pupils. While the first and third user groups mainly use the e-bike for leisure or shopping purposes, the other user groups also use the e-bike for commuting or education-related purposes.

Based on five years of data from the national travel survey, the absolute sizes of the user groups in each of these five years were computed. Between 2013 and 2017, the total number of e-bike

owners in the Netherlands grew from approximately 1.2 million to over 2 million people, an increase of 74%. The two groups with the oldest users, the first and third group, show a slower growth rate of 50 and 39% respectively. As a result, the shares of these two groups (compared to all e-bike owners at one point in time) declined over the years. While the first group had a share of just over 56% in 2013, the share in 2017 was just under 49%. The share of the third group decreased from 15% to 12%. For the other three user groups, a higher growth rate is visible. These three groups all more than doubled in five years. Relatively speaking, the younger part-time working women with children (group 4) is growing the fastest.

It is expected that the three younger groups (group 2, 4 and 5) will keep growing at a higher rate in the coming years. As these groups use the e-bike primarily for commuting or education, the shares of these trip purposes will keep growing. Furthermore, it is likely that substitution effects will become more evident due to these trends. If more people start using the e-bike for commuting, it is likely that the substitution effect that e-bike trips have on car trips can also be observed on the general level.

Study 3: Active travel and increasing overweight and obesity rates

It has been estimated that physical inactivity accounts for roughly 10% of premature mortality globally in any given year, making it one of the leading health risk factors (more important than obesity and smoking) (Lee et al., 2012). The third study addresses the question to what extent active travel and health (body-mass index (BMI) and self-rated health (SRH)) influence each other over time. Three years of data from the MPN (2017-2019) were used to answer this question. Multivariate linear regression models are estimated to provide an initial assessment of the relationship between active travel and the two health outcomes (BMI and SRH), followed by the estimation of several RI-CLPMs to assess whether active travel and health influence each other over time.

The regressions models show that there is a clear relation between the two health outcomes and active travel. People who are overweight or obese make fewer trips and travel less distance by bicycle. For instance, while people in our sample make 1.4 cycling trips over a distance of 3.9 km in three days on average, obese people make on average 0.56 fewer trips and cycle 1.47 km less compared to people with a healthy weight. Similar relationships are found between the BMI and walking, with the only difference that overweight people do not make significantly fewer trips on foot compared to people with a healthy weight.

Results from the RI-CLPMs show that there is a small, but significant negative effect of walking distance on BMI among non-obese people. This result indicates that when people increase their walking distance per three days with 10 km, this results in a decrease of their BMI by 0.16 in the following year. For someone of 1.80 m tall, this translates to 0.52 kilogram of weight loss. A similar (negative) effect is not found for obese people. The effect of active travel on BMI is not present for cycling. For cycling, a reverse effect is found among non-obese people. That is, an increase in the level of BMI in one year results in a decrease in bicycle use in the next year, both in travelled distances and trips. No such effects are found in the obese group. Also between e-bike use and BMI no significant effects are found.

Between active travel and SRH only one statistically significant positive relationship is found for the effect of cycled distance on SRH, indicating that an increase in the travelled distance by bicycle in one year results in a more positive SRH in the next year. No significant effects are found between SRH and walking or using the e-bike.

These results indicate that promoting active travel may only result in a slight decrease of BMI through an increase in walking. The reverse negative effect of BMI on cycling implies that the increasing overweight and obesity rates may have a negative effect on cycling levels.

Formulated positively, if policy makers succeed in reducing obesity levels (e.g. through better diet), the results indicate this may increase levels of active travel.

Study 4: Identifying soft-refusal in (longitudinal) travel behaviour surveys

In travel behavior research, multi-year panels, such as the MPN, have been set up to understand the drivers of (changes in) travel behavior over time. The resulting data from these panels are ideally suited to model and understand the (causal) mechanisms behind travel behavior, and the changes therein over time at the individual level. To use the data effectively for this purpose, it is crucial that the data quality is guaranteed. However, there are several processes that may result in low data quality. One such mechanism relates to the notion of soft-refusal, which describes the tendency of some respondents to refuse participation in a 'soft' way, e.g. by claiming they did not leave their house even though they actually did or by giving sub-optimal answers as a result of speeding through a questionnaire.

In the fourth study three different methods to identify possible soft-refusal in a longitudinal travel behavior panel are presented, based on: 1) predicting out-of-home activity 2) straightlining, and 3) speeding. All methods seem to be able to identify respondents with poor response behavior in a travel behavior context (i.e. a suspiciously high level of reported immobility). While the first method (a binary logit model to predict out-of-home activity) is directly aimed at identifying reporting days on which respondents incorrectly report no trips, it was found that also speeding and straightlining in a questionnaire are strongly related to reported immobility in the travel diary. Similar to earlier research, I found that attrition is correlated with reported immobility. Furthermore, I found that attrition itself is an additional indicator of reported immobility in the final wave of participation. In other words, the three presented methods likely do not capture all soft-refusal.

A latent transition model is used to reveal different behavioral patterns with respect to the soft-refusal indicators and study transitions between these patterns over time. This analysis shows that there are four distinct behavioral patterns in terms of soft-refusal behavior. The largest class consists of respondents who are overall not identified as a possible soft refuser, followed by a class who seem to be speeding and a class with a higher share of straightlining. While their level of reported immobility is higher than the first class, there are only a few differences in their sociodemographic profiles. Only the fourth class (a high-risk soft-refusal class with a very high level of reported immobility) has a distinct sociodemographic profile. Knowing a priori which type of respondents have a higher risk of showing soft-refusal provides the possibility to account for this by oversampling these groups. In the case of the MPN, that would be young and less educated people.

From the transition analysis I found that only when respondents are identified as possible soft refusers on multiple indicators (the high-risk class), the attrition rate is higher. Furthermore, if respondents do not dropout, they tend to stay in the same class over time. This implies that keeping respondents from the high-risk class in the panel will mainly result in these respondents providing the same poor data quality in subsequent measurements. One could therefore argue to remove these respondents entirely from the panel. However, in the specific case of the MPN, removing a single respondent results in removing the entire household from the panel. Since most respondents from the high-risk class are part of a multi-person household, removing them would simultaneously remove more reliable respondents from the panel.

Study 5: The effects of the COVID-pandemic on travel behaviour

The World Health Organization (WHO) declared COVID-19 as a pandemic on the 11th of March 2020. The societal impacts of both the virus and the measures taken to reduce its spread

are severe. The circumstances result in a unique situation in which people have to change their daily life radically. The fifth study shows first insights into how activity patterns, the way we work, and how we travel changed drastically.

To study the effects of the COVID-19 pandemic, a representative sub-sample of the MPN (approximately 2,500 respondents) was invited to participate in an additional measurement including a questionnaire and the three-day travel diary. Since these respondents were already a member of the MPN before the pandemic, reliable measurements of this exact same group of individuals regarding experiences, preferences and behaviour pre-pandemic was available.

The results show that approximately 80% of people reduced their activities outdoors. Older people in particular were much less active than before the crisis. Although most people still experienced enough possibilities for grocery shopping, roughly 40% of people were unhappy with the restricted possibilities for social interaction. The amount of trips and distance travelled were reduced by 55% and 68% respectively when compared to the fall of 2019. The use of public transport was impacted the most with a decrease of over 90% of trips. So-called 'roundtrips' gained in popularity. One in four trips was a roundtrip such as a walking or cycling tour.

The shock to daily life that the pandemic caused may have some structural effects on our mobility. While more than 90% of people who reduced their outdoor activities at the time of the study did not expect this behaviour would continue in the future, more people expect structural changes for the way we work and travel. More than a quarter of home-workers expected to work from home more often in the future after the pandemic. For workers who had more remote meetings, just over a third expected to also do this more often in the future. Similarly, some structural changes on the way we travel can be expected. Roughly 20% of people expected to cycle and walk more in the future. A similar share of people with air travel experience expected to decrease their air travel in the future. While the study gives first indications that the pandemic may have structural impacts on our travel behaviour, more research is needed to confirm this.

Implications of the study

The results in this thesis have several research and policy implications. For research, the studies in this thesis show the importance of using longitudinal data to uncover mechanisms underlying travel behaviour change. While cross-sectional studies allows to study how travel behaviour changes among the population and how several trends in society (e.g. the increasing popularity of the e-bike, or the COVID-19 pandemic) impact travel behaviour on an aggregated level, longitudinal data is needed to explain these trends based on changes that take place on an individual level. Using cross-sectional data to explain travel behaviour changes can result in drawing wrong conclusions about the strengths and direction of effects. For instance, cross-sectional data are suited to show how e-bike use is related to car use, but based on these data, it is not possible to determine whether e-bike use affects car use or vice versa on an individual level. To do so, longitudinal data are needed.

The results highlight several other benefits of using longitudinal data over cross-sectional data. First, it is important to consider bidirectional effects. For instance, while many previous studies on the relationship between health and active travel only consider the effect of active travel on health, this thesis shows that there are also reverse effects. Secondly, it is important to distinguish between within-person and between-person effects. Without doing so, wrong conclusions may be drawn about the existence or the strength of certain effects (this is for instance shown in the study on health and active travel). Furthermore, having a panel with

willing-to-cooperate participants in place allows to quickly act on events in society (e.g. a pandemic) and show how these events impact people's mobility.

This thesis also has several implications for policy makers. First of all, policy makers should realize that travel behaviour is, on average, relatively inert. As a result, the effectiveness of policies aimed at changing travel behaviour may be limited if they are not targeted at specific groups of people. This thesis shows that there are certain moments when changes in travel behaviour occur more often. After the occurrence of a life event (e.g. birth of a child, or moving house) travel behaviour changes more often. These life events should therefore be considered as windows of opportunities for policy makers to change travel behaviour as it is likely that people are more susceptible to policy interventions on such moments when they are reconsidering their travel behaviour. This thesis also shows that if policy makers do not act on these life events, people may adopt a more car-dependent travel pattern.

Second, this thesis shows that the popularity of the e-bike is rapidly increasing. Specifically for commuting, this thesis shows that people use the e-bike as a substitute of the car. Therefore, policy makers should aim to promote e-bike use among the working population as this will likely result in some mode shift from car to e-bike. Furthermore, promoting active travel seems to be possible with policies that are not directly linked to mobility. As results show that a change in BMI negatively affects bicycle use, policy makers could increase cycling levels if they implement policies that turn out to be effective in reducing overweight and obesity rates.

Lastly, the COVID-19 pandemic showed us that many of the changes in the way people work or do activities were not possible without ICT. There is a group of people with limited access to ICT tools or who lack the skills to use them. For policy makers it is important to address these apparent shortcomings of available ICT solutions to facilitate behavioural changes that rely on ICT.

Samenvatting

Achtergrond

Mobiliteit is een belangrijk onderdeel van het dagelijks leven. Met de huidige moderne mobiliteitssystemen hebben mensen toegang tot een scala aan vervoerwijzen waarmee ze in principe elke bestemming kunnen bereiken die ze maar willen. Hoewel mensen vaak uit meerdere opties kunnen kiezen, wordt personenmobiliteit in veel landen en steden, ook in Nederland, gedomineerd door gemotoriseerd wegvervoer vanwege het gebruiksgemak en de hoge mate van flexibiliteit. Deze populariteit stelt overheden voor de uitdaging om hun landen en steden toegankelijk, aantrekkelijk, veilig en leefbaar te houden. Gemotoriseerd wegvervoer brengt namelijk verschillende negatieve effecten met zich mee, zoals toenemende congestie, schade aan het milieu, negatieve effecten op de volksgezondheid als gevolg van emissies, inefficiënt ruimtegebruik en verminderde leefbaarheid van steden.

De oplossing voor deze uitdagingen zit niet enkel in het aanpassen van het mobiliteitssysteem zelf. Met name met het oog op de schaarser wordende fysieke ruimte als gevolg van de toenemende verstedelijking is uitbreiding van de capaciteit van het mobiliteitssysteem door uitbreiding van de infrastructuur niet altijd mogelijk. Om deze uitdagingen het hoofd te bieden, moet ook het gedrag van de gebruikers van het mobiliteitssysteem veranderen. Dit kan zelfs een grotere uitdaging zijn dan het mobiliteitssysteem zelf te veranderen, aangezien eerder onderzoek heeft aangetoond dat reisgedrag inert is; het verandert niet vaak (Chorus & Dellaert, 2012; Gärling & Axhausen, 2003). Om gedragsverandering bij reizigers te bevorderen, is er behoefte aan inzicht in de onderliggende mechanismen van veranderingen in reisgedrag. Inzicht in deze mechanismen maakt het mogelijk om effectief beleid te ontwerpen en te implementeren dat gericht is op het veranderen van reisgedrag.

Doel van dit proefschrift

Hoewel er al decennialang onderzoek naar reisgedrag wordt gedaan, kennen de meeste studies tot op heden de beperking dat ze gebaseerd zijn op cross-sectionele data (data waarbij individuen slechts één keer worden ondervraagd of geobserveerd). Aangezien individuen

slechts één keer deelnemen, is het met cross-sectionele data niet mogelijk om veranderingen die binnen een persoon over de tijd optreden te onderzoeken. Als gevolg daarvan moeten causale relaties tussen veranderingen in reisgedrag worden verondersteld, in plaats van te worden afgeleid uit de data, met het risico dat verkeerde conclusies worden getrokken. Om de mechanismen die ten grondslag liggen aan reisgedragsverandering goed te kunnen onderzoeken, zijn data nodig over het reisgedrag van dezelfde persoon op verschillende tijdstippen, inclusief data over relevante factoren (bv. gebeurtenissen die leiden tot een reisgedragsverandering).

Het doel van dit proefschrift is om verschillende mechanismen achter reisgedragsverandering naar duurzame vervoerwijzen bloot te leggen, gebaseerd op een grootschalig longitudinaal reisonderzoek; het Mobiliteitspanel Nederland (MPN). Omdat dit panel al meerdere aantal jaren bestaat is en een breed scala aan relevante informatie van haar respondenten verzamelt, is het mogelijk om verschillende aspecten van reisgedrag en veranderingen in dat reisgedrag te bestuderen. Dit proefschrift richt zich specifiek op onderwerpen die beleidsmakers helpen bij de uitdagingen met betrekking tot het mobiliteitssysteem zoals die in de vorige paragraaf zijn besproken. Dit proefschrift zal beleidsmakers helpen begrijpen hoe reisgedrag verandert en hen voorzien van kennis om verandering in reisgedrag te bevorderen in de richting van een duurzamer mobiliteitssysteem. Ik richt me op vier onderwerpen die relevant zijn om dit doel te bereiken: de effecten van levensgebeurtenissen op reisgedrag, nieuwe technologieën om een vervoerwijzeverschuiving weg van de auto te bevorderen (in dit geval, de e-fiets), de verbanden tussen gezondheid en actief reizen en effecten van de COVID-19 pandemie op mobiliteit. Om deze onderwerpen correct te bestuderen, zijn longitudinale data nodig, aangezien we de richting van de effecten willen afleiden uit de data in plaats van aannames te doen over deze richting, met het risico dat we verkeerde conclusies trekken (we weten bijvoorbeeld niet of actief reizen een effect heeft op de gezondheid of dat het effect van de gezondheid naar actief reizen loopt). Hoewel deze longitudinale data ideaal zijn om veranderingen in reisgedrag te onderzoeken, is een hoge datakwaliteit belangrijk. Om één van de mogelijke oorzaken van lage datakwaliteit aan te pakken, presenteer ik een vijfde studie gericht op soft-refusal. Soft-refusal beschrijft de neiging van sommige respondenten om een bepaalde strategie toe te passen om de responslast te verlagen, bijvoorbeeld door te rapporteren dat ze thuis zijn gebleven terwijl ze in werkelijkheid wel verplaatsingen hebben gemaakt.

Structuur

De structuur van de thesis is als volgt. De eerste studie richt zich op gedragsveranderingen in de dagelijkse mobiliteit na het plaatsvinden van verschillende levensgebeurtenissen, zoals het krijgen van een baby of een verhuizing (Hoofdstuk 2). De volgende studie richt zich op een nieuwe technologie die kan helpen bij het realiseren van een vervoerwijzeverschuiving weg van de auto (Hoofdstuk 3). In deze studie ligt de focus op de e-fiets. Vervolgens, richt ik me in de derde studie op het bi-directionele effect tussen gezondheid en actief reizen (lopen en fietsen) (Hoofdstuk 4). De vierde studie is van methodologische aard, omdat het zich richt op soft-refusal in (longitudinale) reisgedrag enquêtes (Hoofdstuk 5). Aangezien de COVID-pandemie uitbrak tijdens het schrijven van dit proefschrift, bood dit de unieke gelegenheid om te bestuderen hoe reisgedrag verandert onder de extreme omstandigheden van een pandemie. In de vijfde studie ga ik in op deze effecten (hoofdstuk 6). In de volgende paragrafen worden de resultaten van de afzonderlijke studies samengevat.

Resultaten

Studie 1: Het effect van levensgebeurtenissen op reispatronen

Eerdere studies hebben aangetoond dat reisgedrag niet vaak verandert, maar dat er bepaalde momenten in het leven kunnen zijn waarop veranderingen vaker voorkomen. In de eerste studie worden latente klasse- en transitiemodellen geschat op basis van de eerste drie jaar aan MPN-data (2013-2015) om verschillende reispatronen bloot te leggen en het effect van levensgebeurtenissen en andere exogene variabelen op overgangen tussen deze reispatronen te onderzoeken. Op basis van het latente-klassenmodel blijken er zes verschillende reispatronen te kunnen worden onderscheiden: een strikte autoklasse, een auto- en fietsklasse, een fietsklasse, een auto- en loopklasse, een lage mobiliteitsklasse en een openbaarvervoerklasse.

In lijn met eerdere studies laat de transitieanalyse zien dat het reisgedrag inert is. Mensen behouden over het algemeen hetzelfde reispatroon door de jaren heen. Bovendien hebben mensen met unimodale reispatronen (waarbij voornamelijk steeds dezelfde vervoerwijze wordt gebruikt) een grotere kans om hetzelfde reispatroon te behouden dan mensen met een multimodaal reispatroon. Daarnaast geldt voor alle geïdentificeerde klassen dat de kans dat mensen overgaan naar de openbaar vervoerklasse zeer laag is. Om het effect van levensgebeurtenissen op dagelijkse reispatronen bloot te leggen, wordt de interactie tussen de overgangen tussen reispatronen en zes levensgebeurtenissen onderzocht (verandering in het aantal volwassenen in het huishouden, geboorte van een kind, verandering van baan, stoppen met werken, starten of veranderen van een onderwijsprogramma en een verhuizing).

In het algemeen kan worden geconcludeerd dat veranderingen in reispatronen vaker optreden na een levensgebeurtenis, terwijl de effecten verschillend kunnen zijn afhankelijk van het reispatroon vóór de levensgebeurtenis. Zo hebben gebruikers van het openbaar vervoer na een afname van het aantal volwassen in het huishouden een sterk verhoogde kans om over te stappen op een meer autoafhankelijk reispatroon. Mensen uit de lage mobiliteitsklasse hebben daarentegen een grotere kans om over te stappen naar het fietspatroon. Op dezelfde manier zijn mensen met een auto-fiets of auto-lopen patroon geneigd om na een verhuizing vaker hun reispatroon te veranderen, terwijl strikte auto- of fietsgebruikers slechts in beperkte mate beïnvloed worden door deze levensgebeurtenis.

In het algemeen worden unimodale reizigers minder beïnvloed door levensgebeurtenissen dan multimodale reizigers. Aangezien veranderingen in reisgedrag vaker optreden na een levensgebeurtenis, kan dit erop wijzen dat deze gebeurtenissen geschikte momenten zijn voor beleidsmakers om het reisgedrag te veranderen.

Studie 2: De e-fiets: een nieuwe technologie die een verschuiving naar duurzame mobiliteit kan stimuleren

De laatste jaren is de populariteit van de e-fiets snel toegenomen. Omdat de e-fiets in vergelijking met de gewone fiets hogere snelheden kan halen met minder inspanning, heeft de e-fiets het potentieel om een groot deel van de autoritten te vervangen. Het is echter onbekend in welke mate de e-fiets inderdaad de auto vervangt. Om dit te onderzoeken, heb ik een Random Intercept Cross-Lagged Panel Model (RI-CLPM) geschat op basis van vijf jaar aan MPN-data (2014-2018) om substitutie-effecten tussen vervoerwijzen op binnenpersoonsniveau te onderzoeken. Daarnaast laat ik zien welke e-fiets gebruiksgroepen er bestaan en hoe deze groepen ontwikkelen door tijd heen op basis van een Latente Klasse Analyse met data van vijf jaar van Nederlandse nationale reisonderzoek (OViN).

Substitutie-effecten blijken afhankelijk te zijn van het reismotief, aangezien er verschillende resultaten worden gevonden bij het schatten van aparte modellen voor verschillende

reismotieven. Wanneer alleen naar woon-werkverplaatsingen wordt gekeken, blijkt dat de e-fiets niet alleen de normale fiets vervangt, maar ook de auto. Blijkbaar zien mensen voor woon-werkverplaatsingen de e-fiets niet alleen als vervanging van de gewone fiets, maar ook van de auto. Voor zowel vrijetijds- als winkelverplaatsingen blijkt de e-fiets alleen een significante vervanging te zijn voor de normale fiets.

Uit de latente klassenanalyse blijkt dat er vijf verschillende e-fiets gebruikersgroepen kunnen worden onderscheiden. De eerste en grootste groep (53% van de steekproef) vertegenwoordigt de traditionele e-fiets gebruikers. Vrijwel iedereen in deze groep is ouder dan 65 jaar. De tweede groep (20% van de steekproef) vertegenwoordigt voltijd werkende mensen van middelbare leeftijd. De derde groep (14% van de steekproef) bestaat voornamelijk uit vrouwelijke gebruikers tussen de 50 en 65 jaar oud die voornamelijk huisvrouw zijn of een deeltijdbaan hebben. De vierde klasse (11% van de steekproef) vertegenwoordigt de jongere parttime werkende vrouwen met kinderen. De vijfde en kleinste klasse (1% van de steekproef) vertegenwoordigt studenten en scholieren. Terwijl de eerste en derde gebruikersgroep de e-fiets vooral gebruiken voor vrijetijds- of winkeldoeleinden, gebruiken de andere gebruikersgroepen de e-fiets ook voor de woon-werkreis of onderwijsgerelateerde doeleinden.

Op basis van vijf jaar data van het nationale reisonderzoek zijn de absolute groottes van de gebruikersgroepen in elk van deze vijf jaren berekend. Tussen 2013 en 2017 groeide het totaal aantal e-fietsbezitters in Nederland van ongeveer 1,2 miljoen naar ruim 2 miljoen mensen, een toename van 74%. De twee groepen met de oudste gebruikers, de eerste en derde groep, laten een langzamere groei zien van respectievelijk 50 en 39%. Hierdoor is het aandeel van deze twee groepen (ten opzichte van alle e-fietsbezitters) in de loop der jaren gedaald. Terwijl de eerste groep in 2013 een aandeel van iets meer dan 56% had, was dat in 2017 iets minder dan 49%. Het aandeel van de derde groep daalde van 15% naar 12%. Voor de andere drie gebruikersgroepen is een hoger groeitempo zichtbaar. Deze drie groepen zijn alle drie in vijf jaar tijd meer dan verdubbeld. Relatief gezien groeien de jongere parttime werkende vrouwen met kinderen (groep 4) het snelst.

De verwachting is dat de drie jongere groepen (groep 2, 4 en 5) de komende jaren in een hoger tempo zullen blijven groeien. Omdat deze groepen de e-fiets vooral gebruiken voor woon-werkverkeer of onderwijs, zullen de aandelen van deze reismotieven in de afgelegde afstand per e-fiets blijven groeien. Daarnaast is het aannemelijk dat door deze trends substitutie-effecten duidelijker worden. Als meer mensen de e-fiets gaan gebruiken voor woon-werkverkeer, is het aannemelijk dat het substitutie-effect dat e-fietsverplaatsingen hebben op autoverplaatsingen ook op algemeen niveau kan worden waargenomen.

Studie 3: Actief reizen en de toename in overgewicht en obesitas

Geschat wordt dat lichamelijke inactiviteit ieder jaar verantwoordelijk is voor ongeveer 10% van de vroegtijdige sterfte wereldwijd, waardoor het een van de belangrijkste gezondheidsrisicofactoren is (belangrijker dan obesitas en roken) (Lee et al., 2012). De derde studie gaat in op de vraag in hoeverre actief reizen en gezondheid (body-mass index (BMI) en self-rated health (SRH)) elkaar door de tijd heen beïnvloeden. Drie jaar data van het MPN (2017-2019) zijn gebruikt om deze vraag te beantwoorden. Multivariate lineaire regressiemodellen zijn geschat om een eerste inschatting te doen van de relatie tussen actief reizen en de twee gezondheidsmaten (BMI en SRH), gevolgd door de schatting van verschillende RI-CLPMs om te beoordelen of actief reizen en gezondheid elkaar in de loop van de tijd beïnvloeden.

De regressiemodellen tonen aan dat er een duidelijke relatie bestaat tussen de twee gezondheidsmaten en actieve verplaatsingen. Mensen met overgewicht of obesitas maken

minder verplaatsingen en leggen minder afstand af met de fiets. Bijvoorbeeld, hoewel mensen in onze steekproef gemiddeld 1,4 fietsverplaatsingen over een afstand van 3,9 km in drie dagen maken, maken mensen met obesitas gemiddeld 0,56 minder verplaatsingen en fietsen ze 1,47 km minder in vergelijking met mensen met een gezond gewicht. Vergelijkbare relaties worden gevonden tussen de BMI en lopen, met als verschil dat mensen met overgewicht niet significant minder verplaatsingen te voet maken in vergelijking met mensen met een gezond gewicht.

De resultaten van de RI-CLPM's laten zien dat er een klein, maar significant negatief effect is van de loopafstand op de BMI bij mensen zonder obesitas. Het effect houdt in dat wanneer mensen hun loopafstand per drie dagen verhogen met 10 km, dit resulteert in een afname van hun BMI met 0,16 in het volgende jaar. Voor iemand van 1,80 m lang komt dit neer op 0,52 kg gewichtsverlies. Een vergelijkbaar (negatief) effect wordt niet gevonden voor mensen met obesitas. Het effect van actieve verplaatsingen op de BMI is niet aanwezig voor fietsen. Voor fietsen wordt een omgekeerd effect gevonden bij mensen zonder obesitas. Dat wil zeggen, een toename van het BMI-niveau in een jaar resulteert in een afname van het fietsgebruik in het volgende jaar, zowel in afgelegde afstanden als in verplaatsingen. Dergelijke effecten worden niet gevonden voor mensen met obesitas. Ook tussen e-fietsgebruik en BMI worden geen significante effecten gevonden.

Tussen actief reizen en SRH wordt alleen een statistisch significant positief verband gevonden voor het effect van gefietste afstand op SRH, wat aangeeft dat een toename van de gefietste afstand in een jaar resulteert in een positievere SRH in het volgende jaar. Geen significante effecten worden gevonden tussen SRH en lopen of het gebruik van de e-fiets.

Deze resultaten wijzen erop dat het bevorderen van actief reizen slechts een geringe daling van de BMI tot gevolg kan hebben door een toename van het lopen. Het omgekeerde negatieve effect van BMI op fietsen impliceert dat de stijgende percentages overgewicht en obesitas een negatief effect op de fietsniveaus kunnen hebben. Positief geformuleerd, als beleidsmakers erin slagen het overgewichtsniveau terug te dringen (bijvoorbeeld door betere voeding), kan dit volgens de resultaten leiden tot een toename van het aantal fietsverplaatsingen.

Studie 4: Identificeren van soft-refusal in (longitudinaal) reisgedragonderzoek

In onderzoek naar reisgedrag zijn meerjarige panels, zoals het MPN, opgezet om de drijfveren van (veranderingen in) reisgedrag over de tijd te begrijpen. De resulterende data uit deze panels zijn bij uitstek geschikt om de (causale) mechanismen achter reisgedrag, en de veranderingen daarin over de tijd, op individueel niveau te modelleren en te begrijpen. Om de data hiervoor effectief te kunnen gebruiken, is het van belang dat de kwaliteit van de data gewaarborgd is. Er zijn echter verschillende processen die tot een lage datakwaliteit kunnen leiden. Eén zo'n mechanisme heeft betrekking op het begrip "soft refusal", dat de neiging van sommige respondenten beschrijft om deelname op een "zachte" manier te weigeren, bijvoorbeeld door te beweren dat zij hun huis niet hebben verlaten hoewel zij dat in werkelijkheid wel hebben gedaan of door suboptimale antwoorden te geven als gevolg van het te snel beantwoorden van een vragenlijst.

In de vierde studie worden drie verschillende methoden gepresenteerd om mogelijke soft-refusal in een longitudinaal reisgedragonderzoek te identificeren, gebaseerd op: 1) het voorspellen van uithuizigheid 2) straightlining, en 3) de snelheid waarmee de vragenlijst wordt ingevuld. Alle methoden lijken in staat om respondenten met slecht responsgedrag in een reisgedragcontext te identificeren (d.w.z. een verdacht hoog niveau van gerapporteerde immobiliteit). Hoewel de eerste methode (een binaire logistische regressie om uithuizigheid te voorspellen) gericht is op het identificeren van rapportagedagen waarop respondenten ten onrechte geen verplaatsingen rapporteren, bleek dat straightlining in een vragenlijst en het te

snel invullen van een vragenlijst sterk gerelateerd zijn aan gerapporteerde immobiliteit in het reisdagboek. Net als bij eerder onderzoek blijkt dat uitval uit het panel gecorreleerd is met gerapporteerde immobiliteit. Bovendien blijkt dat uitval zelf een extra indicator is van gerapporteerde immobiliteit in het laatste jaar van deelname. Met andere woorden, de drie gepresenteerde methoden vangen waarschijnlijk niet alle soft refusal.

Een latent transitiemodel wordt gebruikt om verschillende gedragspatronen met betrekking tot de soft-refusal indicatoren aan het licht te brengen en overgangen tussen deze patronen door de tijd te bestuderen. Uit deze analyse blijkt dat er vier verschillende gedragspatronen zijn met betrekking tot soft-refusalgedrag. De grootste klasse bestaat uit respondenten die in het algemeen niet als mogelijke soft refusal worden aangemerkt, gevolgd door een klasse die de vragenlijst te snel lijkt in te vullen en een klasse met een hoger aandeel straightlining. Hoewel hun niveau van gerapporteerde immobiliteit hoger is dan dat van de eerste klasse, zijn er slechts enkele verschillen in hun sociodemografische profielen. Alleen de vierde klasse (een klasse met een hoog risico van soft refusal en een zeer hoog niveau van gerapporteerde immobiliteit) heeft een duidelijk afwijkend sociodemografisch profiel. Wanneer men a priori weet welk type respondenten een hoger risico op soft-refusal vertoont, kan hiermee rekening worden gehouden door deze groepen (bij) te werven. In het geval van het MPN zouden dat jongeren en lager opgeleiden zijn.

Uit de transitieanalyse bleek dat alleen wanneer respondenten op meerdere indicatoren als mogelijke soft refuser worden aangemerkt (de hoogrisicoklasse), het uitvalpercentage hoger is. Bovendien, als respondenten niet uitvallen, blijven ze meestal in dezelfde klasse in de loop van de tijd. Dit impliceert dat het in het panel houden van respondenten uit de hoogrisicoklasse er vooral toe zal leiden dat deze respondenten bij latere metingen dezelfde slechte datakwaliteit leveren. Men zou er daarom voor kunnen pleiten dat deze respondenten volledig uit het panel moeten worden verwijderd. In het specifieke geval van het MPN heeft het verwijderen van één respondent echter tot gevolg dat het hele huishouden uit het panel wordt verwijderd. Aangezien de meeste respondenten uit de hoog risicoklasse deel uitmaken van een meerpersoonshuishouden, zou het verwijderen van deze respondenten tegelijkertijd betrouwbaardere respondenten uit het panel verwijderen.

Studie 5: De effecten van de COVID-pandemie op het reisgedrag

De Wereldgezondheidsorganisatie (WHO) heeft COVID-19 op 11 maart 2020 uitgeroepen tot een pandemie. De maatschappelijke gevolgen van zowel het virus als de maatregelen om de verspreiding ervan tegen te gaan zijn fors. De omstandigheden leiden tot een unieke situatie waarin mensen hun dagelijks leven ingrijpend moeten veranderen. De vijfde studie toont eerste inzichten in hoe activiteitenpatronen, de manier waarop we werken en hoe we reizen drastisch veranderen.

Om de effecten van de COVID-19 pandemie te bestuderen, werd een representatieve steekproef van het MPN (ongeveer 2.500 respondenten) uitgenodigd om deel te nemen aan een extra meting met een vragenlijst en een driedaags reisdagboek. Aangezien deze respondenten al vóór de pandemie lid waren van het MPN, waren betrouwbare metingen van precies dezelfde groep personen met betrekking tot ervaringen, voorkeuren en gedrag vóór de pandemie beschikbaar.

Uit de resultaten blijkt dat ongeveer 80% van de mensen hun activiteiten buitenshuis verminderden. Vooral oudere mensen waren veel minder actief dan vóór de crisis. Hoewel de meeste mensen nog voldoende mogelijkheden ervaarden om boodschappen te doen, was ongeveer 40% van de mensen ongelukkig met de beperkte mogelijkheden voor sociale interactie. Het aantal verplaatsingen en de afgelegde afstand waren met respectievelijk 55% en 68% gedaald in vergelijking met het najaar van 2019. Het gebruik van het openbaar vervoer

werd het sterkst beïnvloed met een daling van meer dan 90% in het aantal verplaatsingen. Zogenaamde rondeverplaatsingen wonnen aan populariteit. Een op de vier reizen was een rondeverplaatsing, zoals een wandel- of fietstocht.

De schok in het dagelijkse leven die de pandemie veroorzaakte, kan een aantal structurele gevolgen hebben voor onze mobiliteit. Hoewel meer dan 90% van de mensen die ten tijde van het onderzoek hun activiteiten buitenshuis hadden verminderd niet verwachtten dat zij deze lagere frequentie van activiteiten in de toekomst zouden volhouden, verwachten meer mensen structurele veranderingen in de manier waarop we werken en reizen. Meer dan een kwart van de thuiswerkers verwachtte na de pandemie in de toekomst vaker thuis te werken. Van de werknemers die vaker op afstand vergaderden, verwachtte iets meer dan een derde dit in de toekomst ook vaker te zullen doen. Ook kunnen enkele structurele veranderingen in de manier waarop we reizen worden verwacht. Ruwweg 20% van de mensen verwachtte in de toekomst meer te gaan fietsen en lopen. Een vergelijkbaar percentage van de mensen met vliegervaring verwacht in de toekomst minder met het vliegtuig te zullen reizen. Hoewel de studie de eerste aanwijzingen geeft dat de pandemie structurele gevolgen kan hebben voor ons reisgedrag, is meer onderzoek nodig om dit te bevestigen.

Implicaties van het onderzoek

De resultaten in dit proefschrift hebben verschillende implicaties voor onderzoek en beleid. Voor onderzoek tonen de studies in dit proefschrift het belang aan van het gebruik van longitudinale data om mechanismen die ten grondslag liggen aan veranderingen in reisgedrag bloot te leggen. Terwijl cross-sectionele studies geschikt zijn om op geaggregeerd niveau te bestuderen hoe reisgedrag verandert en hoe verschillende trends in de samenleving (bv. de toenemende populariteit van de e-fiets, of de COVID-19 pandemie) reisgedrag beïnvloeden, zijn longitudinale data nodig om deze trends te verklaren op basis van veranderingen die plaatsvinden op individueel niveau. Het gebruik van cross-sectionele data om veranderingen in reisgedrag te verklaren kan ertoe leiden dat verkeerde conclusies worden getrokken over de sterkte en de richting van de effecten. Cross-sectionele data zijn bijvoorbeeld geschikt om te laten zien hoe het gebruik van de e-fiets samenhangt met het autogebruik, maar op basis van deze data kan niet worden bepaald of het gebruik van de e-fiets op individueel niveau het autogebruik beïnvloedt of omgekeerd. Daarvoor zijn longitudinale data nodig.

De resultaten in dit proefschrift laten verschillende andere voordelen van het gebruik van longitudinale data ten opzichte van cross-sectionele data zien. Ten eerste is het belangrijk om rekening te houden met bidirectionele effecten. Bijvoorbeeld, terwijl de meeste eerdere studies naar de relatie tussen gezondheid en actief reizen alleen kijken naar het effect van actief reizen op de gezondheid, laat dit proefschrift zien dat er ook omgekeerde effecten zijn. Ten tweede is het belangrijk om onderscheid te maken tussen effecten binnen personen en effecten tussen personen. Zonder dit te doen, kunnen verkeerde conclusies worden getrokken over het bestaan of de sterkte van bepaalde effecten (dit blijkt bijvoorbeeld uit de studie over gezondheid en actief reizen). Bovendien maakt het hebben van een panel met bereidwillige respondenten het mogelijk om snel in te spelen op gebeurtenissen in de samenleving (bijvoorbeeld een pandemie) en te laten zien hoe deze gebeurtenissen de mobiliteit van mensen beïnvloeden.

Dit proefschrift heeft ook verschillende implicaties voor beleidsmakers. Ten eerste moeten beleidsmakers zich realiseren dat reisgedrag gemiddeld genomen relatief inert is. Als gevolg hiervan kan de effectiviteit van beleid gericht op het veranderen van reisgedrag beperkt zijn als het niet gericht is op specifieke groepen mensen. Dit proefschrift laat zien dat er bepaalde momenten zijn waarop veranderingen in reisgedrag vaker voorkomen. Na het optreden van een

levensgebeurtenis (bijvoorbeeld geboorte van een kind, of verhuizing) verandert het reisgedrag vaker. Deze levensgebeurtenissen moeten daarom worden beschouwd als een kans voor beleidsmakers om reisgedrag te veranderen, omdat het waarschijnlijk is dat mensen gevoeliger zijn voor beleidsinterventies op zulke momenten dat ze hun reisgedrag heroverwegen. Dit proefschrift toont ook aan dat als beleidsmakers niet ingrijpen op deze levensgebeurtenissen, mensen een meer auto-afhankelijk reispatroon kunnen aannemen.

Ten tweede toont dit proefschrift aan dat de populariteit van de e-fiets snel toeneemt. Specifiek voor woon-werkverkeer blijkt dat mensen de e-fiets gebruiken als vervanging van de auto. Beleidsmakers zouden zich daarom moeten richten op het bevorderen van het gebruik van de e-fiets onder de werkzame bevolking, omdat dit waarschijnlijk zal resulteren in een zekere vervoerwijzeverschuiving van auto naar e-fiets. Daarnaast lijkt het bevorderen van actief reizen mogelijk te zijn met beleidsmaatregelen die niet direct verband houden met mobiliteit. Aangezien uit de resultaten blijkt dat een verandering in BMI een negatieve invloed heeft op het fietsgebruik, zouden beleidsmakers het fietsgebruik kunnen verhogen als zij beleid invoeren dat effectief is in het terugdringen van overgewicht en obesitas.

Tot slot heeft de COVID-19 pandemie ons laten zien dat veel van de veranderingen in de manier waarop mensen werken of activiteiten uitvoeren, niet mogelijk waren zonder ICT. Er is echter een groep mensen die beperkte toegang heeft tot ICT-instrumenten of die niet over de vaardigheden beschikt om ze te gebruiken. Voor beleidsmakers is het belangrijk deze tekortkomingen van de beschikbare ICT-oplossingen aan te pakken om gedragsveranderingen die afhankelijk zijn van ICT te vergemakkelijken.

1 Introduction

1.1 Background

For most people, mobility is an important part of daily life. With modern mobility systems, people have access to a range of transport modes allowing them to basically reach any destination they want. Although people often have multiple options to choose from, personal mobility is dominated by motorized road transport in many countries and cities, also in the Netherlands, owing to the ease of use and high level of flexibility. This popularity poses challenges for governments to keep their countries and cities accessible, attractive, safe and liveable since motorized road transport comes with several negative effects such as increased congestion, damage to the environment, negative effects on human health due to emissions, inefficient use of space and reduced liveability of cities. For instance, in the top 15 most-congested European cities an average commuter spends between 45 and 101 hours in congestion per year and road transport is responsible for more than 70% of all CO_2 transport emissions and up to 30% of small particulate emissions in the EU (Alonso Raposo et al., 2019). Meanwhile, private motorized transport is up to 28 times less space-efficient for inner-city travel than public and non-motorized transport (de Haas & Hamersma, 2020).

An important development that complicates challenges regarding the mobility system is the increase of urbanization rates. The share of people living in urban areas increased from 34% in 1960 to over 55% in 2018. It is expected that this trend will continue and that almost 70% of people worldwide will live in urban areas by 2050 (The World Bank, 2019). For the EU, urbanization rates will be even higher with an expected 84% of people living in cities by 2050 (Alonso Raposo et al., 2019). Not only will these increased urbanization rates put more pressure on the mobility system as transport demand will increase, it also means that more people will be affected by its negative side effects such as congestion and emissions. On the other hand, increased urbanization rates may offer possibilities for sustainable travel modes such as walking and cycling, as more destinations will be in walking or cycling range.

The solution to these challenges does not only lie in changing the mobility system itself. Especially in light of physical space becoming scarcer, expanding the system's capacity by

expanding the infrastructure is not always possible. To face these challenges, the behaviour of users of the mobility system also has to change. This may even be a bigger challenge than changing the mobility system itself, as earlier research has shown that travellers are behaviourally inert; they do not change their travel behaviour often (Chorus & Dellaert, 2012; Gärling & Axhausen, 2003). To promote behavioural change among travellers, there is a need to understand the determinants of travel behaviour as well as the underlying mechanisms of changes in travel behaviour. Understanding these mechanisms allows to design and implement effective policies that are aimed to change travel behaviour.

1.2 Research objective

Although several decades of travel behaviour studies are available, most studies to date are limited by relying on cross-sectional data, i.e. data in which individuals are only surveyed or observed a single time. Since individuals only participate a single time, cross-sectional data do not allow studying intra-individual changes that occur over time. As a result, directions of causation of travel behaviour change have to be assumed, rather than be inferred from the data with the risk of drawing wrong conclusions. To effectively study the mechanisms underlying travel behaviour change, one needs data on travel behaviour at different time points, including data on the factors of interest (e.g. events leading up to a travel behaviour change).

A relatively simple method to collect data that allows studying travel behaviour change is by conducting retrospective surveys. These types of surveys collect all the needed data at once, but involve asking respondents to report about travel behaviour changes that occurred in the past and any events leading up to that change. An important downside of retrospective surveying is that it may be hard for certain respondents to correctly report about behaviour and events in the past. Since there will be a considerably amount of time between the survey and any events leading to a change in travel behaviour, there is a risk that respondents forget to report relevant information due to memory loss (Lanzendorf, 2003).

To limit the amount or recall bias, data should ideally be collected prospectively. Panel studies are ideally suited as these prospective studies involve repeated surveys among the same group of individuals over time (Chlond & Eisenmann, 2018). However, longitudinal travel surveys are usually costly and very time-consuming to operate and come with a number of challenges, such as (non-random) attrition and panel fatigue. As a result, only a limited number of large-scale longitudinal travel surveys have been conducted around the world. Examples are the American Puget Sound Transportation Panel (PSTP) (Murakami & Watterson, 1992), the Dutch National Mobility Panel (LVO) (Van Wissen & Meurs, 1989), the Chilean Santiago Panel (Yáñez et al., 2010), the German Mobility Panel (MOP) (Ecke et al., 2019; Zumkeller et al., 1997) and the Netherlands Mobility Panel (MPN) (Hoogendoorn-Lanser et al., 2015). Of these panels, only the latter two are still in operation.

The aim of this thesis is to uncover several mechanisms behind travel behaviour change towards sustainable travel modes, based on a large-scale longitudinal travel survey; the Netherlands Mobility Panel (MPN). As this panel has been operating for several years and collects a wide range of relevant information from its respondents, it allows studying numerous aspects of travel behaviour (change). I specifically focus on topics that will support policy makers in facing the challenges regarding the mobility system that I discussed in the previous section. This thesis will help policy makers understand how travel behaviour changes and provide them with knowledge to promote travel behaviour change towards a more sustainable mobility system. I focus on four topics that are imperative to achieve this goal: the effects of life events on travel behaviour, new technologies to promote a mode shift away from car (in this case, the e-bike), the links between personal health and active travel and effects of the COVID-19

pandemic on mobility. To correctly study these topics, longitudinal data is needed, as we want to infer the direction of effects from the data rather than making assumption on this direction, with the risk of drawing wrong conclusions (e.g., we do not know whether active travel has an effect on personal health or that the effect runs from personal health on active travel). While these longitudinal data are ideally suited to study travel behaviour changes, it is crucial that the data quality is guaranteed. To address one possible cause of low data quality, I present a fifth study focused on the notion of soft-refusal, which describes the tendency of some respondents to use a strategy to lower their response burden, e.g. by claiming they did not leave their house even though they actually did.

The Netherlands Mobility Panel (MPN)

The Netherlands Mobility Panel (MPN) is an annual household panel that started in 2013 and consists of approximately 2,000 complete households (Hoogendoorn-Lanser et al., 2015). The MPN was set up to study the short-run and long-run dynamics in travel behavior of Dutch individuals and households and to assess how changes in personal- and household characteristics correlate with changes in travel behavior. Households are recruited from the online access panel of a Dutch fieldwork agency. Before households enter the MPN, the gatekeeper of the household (an adult household member) is asked to fill out a screening questionnaire, as shown in figure 1.1. The screening questionnaire is designed to gather basic information about the household and present information about the design and goal of the MPN.

After entering the panel, households are yearly asked, between September and November, to complete several tasks. First, the gatekeeper of the household is asked to fill out a household questionnaire in which they report information on the household composition, ownership of means of transport and detailed information on cars in the household. Next, all household members of at least 12 years old are asked to complete a three-day travel diary and fill in an extensive questionnaire that includes questions on topics such as occupational status, use of different modes of transport, health and life events in the past year. Respondents are equally distributed over weekdays and have the same starting weekday each year.

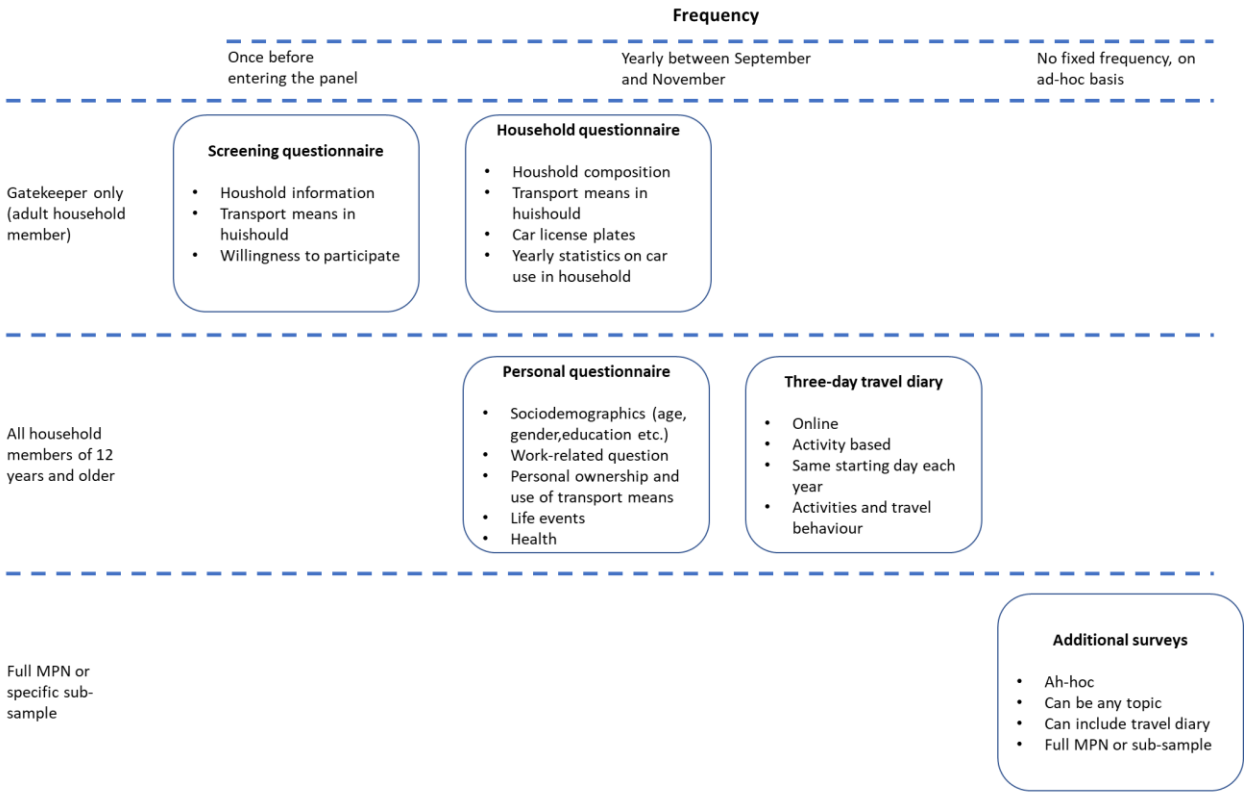

Figure 1.1 Design of the MPN

Besides the yearly questionnaires and the three-day travel diary, the MPN offers the possibility to study specific topics by means of additional questionnaires or repeating the three-day travel diary throughout the year. This possibility allows to create a rich dataset with relatively little efforts, as all additional collected data can be linked to data from the regular yearly waves on an individual level. Additional data has for instance been collected to study the link between well-being and mobility (Delbosc et al., 2020), the potential of on-demand services for urban travel (Geržinič et al., 2022) and the effects of the COVID-19 pandemic on travel behaviour.

In this thesis, I answer several substantive questions related to travel behaviour change on an individual level. The MPN offers (new) possibilities to study these kinds of questions. The general outline is as follows. The first study focuses on behavioural changes in daily mobility after major life events, such as having a baby or changing jobs. The following study is focused on a new technology that may help in realizing a modal shift away from car. In this study, the focus is on the e-bike. Next, in the third study I focus on the bi-directional effect between health and active travel (i.e. walking and cycling). The fourth study is of a more methodological nature as it addresses the issue of soft-refusal in (longitudinal) travel behaviour surveys. As the COVID-pandemic occurred during the process of writing this thesis, this presented the unique opportunity to study how travel behaviour changes under the extreme conditions of a pandemic. In the fifth study I address these effects.

1.3 Research gaps

1.3.1 Study 1: The effect of life events on daily travel patterns

Since many travel behaviour studies are based on cross-sectional data, any events leading up to changes cannot be modelled. A relatively new approach to study travel behaviour change is the mobility biographies approach. Mobility biographies studies take a life-course approach and assume there are certain key events (life events) in an individual's life course that trigger change in travel behaviour (Lanzendorf, 2003). Mobility biographies studies are often based on longitudinal data to analyse individual changes over time.

These life events have been described as 'windows of opportunity' to change daily routines (Schäfer et al., 2012). Multiple studies have shown that people are indeed more susceptible to interventions after life events such as a residential move or changing jobs (Anable, 2013; Thøgersen, 2012; Verplanken & Roy, 2016). Recent overviews of mobility biographies studies are provided by Müggenburg et al. (2015) and Schoenduwe et al. (2015). Knowledge about these windows of opportunity could benefit transport policy that is aimed at changing travel behaviour or realizing a modal shift.

Most mobility biographies studies are, however, of a very explorative nature and do not consider the events and their effects in a broader theoretical framework (Müggenburg et al., 2015). A number of theoretical frameworks have been proposed over the years (Clark et al., 2014; Lanzendorf, 2003; Müggenburg et al., 2015; Scheiner, 2007). While these frameworks are all, an important notion by Clark et al. (2014) is that the deliberation of travel behaviour that takes place after certain life events is influenced by mediating factors, such as an individual's personal history (e.g. initial travel behaviour) and intrinsic motivations (e.g. economic reasons). Most mobility biographies studies, however, only assess the direct effects of life events on travel behaviour and often do not consider the interaction with past travel behaviour. Some mobility biographies studies do include past travel behaviour (see e.g. Prillwitz et al. (2006), Scheiner and Holz-Rau (2013), Yamamoto (2008)), but they often do not consider interactions between past travel behaviour and the effects of life events (with the exception of Kroesen (2014)). This study aims to answer the following research question:

How do life events (e.g. having a baby or moving house) interact with previous behaviour in shaping new behavioural patterns?

To answer this question, a latent transition model is estimated based on the first three years of data from the MPN (2013-2015). Six life events within the household-, employment- and residential biography are included in this to assess their effect's on people's transition between travel patterns over time.

1.3.2 Study 2: The e-bike: a new technology that may promote a shift towards sustainable travel

In the Netherlands, 47% of all car trips are under 7.5 kilometres and 64% are under 15 kilometres (Statistics Netherlands, 2020). Policy makers worldwide aim to realize a mode shift away from car, towards more sustainable modes. New innovative transport modes, such as the e-bike, may assist in this. As the e-bike allows travelling at greater speeds with less effort compared to a conventional bicycle, it has the potential to replace a substantial part of these car trips. As an e-bike emits 40 times less carbon dioxide (Shao et al., 2012) compared to a car, a substitution of car trips with e-bike would benefit the environment, as well as helping reduce road congestion. However, whether the e-bike brings environmental and other benefits depends on the mode it is replacing (Cherry & Cervero, 2007). If the e-bike is mainly substituting non-motorized modes such as the conventional bicycle and walking, benefits could even be negative.

Several studies have already focused on the effect that the advent of the e-bike has on travel behaviour. These studies generally report that the e-bike substitutes not only the conventional bicycle, but also, to a certain degree, the car and public transport, depending on local context. For instance, two studies with a geographic focus on China show that in areas with a high quality public transport network, the e-bike is seen as an affordable alternative to public transport (Cherry & Cervero, 2007), whereas in areas without sufficient public transport facilities the e-bike mainly substitutes the conventional bicycle (Weinert et al., 2007b). A limitation of previous studies is, however, that they are either based on a cross-sectional survey or in-depth interviews which only allow for comparisons between individuals (differences in travel mode choices) and do not allow an evaluation of within-person effects (changes in travel mode choices) over time. As such, the current state of the art of the literature into e-bike substitution effects provides an incomplete picture, hampering the derivation of sound policies in this regard. Therefore, the second study aims two answer the following two question:

1. *To what extent does the use of the e-bike substitute the use of other modes on an individual level?*
2. *Which homogenous groups are present within the e-bike population and how do these groups develop over time?*

To answer the first question, a random intercept cross-lagged panel model (RI-CLPM) is estimated using data from five waves of the MPN (2014-2018). The second question is answered based on data from the Dutch national travel survey (OViN), operated by Statistics Netherlands (Statistics Netherlands, 2018b). The OViN is a continuously running cross-sectional survey that reflects the mobility of the Netherlands. Since 2013, the e-bike is a distinguished mode in OViN. A latent class model is estimated to uncover different user groups among the e-bike population and their development over time based on five years of OViN data (2013-2017).

1.3.3 Study 3: Active travel and increasing overweight and obesity rates

It has been estimated that physical inactivity accounts for roughly 10% of premature mortality globally in any given year, making it one of the leading health risk factors (more important than obesity and smoking) (Lee et al., 2012). Globally, around a third of the adult population does not meet public health guidelines for recommended levels of physical activity (Hallal et al., 2012), but in Western societies this is typically even higher (e.g. in the Netherlands half of the population does not satisfy the norm).

While there are many studies available on the relation between active travel and health, most are based on cross-sectional data and are therefore unable to determine the direction of causation. Only a limited number of longitudinal studies are available. Most of these longitudinal studies did not consider a bidirectional effect between health and active travel, but only an effect of active travel on health. While studies have shown that active travel may lead to a better health (e.g. a lower body-mass index (BMI)), the reverse effect may also be present. People with a lower BMI may be more inclined to travel actively because this takes less effort for individuals with a healthy weight compared to obese individuals. The existence of such an effect would imply that promoting active modes to reach sustainability goals would be hindered by the increasing rates of overweight and obesity. To this end, the third study aims to answer the following question:

To what extent do active travel (bicycle, e-bike, walking) and health (body-mass index (BMI) and self-rated health (SRH)) influence each other over time?

To answer this question, three waves of data from the MPN are used (2017-2019). As health related questions were not included in the first four waves of the MPN, these waves are not suited for this study. To provide an initial assessment of the relationship between active travel and the two health outcomes, multivariate regression models are estimated. To study the direction of causation, Random-Intercept Cross-Lagged Panel Models (RI-CLPM) are estimated based on the three previously mentioned waves of the MPN.

1.3.4 Study 4: Identifying soft-refusal in (longitudinal) travel behaviour surveys

In travel behavior research, multi-year panels, such as the MPN, have been set up to understand (changes in) the drivers of travel behavior over time. Participants in these panels typically complete – on a regular basis (e.g., every year) – a (self-reported) multiple-day travel diary along with a questionnaire containing personal and psychographic information. The resulting data are ideally suited to model and understand the (causal) mechanisms behind travel behavior, and the changes therein over time at the individual level (see e.g. Scheiner et al. (2016) and de Haas et al. (2022b)).

To use the data effectively for this purpose, it is crucial that the data quality is guaranteed. However, there are several processes that may result in low data quality. One such mechanism relates to the notion of soft-refusal, which describes the tendency of some respondents to refuse participation in a ‘soft’ way, e.g. by claiming they did not leave their house even though they actually did or by giving sub-optimal answers as a result of speeding through a questionnaire. Identifying these “soft refusers” is important, e.g., in the context of research that is focused on identifying vulnerable groups with actual low mobility. Obviously, having these vulnerable groups mixed with soft refusers complicates research efforts focused on questions related to this subject.

While there is ample evidence that soft-refusal may have an effect on data quality, no study is available that assesses different indicators of soft-refusal in a travel behavior context and its relationship with reported travel behavior. Furthermore, given the multi-year context of a panel, it is relevant to study how soft-refusal behavior develops over time among individuals. This study aims to answer the following questions:

1. *How can soft-refusal be identified in (longitudinal) travel surveys and to what extent is soft-refusal correlated with reported immobility?*
2. *To what extent is soft-refusal behaviour constant over time?*

To identify soft-refusal, three different methods are developed, based on 1) predicting out-of-home activity 2) straightlining, and 3) speeding. These methods are used to explore the link between soft-refusal and attrition in the first seven waves of the MPN (2013-2019). To answer the second question, respondents are classified into different response behavior classes with a latent class model based on the indicators of soft-refusal. Transitions between these classes over time are studied using a latent transition analysis.

1.3.5 Study 5: The effects of the COVID-pandemic on travel behaviour

After spreading around the world at an alarming rate, the World Health Organization (WHO) declared COVID-19 as a pandemic on the 11th of March 2020 (WHO, 2020). The societal impacts of both the virus and the measures taken to reduce its spread are severe. The circumstances result in a unique situation in which people have to change their daily life radically. Activity patterns, the way we work, and how we travel are three facets of daily life that have changed drastically. For policy makers, it was important to quickly have up-to-date knowledge about the effects of the pandemic and all measures on mobility and how this may change future behaviour.

While this study was not a planned part of this PhD, the pandemic offered a unique situation to fully use the potential of a mobility panel such as the MPN. Since respondents were part of the MPN before the pandemic, the MPN offers the possibility to reliably study the effects of the pandemic on people's travel behaviour since a fixed group of people is followed through time who's travel behaviour pre-pandemic is known.

As people in the Netherlands (and many other countries) were urged to stay at home (during several stages of the pandemic), many people were experiencing new activities or doing activities differently. These experiences might affect future behaviour, long after the virus itself will be eradicated. People might for instance prefer to work from home in the future, now that they have experienced what it is like for a longer period of time. To understand possible effects of COVID-19 and the lockdown on travel behaviour in a future without the disease insights are needed into how people are experiencing its current effects and how this relates to travel behaviour. Since this study was done in the beginning of the pandemic (March/April 2020), it could not study any structural effects, but it aims to answer the following question:

How do the COVID-pandemic and the measures to reduce the spread of the virus change activities, work and travel behaviour in the Netherlands?

To answer this question, a sub-sample of the MPN was used. This sub-sample of approximately 2,500 respondents participated in at least the 2018 and 2019 wave of the MPN and completed an additional measurement in March/April 2020. This additional measurement included an extensive survey as well as the three-day travel diary. Descriptive analyses along with bivariate statistical tests are used to assess the differences in behaviour pre-COVID and during the pandemic.

1.4 Outline of thesis

The outline of this thesis follows the five studies. In the conclusion chapter, besides addressing the conclusions of each of the individual studies, I will discuss a number of general conclusions about the use of mobility panels and the policy implications of the studies. Furthermore, I will reflect on the studies and do recommendations for future research.

2 The effect of life events on daily travel patterns

This chapter is based on the following article:

de Haas, M. C., Scheepers, C. E., Harms, L. W. J., & Kroesen, M. (2018). Travel pattern transitions: Applying latent transition analysis within the mobility biographies framework. *Transportation Research Part A: Policy and Practice, 107*, 140-151. doi: https://doi.org/10.1016/j.tra.2017.11.007

Abstract

This paper applies the relatively new method of latent transition analysis within the mobility biographies framework to assess how life events influence changes in travel behaviour. Using transition analysis, it is assessed how people switch between different travel patterns over time. Data from the first three waves of the Netherlands Mobility Panel (MPN) are used to reveal different travel patterns and analyse transitions between these patterns over time. Six different meaningful travel patterns are revealed. Four exogenous variables and six life events within the household, employment and residential biography are included to assess their effects on people's transitions between the travel patterns over time. For all life events significant effects are found, indicating that there might indeed be 'windows of opportunity' to change travel behaviour when a life event occurs. The results show that, on average, people who only use a single mode are less likely to change their travel pattern compared to multimodal travellers. In addition, the effects of life events and exogenous variables depend on the initial travel pattern. In general, single-mode travellers are less affected by life events than multimodal travellers. This indicates that it is important to include past travel behaviour within mobility biographies studies.

2.1 Introduction

Travel behaviour can generally be described as inert or habitual behaviour; it does not change very often (Chorus & Dellaert, 2010; Gärling & Axhausen, 2003). It is therefore interesting to gain more insight into when travel behaviour does change. Since a lot of travel behaviour studies are based on cross-sectional data, any events leading up to changes cannot be modelled. A relatively new approach to study travel behaviour change is the mobility biographies approach. Mobility biographies studies take a life-course approach and assume there are certain key events (life events) in an individual's life course that trigger change in travel behaviour (Lanzendorf, 2003). Mobility biographies studies are often based on longitudinal data to analyse individual changes over time.

These life events have been described as 'windows of opportunity' to change everyday routines (Schäfer et al., 2012). Multiple studies have shown that people are indeed more susceptible to interventions after life events such as a residential move or changing jobs (Anable, 2013; Thøgersen, 2012; Verplanken & Roy, 2016). Recent overviews of mobility biographies studies are provided by Müggenburg et al. (2015) and Schoenduwe et al. (2015). Knowledge about these windows of opportunity could benefit transport policy that is aimed at changing travel behaviour or realizing a modal shift.

Most mobility biographies studies are, however, of a very explorative nature and do not consider the events and their effects in a broader theoretical framework (Müggenburg et al., 2015). A number of theoretical frameworks have been proposed over the years (Clark et al., 2014; Lanzendorf, 2003; Müggenburg et al., 2015; Scheiner, 2007). All frameworks are comparable in the fact that they distinguish different domains of life events that might have an influence on an individual's travel behaviour. Scheiner (2007) distinguishes three domains of life events that interact with the mobility biography; events in the household biography, the employment biography and the residential biography. Besides effects on the mobility biography, Scheiner (2007) argues that there are interrelations between the domains of life events. An important extension to this, as well as the other frameworks is given by Clark et al. (2014) who proposes that the deliberation of travel behaviour that takes place after certain life events is influenced by mediating factors, such as an individual's personal history (e.g. initial travel behaviour) and intrinsic motivations (e.g. economic reasons). Most mobility biographies studies, however, only assess the direct effects of life events on travel behaviour and often do not consider the interaction with past travel behaviour.. Some mobility biographies studies do include past travel behaviour (see e.g. Prillwitz et al. (2006), Scheiner and Holz-Rau (2013), Yamamoto (2008)), but they often do not consider interactions between past travel behaviour and the effects of life events (with the exception of Kroesen (2014)). To date, there is therefore limited empirical support for the mediating factors (in terms of initial travel behaviour) as proposed by Clark et al. (2014).

This paper aims to apply the relatively new latent class transition analysis within the mobility biographies framework to reveal different travel patterns and assess the influence of life events on changes in travel behaviour. This is done by extending the latent class model to a latent transition model. While traditional clustering techniques deterministically assign people to clusters, latent class analysis takes measurement error into account by probabilistically assigning people to clusters. Latent class- and transition analysis have already successfully been used to identify different types of multimodal travellers (Molin et al., 2016) and to assess the influence of several exogenous variables on changes in travel behaviour (Kroesen, 2014).

The first contribution of this study is that it applies a latent clustering- and transition analysis within the mobility biographies framework. This paper considers travel patterns, defined by self-reported trip rates, instead of the use or ownership of a single mode. Most mobility

biographies studies only consider a single mode (see e.g. Clark et al. (2014) and Oakil et al. (2011)) or multiple modes in different models (see e.g. Beige and Axhausen (2012) and Scheiner and Holz-Rau (2013)). Only a limited number of studies consider multimodal travel patterns, see e.g. Kroesen (2014) and Scheiner et al. (2016). Considering multimodal travel patterns within the mobility biographies framework offers a holistic view of travel behaviour and the effects of life events. This also offers the possibility to assess how the use of different travel modes influences the probabilities that one will change its travel pattern, even without the occurrence of a life event. It can, for instance, be expected that people who use different modes, are more prone to change their behaviour since they are already familiar with multiple modes. Diana (2010) showed that multimodal travellers show a stronger propensity to use other modes, something that was also concluded by Kroesen (2014).

The second contribution is the fact that the influences of both life events and other exogenous variables on changes in travel patterns as a whole are assessed. Besides six life events (change in the number of adults in the household, changing jobs, stop working, moving house, birth of a child and start or changing education), nine exogenous variables are included in the analyses (gender, age, educational level, household composition, income, working hours per week, level of urbanization, distance to a train station and number of reported weekend days). While most mobility biographies studies include one or more exogenous variables, they do not consider the effects of these variables on changes in the travel pattern as a whole, but rather on a single mode, as explained in the previous paragraph. Besides having an influence on initial travel behaviour, it could be argued that several personal- and household characteristics have an influence on changes in travel behaviour. For instance, people with a low income may have fewer financial possibilities to change their travel behaviour and might show more inert behaviour compared to people with a higher income. The same holds for people living in rural areas where public transport is often less of an option than for people living in densely populated areas where there is often a better public transport network. Therefore, people in densely populated areas might show more changes in their travel behaviour. It can therefore be expected that these exogenous variables not only have an influence on an individual's initial travel pattern, but also on the transition probabilities.

The third contribution of this paper is that it considers the initial travel pattern of people when analysing changes in travel patterns and especially the interaction between past travel behaviour and life events. It has been argued that past behaviour is an important predictor of future behaviour (Ouellette & Wood, 1998). Although initial travel behaviour is sometimes included in mobility biographies studies, interactions between past travel behaviour and life events are often not. This paper explicitly considers interactions between life events and initial travel behaviour to assess whether effects of life events are different, depending on one's past travel behaviour.

2.2 Model conceptualization

Latent class- and transition analysis will be used to reveal different travel patterns and assess how transitions between these classes are influenced by the occurrence of different life events. Figure 2.1 shows the conceptual model for the latent transition analysis.

At each point in time, a latent class model is specified to cluster respondents based on their similarities with respect to the included indicators. Latent class analysis is built on the assumption that the associations between the indicators are explained by an underlying latent variable (McCutcheon, 1987). The latent variable is not directly measured, but it is inferred

from observed indicators. In this study, trip rates of different modes (car, bike, public transport and walking) are used as indicators. As a result, the latent categorical variable represents an individual's travel pattern.

After defining the different travel patterns, transitions between these patterns are assessed by extending the latent class model to a latent transition model. A latent transition model can be described as repeated latent cluster analyses over-time where the same travel patterns are defined at each time point to assess transitions between the patterns (Collins & Lanza, 2009). The parameter estimates from the latent transition analysis can be used to compute transition probability matrices.

Latent class- and transition analysis allow for the use of covariates (exogenous variables and life events). The exogenous variables are used to predict initial cluster membership and interact with transitions between clusters. The life events are only used to interact with transitions between clusters. The effects of the covariates are able to vary for every latent class (as indicated by the interaction effect in Figure 2.1). By interacting life events and other exogenous variables with transitions, their effect on transition probabilities can be assessed by computing different transition matrices. Latent transition analysis thereby allows assessing whether people with different travel patterns are differently affected by life events.

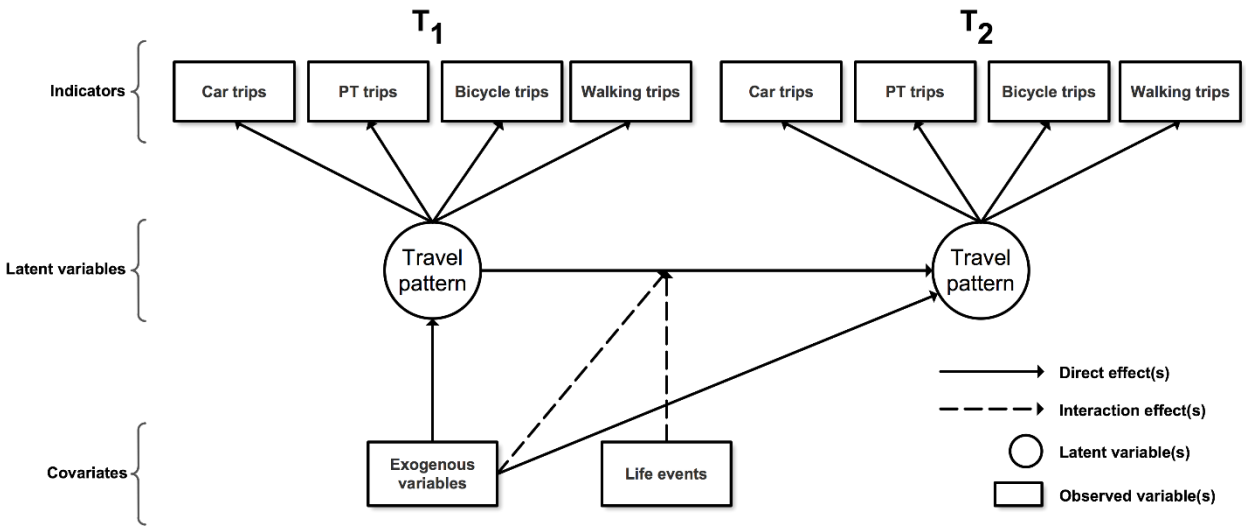

Figure 2.1 Conceptual model of the latent class- and transition analysis

In total, nine active covariates are included as predictors for initial cluster membership; gender, age, educational level, household composition, income, working hours per week, level of urbanization, distance to a train station and a variable to control for the number of reported weekend days. The life events are not used as predictors for initial cluster membership, but are assumed to influence the transitions between clusters.

Within the mobility biographies framework, three domains of life events are typically considered; events in the household biography, the employment biography and the residential biography (Schoenduwe et al., 2015). Within these three domains, six life events are included to assess their effects on transitions between travel patterns. With respect to the household biography a change in the number of adults and the birth of a child are included. A change in the number of adults could occur due to multiple life events such as partners who start living together or divorce. With respect to the employment biography changing jobs, stop working

and starting or changing an educational programme are included. Finally, with respect to the residential biography a residential move is included.

2.3 Method

2.3.1 Data and method

To assess over-time changes of individuals, longitudinal data is required. In this study, panel data from the Netherlands Mobility Panel (MPN) are used. The MPN is an annual household panel that started in 2013 and consists of approximately 2000 households. Each year, household members of at least 12 years old are asked to complete a three-day travel diary and fill in a questionnaire that includes questions about different events in the past year. Every household is also asked to fill in a questionnaire about household related characteristics, such as information about household composition and ownership of means of transport. More information about the MPN can be found in Hoogendoorn-Lanser et al. (2015). Currently, data from the first three waves are available and used for the present analysis.

The occurrence of the different life events are directly measured in the questionnaires that respondents fill out every year. For changing jobs, stop working, a change in the number of adults in the household and a residential move, however, the occurrence is also calculated based on other changes that can be observed between waves to account for respondents forgetting to report the life event. For instance, if a respondent reported to be unemployed in wave 1, but reported to have a job in wave 2, he is treated as having changed jobs regardless of whether he reported this in the questionnaire. The other way around goes for stop working. A change in the number of adults in the household is measured through a change in the reported household composition, while a residential move is also calculated based on a change in the respondents' postal code.

Travel patterns can be defined in different ways. Different types of indicators can be used to distinguish the different patterns. In this study trip rates of four modes are used. In the MPN travel diary all trips are reported including the mode, distance and duration of the trip. Due to the self-reported nature of the travel diary, distance and duration might be biased due to rounding errors (Rietveld, 2001). The trip rate is assumed to be the most accurate reported indicator. The trip rates are count variables. Their distributions can therefore be approximated by the Poisson distribution and Poisson regression models can be used to model the relationships between the latent class variable and the indicators (Vermunt & Magidson, 2002).

If a multi-modal trip is reported, only the main mode of transport is considered to estimate the different clusters. Including access and egress modes would bias the data since the total trip rate of multi-modal clusters would seem higher compared to unimodal clusters. Furthermore, it would become unclear whether a mode is used as access or egress mode, or as the main mode of transport.

Although household members older than 12 years are asked to participate in the MPN, information about life events is not requested until respondents are at least 16 years old. Children younger than 16 years are therefore removed from the sample. The sample consists of 6880 respondents from 3921 households who completed at least one wave.

To uncover transitions between travel patterns, respondents should have completed at least two consecutive waves. In total there are 3,807 respondents who completed at least two consecutive waves, of which 1711 completed all three waves. The data is organized as a pooled wave-pair sample, similar to the approach described by Golob (1990). The alternative to using a pooled-wave pair sample is using a pure-stayer sample, where only respondents who participated all

three waves are included. An advantage of pooling wave-pairs over using a pure-stayer sample is the fact that no data is lost. Using a pure-stayer sample would decrease the sample size to 1711 individuals, while the wave-pair approach allows to include all 3807 respondents who completed at least two consecutive waves. Especially since life events do not occur regularly and their frequency is therefore rather low, removing data is not desired. The pooled wave-pair sample consists of 5518 wave pairs from 3807 respondents (2519 unique households).

A clear disadvantage of pooling wave-pairs is the fact that redundant information is present in the data for consecutive wave-pairs from the same respondent (Golob, 1990). Observations are therefore no longer independent. If no correction is applied, the wave-pairs would be treated as independent observations in the analysis. Besides dependencies due to pooling wave-pairs, there are also dependencies due to the fact that there are multiple respondents from the same household in the panel. Earlier studies have already shown that travel decisions are not independent between household members, see e.g. (Gliebe & Koppelman, 2005; Timmermans, 2009). The standard errors can be corrected for dependencies between observations by defining an independent observational unit (Vermunt & Magidson, 2016). If the respondents would be defined as the independent observational unit, the wave-pairs would no longer be assumed to be independent, but respondents from the same household would be. If the household would be defined as the independent observational unit, all observations within the household, both between household members and between wave-pairs, would not be assumed to be independent. Therefore, the household is treated as the independent observational unit.

The statistical software package Latent Gold is used to estimate both the latent class- and the latent transition models (Vermunt & Magidson, 2005). The latent class model is estimated using data from both waves simultaneously. Measurement invariance over time is therefore assumed. Unfortunately, Latent Gold does not support an analysis to test measurement invariance over time. Estimating two different latent class models for both waves separately showed, however, that the same clusters are present in both waves with only minimal differences.

To decide on the appropriate number of clusters, two methods are used, as described by Magidson and Vermunt (2004). The first method relies on the Bayesian Information Criterion (BIC). The BIC takes into account both model fit and parsimony. A model with a lower BIC is preferred over a model with a higher BIC. The second method uses the L^2 of the 1-class model as a baseline measure of the total amount of association in the data. By comparing the L^2 of the higher class models with the L^2 of the 1-class solution, the reduction in L^2 represents the total association that is explained by the model. When the amount of reduction of L^2 becomes relatively small, it is no longer justified to add an extra class to the model.

Although nine active covariates are used as predictors for initial cluster membership, not all are used to interact with transitions between waves. This would result in a high number of parameters which could lead to estimation problems. Therefore, besides the six life events, four covariates (gender, age, educational level and level of urbanization) are interacted with transitions. These covariates were chosen because they are also often taken into account in previous studies, see e.g. (Clark et al., 2014; Kroesen, 2014).

2.3.2 Descriptive statistics

Table 2.1 shows the measurement and distribution of variables in the sample. Age is included both as a standardized linear variable and the quadratic term of this variable to account for the non-linear effect of age. For simplicity reasons, the table only shows the mean and standard deviation of age. As can be seen, the frequency of the included life events is rather low. A decrease in the number of adults in the household shows the lowest occurrence rate with only 2.6%. Changing jobs is the most frequently observed life event with 8.9%.

Table 2.1 Sample Composition (N = 5518 Wave Pairs)

Variable		
Indicators		
Car trip rate (over three days)	Mean (SD)	4.6 (4.3)
PT trip rate (over three days)	Mean (SD)	0.5 (1.3)
Bike trip rate (over three days)	Mean (SD)	2.5 (3.6)
Walking trip rate (over three days)	Mean (SD)	1.5 (2.6)
Active covariates		
Gender	Male	46%
	Female	54%
Age	Mean (SD)	46.7 (17.0)
Educational level	Low	26%
	Mid	40%
	High	34%
Working hours	Less than 12 h/week	25%
	12-35 h/week	31%
	35+ h/week	44%
Personal net income per year	No income	10%
	Less than €12,000	19%
	€12,000 - €24,000	36%
	€24,000 - €36,000	20%
	More than €36,000	5%
	Missing	10%
Level of urbanization	Urban (1500+ inhabitants/km²)	48%
	Sub-urban (1000-1500 inhabitants/km²)	24%
	Rural (less than 1000 inhabitants/km²)	29%
No. HH-members 12-	Mean (SD)	0.3 (0.7)
No. HH-members 12+	Mean (SD)	2.3 (1.1)
Distance to train station (km)	Mean (SD)	3.4 (3.6)
No. of weekend days reported	Mean (SD)	0.9 (0.8)
Change in number of adults in HH (%)	Decrease	2.6%
	Increase	5.9%
Birth of a child (%)		3.3%
Changing jobs (%)		8.9%
Stop working (%)		4.9%
Start/change education (%)		4.0%
Residential move (%)		4.0%
Inactive covariates		
Car ownership		74%
PT card ownership		31%
Occupational status	Paid job	57%
	Student	8%
	Retired	19%
	Other	16%

2.4 Results

2.4.1 Travel patterns

As described in section 2.3.1, the BIC and reduction of L^2 are used to decide on the appropriate number of clusters. A 1-class to 10-class model is estimated without any covariates to assess only the variance between the indicators. The BIC value suggests that a model with a least 10 classes would be appropriate. After the 6-class solution, however, the reduction of L^2 becomes rather small (less than 3%). This suggests that using a model with 6 classes would be appropriate

to model the data. Since a model with a high number of classes would be hard to interpret, the 6-class model is used.

Table 2.2 presents the profiles of the 6-class model, including all covariates. Based on the Wald-statistics it can be concluded that the indicators and all active covariates, except gender, are significant. All indicators significantly differ between the classes and all active covariates, except gender, significantly affect class membership. Apparently, whether a respondent is male or female is no significant predictor of an individual's travel pattern. It can, however, be seen that the distribution of gender does differ among the classes.

The first and largest class (30% of the sample) represents strict car users. Besides making on average 8 trips by car in three days, they barely use other modes to travel. The strict car class is the only class with a higher share of men. Strict car users show the highest employment rate of 71%, with 44% of the class members working fulltime. A relatively high share of strict car users lives in rural areas. This could be explained because rural areas usually are not well-connected by public transport and distances are too large to travel by bike.

The second class (19% of the sample) are respondents who also show high car usage, but complement this with the bike. On average, they show a car trip rate of 1.6 trips lower compared to the strict car users, but besides car trips, they make over 4 trips by bike. Their overall trip rate is therefore higher than the strict car users. In terms of household composition, level of urbanization and education level, the second class is comparable with the first class. The second class, however, represents more women with a lower employment rate. The bike is primarily used for non-work related trips.

The third class (16% of the sample) consists of people who mostly use the bike. The bike class shows the highest share of females and a high share of people without a job. The class has a relatively high share (17%) of students. As expected, most respondents in this class live in urban areas. Over a third of respondents within this class are part of a 1-person household. Besides making almost 8 trips by bike in three days, they also occasionally use the car. The 0.8 car trips per three days translates to just under 2 trips per week (1 two-way trip).

The fourth class (13% of the sample) primarily make their trips by car or walking. They also make an occasional bike trip but rarely travel by public transport. The average age of this class is the highest of all classes. This is also reflected in the fact that this class shows the lowest employment rate and 29% of the people is retired. As a result, this class shows the highest leisure trip rate of all classes. People in this class walk on average 6.9 kilometres in three days. This is, compared to the walking distance of other classes, remarkably high.

The fifth class (11% of the sample) shows a very low overall trip rate. On average, people in this class only report a total of 1.3 trips in three days. The class shows a relatively high share of low-educated people (34%). Besides the low education level, there are no remarkable characteristics that could explain the low mobility. The average number of weekend days reported is the highest for this class.

The sixth and smallest class (10% of the sample) represents multimodal travellers who primarily use public transport. The average age of this class is the lowest and it has the highest share of students (31%). However, since there is only one public transport class, different types of public transport users are grouped in this cluster. From the students who belong to this class, 85% works less than 12 h per week and 98% has a yearly income of less than €12.000. If students are not considered, 74% of public transport users have a job of at least 12 h per week and 51% is highly educated. It can therefore be concluded that two types of people belong to the public transport class; students and highly educated working people.

Table 2.2 Profiles Of The 6-Class Latent Class Model

	Class*	SC	CB	B	CW	LM	PT
Indicators	Class size (%)	30	19	16	13	11	10
Trips by car (Wald = 1401, p < 0.00)	Mean	8.1	6.5	0.8	4.4	0.8	1.3
Trips by PT (Wald = 1456, p < 0.00)	Mean	0.1	0.1	0.3	0.2	0.0	3.4
Trips by bike (Wald = 1065, p < 0.00)	Mean	0.0	4.5	7.9	1.4	0.3	1.4
Trips by walking (Wald = 2997, p < 0.00)	Mean	0.5	0.6	1.2	6.3	0.2	1.5
Active covariates							
Gender (%) (Wald = 8 p = 0.14)	Male	53	45	38	42	48	45
	Female	47	55	62	58	52	55
Age (Wald = 183 p < 0.00)	Mean	46.8	49.4	44.3	53.3	47.1	36.5
Educational level (%)	Low	21	22	30	28	34	28
(Wald = 42 p < 0.00)	Mid	45	41	35	37	41	34
	High	34	37	35	35	25	38
Working contract (%)	Part-time (12-35 h/wk)	26	31	24	25	20	19
(Wald = 79 p < 0.00)	Fulltime (>35 h/wk)	44	29	19	20	28	32
	No job (<12 h/wk)	30	40	57	55	53	50
Net income per year (%)	No income	4	7	17	9	13	18
(Wald = 62 p < 0.00)	Less than €12,000	12	18	28	19	22	27
	€12,000 to €24,000	42	35	29	38	35	27
	€24,000 to €36,000	24	23	14	21	14	18
	more than €36,000	6	6	3	5	4	4
	Missing	12	11	9	9	12	7
Level of urbanization (%)	Urban	40	40	56	51	49	66
(Wald = 70 p < 0.00)	Sub-urban	23	28	23	22	21	18
	Rural	36	32	21	27	30	16
Household members 12 years or older (%)	1	20	20	34	29	23	34
(Wald = 23 p < 0.00)	2	54	50	35	53	46	30
	3+	27	30	31	18	30	36
Children 12- in household (Wald =39 p < 0.00)	%	23	21	14	16	16	6
Number of weekend days (Wald = 28 p < 0.00)	Mean	0.84	0.92	0.75	0.92	0.98	0.87
Distance to train station (Wald = 50 p < 0.00)	Mean (km)	3.9	3.5	2.8	3.3	3.5	2.5
Inactive covariates							
Car ownership (%)	One or more cars	94	88	47	79	67	37
PT card ownership (%)	One or more cards	16	23	45	31	22	78
Occupational status (%)	Paid job	71	62	46	46	49	50
	Student	2	4	17	2	6	32
	Retired	16	21	17	29	17	11
	Other	11	12	20	23	28	8
Car trip purpose	Working trips	2.3	1.2	0.1	0.7	0.2	0.3
	Shopping trips	1.5	1.3	0.1	1.0	0.2	0.2
	Leisure trips	2.2	2.3	0.4	1.6	0.3	0.6
	Other trips	2.0	1.6	0.2	1.1	0.1	0.2
PT trip purpose	Working trips	0.0	0.0	0.1	0.0	0.0	2.1
	Shopping trips	0.0	0.0	0.0	0.0	0.0	0.3
	Leisure trips	0.0	0.0	0.1	0.1	0.0	0.7
	Other trips	0.0	0.0	0.1	0.0	0.0	0.3
Bike trip purpose	Working trips	0.0	0.9	2.1	0.2	0.1	0.3
	Shopping trips	0.0	1.2	2.3	0.4	0.1	0.3
	Leisure trips	0.0	1.4	2.3	0.5	0.1	0.6
	Other trips	0.0	1.0	1.3	0.3	0.0	0.2
Walking trip purpose	Working trips	0.0	0.0	0.1	0.3	0.0	0.2
	Shopping trips	0.1	0.1	0.4	1.6	0.0	0.5
	Leisure trips	0.3	0.4	0.6	3.3	0.1	0.6
	Other trips	0.1	0.1	0.2	1.0	0.0	0.1
Distance (km)	Car	144.8	106.5	15.0	66.4	21.4	29.5
	PT	2.5	3.7	13.6	10.0	0.2	124.9
	Bike	0.1	12.5	23.4	4.3	1.2	4.4
	Walk	0.7	0.8	1.6	6.9	0.2	2.7

* SC: Strict Car, CB: Car and Bike, B : Bike, CW: Car and Walk, LM: Low Mobility, PT: Public Transport

2.4.2 Latent transition analysis

The parameter estimates of the 6-class transition model can be found in Table 2.4 in the appendix. The parameters indicate the influence of variables on class membership in the next wave. A negative parameter indicates a decreasing probability of transitioning to the specific class and vice versa. The obtained parameters, as shown in Table 2.4 in the appendix, are used to compute different transition probability matrices for every combination of covariates and life events, using a multinomial logit model.

Table 2.3 shows the average transition probabilities of the sample. As expected, the unimodal classes (strict car and bike) show higher probabilities of staying in the same class compared to the more multimodal classes (car and bike, car and walk and public transport). All classes show a very low probability of going to the public transport class in the second wave. The bike and car/walk classes show the highest transition rates to public transport, but still with a probability of only 4%. Higher probabilities are shown towards the bike cluster, or the cluster that combines car with bike. All classes, except for the bike class, show a relatively high probability of becoming strict car users in wave 2 (ranging from 8% to 23%). This is in line with findings by Kroesen (2014).

In total, 72 significant parameters are found. Almost all constants have a significant negative parameter. This indicates that class membership has a positive effect on itself. In other words, initial class membership in wave 1 is a strong indicator for membership in the same class in wave 2. As expected, dependent on the initial travel pattern, effects of life events and other exogenous variables are different.

Table 2.3 Transition Matrices For Different Life Events

Average transition probabilities							**Residential move**						
	SC	CB	B	CW	LM	PT		SC	CB	B	CW	LM	PT
Strict Car (SC)	0.70	0.13	0.00	0.05	0.09	0.02	SC	0.67	0.16	0.00	0.05	0.10	0.02
Car and Bike (CB)	0.23	0.53	0.13	0.05	0.05	0.01	CB	0.37	0.42	0.12	0.08	0.01	0.00
Bike (B)	0.02	0.14	0.74	0.03	0.03	0.04	B	0.03	0.16	0.72	0.02	0.02	0.05
Car and Walk (CW)	0.10	0.08	0.08	0.64	0.06	0.04	CW	0.05	0.12	0.07	0.30	0.27	0.19
Low Mobility (LM)	0.11	0.08	0.08	0.03	0.69	0.02	LM	0.12	0.09	0.08	0.28	0.41	0.01
Public Transport (PT)	0.08	0.04	0.02	0.07	0.12	0.67	PT	0.00	0.10	0.11	0.26	0.00	0.52
Decrease of the number of adults in HH							**Birth of a child**						
	SC	CB	B	CW	LM	PT		SC	CB	B	CW	LM	PT
Strict Car (SC)	0.67	0.14	0.01	0.08	0.09	0.00	SC	0.70	0.07	0.00	0.15	0.08	0.01
Car and Bike (CB)	0.15	0.62	0.15	0.00	0.01	0.07	CB	0.27	0.32	0.00	0.38	0.02	0.00
Bike (B)	0.00	0.02	0.88	0.00	0.04	0.05	B	0.03	0.16	0.12	0.64	0.05	0.00
Car and Walk (CW)	0.13	0.11	0.19	0.56	0.00	0.01	CW	0.21	0.39	0.00	0.31	0.00	0.09
Low Mobility (LM)	0.01	0.05	0.36	0.02	0.54	0.02	LM	0.36	0.08	0.04	0.04	0.45	0.03
Public Transport (PT)	0.35	0.12	0.03	0.01	0.00	0.48	PT	0.17	0.00	0.02	0.29	0.30	0.21
Increase of the number of adults in HH							**Start or change of education**						
	SC	CB	B	CW	LM	PT		SC	CB	B	CW	LM	PT
Strict Car (SC)	0.70	0.16	0.00	0.02	0.11	0.00	SC	0.77	0.03	0.00	0.07	0.01	0.11
Car and Bike (CB)	0.27	0.58	0.13	0.00	0.02	0.00	CB	0.29	0.27	0.18	0.06	0.16	0.04
Bike (B)	0.01	0.11	0.71	0.03	0.10	0.05	B	0.02	0.17	0.46	0.22	0.00	0.14
Car and Walk (CW)	0.11	0.00	0.18	0.64	0.07	0.00	CW	0.06	0.08	0.06	0.70	0.07	0.04
Low Mobility (LM)	0.02	0.02	0.14	0.04	0.74	0.04	LM	0.21	0.23	0.01	0.00	0.17	0.38
Public Transport (PT)	0.10	0.04	0.00	0.00	0.06	0.80	PT	0.03	0.02	0.00	0.01	0.40	0.55
Changing jobs							**Stop working**						
	SC	CB	B	CW	LM	PT		SC	CB	B	CW	LM	PT
Strict Car (SC)	0.66	0.20	0.00	0.05	0.05	0.04	SC	0.54	0.22	0.02	0.02	0.17	0.04
Car and Bike (CB)	0.29	0.45	0.15	0.04	0.05	0.01	CB	0.02	0.50	0.20	0.15	0.06	0.07
Bike (B)	0.15	0.14	0.60	0.01	0.04	0.05	B	0.00	0.06	0.69	0.14	0.06	0.04
Car and Walk (CW)	0.30	0.20	0.09	0.34	0.07	0.01	CW	0.01	0.03	0.08	0.79	0.05	0.05
Low Mobility (LM)	0.12	0.04	0.14	0.02	0.62	0.06	LM	0.05	0.04	0.02	0.15	0.74	0.00
Public Transport (PT)	0.05	0.09	0.02	0.05	0.33	0.47	PT	0.06	0.01	0.01	0.17	0.28	0.47

* To compute the transition matrices, all parameters from Table 2.4 are used, both the significant and non-significant parameters

Since the main focus of this paper is on assessing the effect of life events on transitions between travel patterns, the effect of the other exogenous variables will not be discussed in detail. The found significant effects are, however, in line with expectation. For instance, for the effect of age it is found that strict car users tend to shift towards the car and walk profile at older age, while for the car and bike users the probability of becoming public transport users decreases at older age.

For all life events significant effects are found, indicating that there might indeed be ‘windows of opportunity’ to change travel behaviour when a life event occurs. The bold parameters in Table 2.4 in the appendix indicate significant effects. The effect on the average transition probabilities of the life events will shortly be discussed.

Besides the average transition probabilities for the whole sample, Table 2.3 also presents the average transition probabilities in case of the different life events. If the event does not occur, the transition matrix is almost identical to the average transition matrix of the whole sample. This can be explained by the low frequency of the life events in the sample. These matrices are therefore not shown.

For the change in the number adults in the household, a matrix for both a decrease and increase in the number of adults is shown. When the number of adults in the household decreases, the public transport users are most strongly affected by showing a strong increase in the probability of changing to a travel pattern where car plays an important role. Their probability of becoming a strict car user increases from 8% to 35% and the probability of becoming a car and bike user increases from 4% to 12%. The low mobility class, however, shows an increased probability of transitioning to the bike class from 8% to 36%. A decrease in the number of adults could represent an event such as a divorce. The remaining household member(s) has to make trips which were previously done by the partner and therefore the travel pattern has to be adjusted. Earlier research has shown that the loss of a partner is related to a decrease in household car ownership (Clark et al., 2014). It is therefore an unexpected result that public transport users show a large increase in probabilities of switching to a more car dependent travel pattern. However, other research found lagged effects from a divorce in the form of both a mode shift towards and a mode shift away from car (Oakil et al., 2011). This indicates that the effect of a decrease in the number of adults in the household is dependent on a number of variables. For example, if partners shared a car before splitting up, the partner that keeps the car now always has a car available, whereas the other partner is left with no car availability, until a new car is bought. Both partners will therefore probably show a different reaction to splitting up, in terms of travel behaviour. Further analysis is therefore needed to fully understand why the public transport users shift towards a class with relatively high car use.

An increase in the number of adults in the household, which could be because partners started living together, increases chances of remaining in the same travel pattern for the car and bike, low mobility and public transport class. For the remaining classes the probability of keeping the same travel pattern does not change much. Earlier studies also found that an increase in the number of adults in the household has little to no effect on travel behaviour. Beige and Axhausen (2012) found that changes in terms of mobility tools ownership (such as cars or public transport cards), are less likely when the household size increases, Oakil et al. (2011) found that cohabitation has no significant influence on a mode shift from or to car for commuting and Scheiner and Holz-Rau (2013) only found a small increase in the chance that people travel by car as passenger.

The overall effect of changing jobs is an increased probability of becoming a member of one of the three car classes. Except the public transport class, all classes show an increase in the probability of becoming a strict car user. The probability of becoming a car and walk user decreases. Oakil et al. (2011) also found that changing jobs leads to a mode shift to car, but also to a shift away from car, while Kroesen (2014) found that a change of jobs is associated with an increase in public transport use (although it should be noted that Kroesen used data from the 1980s making it somewhat harder to compare results). A remarkable and unexpected effect is observed for the public transport class. The probability of transitioning to the low mobility class increases with 20%. A new job, or changing jobs, usually implies that work trips have to be made, while the low mobility class represents almost no trips. In-depth analysis (results not shown) revealed that most of the public transport users with a new job who transition toward the low mobility class increased their working hours due to the new job. The fact that they became a member of the low mobility class is therefore unexpected. It might indicate that these respondents started working from home in their new job. It is, however, not expected that this is true for all respondents. A more plausible explanation could be the fact that, because they have less free time due to the increase in working hours, they show a form of soft refusal and underreport their trips. The presence of possible soft refusal in the MPN has been shown in de Haas et al. (2017), but more research is needed to confirm that the observed shift towards the low mobility class is due to soft refusal.

A residential move also shows different effects for the different classes. For the unimodal classes (strict car and bike) the probabilities do not change much. The other classes are differently affected. The car and bike class show an increase in the probability of becoming a strict car user, while the car and walk class shows a strong increase in the probability of becoming a member of the low mobility or public transport class. One explanation of finding these different effects could be the fact that a residential move is included as a single variable, while it can be expected that the effect of moving from a rural area to an urban area will have a different effect than a move from an urban tot a rural area or move to an area with the same level of urbanization, something that was also shown by Clark et al. (2014) and Prillwitz et al. (2006). It was, however, found that over 85% of the respondents moved to an area with the same level of urbanization, which makes it difficult to explicitly model the effects of a change in the level of urbanization.

After the birth of a child, all classes show an increasing probability of becoming a strict car user. All classes also show an increase in the probability of becoming a member of the car and walk class, in accordance with results found by Scheiner and Holz-Rau (2013). The car and bike class shows a high probability of becoming a car and walk user and vice versa. An increase in car dependency after the birth of a child has also been found in other studies (Fatmi & Habib, 2016; Oakil et al., 2011; Prillwitz et al., 2006) and could be explained because the car is a convenient mode of transport to travel with a baby.

The start or change of education increases the probability of becoming a public transport user for most classes. This is an expected result, since students are provided with a free public transport card in the Netherlands. The low mobility class shows the greatest changes. The probability of remaining in the low mobility class decreases from 69% to only 17%. It should be noted that the group of respondents that started or changed education consists for two-thirds of people under 30 years old, whereas a quarter is over 40 years. This could explain the fact that some students within the sample show low mobility, as this group does not only consist of young people, whom can usually be assumed to be active. Other studies found that changing education leads to a decrease in car availability (Beige & Axhausen, 2008), but no effects on mode choice were found (Scheiner & Holz-Rau, 2013). However, because students are provided with a free public transport card in the Netherlands, it is hard to compare results with studies from other countries.

Overall, it can be observed that the strict car users show very inert behaviour. For all events, except for stop working, the probability of remaining a strict car user after a life event stays similar to the probability when the event does not happen. The bike users, who are also more or less unimodal travellers, show less inert behaviour. This could be explained because a car is usually suitable for all kinds of trips, while a bike is limited due to its speed and lack of possibilities such as taking a baby with you.

2.5 Conclusions and recommendations

In this paper, latent class- and transition analysis are applied on panel data within the mobility biographies framework to reveal different travel patterns and assess the effect of life events and other exogenous variables on transitions between these travel patterns. Six different meaningful and distinguishable travel patterns were identified. For all life events significant effects on transition probabilities were found. The transition analysis confirms that travel behaviour is inert. In addition, unimodal travellers show a higher probability of remaining in the same travel pattern, compared to multimodal travellers. All identified travel patterns show a very low probability of transitioning towards the public transport travel pattern.

Latent transitions analysis has been shown to provide meaningful insights in the effects of different life events and exogenous variables on changes between travel patterns. Latent transition analysis can be a useful method within the mobility biographies studies as it offers the possibility to account for past travel behaviour when assessing the effect of different life events.

The results offer some interesting insights. After, for instance, the birth of a child a rise in the car dependency is observed, regardless of the initial travel pattern. Apparently, people see the car as one of the few suitable means of transport with a baby. This might indicate that people are not well informed about the possibilities of travelling by bike or public transport with a baby. Future research could assess whether a moment such as birth registration could be used to inform people about other safe possibilities to travel with their child besides car.

It is also observed that, for most classes, public transport use only increases after the start or change of education. A change of jobs, which also reflects students who start their first job after finishing their education, shows a shift towards car use again. Future research could focus on how students could be tempted to remain public transport users, even after they finished their education.

An important drawback of latent transition analysis is the fact that it requires a large sample to reveal significant effects. In this study, the latent transition analysis is used to assess the effect of life events on changes in travel patterns. One of the characteristics of life events is the fact that they do not occur regularly. Since six different travel patterns were identified, the transition matrix consisted of 36 cells (6 initial clusters x 6 future clusters). Because travel behaviour is inert, most people will remain in the same class. The computation of the off-diagonal probabilities is therefore done with a limited number of observations. This is probably the main reason for finding ‘only’ 72 significant parameters, of which 27 are constants. Of the parameters that indicate the effect exogenous variables and life events, little over 10% are significant. Fortunately, the MPN will be continued the next years. The observed frequency of life events, as well as observed transitions, will therefore grow, increasing the chances of finding significant effects. It is therefore recommended that another latent transition model will be estimated when data from more waves is available.

For a number of life events unexpected results or results that are difficult to interpret are found. One important reason for this is probably the fact that a number of life events have different underlying events. For instance an increase in the number of adults in the household could be because partners started living together, or just because a room in the household was rented out to an adult or a child turned 18. The first event will probably have a larger effect than the others. It is therefore recommended to analyse the effects of life events in more detail. To be able to distinguish more detailed life events, data from more waves are needed. If more data are available, a distinction could be made between, for instance, moving from rural areas to urban areas and vice versa, changing from a full-time to a part-time job and vice versa, stop working due to retirement and due to involuntarily losing a job et cetera.

Another recommendation is aimed at the indicators that are used to define the travel patterns. A limitation of relying on the self-reported trip rates to define the travel patterns is the fact that respondents only reported three days of travel. Since it can be assumed that travel behaviour is different during weekdays compared to the weekend, the data might be biased because travel behaviour has only been reported for three days. Fortunately, respondents were assigned the same starting day every wave and therefore reported the same days every year. Starting from wave 2, respondents are also asked on their weekly frequency of mode use. It is recommended that this will be combined with the self-reported trip rates to get a more accurate overview of

their travel behaviour in future research using the MPN data. Since the stated mode use is not available for the first wave, this study could only rely on the self-reported trip rates.

The last recommendation for further research is to include lagged effects to the analysis. It could, for instance, be that after a residential move people change their travel behaviour on the short term, but change this behaviour again on the long term (more than 1 year). Including lagged effects could reveal such behaviour. Modelling lagged effects would require the sample to consist of respondent who participated at least three consecutive waves. Only when data from more waves are available this becomes a viable option.

Appendix: parameter estimates of the 6-class transition model

Table 2.4 6-Class Transition Parameters

Wave 1 class membership	Wave 2 class membership					
	Strict car (SC)	Car and bike (CB)	Bike (B)	Car and walk (CW)	Low mobility (LM)	Public transport (PT)
SC						
Constant	0	**-2.25 (0.00)**	**-2.87 (0.03)**	**-2.96 (0.00)**	**-2.46 (0.00)**	**-3.56 (0.00)**
Female (ref. male)	0	**0.44 (0.01)**	0.05 (0.97)	**0.63 (0.03)**	0.31 (0.19)	-0.17 (0.74)
Age (standardized)	0	0.08 (0.54)	-0.73 (0.49)	**0.42 (0.03)**	0.27 (0.11)	-0.30 (0.30)
Age squared	0	-0.11 (0.33)	-0.94 (0.56)	-0.01 (0.93)	-0.05 (0.74)	0.38 (0.15)
Middle educated (ref. low)	0	0.31 (0.22)	-0.26 (0.75)	-0.09 (0.82)	**0.66 (0.05)**	0.00 (1.00)
High educated (ref. low)	0	0.52 (0.05)	-1.49 (0.32)	0.27 (0.50)	0.14 (0.71)	0.53 (0.48)
Sub-urban (ref. urban)	0	0.26 (0.30)	-1.38 (0.33)	0.12 (0.72)	0.25 (0.41)	0.02 (0.97)
Rural (ref. urban)	0	**0.44 (0.04)**	-1.38 (0.25)	-0.54 (0.12)	-0.03 (0.92)	-1.16 (0.15)
Decr. # adults (ref. = no change)	0	0.08 (0.87)	1.03 (0.50)	0.54 (0.46)	0.01 (0.99)	-2.19 (0.07)
Incr. # adults (ref. = no change)	0	0.18 (0.64)	-1.18 (0.09)	-0.81 (0.51)	0.14 (0.80)	-2.18 (0.28)
New job (ref. = no)	0	0.42 (0.20)	-0.89 (0.12)	0.20 (0.77)	-0.54 (0.45)	0.49 (0.54)
Residential move (ref. = no)	0	0.19 (0.74)	-0.03 (0.97)	0.20 (0.82)	0.05 (0.96)	-0.29 (0.81)
Birth of a child (ref. = no)	0	-0.67 (0.30)	-0.51 (0.51)	**1.14 (0.03)**	-0.23 (0.78)	-0.95 (0.49)
Start/change education (ref. = no)	0	-1.49 (0.13)	-0.68 (0.62)	0.25 (0.82)	-2.17 (0.19)	**1.50 (0.04)**
Stop working (ref. = no)	0	0.73 (0.11)	1.75 (0.14)	-0.63 (0.68)	0.80 (0.14)	0.73 (0.38)
CB						
Constant	**-1.17 (0.00)**	0	**-1.94 (0.00)**	**-2.27 (0.00)**	**-1.86 (0.02)**	**-3.88 (0.00)**
Female (ref. male)	-0.24 (0.23)	0	**0.84 (0.01)**	-0.30 (0.39)	0.39 (0.42)	0.35 (0.59)
Age (standardized)	-0.22 (0.06)	0	-0.03 (0.82)	0.38 (0.18)	-0.32 (0.12)	**-1.04 (0.00)**
Age squared	**0.20 (0.05)**	0	**0.50 (0.00)**	-0.08 (0.71)	0.40 (0.06)	**0.78 (0.00)**
Middle educated (ref. low)	0.39 (0.18)	0	-0.61 (0.08)	0.29 (0.55)	**-1.07 (0.03)**	0.15 (0.80)
High educated (ref. low)	0.12 (0.70)	0	-0.36 (0.29)	0.34 (0.49)	-0.84 (0.18)	-2.09 (0.18)
Sub-urban (ref. urban)	-0.09 (0.71)	0	-0.08 (0.82)	0.38 (0.33)	-0.38 (0.49)	-0.28 (0.71)
Rural (ref. urban)	0.29 (0.22)	0	-0.22 (0.52)	-0.19 (0.70)	-0.86 (0.13)	-0.94 (0.25)
Decr. # adults (ref. = no change)	-0.58 (0.46)	0	0.00 (1.00)	**-3.88 (0.04)**	-1.45 (0.10)	1.71 (0.07)
Incr. # adults (ref. = no change)	0.09 (0.85)	0	-0.08 (0.89)	-3.30 (0.13)	-0.99 (0.24)	-2.34 (0.06)
New job (ref. = no)	0.40 (0.38)	0	0.31 (0.53)	-0.17 (0.85)	0.07 (0.92)	0.47 (0.62)
Residential move (ref. = no)	0.71 (0.28)	0	0.17 (0.78)	0.57 (0.52)	-1.43 (0.06)	**-3.33 (0.04)**
Birth of a child (ref. = no)	0.68 (0.57)	0	**-2.73 (0.03)**	**2.42 (0.01)**	-0.48 (0.48)	-0.79 (0.42)
Start/change education (ref. = no)	0.93 (0.25)	0	1.04 (0.19)	0.66 (0.63)	**1.78 (0.04)**	1.94 (0.17)
Stop working (ref. = no)	-2.42 (0.38)	0	0.54 (0.49)	1.03 (0.26)	0.20 (0.81)	1.93 (0.06)

Wave 1 class membership	Wave 2 class membership					
	Strict car (SC)	Car and bike (CB)	Bike (B)	Car and walk (CW)	Low mobility (LM)	Public transport (PT)
B						
Constant	**-2.68 (0.01)**	**-1.79 (0.00)**	0	**-3.47 (0.00)**	-1.51 (0.15)	**-3.76 (0.00)**
Female (ref. male)	-0.56 (0.36)	-0.33 (0.22)	0	0.51 (0.33)	-0.25 (0.56)	0.09 (0.83)
Age (standardized)	-0.22 (0.71)	0.28 (0.08)	0	0.64 (0.10)	-0.81 (0.49)	**-0.65 (0.01)**
Age squared	-0.51 (0.34)	-0.08 (0.58)	0	-0.14 (0.60)	-0.57 (0.56)	0.29 (0.18)
Middle educated (ref. low)	-0.07 (0.92)	0.06 (0.88)	0	0.51 (0.46)	-0.64 (0.40)	0.77 (0.13)
High educated (ref. low)	-0.89 (0.35)	0.39 (0.28)	0	0.66 (0.34)	-1.82 (0.18)	0.92 (0.06)
Sub-urban (ref. urban)	0.12 (0.87)	0.39 (0.26)	0	-0.63 (0.33)	0.20 (0.71)	-0.41 (0.41)
Rural (ref. urban)	0.71 (0.45)	0.23 (0.55)	0	-0.18 (0.78)	-0.05 (0.92)	-0.49 (0.27)
Decr. # adults (ref. = no change)	-2.69 (0.20)	-1.98 (0.59)	0	-9.26 (0.13)	0.02 (0.98)	0.24 (0.89)
Incr. # adults (ref. = no change)	-0.47 (0.69)	-0.15 (0.81)	0	-0.08 (0.95)	**1.10 (0.04)**	0.30 (0.62)
New job (ref. = no)	2.23 (0.05)	0.24 (0.73)	0	-0.68 (0.74)	0.27 (0.68)	0.63 (0.20)
Residential move (ref. = no)	0.44 (0.68)	0.23 (0.76)	0	-0.65 (0.57)	-0.75 (0.53)	0.36 (0.63)
Birth of a child (ref. = no)	2.17 (0.29)	2.01 (0.36)	0	**4.79 (0.02)**	2.17 (0.35)	-1.95 (0.43)
Start/change education (ref. = no)	0.29 (0.91)	0.73 (0.34)	0	2.37 (0.11)	-4.57 (0.15)	**1.81 (0.01)**
Stop working (ref. = no)	-1.78 (0.33)	-0.67 (0.56)	0	**1.54 (0.04)**	0.63 (0.36)	0.21 (0.79)
CW						
Constant	**-1.50 (0.00)**	-0.07 (0.90)	-1.32 (0.06)	0	**-1.64 (0.03)**	**-2.31 (0.00)**
Female (ref. male)	-0.49 (0.13)	**-1.06 (0.01)**	0.13 (0.77)	0	0.27 (0.59)	-0.09 (0.87)
Age (standardized)	0.31 (0.50)	-0.36 (0.16)	-0.54 (0.06)	0	0.29 (0.46)	**-0.88 (0.03)**
Age squared	-0.59 (0.12)	**-0.49 (0.04)**	0.03 (0.88)	0	-0.35 (0.14)	0.66 (0.06)
Middle educated (ref. low)	0.58 (0.19)	-0.49 (0.29)	-0.75 (0.18)	0	0.05 (0.91)	-1.19 (0.23)
High educated (ref. low)	0.30 (0.56)	**-1.11 (0.05)**	-0.81 (0.24)	0	-0.90 (0.15)	-0.35 (0.60)
Sub-urban (ref. urban)	0.56 (0.20)	0.20 (0.63)	0.12 (0.80)	0	-0.31 (0.59)	-0.25 (0.76)
Rural (ref. urban)	0.13 (0.76)	-1.15 (0.09)	-1.34 (0.12)	0	-0.71 (0.20)	-1.23 (0.09)
Decr. # adults (ref. = no change)	0.38 (0.77)	0.37 (0.76)	1.04 (0.27)	0	-3.92 (0.18)	-1.27 (0.48)
Incr. # adults (ref. = no change)	0.14 (0.88)	-5.11 (0.16)	0.87 (0.17)	0	0.18 (0.86)	-2.63 (0.10)
New job (ref. = no)	**1.75 (0.02)**	**1.45 (0.04)**	0.79 (0.32)	0	0.81 (0.41)	-1.03 (0.70)
Residential move (ref. = no)	0.03 (0.99)	1.08 (0.43)	0.75 (0.48)	0	2.28 (0.06)	2.23 (0.15)
Birth of a child (ref. = no)	1.44 (0.45)	2.21 (0.10)	-2.92 (0.09)	0	-2.05 (0.23)	1.41 (0.24)
Start/change education (ref. = no)	-0.68 (0.76)	-0.25 (0.78)	-0.28 (0.79)	0	0.04 (0.98)	-0.19 (0.94)
Stop working (ref. = no)	-2.55 (0.71)	-1.31 (0.40)	-0.14 (0.87)	0	-0.43 (0.66)	-0.09 (0.92)
LM						
Constant	**-2.70 (0.00)**	**-3.15 (0.00)**	**-2.86 (0.00)**	**-3.71 (0.00)**	0	**-5.55 (0.00)**
Female (ref. male)	-0.02 (0.97)	0.35 (0.48)	-0.28 (0.49)	0.32 (0.65)	0	0.52 (0.40)
Age (standardized)	-0.09 (0.64)	0.03 (0.91)	-0.23 (0.25)	0.23 (0.63)	0	-0.38 (0.27)
Age squared	-0.10 (0.64)	-0.08 (0.72)	0.20 (0.25)	0.02 (0.94)	0	0.00 (0.99)
Middle educated (ref. low)	0.71 (0.19)	0.47 (0.47)	0.46 (0.47)	0.22 (0.78)	0	0.79 (0.45)
High educated (ref. low)	0.77 (0.18)	**1.44 (0.03)**	**1.36 (0.02)**	1.09 (0.19)	0	**2.86 (0.01)**
Sub-urban (ref. urban)	0.75 (0.14)	0.29 (0.60)	0.25 (0.65)	0.15 (0.87)	0	0.00 (1.00)
Rural (ref. urban)	0.64 (0.19)	0.13 (0.84)	-0.50 (0.40)	-0.10 (0.92)	0	-0.09 (0.90)
Decr. # adults (ref. = no change)	-1.75 (0.09)	-0.20 (0.91)	**1.82 (0.04)**	-0.16 (0.92)	0	0.53 (0.63)
Incr. # adults (ref. = no change)	-1.57 (0.16)	-1.22 (0.08)	0.56 (0.50)	0.13 (0.89)	0	1.01 (0.45)
New job (ref. = no)	0.25 (0.79)	-0.62 (0.45)	0.78 (0.25)	-0.65 (0.83)	0	**1.67 (0.05)**
Residential move (ref. = no)	0.66 (0.36)	0.74 (0.51)	0.63 (0.62)	**2.67 (0.02)**	0	-0.07 (0.95)
Birth of a child (ref. = no)	**1.69 (0.01)**	0.56 (0.53)	-0.17 (0.85)	0.63 (0.49)	0	1.16 (0.31)
Start/change education (ref. = no)	2.11 (0.19)	2.58 (0.11)	-0.43 (0.73)	-2.51 (0.34)	0	**4.83 (0.01)**
Stop working (ref. = no)	-0.73 (0.42)	-0.64 (0.50)	-1.53 (0.05)	1.48 (0.13)	0	**-5.22 (0.01)**

Wave 1 class membership	Wave 2 class membership					
	Strict car (SC)	Car and bike (CB)	Bike (B)	Car and walk (CW)	Low mobility (LM)	Public transport (PT)
PT						
Constant	**-2.13 (0.01)**	**-3.94 (0.00)**	**-3.71 (0.00)**	**-2.62 (0.00)**	**-2.48 (0.00)**	0
Female (ref. male)	0.08 (0.87)	-0.40 (0.64)	**2.35 (0.01)**	0.21 (0.68)	0.63 (0.18)	0
Age (standardized)	0.29 (0.32)	0.34 (0.21)	-0.60 (0.25)	**1.02 (0.00)**	**0.78 (0.01)**	0
Age squared	-0.46 (0.12)	0.25 (0.40)	-0.30 (0.47)	-0.08 (0.70)	-0.18 (0.55)	0
Middle educated (ref. low)	1.24 (0.12)	0.66 (0.42)	-1.97 (0.18)	0.73 (0.35)	0.02 (0.97)	0
High educated (ref. low)	0.39 (0.66)	0.83 (0.34)	-0.13 (0.86)	0.86 (0.22)	-0.05 (0.93)	0
Sub-urban (ref. urban)	0.34 (0.52)	0.43 (0.72)	-0.25 (0.76)	-0.71 (0.37)	0.61 (0.31)	0
Rural (ref. urban)	-0.95 (0.81)	1.09 (0.32)	0.53 (0.50)	0.15 (0.90)	**1.73 (0.01)**	0
Decr. # adults (ref. = no change)	1.79 (0.08)	1.54 (0.30)	0.77 (0.43)	-1.65 (0.17)	**-4.98 (0.05)**	0
Incr. # adults (ref. = no change)	0.00 (1.00)	-0.17 (0.90)	-1.78 (0.31)	**-3.28 (0.00)**	-0.89 (0.38)	0
New job (ref. = no)	-0.15 (0.95)	1.25 (0.11)	0.41 (0.47)	-0.21 (0.83)	1.32 (0.14)	0
Residential move (ref. = no)	-2.73 (0.16)	1.28 (0.19)	1.93 (0.12)	1.41 (0.30)	**-4.42 (0.00)**	0
Birth of a child (ref. = no)	1.91 (0.23)	-2.03 (0.85)	1.17 (0.28)	2.44 (0.12)	2.04 (0.27)	0
Start/change education (ref. = no)	-0.93 (0.32)	-0.47 (0.75)	-1.92 (0.06)	-2.35 (0.07)	1.37 (0.08)	0
Stop working (ref. = no)	0.07 (0.96)	-1.26 (0.91)	-0.15 (0.84)	1.12 (0.30)	1.17 (0.27)	0

P-values are presented in parentheses, parameters with $p<0.05$ are bold

3 The e-bike: a new technology that may promote a shift towards sustainable travel

This chapter is based on the following article:

de Haas, M., Kroesen, M., Chorus, C., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2022). E-bike user groups and substitution effects: evidence from longitudinal travel data in the Netherlands. *Transportation, 49*(3), 815-840. doi: https://doi.org/10.1007/s11116-021-10195-3

Abstract

In recent years, the e-bike has become increasingly popular in many European countries. With higher speeds and less effort needed, the e-bike is a promising mode of transport to many, and it is considered a good alternative for certain car trips by policy-makers and planners. A major limitation of many studies that investigate such substitution effects of the e-bike, is their reliance on cross-sectional data which do not allow an assessment of within-person travel mode changes. As a consequence, there is currently no consensus about the e-bike's potential to replace car trips. Furthermore, there has been little research focusing on heterogeneity among e-bike users. In this respect, it is likely that different groups exist that use the e-bike for different reasons (e.g. leisure vs commute travel), something which will also influence possible substitution patterns. This paper contributes to the literature in two ways: 1) it presents a statistical analysis to assess the extent to which e-bike trips are substituting trips by other travel modes based on longitudinal data; 2) it reveals different user groups among the e-bike population. A Random Intercept Cross-Lagged Panel Model is estimated using five waves of data from the Netherlands Mobility Panel. Furthermore, a Latent Class Analysis is performed using data from the Dutch national travel survey. Results show that, when using longitudinal data, the substitution effects between e-bike and the competing travel modes of car and public transport are not as significant as reported in earlier research. In general, e-bike trips only significantly reduce conventional bicycle trips in the Netherlands, which can be regarded an unwanted effect from a policy-viewpoint. For commuting, the e-bike also substitutes car trips. Furthermore, results show that there are five different user groups with their own distinct behaviour patterns and socio-demographic characteristics. They also show that groups that use the e-bike primarily for commuting or education are growing at a much higher rate than groups that mainly use the e-bike for leisure and shopping purposes.

3.1 Introduction

The e-bike is gaining popularity in many Asian and European countries in recent years. While total bicycle sales in the EU grew with only 0.4% between 2010 and 2016, e-bike sales saw a growth of 284% in the same period and now accounts for 8.1% of total bicycle sales (CONEBI, 2017). Germany, The Netherlands, Belgium, France and Italy account for almost 80% of e-bike sales in the EU in 2016. Relatively speaking, the share of e-bike sales is the highest in The Netherlands. In 2018, with 40% of new bicycles sold being an e-bike, more e-bikes were sold than conventional city bikes in the Netherlands (Stichting BOVAG-RAI Mobiliteit, 2019).

When the e-bike was introduced in the Netherlands, the main adopters turned out to be older people, who primarily used the e-bike for leisure trips (Hendriksen et al., 2008). However, in recent years a shift can be observed based on data from the Dutch national travel survey (Statistics Netherlands, 2013-2017). While in 2013 54% of e-bike kilometres were travelled by people of 65 years and older, in 2017 this share decreased to 46%. This indicates that also younger age groups are adopting the e-bike. It may be expected that these groups will use the e-bike differently. Indeed, this is reflected in a shift in trip purposes. In 2013 18% of e-bike kilometres were work related, whereas in 2017 this share increased to 23%. In 2017, 13% of all bicycle trips and 18% of the bicycle distance were travelled with an e-bike.

In the Netherlands, 50% of all car trips are under 7.5 kilometres and 67% are under 15 kilometres (Statistics Netherlands, 2013-2017). As the e-bike allows travelling at greater speeds with less effort compared to a conventional bicycle, it has the potential to replace a substantial part of these car trips. As an e-bike emits 40 times less carbon dioxide (Shao et al., 2012) compared to a car, a substitution of car trips with e-bike would benefit the environment, as well as helping reduce road congestion. However, whether the e-bike brings environmental and other benefits depends on the mode it is replacing (Cherry & Cervero, 2007). If the e-bike is mainly substituting non-motorized modes such as the conventional bicycle and walking, benefits could even be negative.

Several studies have already focused on the effect that the advent of the e-bike has on travel behaviour. These studies generally report that the e-bike substitutes not only the conventional bicycle, but also, to a certain degree, the car and public transport, depending on local context. For instance, two studies with a geographic focus on China show that in areas with a high quality public transport network, the e-bike is seen as an affordable alternative to public transport (Cherry & Cervero, 2007), whereas in areas without sufficient public transport facilities the e-bike mainly substitutes the conventional bicycle (Weinert et al., 2007b). A limitation of previous studies is, however, that they are either based on a cross-sectional survey or in-depth interviews which only allow for comparisons between individuals (differences in travel mode choices) and do not allow an evaluation of within-person effects (changes in travel mode choices) over time. As such, the current state of the art of the literature into e-bike substitution effects provides an incomplete picture, hampering the derivation of sound policies in this regard.

The contribution of this study to the literature is twofold. The first aim is to assess whether substitution effects of the e-bike can be observed at an individual level; that is, we study whether the advent of the e-bike has led to actual changes in travel mode choices. To do so, longitudinal data from the Netherlands Mobility Panel (MPN) is used, which – in contrast to cross-sectional data – allows for such analyses. Note that the Netherlands Mobility Panel is representative for the Dutch population and includes both e-bike owners and non-e-bike owners.

The second goal of this study is to assess trends in the population of e-bike users, with a particular focus on heterogeneity in user-groups and their e-bike behaviours. Although a shift in the use of e-bike can be observed in terms of age and trip purpose, little is known about the heterogeneity among e-bike users in terms of their usage patterns. It is likely that different groups exist that use the e-bike for different reasons and in different ways. By considering different types of e-bike users in terms of their socio-demographic characteristics as well as their usage patterns, it can be assessed whether it is likely that any substitution effects might change in the future. We use 5 years of data (2013 – 2017) of the Dutch national travel survey (Statistics Netherlands, 2013-2017) to reveal different e-bike user groups and assess how these groups developed over the years.

The remainder of this paper is structured as follows. First, a brief overview of relevant studies regarding the effects of the e-bike on travel behaviour is provided. The next section shows how e-bike trips substitute trips with other modes. In the following section, we discuss the different e-bike user groups and their development over the years. The final section presents conclusions and recommendations for future research.

3.2 Background literature

Together with the increase in popularity of the e-bike, more studies on substitution effects of e-bikes are emerging. What modes of transport the e-bike is replacing differs greatly between areas. Several studies in Asia, where the e-bike was adopted first, focus on China. This may be explained by the popularity of the e-bike in China in comparison with other Asian countries. One reason for the uptake of the e-bike in China were local government policies. In the late 1990s several major Chinese cities banned the sale of gasoline-powered scooters which was one of the most competitive modes to the e-bike (Weinert et al., 2007a). Several studies in China found that people (inhabitants of the cities Kunming, Shanghai and Jinan) would use the bus if they would not own an e-bike, suggesting the e-bike is seen as an affordable, higher quality mobility alternative to public transport (Cherry & Cervero, 2007; Cherry et al., 2016; Montgomery, 2010). Another study in Asia focusing on the Chinese city Shijiazhuang, however, found that most e-bike users considered the conventional bicycle as the next best alternative to e-bike (Weinert et al., 2007b). The authors of the latter study hypothesize that these differences might be explained by the differences in quality of the bus service and the city size differences, as Shijiazhuang is smaller, resulting in shorter trip distances. For studies that focus on Asian countries, it should be noted that electrical scooters (without pedal assistance) are also considered e-bikes. In the present study, only pedal-assisted electrical bicycles are considered e-bikes.

In studies that focused on areas outside Asia, it was found that people mainly bought an e-bike to replace (some of) their car trips. This was for instance concluded from a study that focused on Australia (Johnson & Rose, 2013) and North America (MacArthur et al., 2014; MacArthur et al., 2018). In Sweden, Hiselius and Svensson (2017) found, based on a relatively small survey among e-bike users, that the car is the main mode that is replaced by e-bike and that in urban areas more people replace the conventional bicycle by e-bike compared to rural areas. Jones et al. (2016) concluded, based on a small sample of English and Dutch e-bike owners, that the e-bike was primarily bought to replace a conventional bicycle, but that both conventional bicycle and car use decreased after the purchase.

Kroesen (2017) studied effects of e-bike ownership on various indicators of travel behaviour. Data from the Dutch national travel survey was used to assess whether e-bike substitutes other modes of transport. It was shown that e-bike use not only has significant effects on conventional bicycle, car and public transport use but also has a substantial generative effect on the total

distance travelled. However, since cross-sectional data was used for this study, causal directions (for instance from vehicle ownership to mode use) had to be assumed rather than being derived from the data.

From previous studies it seems that the local context is an important factor in the effects that the e-bike has on travel behaviour. As previous findings show that the e-bike mainly replaces public transport in areas with a high-quality public transport network and mainly the car in more car-oriented areas, this may have implications for the present study. As the focus is on the Netherlands, it should be noted that in the Netherlands people travel mostly by car or bicycle. Approximately 29% of trips are travelled by car as a driver and 26% by bicycle (either conventional or electric) (Kennisinstituut voor Mobiliteitsbeleid, 2019). It can therefore be expected based on earlier studies, that mainly the car or the conventional bicycle will be substituted by the e-bike in the Netherlands.

Other Dutch local context that is relevant for this study is the fact that bicycle ownership is very high. There are more bicycles than inhabitants in the Netherlands (Fietsersbond, 2019). While there are some local e-bike sharing systems, the e-bike sharing market in the Netherlands is very small in comparison with total e-bike use. Furthermore, until 2020, there were no national policies to promote the use and ownership of the e-bike specifically. In 2020 a new tax scheme was introduced, enabling companies to provide their employees an e-bike with limited costs for the employee. Since this policy was introduced after the last wave of data collection that was used in this study (see “data” section below) we assume that it did not affect the results.

One recent study by Sun et al. (2020) studied effects of acquiring an e-bike on travel behaviour based on four years of panel data from the Netherlands Mobility Panel. Results showed that the year after acquiring an e-bike, conventional bicycle use reduced significantly as well as car, walking and public transport use, but to a smaller extent. While these results are in line with Kroesen (2017), they only reflect short-term effects. Therefore, the main contribution of the present study is that it shows yearly effects of using an e-bike on the use of other transport modes. In addition, to assess whether it is likely that substitution effects will change in the future, trends in different user groups of the e-bike are analysed.

Assessing substitution effects of the e-bike and trends in the different user groups can be regarded as two different studies, as both analyses have their own method, data and results. For readability reasons, the method, data and results of the analysis of substitution effects (study 1) will be discussed first, followed by the same sections for the analysis of trends in user groups (study 2).

3.3 Study 1: Substitution effects of the e-bike

In this section, substitution effects of e-bike use are assessed. First, we present the methodology followed by results.

3.3.1 Methods

Here, we briefly describe the various elements of the methodology proposed to study the hypothesised substitution effects.

3.3.1.1 Model conceptualisation

In this study, it will be assessed how the use of different travel modes influences the use of other travel modes over time. By studying these effects over time, it can be assessed whether e-bike substitutes and/or complements travel by other modes. Similar to Golob and Meurs (1987), we study possible substitution effects by looking at trip rates with different travel modes over

time. As the e-bike is in theory a travel mode that is not only suited to replace conventional bicycle trips, but also car or public transport, trip rates with the most important travel modes in the Netherlands (car, train, BTM (bus, tram or metro), bicycle, e-bike and walking) are considered in the present study.

To analyse the effects of mode use over time, a Cross-Lagged Panel Model (CLPM) will be used. A CLPM is a structural equation model (SEM) that allows examining (causal) relationships between variables that are measured at two or more moments in time. There is, however, an important limitation of the traditional CLPM. In a traditional CLPM, the stability of constructs is controlled for by including autoregressive relationships. After controlling for stability, the cross-lagged relationships are assumed to be a correct representation of causal influences and a CLPM is often used to show which of the variables is causally dominant. However, Hamaker et al. (2015) showed that when the stability of the constructs is to some extent of a trait-like, time-invariant nature, the autoregressive parameters are not able to correctly control for this. In other words, the traditional CLPM is not able to fully account for time-invariant between-person differences. As a result, the model is not able to isolate within-person changes. Hamaker et al. (2015) found that this could, in some cases, result in drawing wrong conclusions about the presence of causal relationships, the causal dominance of constructs or about the sign of causal relationships.

To cope with this limitation, Hamaker et al. (2015) present an alternative to the traditional CLPM, the Random Intercept Cross-Lagged Panel Model (RI-CLPM). In this approach, to correct for time-invariant between-person differences, the variance of the observed indicators is split into a between-person level random intercept that represents the individual's trait-like deviation from the means and within-person level temporal deviations from their expected scores (the mean plus the random intercept).

Figure 3.1 shows the conceptual model of the RI-CLPM. For clarity of communication, only two observed indicators are shown in the figure. In the full model, six indicators are included (car, train, BTM, bicycle, e-bike and walking). The random intercepts are latent variables with their factor loadings constrained to 1. In contrast to a regular CLPM, the autoregressive parameters (α, α_2, δ and δ_2) do not represent rank-order stability of individuals, but a within-person carry-over effect (Hamaker et al., 2015). In other words, a positive parameter implies that when an individual makes more trips with a certain mode than expected based on the temporal group mean and the random intercept, he or she is likely to also make more trips than expected in a following year. The cross-lagged parameters (β and γ) indicate the within-person effect of the use of a certain travel mode on the use of other modes in the following year.

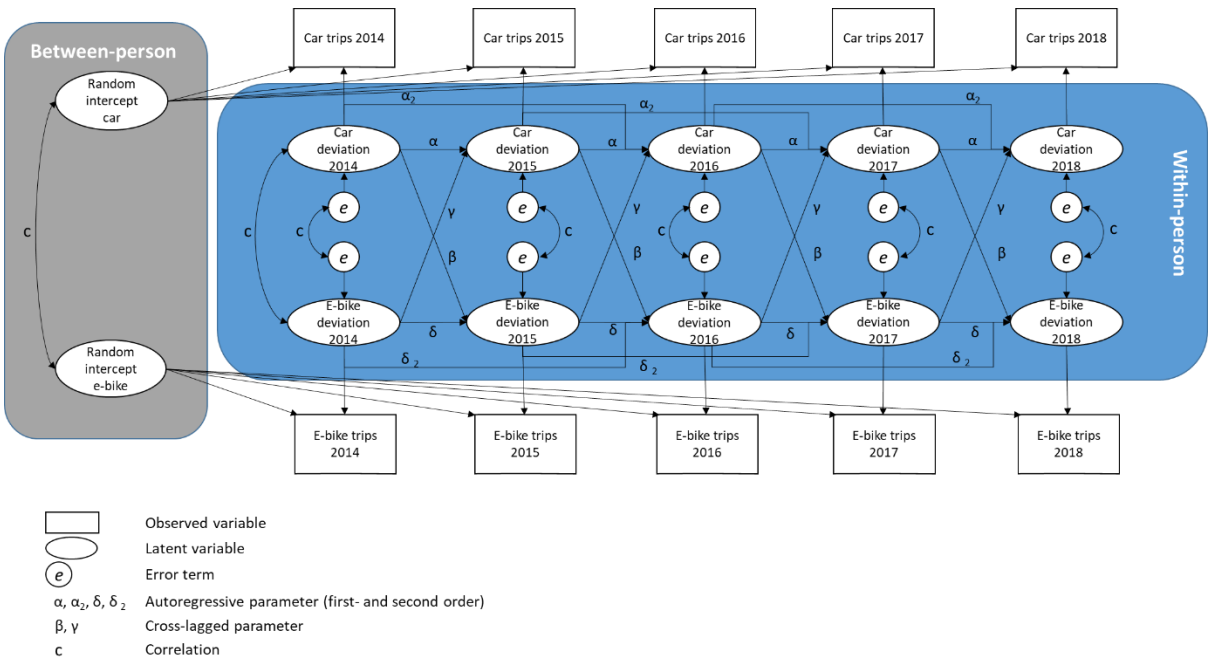

Figure 3.1. Partial conceptual model of the Random Intercept Cross-Lagged Panel Model; the figure shows a five-wave, two-variable model for clarity of communication. The full model includes six indicators (car, train, BTM, bicycle, e-bike and walking).

3.3.1.2 Data

To estimate the RI-CLPM, longitudinal data are required. In the present study, panel data from the Netherlands Mobility Panel (MPN) are used. The MPN is an annual household panel that started in 2013 and consists of approximately 2000 complete households. Each year, household members of at least 12 years old are asked to complete a 3-day travel diary and fill in an extensive questionnaire that includes questions on topics such as occupational status, use of different modes of transport and life events in the past year. Furthermore, every household is asked to fill in a questionnaire about household related characteristics, such as information about household composition and ownership of means of transport. More information about the MPN can be found in Hoogendoorn-Lanser et al. (2015). Currently, data from the first six waves (2013-2018) are available. However, the first wave of the MPN is not used in the analyses as including this wave led to estimation problems. This will be discussed in detail in section 3.3.1.3.

To account for panel attrition (respondents dropping out of the panel between waves), new respondents are recruited yearly. Table 3.1 shows the number of respondents and their response patterns for the first through the sixth wave (e.g. pattern 000001 indicates a respondent that only participated in wave 6, while pattern 111111 represents respondents that participated in wave 1 through 6). Since the first wave of MPN is not used, all respondents of the second through sixth wave that participated in at least one wave are included in the analysis, 11,152 in total. In the ensuing, it is explained how missing data is handled.

Table 3.1. Participation patterns of the MPN, wave 1 through 6 (2013-2018) (n=12,215)

Pattern	#	%	Pattern	#	%	Pattern	#	%	Pattern	#	%
000001	1100	9.0	010001	25	0.2	100001	12	0.1	110010	5	0.0
000010	615	5.0	010010	4	0.0	100011	5	0.0	110011	18	0.1
000011	1813	14.8	010011	9	0.1	100100	22	0.2	110100	84	0.7
000100	394	3.2	010100	153	1.3	100101	10	0.1	110101	18	0.1
000101	154	1.3	010101	29	0.2	100110	3	0.0	110110	30	0.2
000110	164	1.3	010110	15	0.1	100111	8	0.1	110111	102	0.8
000111	643	5.3	010111	79	0.6	101000	156	1.3	111000	355	2.9
001000	142	1.2	011000	453	3.7	101001	6	0.0	111001	23	0.2
001001	12	0.1	011001	37	0.3	101010	5	0.0	111010	39	0.3
001010	1	0.0	011010	32	0.3	101011	9	0.1	111011	115	0.9
001011	10	0.1	011011	73	0.6	101100	40	0.3	111100	149	1.2
001100	63	0.5	011100	195	1.6	101101	25	0.2	111101	125	1.0
001101	27	0.2	011101	170	1.4	101110	17	0.1	111110	115	0.9
001110	13	0.1	011110	79	0.6	101111	77	0.6	111111	858	7.0
001111	55	0.5	011111	443	3.6	110000	492	4.0			
010000	1217	10.0	100000	1063	8.7	110001	10	0.1	Total	12215	100.0

Mode use is included in the model as the trip rates per mode of transport in 3 days. These trip rates are reported in the travel diary that respondents of the MPN complete every year for the same 3 days. As indicated in the previous section, six modes of transport are included in the model, which are car (as driver), train, BTM, bicycle, e-bike and walking. If a multi-modal trip is reported, only the main mode of transport is considered. As travel times and distances of individual trip legs are unknown in the MPN, assumptions have to be made to determine the main mode of transport. If a multi-modal trip is reported, the first mode on the following list is considered the main mode: train, BTM, car, e-bike, bicycle, walking. Table 3.2 shows the sample composition. In this table, only data from the most recent wave of a respondent are used, since some variables are time-variant. The sample composition is fairly representative of the Dutch population. It can be seen that just over one in six (17%) respondents owns an e-bike, while 70% owns a conventional bicycle. It should be noted that a considerable amount (37%) of e-bike owners also owns a conventional bicycle.

Table 3.2. Sample composition MPN wave 2 through 6 (2014-2018) (n=11,152)

Variable		
Car (as driver) trip rate (over three days)	Mean (SD)	3.00 (3.91)
Train trip rate (over three days)	Mean (SD)	0.26 (0.92)
BTM trip rate (over three days)	Mean (SD)	0.20 (0.80)
Bicycle trip rate (over three days)	Mean (SD)	1.88 (3.10)
E-bike trip rate (over three days)	Mean (SD)	0.40 (1.57)
Walking trip rate (over three days)	Mean (SD)	1.24 (2.39)
Gender	Male	46%
	Female	54%
Age	Mean (SD)	44.5 (19.0)
Educational level	Low	35%
	Mid	37%
	High	28%
Occupational status	Employed	54%
	Unemployed	10%
	Incapacitated	5%
	Student	16%
	Retired	16%
Personal net income per month	No income	26%
	Less than €1,500	34%
	€1,500 - €2,500	29%
	More than €2,500	13%
Car ownership		68%
Bicycle ownership		70%
E-bike ownership		17%

3.3.1.3 Model estimation

To estimate the RI-CLPM, the R package lavaan is used (Rosseel, 2012). Since all respondents that participated at least 1 year are included in the analysis, the model has to handle missing data. To this end, the model is estimated using Full Information Maximum Likelihood (FIML), which has been shown to effectively handle missing data by Enders and Bandalos (2001). Furthermore, to increase precision of the parameter estimates and ease interpretation, all autoregressive and cross-lagged parameters and within-wave correlations are constrained to be equal across waves. As it is expected that possible substitution effects may be different between trip purposes, four models are estimated; a general model without distinction between trip purposes and three models specifically for commuting-, leisure- and shopping trips. For the model with commuting trips, including all six waves of the MPN data results in estimation problems. It is expected that these problems are caused by having too few respondents who use an e-bike for commuting and participated in both the first and second wave as removing the first wave of data solves these problems. In order to use the same data for the different models, all models are estimated using the second through sixth wave of the MPN.

3.3.2 Results

Here, we discuss the key results of the four estimated models. First, we discuss the results of the model without distinction between trip purposes, followed by a discussion of substitution effects specifically for commuting, leisure of shopping trips.

3.3.2.1 Substitution effects without distinction between trip purposes

Table 3.3 shows the regression parameters of the RI-CLPM with all trips included. The model has a *Comparative Fit Index* (CFI) of 0.983, a *Root Mean Square Error of Approximation* (RMSEA) of 0.013 and a *Standardized Root Mean Square Residual* (SRMR) of 0.027. All these values suggest a good model fit (Brown, 2014). As discussed in the paragraph 'Model conceptualisation', in contrary to a regular CLPM, the autoregressive parameters do not represent rank-order stability of individuals, but a within-person carry-over effect (Hamaker et al., 2015).

All first-order autoregressive parameters are positive and significant, indicating that when an individual uses a certain mode at time *t-1* more than would be expected based on the mean and random intercept, it is likely that this individual will also show a higher use of this mode on time *t* and vice versa. For the second-order parameters the same interpretation holds, except that they show the effect of the use at time *t-2* on the use on time *t*. As the interest in this study is on the cross-lagged parameters, the autoregressive parameters will not be discussed in the following models.

From the cross-lagged parameters it can be seen that the e-bike only has a significant substitution effect on the conventional bicycle. This result contrasts results obtained in previous studies, as they often conclude that the e-bike not only substitute the conventional bicycle but also the car and public transport (e.g. Jones et al. (2016) and Kroesen (2017)).

Besides this effect of the e-bike on the conventional bicycle, there are some other significant effects. Both the train and BTM appear to be substitutes of the conventional bicycle. Regarding the train mode, this is somewhat unexpected, as in the Netherlands the train is often used for longer distances than the bicycle. Furthermore, we find that an increase in bicycle use leads to a decrease in car use. Finally, an increase in walking trips leads to a small increase in car trips, an effect that is difficult to explain.

Table 3.3. Regression parameters of the RI-CLPM, no distinction between trip purposes (MPN 2014-2018)

	Effect on: Car as driver	Train	BTM	Bicycle	E-bike	Walk
Autoregression (1st-order)	**0.199 (0.000)**	**0.243 (0.000)**	**0.196 (0.000)**	**0.221 (0.000)**	**0.344 (0.000)**	**0.347 (0.000)**
Autoregression (2nd-order)	**0.115 (0.000)**	**0.074 (0.000)**	**0.013 (0.553)**	**0.095 (0.000)**	**0.200 (0.000)**	**0.186 (0.000)**
Car as driver (t-1)		-0.006 (0.051)	0.000 (0.930)	-0.083 (0.064)	-0.007 (0.367)	0.011 (0.211)
Train (t-1)	0.020 (0.692)		-0.000 (0.977)	**-0.023 (0.024)**	0.010 (0.684)	0.035 (0.292)
BTM (t-1)	-0.034 (0.565)	0.002 (0.889)		**-0.097 (0.014)**	0.008 (0.146)	-0.031 (0.430)
Bicycle (t-1)	**-0.035 (0.040)**	-0.001 (0.868)	-0.000 (0.950)		-0.000 (0.990)	-0.010 (0.392)
E-bike (t-1)	-0.012 (0.675)	-0.000 (0.993)	0.001 (0.922)	**-0.092 (0.000)**		0.011 (0.528)
Walk (t-1)	**0.046 (0.017)**	0.005 (0.267)	-0.001 (0.822)	0.001 (0.932)	-0.000 (0.970)	

P-values are presented in parentheses, parameters with p<0.05 are bold

3.3.2.2 Substitution effects for commuting trips

To study the substitution effects specifically for commuting trips, only commuting trips of employed respondents are used in the model estimation. This reduces the sample size to 6009 respondents. Furthermore, BTM is not included as it turned out there were too few commuting trips by BTM in the MPN. This is partly caused by the bus, tram and metro mainly being used as access- and egress- modes, while only the main mode of transport is considered in the model. This model also shows a good model fit with a CFI of 0.955, a RMSEA of 0.024 and a SRMR of 0.043. The regression parameters of the RI-CLPM with only commuting trips are shown in Table 3.4.

Interestingly, the results show that specifically for commuting trips, the e-bike not only substitutes the conventional bicycle, but also the car. Apparently, for commuting trips people consider the e-bike not only as a replacement for the conventional bicycle but also for the car. Furthermore, for commuting, the car acts as a substitute for the train, while the conventional bicycle stimulates walking and walking stimulates train use.

Table 3.4. Regression parameters of the RI-CLPM, only commuting trips (MPN 2014-2018, n=6.009)

	Effect on: Car as driver	Train	Bicycle	E-bike	Walk
Autoregression (first-order)	**0.269 (0.000)**	**0.281 (0.000)**	**0.208 (0.000)**	**0.389 (0.000)**	**0.481 (0.000)**
Autoregression (second-order)	**0.060 (0.024)**	**0.053 (0.036)**	0.034 (0.125)	**0.263 (0.000)**	**0.205 (0.000)**
Car as driver (t-1)		**-0.020 (0.003)**	-0.016 (0.171)	-0.007 (0.398)	-0.004 (0.479)
Train (t-1)	-0.068 (0.148)		-0.028 (0.347)	-0.005 (0.333)	0.004 (0.764)
Bicycle (t-1)	-0.006 (0.835)	-0.018 (0.067)		-0.019 (0.197)	0.017 (0.045)
E-bike (t-1)	**-0.102 (0.017)**	-0.005 (0.760)	**-0.056 (0.047)**		0.003 (0.797)
Walk (t-1)	-0.083 (0.146)	**0.045 (0.030)**	-0.012 (0.742)	0.010 (0.508)	

P-values are presented in parentheses, parameters with p<0.05 are bold

3.3.2.3 Substitution effects for leisure trips

To model the substitution effects specifically for leisure trips, all respondents are included. Again, this model shows a good model fit with a CFI of 0.952, a RMSEA of 0.016 and a SRMR of 0.030. Table 3.5 shows the regression parameters of this RI-CLPM.

For leisure trips it turns out that the e-bike only substitutes the conventional bicycle as this is the only significant parameter estimate of e-bike trips at t-1. The use of BTM stimulates e-bike use. Furthermore, there are substitution effects of the car on the conventional bicycle and BTM on walking. Just as in the general model, there is a positive effect of walking on car use. For leisure trips, a possible explanation might be found in the fact that walking for leisure purposes often consists of walking as the activity, without a specific destination (e.g. walking in a forest). It is possible that people would like to make a walking tour in different areas, for which they need a car to reach these areas.

Table 3.5. Regression parameters of the RI-CLPM, only leisure trips (MPN 2014-2018)

	Effect on: Car as driver	Train	BTM	Bicycle	E-bike	Walk
Autoregression (1st-order)	**0.059 (0.001)**	0.009 (0.566)	**0.052 (0.002)**	**0.089 (0.000)**	**0.313 (0.000)**	**0.329 (0.000)**
Autoregression (2nd-order)	0.025 (0.182)	**-0.045 (0.010)**	**-0.018 (0.308)**	**0.061 (0.000)**	**0.176 (0.000)**	**0.157 (0.000)**
Car as driver (t-1)		**-0.005 (0.039)**	0.004 (0.134)	**-0.122 (0.007)**	0.011 (0.101)	0.022 (0.058)
Train (t-1)	0.018 (0.724)		0.011 (0.281)	0.014 (0.138)	-0.026 (0.255)	0.008 (0.871)
BTM (t-1)	**0.125 (0.024)**	0.006 (0.587)		-0.004 (0.925)	**0.011 (0.033)**	**-0.120 (0.025)**
Bicycle (t-1)	0.010 (0.520)	0.001 (0.862)	-0.006 (0.063)		0.008 (0.706)	0.000 (0.976)
E-bike (t-1)	0.031 (0.232)	-0.005 (0.403)	-0.006 (0.256)	**-0.045 (0.033)**		0.038 (0.120)
Walk (t-1)	**0.037 (0.006)**	0.002 (0.596)	-0.001 (0.585)	0.006 (0.602)	0.007 (0.161)	

P-values are presented in parentheses, parameters with p<0.05 are bold

3.3.2.4 Substitution effects for shopping trips

Table 3.6 shows the regression parameters of the final RI-CLPM with only shopping trips included. The CFI of this model is just under the limit value of 0.95 to be considered as good model fit. However, with a CFI of 0.934 it can still be considered acceptable (Brown, 2014).

The RMSEA and SRMR can both be considered as an indication of a good model fit with values of respectively 0.019 and 0.035.

There are only a few significant effects for shopping trips. Again, for the e-bike it can be seen that it only substitutes the conventional bicycle. Furthermore, walking substitutes the e-bike to a certain extent and BTM substitutes the conventional bicycle. Lastly, train use has a positive effect on the number of walking trips.

Table 3.6. Regression parameters of the RI-CLPM, only shopping trips (MPN 2014-2018)

	Effect on: Car as driver	Train	BTM	Bicycle	E-bike	Walk
Autoregression (1st-order)	**0.140 (0.000)**	**-0.112 (0.000)**	-0.030 (0.062)	**0.118 (0.000)**	**0.182 (0.000)**	**0.181 (0.000)**
Autoregression (2nd-order)	**0.124 (0.000)**	**-0.108 (0.000)**	**-0.040 (0.018)**	**0.068 (0.000)**	**0.133 (0.000)**	**0.107 (0.000)**
Car as driver (t-1)		0.001 (0.480)	-0.001 (0.734)	0.020 (0.714)	-0.013 (0.088)	-0.003 (0.755)
Train (t-1)	-0.051 (0.556)		0.022 (0.160)	0.015 (0.170)	0.018 (0.590)	**0.282 (0.000)**
BTM (t-1)	-0.071 (0.254)	-0.004 (0.528)		**-0.166 (0.027)**	-0.002 (0.784)	-0.053 (0.282)
Bicycle (t-1)	0.014 (0.297)	0.001 (0.430)	0.002 (0.361)		0.039 (0.405)	-0.015 (0.151)
E-bike (t-1)	-0.035 (0.120)	0.001 (0.822)	0.004 (0.335)	**-0.075 (0.000)**		0.002 (0.891)
Walk (t-1)	0.005 (0.754)	**0.003 (0.047)**	-0.004 (0.119)	-0.012 (0.380)	**-0.021 (0.010)**	

P-values are presented in parentheses, parameters with p<0.05 are bold

3.3.3 Conclusion substitution effects

The analyses into substitution effects of e-bike use showed that at a general level – that is, taking all trip purposes together – e-bike trips only substitute conventional bicycle trips. Only for commuting trips it was found that e-bike trips, in addition to substituting conventional bicycle trips, also substitute trips made by car. This implies that if the share of commuting in e-bike use would increase, this substitution effect will probably also be observed at the general level in due time. To assess whether it is likely that substitution effects will indeed change in the future, it is important to know which different e-bike user groups exist and how these groups are growing or shrinking over the years as a share of the total population of travellers. This is assessed in the next section.

3.4 Study 2: E-bike user groups

The previous section showed that it is important to know which different e-bike user groups exist and how these groups are growing or shrinking over the years. In this section, we present a statistical analysis to reveal the different user groups.

3.4.1 Methods

Here, we briefly describe the various elements of the methodology proposed to study the different e-bike user groups.

3.4.1.1 Model conceptualisation

To reveal the different e-bike user groups, a latent class analysis (LCA) will be used. The idea behind LCA is that observed associations between different indicators are explained by an underlying latent variable (McCutcheon, 1987). The latent variable is not directly measured, but is inferred from observed indicators. Crucially, LCA differs from conventional segmentation analysis by letting the classes emerge from correlations in the data, as opposed to being a priori imposed by the researcher. An important difference between LCA and standard cluster analysis is that LCA is a model-based clustering approach in which objects are probabilistically assigned to classes (Vermunt & Magidson, 2002).

E-bike user groups can be defined in different ways. One could cluster the e-bike users based on how they use the e-bike (for instance trip rates with the e-bike for different purposes) or based on sociodemographic variables. In this study the user groups will be defined using socio-demographic variables, while the trip frequencies of e-bike for various purposes are included as (inactive) covariates of the model. This is because the behavioural variables (trip rates for different purposes) are more volatile and therefore subject to random fluctuations (e.g. a person may not use the e-bike on a particular day for a trivial reason, such as having a day off from work or having no out-of-home activities). In our case, strong fluctuations are especially likely since we rely on data from the Dutch national travel survey which only measures the travel behaviour of respondents for a single particular day. The socio-demographic variables, on the other hand, can provide a stable picture of the various e-bike user groups and are informative on how people *generally* use the e-bike. For example, it may be expected that the typical old-age retired e-bike user will use the e-bike mostly for recreational purposes (and therefore it is not expected to substitute trips by car) while a middle-aged employed individual may be expected to use the e-bike for commuting trips (which may previously have been made by car). Figure 3.2 shows the conceptual model for the latent class analysis. To cluster e-bike users, five sociodemographic variables (gender, age, education level, work status and household composition) are used as indicators.

Latent class analysis allows for the use of covariates. Covariates are exogenous variables that are used to predict class membership (Vermunt & Magidson, 2002). In this study, the survey year is included as an exogenous variable. As already discussed, the share of people of 65 years and older in terms of travelled e-bike kilometres has decreased in recent years. This implies that the user group is changing over time. As the interest is on assessing how the different user groups have grown over the years, the survey year is included as a covariate.

To have an indication of e-bike use per user group, so-called inactive covariates, reflecting the reported e-bike trip rates for various purposes on the reporting day, are added to the model. Inactive covariates do not influence the model in any way and are merely used to describe the different groups.

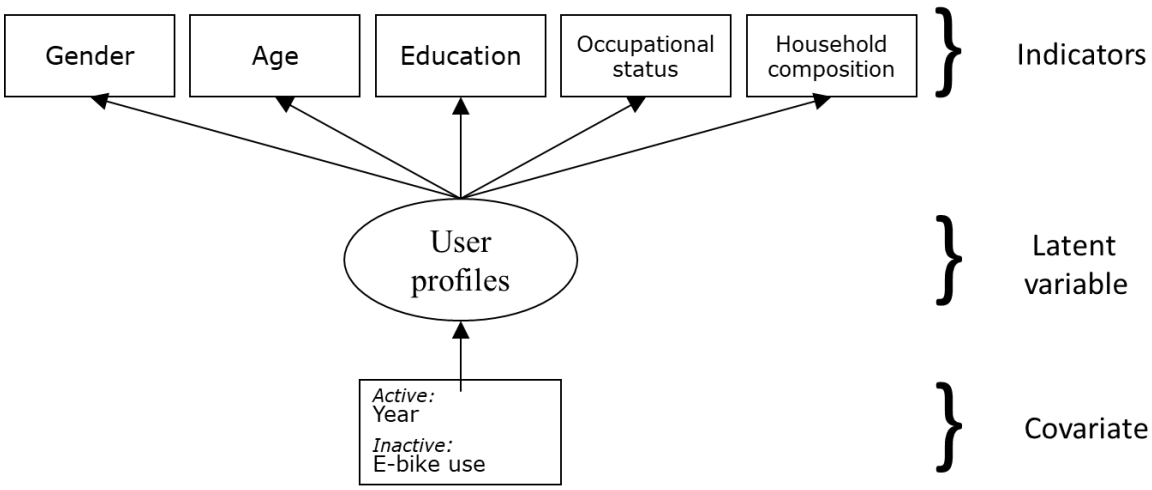

Figure 3.2. Conceptual model of the latent class analysis

3.4.1.2 Data

To estimate the LCA, data from the Dutch national travel survey OViN (in Dutch: Onderzoek Verplaatsingen in Nederland) are used (Statistics Netherlands, 2013-2017). The Dutch national travel survey is a cross-sectional travel survey in which participants are asked to record all the

trips they made for a single, predefined day. Compared to the MPN, which was used to study substitution effects, the national travel survey is larger in terms of number of respondents. Between 37,000 and 43,000 respondents participate yearly. In addition, because of its (repeated) cross-sectional nature, it is better suited than a mobility panel to study the changing composition of e-bike users over time. Whereas a mobility panel (like the MPN) is (by definition) affected by a cohort effect (for one, members in a panel get older over time), a repeated cross-sectional survey is not affected by such biases. Hence, each survey provides a 'fresh' snapshot view of the different e-bike groups and their respective sizes The respondents participating in the national travel survey are randomly drawn from the Dutch Personal Records Database (in Dutch: Basisregistratie Personen (BRP), which contains information on all Dutch residents), resulting in a representative sample of the Dutch population.

Besides keeping a 1-day travel diary, a short questionnaire is included to gather some information on the personal- and household level, such as household composition and ownership of means of transport. Starting from 2013, the e-bike was included in the national travel survey. From this moment respondents were able to report the ownership and use of the e-bike. Before 2013, no distinction was made between the conventional bicycle and the e-bike.

The present study uses data from 2013 to 2017. In 2018 the set-up of the Dutch national travel survey changed and e-bike ownership is no longer measured on an individual level. Therefore, data from 2018 onwards cannot be used in this study. As the goal is to reveal different e-bike user groups, only respondents that own an e-bike are used in the analysis. Between 8.1 and 13.9% of respondents own an e-bike. The effective sample sizes are as follows: 3413, 4170, 4014, 4404 and 5129 for the years 2013 through 2017 respectively. This results in a total sample size of 21,130 respondents.

3.4.1.3 Model estimation

To estimate the LCA, the statistical software package Latent Gold is used (Vermunt & Magidson, 2005). To decide on the number of classes, two methods are used, as described by Magidson and Vermunt (2004). The first method uses the Bayesian Information Criterion (BIC). The BIC takes model fit and parsimony into account. A model with a lower BIC is preferred over a model with a higher BIC. The second methods uses the L^2 of the 1-class model as a baseline measure of the total amount of association within the data. When the L^2 of a model with more classes is compared to the L^2 of the 1-class model, the reduction in L^2 represents the additional explained association. When the reduction in L^2 becomes relatively low, it is no longer justified to add an extra class to the model.

3.4.2 Results

Here, we discuss the key results of latent class analysis and discuss the trends in e-bike user groups.

3.4.2.1 E-bike user groups

As described in the section 'Model estimation', the BIC and reduction of L^2 are used to decide on the appropriate number of clusters in the LCA. A 1-class to 10-class model is estimated without any covariates to assess only the variance between the indicators. The BIC value suggests that a model with a least 10 classes would be appropriate, as this model has the lowest BIC value. Since a model with such a high number of classes would be impossible to interpret meaningfully, we instead relied only on the relative reduction in L^2 as the criterion to decide on the optimal number of classes (Magidson & Vermunt, 2004). With respect to this criterion, it was found that after the 5-class solution, the reduction of L^2 became small (less than 3%),

suggesting that the 5-class model provides a good balance between model fit and model parsimony.

Table 3.7 shows the profiles of the five different classes from the final model. It should be noted that the class sizes indicate the average shares of the classes in the years 2013 through 2017. The shares per year are calculated in the next section. The table also shows the composition of the total e-bike user sample. From the composition of the total sample, the high share of women and retired people and the relatively high average age stand out. Apparently, the e-bike user group is still dominated by the initial adopters in the Netherlands; the older retired people (Hendriksen et al., 2008). In contrast with other studies, we find that the e-bike users in the Netherlands are predominantly female (see, e.g. MacArthur et al. (2018) and Wolf and Seebauer (2014)).

The first and largest class (53% of the sample) represents the retired older leisure users. This group is comprised of the traditional e-bike users, with virtually everyone in this group aged 65+. This group's average age is 72 years old. Consequently, nearly everyone in this group is retired. This user group primarily uses e-bikes for leisure or shopping purposes.

The second class (20% of the sample) represents the middle-aged full-time working people. These users are considerably younger than those in the first class, with an average age of around 53 years old. Most of the people in this group have full-time jobs (78%), which is also reflected in the relatively high share of work-related trips in this group.

The third class (14% of the sample) represents mostly female and relatively older leisure users. This third group consists primarily of women aged between 50 and 65 years old. This group consists almost equally of people with part-time jobs and people who are primarily homemakers. Similar to the first class, this group mainly uses e-bikes for leisure or shopping purposes.

The fourth class (11% of the sample) represents the younger part-time working women with children. This group is largely comprised of women. With an average age of 46 years old, this group is relatively young compared to the previous groups, with most of the people in this group having part-time jobs. Notably, over 80% of the people in this group reside in households consisting of two adults (partners) with children. This group uses e-bikes for work-related trips, as well as for leisure and shopping purposes.

The fifth and smallest class (1% of the sample) represents students and pupils. This group largely consists of teenagers: 94% of this group is aged 12 to 20 years old. Given this group's young average age, the group includes a high proportion of lower educated people. Moreover, 90% of the people in this group are high school or college students, which is also reflected in the fact that people in this group frequently use e-bikes for education-related purposes.

Identifying the various e-bike user groups not only revealed groups who frequently use the e-bike, but also those who are not yet using e-bikes. Notably, for example, the various user groups rarely included 20 to 40 year olds; for example, in Group 2, comprised mainly of people with full-time jobs, only 10% of users are aged between 20 and 40 years old. Group 4 meanwhile has the most users aged 20 to 40: 29% of those in this group are aged between 20 and 40 years old with the majority of users having part-time jobs.

Table 3.7. Profiles of the 5-class Latent Class Model

	Class*	RO	MF	OF	YF	ST	Total
Indicators	Class size (%)	53	20	14	11	1	-
Gender (%) (Wald = 618, p < 0.00)	Male	44	65	7	2	46	38
	Female	56	35	93	98	54	62
Age (Wald = 440, p < 0.00)	12-21 years	0	0	0	0	94	1
	21-30 years	0	2	0	10	6	2
	31-40 years	0	8	0	19	0	4
	41-50 years	0	25	2	31	0	9
	51-64 years	4	65	98	40	0	34
	65 and older	96	0	0	0	0	51
	Mean	72.3	52.6	58.8	46.3	16.2	62.7
Educational level (%) (Wald = 1447, p < 0.00)	Low	54	25	47	21	77	44
	Mid	26	39	36	48	20	32
	High	17	34	15	30	2	22
	Unknown	2	2	2	1	1	2
Occupational status (%) (Wald = 2465, p < 0.00)	Works 12-30 hours/week	1	4	38	57	3	13
	Works 30+ hours/week	1	78	2	11	5	18
	Works in household	0	1	35	20	0	7
	Student	0	0	0	1	90	2
	Unemployed	0	4	5	2	1	2
	Incapacitated	0	10	10	5	0	4
	Retired	98	1	3	0	0	53
	Other	0	2	7	4	2	2
Household composition (%) (Wald = 2754, p < 0.00)	Single	24	17	10	5	6	18
	Couple without children	73	44	82	9	0	60
	Couple with children	2	35	7	79	82	19
	Other	1	4	1	7	11	3
Active covariates							
Reporting year (%)	2013	18	13	18	14	14	16
	2014	21	18	21	18	16	20
	2015	18	20	21	19	18	19
	2016	20	23	19	21	22	21
	2017	24	25	22	29	30	25
Inactive covariates							
E-bike trip on reporting day** (%)	Work	1	12	8	11	4	5
	School	0	0	0	1	12	0
	Shopping	11	6	13	12	3	11
	Leisure	15	9	12	13	8	13

**RO*: Retired older leisure users, *MF*: Middle-aged fulltime working people, *OF*: Older female leisure users, *YF*: Younger part-time working women with children, *ST*: Students

**Respondents in the Dutch national travel survey report their travel behaviour for a single day. The shown percentages reflect the share of people that used the e-bike for that specific purpose on the reporting day.

3.4.2.2 Trends in e-bike user groups

As indicated, the discussed class sizes in the previous section reflect the average class sizes over the years 2013 through 2017. As the year that a respondent participated in the Dutch national travel survey is known, the class sizes can be computed per year. Furthermore, population weight factors are included in the national travel survey. These weight factors are calculated based on a number of background characteristics such as age, gender, income and possession of means of transport (Statistics Netherlands, 2018b). With these weight factors, the absolute sizes of the different classes per year are calculated. This provides insight into how the five groups have grown over the years.

The shares and absolute sizes of the five groups over the years are shown in Table 3.8. The absolute sizes are rounded to the nearest thousand as it cannot be assumed that the weight factors in the national travel survey are accurate enough to calculate more detailed numbers. They are, however, believed to give a good indication of the absolute sizes.

Table 3.8. Development of the e-bike user groups, share and absolute size

Share	Group 1	Group 2	Group 3	Group 4	Group 5	Total (x 1,000)
2013	56.1%	17.9%	15.4%	9.2%	1.3%	1,170
2014	53.8%	19.8%	14.5%	10.5%	1.3%	1,369
2015	49.5%	22.9%	15.4%	10.7%	1.5%	1,630
2016	49.8%	24.5%	12.6%	11.4%	1.7%	1,832
2017	48.6%	23.6%	12.3%	13.6%	1.9%	2,033
Absolute size (x 1,000)	Group 1	Group 2	Group 3	Group 4	Group 5	
2013	657	209	180	108	16	1,170
2014	737	272	199	144	18	1,369
2015	807	374	250	175	24	1,630
2016	912	449	230	209	32	1,832
2017	988	480	250	276	39	2,033
Growth 2013-2017	Group 1	Group 2	Group 3	Group 4	Group 5	Total
Growth (%)	50%	129%	39%	156%	150%	74%

Between 2013 and 2017, the total number of e-bike users grew from approximately 1.2 million to over 2 million people, an increase of 74%. In 2017, the Netherlands had 17.1 million inhabitants, resulting in just under 12% of Dutch people owning an e-bike. Looking at the increases in the individual groups, it becomes apparent that the two groups with the oldest users, the first and third group, show a slower growth rate of 50 and 39% respectively. As a result, the shares of these two groups (compared to all e-bike owners at one point in time) declined over the years. While the first group had a share of just over 56% in 2013, the share in 2017 was just under 49%. A growing share is visible for the second, fourth and fifth group. These three groups more than doubled in size in 5 years. This also explains the relatively large growth of the share of work related e-bike kilometres as discussed in the introduction, as these groups use the e-bike primary for work- of education related trips instead of only for leisure of shopping.

Relatively speaking, the younger part-time working women with children (group 4) is growing the fastest. Next to this, the growth rate of the fifth class (consisting of young people) also stands out. From a substantive viewpoint, several reasons can be identified explaining why the e-bike is becoming popular among students and pupils. First, while many students and especially pupils live relatively close to their educational location, some live too far away to travel with a regular bicycle. In this case, the e-bike may offer an attractive (and in some cases cheaper) alternative to public transport. This may especially be the case in more rural areas of the Netherlands. And secondly, up to 2010 people in The Netherlands of 16 years and older were allowed to drive a scooter/moped after passing a theory exam. This was a relatively popular mode for pupils. In 2010, the age limit was raised to 17 and a practical exam was introduced, lowering the attractiveness of a scooter/moped. The e-bike may be seen as an alternative to a scooter/moped.

While in absolute terms the fifth segment is still quite small, the fact that a group of young people is now taking up this mode of transport means that the traditional image of the e-bike (as a mode of transport for elderly people, see Hendriksen et al. (2008)) is indeed shifting. As the image was previously found to be an inhibiting factor, this trend may therefore be expected to boost the adoption of the e-bike. Figure 3.3 shows the growth of each user group compared

to 2013. It is clear from the graph that the first and third group have been growing slower than the average growth of all groups since 2013. Although no data is available after 2017, it is not expected that these trends will suddenly change. Therefore it is expected that the three younger groups (group 2, 4 and 5) will keep growing at a higher rate. As these groups use the e-bike primarily for commuting or education, the shares of these trip purposes will keep growing. Furthermore, it is likely that substitution effects will become more evident due to these trends. If more people start using the e-bike for commuting, it is likely that the substitution effect that e-bike trips have on car trips can also be observed on the general level.

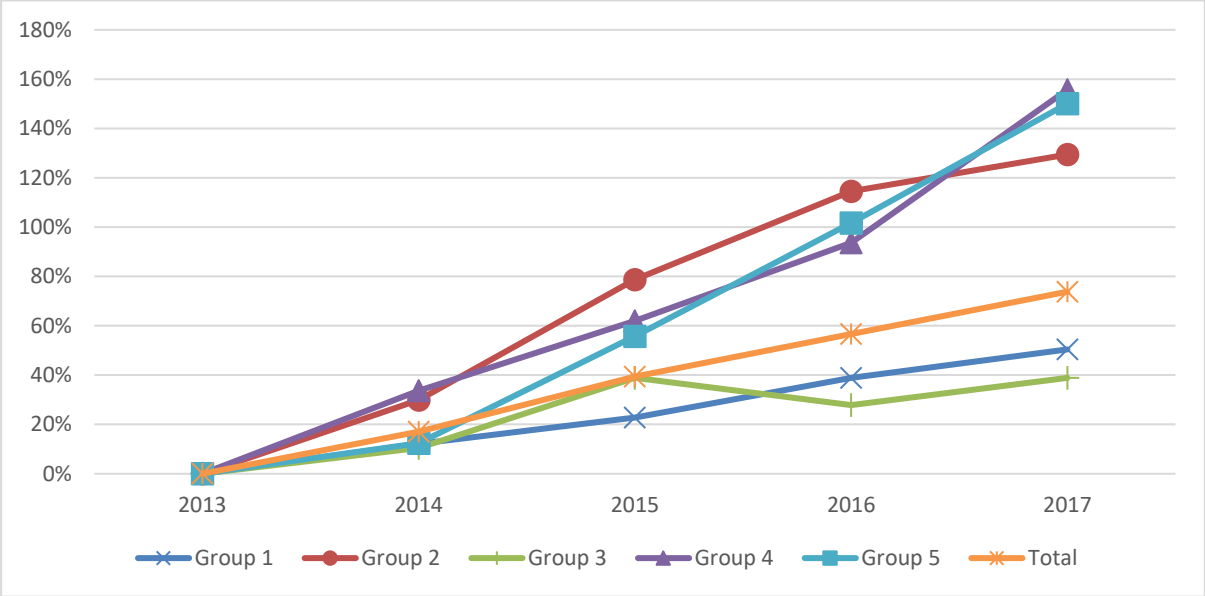

Figure 3.3. Growth of e-bike user groups compared to 2013

3.5 Conclusions and future research

In this study, different user groups of the e-bike are revealed and substitution effects of the e-bike are examined based on longitudinal data to study substitution patterns and cross-sectional data to infer user groups. The main contributions of the present study are that substitution effects of the e-bike are identified based on longitudinal data and that trends in different e-bike user groups are analysed based on cross-sectional data to assess whether it is likely that substitution effects will change in the future. Our approach allows us to draw conclusions regarding substitution effects in terms of within-person changes in e-bike use and the use of other modes.

3.5.1 Conclusions

The present study is the first that uses a large-scale panel to address the question of substitution effects of using an e-bike. By making use of a Random Intercept Cross-Lagged Panel Model, within-person substitution effects are revealed. The outcomes show that in general, e-bike trips only substitute conventional bicycle trips. Specifically for commuting trips it was found that e-bike trips do substitute car trips, but this effect is not (yet) strong enough to be observed when modelling all trip purposes together. This contradicts earlier studies that often conclude that the e-bike also replaces the car and public transport to a certain level, and highlights the importance of using longitudinal data when doing such analyses.

Our finding that the e-bike is only substituting the conventional bicycle at a general level (i.e. combining all trip purposes), raises the question whether the e-bike has a positive effect on the environment, road congestion and health. Although there are no emissions while using the e-

bike, there are charging-related emissions, making the e-bike less environmentally friendly compared to the conventional bicycle (Otten et al., 2015). With regards to health, several studies have shown that using an e-bike can be regarded as physical activity, but the level of intensity is lower compared to a conventional bicycle (Bourne et al., 2018).

Based on 5 years of data from the Dutch national travel survey we find that there are five different user groups within the e-bike population, each having a distinct usage pattern and socio-demographic composition. These groups range from the classical e-bike users in the Netherlands, the retired older people who use the e-bike primarily for leisure purposes to a (small) group of students who use the e-bike for education related trips. Although the first group is still the largest, its growing at a slower rate compared to the user groups that use the e-bike primarily for work or education purposes. Due to these trends in the different user groups of the e-bike, it is likely that substitution effects will change in the future. When enough people with a job own an e-bike, the substitution effect for commuting can probably also be observed on the general level.

Findings from the literature overview indicated that local context plays in a role in the substitution effects of the e-bike. Due to the important role of the bicycle in daily mobility in the Netherlands, it is likely that the results from this study are only valid for the Netherlands and countries where cycling is popular, such as Denmark or Germany.

3.5.2 Policy recommendations

From a policy point of view, we can draw important implications from the present study. Again, as local context is relevant, it is likely that these policy recommendations are only valid for the Netherlands and countries where the bicycle is popular, such as Denmark or Germany. The five different user groups show the profiles of people who are already adopting the e-bike. Apparently, people with these profiles are open to using an e-bike. Therefore, it might be relatively easy to promote the e-bike by specifically targeting these groups. For instance, the second largest e-bike user group consists of middle-aged full-time workers who primarily use the e-bike for commuting. To promote e-bike use among people with this profile who do not own an e-bike yet, a trial period in which people can experience their commute by e-bike might be effective in promoting the e-bike. Several companies and government agencies already started to offer this to their employees in the Netherlands.

On the other hand, promoting the e-bike among groups who are underrepresented in the e-bike population might be more difficult. For instance, 21-40 year olds as well as unemployed people are underrepresented in the e-bike population. To design effective policies to promote the e-bike among these groups more research is needed to determine why these people are not (yet) adopting the e-bike.

Furthermore, while on a general level only a substitution effect on the conventional bicycle is observed, the user groups that are growing at the highest rate are the groups that use the e-bike for commuting. Apparently, the working population is just starting to discover the e-bike as a mode of transport. As the e-bike substitutes the car (as well as other travel modes) for commuting trips, promoting e-bike use among employed people may result in a modal shift from car towards e-bike. This may result in positive effects on the environment, health and congestion.

3.5.3 Directions for future research

A limitation of this study is that it is unknown why people purchased an e-bike. This is important to know as it has an impact on the potential of the e-bike in terms of substitution

effects. It could, for instance, be the case that the respondents that show a decrease in car use due to using the e-bike for commuting already had the desire to reduce their car use for commuting. If people only substitute the car by e-bike if they have this desire, promoting the e-bike among current non-users may have lower usage levels and substitution effects than expected by policy makers. In general, we hypothesize that those who bought an e-bike in 'early' years (when the e-bike was relatively expensive) use it more regularly than those who might choose to buy an e-bike in future years (possibly stimulated by monetary incentives from the government). The reason for this hypothesis, is that early adopters willing to spend a considerable sum of money on an e-bike, will most likely have done so based on the expectation that they will frequently and intensively use the e-bike for their personal travel. In contrast, those who currently do not own an e-bike but might be lured into buying one in future years as they get cheaper (possibly aided by tax-incentives), will be likely to use it less often than those early adopters – otherwise they would have bought one already when prices were higher. Assessing the motivations behind purchasing an e-bike would be an interesting avenue for future research, with clear and profound policy-relevance. This will also help in understanding why certain groups of people are not (yet) adopting the e-bike.

Another direction for future research arises from another limitation of this study. As the five identified user groups are different from each other in terms of sociodemographic and in terms of their purpose for using the e-bike, it might be that the substitution effects also differ between these groups. While the LCA made use of data from the Dutch national travel survey, the MPN includes the same indicators, making it possible to include MPN respondents in the LCA in order to identify to which user group each respondent belongs. However, as the MPN is relatively small compared to the national travel survey, the number of respondents per user group is too low to model substitution effects per user group. However, if e-bike ownership is developing at the same rate the coming years, the number of e-bike users within the MPN will also grow allowing for the estimation of the RI-CLPM per user group.

A third direction for future research is to study the relation between time-invariant factors and substitution effects. As the RI-CLPM assesses substitution effects at the within-person level, time-invariant factors are automatically controlled for. As a result, it is unclear whether these time-invariant factors play a role in the substitution effects. However, substitution effects might be influenced by these factors. For instance, Kroesen (2017) showed that e-bike ownership decreases with residential density. It may be that people in more rural areas are less open to the e-bike because travel distances are too high. This may also have an influence on substitution effects. It is therefore relevant to assess the effects of time-invariant factors on substitution effects.

Another direction is to also look at other effects than substitution. An earlier study by Kroesen (2017) concluded that e-bike ownership has a generative effect on the total distance travelled. As this study was based on cross-sectional data, it would be interesting to assess this effect based on panel data. If the e-bike indeed results in larger travelled distances, it might be that the effect that e-bike has on health is positive, even if it is also substituting the conventional bicycle at the same time.

A fifth direction for future research is to assess the distance that people find acceptable to travel by e-bike. In the present study, trips of all distances are included, but for long trips it may be assumed that people do not consider the e-bike as an option. By taking acceptable distances into account, substitution effects can be estimated for trips that could, in theory, be travelled by e-bike. It can, for instance, be expected that substitution effects for commuting are larger among people who live within 15 to 20 km from their work compared to people who live further away.

A final direction for future research is related to the segmentation of the e-bike population. In the latent class analyses, we made use of all e-bike owners in the Dutch national travel survey. A limitation of this is that people who use an e-bike but are not e-bike owners are not included in the segmentation. This could for instance be users of e-bike sharing systems. As indicated, these systems are not widely available yet in the Netherlands. However, if these sharing systems will play a more significant role in e-bike use in the future, it is relevant to study the user groups of these systems.

4 Active travel and increasing overweight and obesity rates

This chapter is based on the following article:

de Haas, M., Kroesen, M., Chorus, C., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2021). Causal relations between body-mass index, self-rated health and active travel: An empirical study based on longitudinal data. *Journal of Transport & Health, 22*, 101113. doi: https://doi.org/10.1016/j.jth.2021.101113

Abstract

Introduction: It has been estimated that physical inactivity accounts for roughly 10% of premature mortality globally in any given year. Active travel (walking and cycling) has been promoted as an effective means to stimulate physical activity. However, many of the available studies on the relation between active travel and health are based on cross-sectional data and are therefore unable to determine the direction of causation. This study aims to unravel the bidirectional relationships between active travel measured by the active modes bicycle, e-bike and walking, on the one hand, and two health outcomes, namely body-mass index (BMI) and self-rated health (SRH), on the other.

Methods: To provide an initial assessment of the relationship between active travel and the two health outcomes, multivariate regression models are estimated. To study the direction of causation, Random-Intercept Cross-Lagged Panel Models (RI-CLPM) are estimated using three waves of the Netherlands Mobility Panel (MPN). Active travel is measured as travelled distances and trips with the bicycle, e-bike and walking. BMI is calculated based on weight and height, SRH is measured with a single question.

Results: The regression models show that a higher BMI and lower SRH are associated with less walking and cycling, while being obese is associated with more e-bike use. The results of the RI-CLPM indicate that cycling distance has a positive effect on SRH. Furthermore, walking distance has a negative effect on BMI and BMI has a negative effect on bicycle use among people without obesity. No relationships between BMI and active travel are found for people with obesity.

Conclusion: The results highlight the importance of longitudinal analyses when estimating the relationship between active travel and health. In addition, the results suggest that, relatively speaking, the increasing overweight and obesity rates may result in a decrease of bicycle use.

4.1 Introduction

It has been estimated that physical inactivity accounts for roughly 10% of premature mortality globally in any given year, making it one of the leading health risk factors (more important than obesity and smoking) (Lee et al., 2012). Globally, around a third of the adult population does not meet public health guidelines for recommended levels of physical activity (Hallal et al., 2012), but in Western societies this is typically even higher (e.g. in the Netherlands half of the population does not satisfy the norm). Given the strong impacts of physical (in)activity on our health it must be seen as one of the corner stones of preventive medicine.

For various reasons, active travel (walking and cycling) can be identified as a potentially effective means to stimulate physical activity. For one, this form of behaviour can easily be incorporated in the daily routine and, as such, become a habitual form of behaviour. Secondly, it is a 'proven' way to stimulate physical activity; recent research in the Netherlands has shown that 30% of the adult population already reaches the physical activity norm just by travelling actively (de Haas & van den Berg, 2019). And thirdly, there is still much scope to increase levels of active travel, considering that a substantial share of the short distance trips (<5 km) is already made by car.

While there are many studies available on the relation between active travel and health, most are based on cross-sectional data and are therefore unable to determine the direction of causation. Only a limited number of longitudinal studies are available. Most of these longitudinal studies did not consider a bidirectional effect between health and active travel, but only an effect of active travel on health. While studies have shown that active travel may lead to a better health (e.g. a lower body-mass index (BMI)), the reverse effect may also be present. People with a lower BMI may be more inclined to travel actively because this takes less effort for individuals with a healthy weight compared to obese individuals.

Compared to conventional active travel modes, the e-bike, having been introduced rather recently, occupies a special place. Due to the recent uptake of the e-bike in Western countries, the e-bike now plays a significant role in active travel in many countries. For instance, in 2019, the e-bike accounted for 18% of all bicycle trips and 26% of the total distance cycled in the Netherlands. While less effort is required to ride an e-bike to a regular bicycle, a systematic review showed that the needed physical activity intensity to ride an e-bike is high enough for the e-bike to be considered an active mode (Bourne et al., 2018). However, given that less effort is needed to ride an e-bike, it may be that the relation with health is different. For example, it may be that the potential health benefits are lower due to the lower physical activity intensity. On the other hand, the e-bike may offer a good alternative to the regular bicycle for people who are limited to cycle by their health. The relation between e-bike use and health has not been studied adequately yet.

This paper contributes to the scientific literature by empirically identifying the causal bidirectional relations between active travel (use of bicycle, e-bike and walking) and Body Mass Index (BMI) and self-rated health (SRH), based on longitudinal data. More specifically, we base our empirical analyses on three waves of panel data from the Netherlands Mobility Panel (MPN). In the remainder of the paper, findings from previous studies are discussed first, followed by a description of the applied methods and data and the results of the analyses.

4.2 Literature

In this section, relevant studies on the relation between active travel and BMI are discussed first, followed by studies on the relation between active travel and self-rated health. Due to the

limited availability of longitudinal studies between the two health indicators and active travel, studies that focus on the relation between general physical activity and the health indicators are also included in the discussion.

Most of the available studies on the relationship between active travel and BMI are based on cross-sectional data. These studies generally found that active travel is inversely related to a person's weight (gain), i.e. higher levels of active travel are associated with lower levels of BMI or lower overweight and obesity rates and vice versa (Bassett et al., 2008; Berglund et al., 2016; Flint et al., 2014; Laverty et al., 2013; Millett et al., 2013). Only a limited number of *longitudinal* studies that focus on the relationship between active travel and BMI can be identified. Martin et al. (2015) and Flint et al. (2016) found that switching from car to active travel for commuting results in a decrease in the BMI, while a shift from active travel to car resulted in an increase in BMI. Mytton et al. (2016) found that maintaining cycling levels for commuting resulted in a lower BMI and that an increase in walking is associated with a reduction in BMI. None of these three longitudinal studies distinguished between using a regular bicycle or an e-bike. Littman et al. (2005), in a study on the association between physical activity and weight gain, found that the inverse relationship between walking (but also other forms of physical activity) and weight gain is stronger among obese people than among non-obese people.

While the aforementioned longitudinal studies found effects of active travel on BMI, they did not consider a reverse effect of BMI on active travel. Several studies on the relationship between *general* physical activity and BMI did consider the existence of a bidirectional relationship. A longitudinal study on the long-term relationship between physical activity and obesity in adults did not find any significant effects of physical activity on later BMI levels, but found that a high BMI increased the odds of later physical inactivity (Petersen et al., 2004). Similarly, Bak et al. (2004) and Mortensen et al. (2006) found that a higher BMI is a determinant for physical inactivity or becoming sedentary, while reverse effects were not found.

Since all the studies discussed above are based on self-reported measures of active travel or physical activity and BMI, they might be subject to a reporting bias (e.g. a recall bias or social-desirability bias). However, similar results have been found in studies that objectively measured physical activity and BMI. Ekelund et al. (2008) measured sedentary behaviour with heart rate monitors, fat mass with bio-impedance and assessed body weight, BMI and waist circumference by standard clinical procedures. After a 5.6-year follow-up they concluded that sedentary time did not predict any of the obesity indicators. However, body weight, BMI and waist circumference were found to predict sedentary time. Similarly, Golubic et al. (2015) found that, after a 7-year follow-up, higher fat indices (total fat mass, percentage body fat and waist circumference) were associated with a reduction in moderate-to-vigorous physical activity and longer sedentary times. In addition, they found evidence that physical activity and longer sedentary times were associated with an increase on the fat indices.

Self-rated health (SRH), which can be assessed with a single question, is found to be strongly associated with all-cause mortality (DeSalvo et al., 2006; Idler & Benyamini, 1997). Similar to studies on the relationship between BMI and active travel, studies on the relationship between SRH and active travel are mainly based on cross-sectional data. These studies generally find that active travel is positively associated with SRH, either in general (Avila-Palencia et al., 2018; Berglund et al., 2016; Scheepers et al., 2015) or specifically for commuting (Bopp et al., 2013; Humphreys et al., 2013).

When focusing on physical activity in general rather than on active travel alone, a number of longitudinal studies are available. In a study on patterns in physical activity and sedentary behaviour from mid-life to early old age it was found that SRH was positively associated with

physical activity at follow-up (Hamer et al., 2012). Similar results were found in a study on 10-year changes in health status among older Europeans which showed that physical inactivity increased the risk of a decline is SRH (Haveman-Nies et al., 2003). Sargent-Cox et al. (2014) found, in a sample of three adult age cohorts, that overall SRH decreased over an 8-year period, but that maintaining or increasing levels of physical activity was associated with less decline in SRH.

While the discussed cross-sectional and the longitudinal studies indicate that active travel or physical activity are positively related to SRH, no studies were found that considered a bidirectional relationship. The direction of causation between SRH and active therefore remains uncertain. Studies on the relationship between BMI and physical activity that considered reciprocal effects indicate that the effect of BMI on physical activity may be stronger than the reverse effect (e.g. Petersen et al. (2004) and Ekelund et al. (2008)). However, only the latter effect is usually considered in studies on the relationship between active travel and BMI (e.g. Martin et al. (2015), Flint et al. (2016) and Mytton et al. (2016)). Therefore, this study aims to assess the reciprocal effects between active travel, on the one hand, and BMI and SRH on the other.

A recent study by Kroesen and De Vos (2020) assessed the bidirectional relationship between BMI and mental health, on the one hand, and walking on the other, based on longitudinal Dutch data. Results showed that walking does not influence BMI, but that the reverse effect is present. For the relationship between mental health and walking the opposite was concluded. While SRH and mental health are two different measures of health, the two are positively associated (Mavaddat et al., 2011; Meyer et al., 2014). One added value of the present study is that active travel is measured with a higher level of detail. Kroesen and De Vos (2020) only had information on how many days respondents walked for at least 10 minutes in the past seven days. In the present study, also cycling and e-bike are considered, and active travel is measured in terms of trips and travelled distances. With these detailed indicators of active travel it is expected that the present study will provide more valid results.

4.3 Methods and data

To provide an initial assessment of the relationships between active travel and the two health outcomes, multivariate linear regression models are estimated for travelled distances and number of trips with active modes. Based on the evidence that we find from literature that BMI may be a stronger predictor of active travel than vice versa, we are treating the health outcomes as independent variables in the regression models. The advantage of using multivariate regression models instead of simply comparing mode use in groups with different values on the health outcomes, is that it allows controlling for factors that might influence mode use or the health outcomes. Besides BMI and SRH, the regression will be controlled for age, gender, education level, level of urbanisation of the residential location, income and origin of the respondent (native or immigrant).

The regression models will show how active mode use is different between people with different BMIs and SRH while controlling for relevant variables. However, these models cannot be used to draw conclusions about the direction of causation between active mode use and the health outcomes. To test the relationship between active travel and the health outcomes over time, a structural equation model (SEM) will be used. More specifically the Random Intercept Cross-Lagged Panel Model (RI-CLPM) is used. In a traditional Cross-Lagged Panel Model (CLPM), after controlling for stability by including autoregressive relationships, the cross-lagged relationships are assumed to represent causal influences. However, Hamaker et al. (2015) argued that, if the stability of the constructs is to some extent of a trait-like, time-

invariant nature, the autoregressive parameters are not able to correctly control for this. In that case, the traditional CLPM is not able to fully account for time-invariant between-person differences. Both for active travel, as well as for the health outcomes it may be assumed that there exist stable individual differences over time. To cope with this limitation of the CLPM, Hamaker et al. (2015) proposed the RI-CLPM.

Figure 3.1 shows the model structure of the RI-CLPM. For each of the observed variables (x_t and y_t, representing active travel and the health outcomes in the present study) a latent variable is estimated (ξ_t and η_t) with the paths linking the observed and latent variables set to 1. Temporal group means are represented by μ_t and π_t. The random intercepts ω and κ capture the individual's stable score over all measurements and represents between-person differences. In other words, these random intercepts capture the individual's trait-like, time invariant deviations from the temporal means. With these temporal means and random intercepts, the latent variables ξ_t and η_t represent an individual's deviation from his expected score based on the combination of the temporal group mean and the random intercept. If the variance and covariance of the random intercepts would be fixed to zero, the model would collapse into a traditional CLPM.

In a traditional CLPM, the autoregressive parameters α_t and δ_t are included to account for stability of the constructs. In a RI-CLPM, the autoregressive parameters no longer represent the stability of the constructs, but rather a within-person carry-over effect. A positive autoregressive parameter indicates that occasions on which an individual scored higher than his expected score (based on the temporal mean and random intercept), this is likely followed by an occasion on which this individual also scores higher than his expected score and vice versa. The main interest is on the cross-lagged effects, represented by the parameters β_t and γ_t. These parameters indicate to which extent the variables influence each other on the within-person level. The within-person level is of interest in this study, as this is the level where the presumed causal effects actually occur.

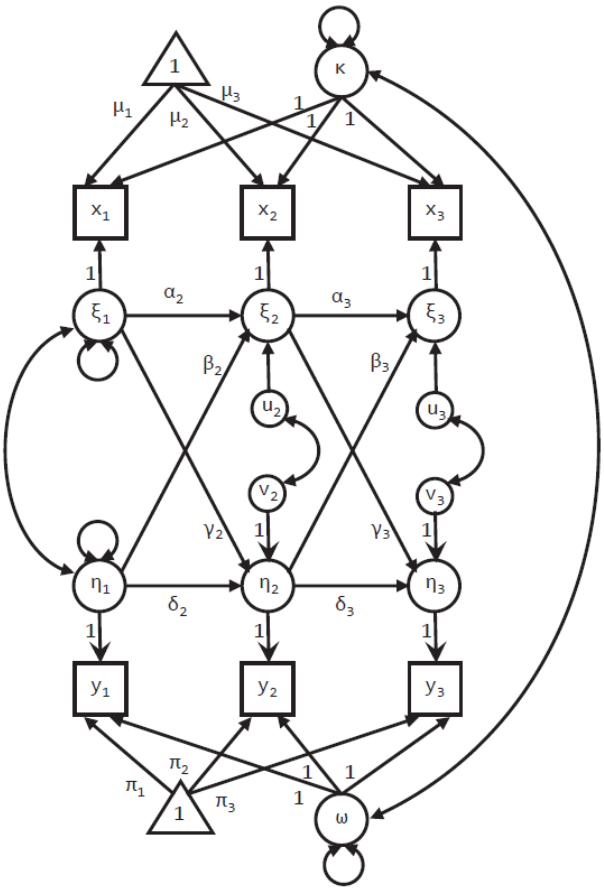

Figure 4.1. Model structure three-wave Random Intercept Cross-Lagged Panel Model (Hamaker et al., 2015)

4.3.1 Data

To assess the causal relationships between active travel and the two health outcomes, longitudinal data are required. In the present study, panel data from the Netherlands Mobility Panel (MPN) are used. The MPN is an annual household panel that started in 2013 and consists of approximately 2000 complete households. The MPN was set up with the goal to study the short-run and long-run dynamics in travel behaviour of Dutch individuals and households and to assess how changes in personal- and household characteristics correlate with changes in travel behaviour. To this end, household members of at least 12 years old are asked to complete a three-day travel diary each year and fill in an extensive questionnaire that includes questions on topics such as occupational status, use of different modes of transport and life events in the past year. Respondents are equally distributed over weekdays and have the same starting weekday each year. Furthermore, every household is asked to fill in a questionnaire about household related characteristics, such as information about household composition and ownership of means of transport. A more extensive description of the MPN can be found in Hoogendoorn-Lanser et al. (2015).

Starting from the fifth wave in 2017, a number of health-related questions are part of the individual questionnaire. The respondents' BMI is determined based on self-reported height and length (with the formula BMI = weight (kg) / length $(m)^2$). SRH is measured with the question 'How would you rate your health in general?'. The five possible answers are excellent, very good, good, moderate or bad. Data from 2017, 2018 and 2019 are used in this study.

Earlier research has shown that people tend to report a greater body height and lower body weight when working with self-reported measures (Gorber et al., 2007). This would result in an underestimation of the BMI. Since the same respondents participate yearly in the MPN, it is likely that, if this bias is also present in the MPN, the measurement error will be the same each year. If the measurement error is indeed constant over the years, this measurement error would be captured by the random intercept in the RI-CLPM. Therefore, it is likely that this has little influence on the results. As there is no possibility to validate the reported height and weight, only extreme values are removed from the sample. Eight respondents with a BMI below 15 (very severely underweight) or above 50 (super obese) are removed from the sample. From Table 4.1 it is evident that the distribution of BMI in the MPN is representative of distribution of the Dutch population, with a very slight overrepresentation of overweight and obese people.

In the three-day travel diary, respondents report all their trips for three consecutive days. Several possible indicators to describe a person's travel behaviour are available, such as trip count, travel distances and travel times. It is known that distance and duration might be biased due to round-off errors when working with self-reported travel diaries (Rietveld, 2001). However, it can be assumed that round-off errors are not dependent on health status. Therefore, as round-off errors may be considered to be random it is not expected that the results will be biased because of them. In this study, both trip counts and travel distances are used to measure active travel.

In this study, only the main mode of transport is considered. When a multi-modal trip is reported, access and egress modes are not included in the analyses. Travel distances and times are only known for the total trip in the MPN. As a result, it cannot be determined how long and how far respondents travelled with the access and egress mode. A downside of not being able to include access and egress mode is that especially for public transport users the amount of active travel is somewhat underrepresented as it is known that a considerable share of public transport trips in the Netherlands are combined with cycling or walking as access or egress modes (Jonkeren et al., 2018).

Although children between the ages of 12 and 18 also participate in the MPN, only adult respondents of 18 years and older are included in this study. Children are still developing physically and as a result especially the BMI of children will show relatively strong changes. As this would bias the results, children are not included in this study. This results in a sample of 6745 respondents. Table 4.1 shows the composition of the 2019 sample and the composition of the Dutch population based on the so-called 'Gold Standard' (MOA, 2019). The Gold Standard is a calibration tool for sampling in the Netherlands. The table shows that the sample is representative for the Dutch population for most variables. Young adults between 18 and 30 years old are somewhat underrepresented, while people with a high education level and adult households are overrepresented. Since the regression models are controlled for several sociodemographic variables and the RI-CLPM automatically controls the estimated (within-person) effects for all (unobserved) time-invariant variables it is not expected that the results are biased due to these small deviations from the Dutch population.

Table 4.1. Sample (MPN wave 2019, n = 4511) and Gold standard distributions

Variable		MPN (2019) (%)	Gold Standard (2019) (%)
Gender	Male	47.9	49.3
	Female	52.1	50.7
Age	18-30	14.5	20.4
	31-40	17.1	15.0
	41-50	14.9	17.3
	51-64	27.0	24.4
	65+	26.4	22.9
Education level	Low	27.0	28.5
	Medium	38.9	42.9
	High	33.9	28.6
Work status	Working	54.5	54.6
	Not working	11.1	12.0
	Incapacitated	6.3	3.9
	Student	4.9	6.8
	Retired	23.1	22.6
Household situation	Single household	22.2	22.0
	Adult household	54.1	49.6
	Household with child ≤ 12 years old	17.6	20.3
	Household with child between 13 and 17 years old	6.1	8.1
Level of urbanization*	Non-urbanised (<500 addresses/km^2)	8.0	7.8
	Slightly urbanised (500 to 1000 addresses/km^2)	21.5	21.6
	Moderately urbanised (1000 to 1500 addresses/km^2)	18.8	15.6
	Highly urbanised (1500 to 2500 addresses/km^2)	31.8	30.3
	Very highly urbanised (≥2500 addresses/km^2)	19.8	24.6
Weight class**	Healthy weight (BMI < 25)	47.3	49.9
	Overweight (BMI 25-30)	36.2	35.4
	Obese (BMI ≥ 30)	16.5	14.7
Experienced health***	Excellent	11.2	-
	Very good	23.7	-
	Good	49.1	-
	Moderate	13.7	-
	Bad	2.2	-

*Distribution of level of urbanization based on the Gold Standard shows the distribution for all Dutch inhabitants of 13 years and older. A distribution for Dutch inhabitation of 18 years and older is not available.
**Distribution of weight classes in the Dutch population is based on (CBS & RIVM, 2019)
***No information on the distribution of experienced health in the Netherlands is available

Table 4.2 shows the correlation between the dependent variables in the RI-CLPM in the pooled MPN sample. While cycling and walking are negatively correlated with BMI, e-bike use is positively correlated with BMI. The correlation between e-bike and experience health is also in another direction than the correlation between experienced health and bicycle and walking. There are also some significant correlations between the use of the different active modes. All correlations are relatively small.

Table 4.2. Correlation between dependent variables RI-CLPM, pooled MPN sample 2017-2019 (lower left triangle represents trips, upper right triangle distance

	B	E	W	BMI	EH	B
Bicycle (B)	1	-0.045**	0.016*	-0.092**	0.100**	1
E-bike (E)	-0.116**	1	-0.016	0.019*	-0.009	-0.045**
Walking (W)	0.023**	-0.015	1	-0.053**	0.016	0.016*
BMI	-0.117**	0.059**	-0.031**	1	-0.255**	-0.092**
Experienced health (EH)	0.117**	-0.051**	0.016*	-0.255**	1	0.100**

*Correlation is significant at the 0.05 level (2-tailed)
**Correlation is significant at the 0.01 level (2-tailed)

4.3.2 Model estimation and coding

The RI-CLPM is estimated with the statistical software package Mplus (Muthén & Muthén, 1998-2017). Due to attrition and recruitment of new respondents, not all respondents participated in all three used MPN waves. Table 4.3 shows the participation patterns of respondents in the fifth through seventh wave of the MPN (e.g. pattern 001 indicates respondents who only participated in 2019, while pattern 111 represents respondents who participated in all three waves). All respondents that participated in at least one wave are included in the RI-CLPM. To handle this missing data, the RI-CLPM is estimated using the Full Information Maximum Likelihood (FIML) estimator, which has been shown to effectively handle missing data by Enders and Bandalos (2001). To estimate the regression models, only a single year of data is required. The most recent data from 2019 is used for the regression models.

Table 4.3. Participation patterns of MPN respondents, wave 5 through 7 (2017-2019)

Pattern	#	%	Pattern	#	%
001	443	6.6	101	314	4.7
010	669	9.9	110	743	11.0
011	923	13.7	111	2831	42.0
100	822	12.2	Total	6745	100

The Maximum Likelihood estimator assumes that all variables in the model are continuous and are normally distributed. In our model, self-rated health is measured on a five point ordinal scale. In that case, using an alternative estimator (e.g. a least squares estimator) may be preferable. However, it is (currently) not possible to estimate the RI-CLPM in Mplus using a least squares estimator. Therefore, also the models including self-rated health are estimated using the ML estimator. It is expected this has little influence on the results, as Rhemtulla et al. (2012) showed that with ordinal variables with at least five categories, the ML estimator results in equal or even better results compared to least squares.

Since our main interest is in the relation between active travel and the two health outcomes, separate RI-CLPMs are estimated for the bicycle, e-bike and walking. Modelling the three active modes in an integrated model would result in a much more complex model, while the estimated relationships between the active modes and the health outcomes would be the same. An advantage of estimating a single model (including all modes) would be that the extent to which active modes substitute each other over the years would also become clear from the analysis. However, assessing such substitution effects has already been done by de Haas et al. (2022b) and is outside the scope of the current study.

Furthermore, earlier research suggests that the relationship between BMI and physical activity may be different among obese people compared to non-obese. Littman et al. (2005) showed that the inverse relationship between physical activity and weight gain is stronger among obese people. Therefore, to study the relationship between BMI and active travel, a multi-group RI-CLPM is estimated in which obese people are distinguished from non-obese people.

4.4 Results

4.4.1 Regression models

As described in the previous section, multivariate regression models are used to assess whether the two health outcomes (BMI and self-rated health (SRH)) and the use of active modes are related. This allows controlling for confounding variables. The use of active modes is used as the dependent variable with the health indicators as independent explanatory variables. Separate models are estimated for the number of trips and for the travelled distances. Table 4.4 shows the parameter estimated for the health related variables. The parameter estimates of the control variables are not shown to limit the table size.

Table 4.4. Parameter estimates of the health outcomes multiple regression models without distinction between trip motives

	Trips (# per three days)			Distance (kilometres per three days)		
	Bicycle	E-bike	Walking	Bicycle	E-bike	Walking
Overweight (ref. healthy weight)	-0.30 (-3.22)	0.04 (0.72)	-0.08 (-0.87)	-1.13 (-3.23)	0.59 (1.12)	-0.36 (-2.25)
Obese (ref. healthy weight)	-0.56 (-4.66)	0.21 (2.60)	-0.35 (-3.02)	-1.47 (-3.26)	0.33 (0.49)	-0.88 (-4.24)
Good self-rated health	0.61 (4.97)	0.11 (1.34)	0.52 (4.36)	1.99 (4.30)	1.12 (1.60)	0.81 (3.82)
R-squared	0.049	0.039	0.034	0.035	0.009	0.029
Average in sample	1.40	0.57	1.51	3.9	2.4	2.1

t-values are presented in parentheses, parameters with |t|>1.96 are bold

To ease interpretation, BMI is included as a categorical variable (BMI < 25, BMI 25-30 and BMI ≥ 30) and SRH is included as a binary variable. People who rate their health as excellent, very good or good are included as having a good self-rated health, while people who rate their health as moderate or bad are the reference. There is a clear relation between the two health outcomes and active travel. People who are overweight or obese make fewer trips and travel less distance by bicycle. As these are unstandardized parameters, they can be directly interpreted as differences in number of trips or travelled distances. For instance, while people in our sample make 1.4 cycling trips over a distance of 3.9 km in three days on average, obese people make on average 0.56 fewer trips and cycle 1.47 km less compared to people with a healthy weight. Similar relationships are found between the BMI and walking, with the only difference that overweight people do not make significantly fewer trips on foot compared to people with a healthy weight.

While the results suggest that, in line with literature, people with a higher BMI make less use of active modes, this does not hold for the e-bike. Obese people make more trips by e-bike compared to people with a healthy weight. The difference in travelled distances is not statistically significant, indicating that the extra trips on e-bike by obese people are likely to be relatively short trips. This difference in e-bike use raises the question whether obese people make more use of the e-bike because of their weight (since the e-bike provides them with a relatively easy method of active travel) or that the e-bike use contributes to a higher weight (because the physical intensity might be lower compared to a non-electric bicycle).

Positive relationships between SRH and cycling and walking are found. This indicates that people with a good SRH walk and cycle more compared to people who do not rate their health as good. It was found that SRH is correlated with the weight classes, as shown in Table 4.5. People in a lower weight class more often have a more positive SRH (χ^2 (8, N = 4511) = 314.501, p = 0.000). Considering this association, the difference in cycling and walking between people with a healthy weight and people with a higher weight is even larger than indicated by the negative parameters for the weight classes. The more positive SRH by people with a healthy weight results in an additive effect of SRH on the effect of BMI on walking and cycling.

Table 4.5. Self-rated health per weight class MPN 2019

	Self-rated health (%)					
Weight class	Excellent	Very good	Good	Moderate	Bad	Total
Healthy weight (BMI < 25)	16.4	29.1	43.8	9.2	1.5	100
Overweight (BMI 25 -30)	7.7	22.4	52.9	15.0	2.0	100
Obese (BMI ≥ 30)	4.1	11.5	56.1	23.5	4.7	100

It should be stressed again, that based on the multivariate regression models, no conclusions can be drawn about causality between the two health outcomes and active travel. The health indicators could also be used as dependent variables and the trips or distances with the different active modes as predictors. This would lead to similar conclusions.

4.4.2 Random Intercept Cross-Lagged Panel Models

Twelve separate RI-CLPMs are estimated resulting from the combination of two indicators of active travel (distances and trips) with three active modes (bicycle, e-bike and walking) and two health outcomes. All models show a good to excellent model fit, as based on the model fit indices shown in Table 4.6.

Table 4.6. Model fit of RI-CLPMs

Model	Chi-square	RMSEA*	CFI*	SRMR*
BMI and cycling (distance)	4.000, df = 6, p=0.677	0.000	1.000	0.005
BMI and e-bike (distance)	5.655, df = 6, p=0.463	0.000	1.000	0.006
BMI and walking (distance)	3.473, df = 6, p=0.748	0.000	1.000	0.006
BMI and cycling (trips)	2.955, df = 6, p=0.815	0.000	1.000	0.005
BMI and e-bike (trips)	7.357, df = 6, p=0.289	0.008	1.000	0.007
BMI and walking (trips)	8.119, df = 6, p=0.230	0.010	1.000	0.009
SRH and cycling (distance)	3.634, df = 3, p=0.304	0.006	1.000	0.006
SRH and e-bike (distance)	3.895, df = 3, p=0.273	0.007	1.000	0.006
SRH and walking (distance)	4.737, df = 3, p=0.192	0.009	1.000	0.006
SRH and cycling (trips)	4.912, df = 3, p=0.178	0.010	1.000	0.007
SRH and e-bike (trips)	4.523, df = 3, p=0.210	0.009	1.000	0.006
SRH and walking (trips)	7.332. df = 3. p=0.062	0.015	1.000	0.007

*A Root Mean Square Error of Approximation (RMSEA) < 0.05, a Comparative Fit Index (CFI) > 0.95 and a Standardized Root Mean Square Residual (SRMR) <0.08 indicate a good model fit (Brown, 2014)

Table 4.7 presents the cross-lagged parameter estimates of the multi-group RI-CLPMs concerning the relation between active travel and BMI. RI-CLPMs focusing on the relation between BMI and active travel were also estimated without distinguishing between weight class. These models also showed a good model fit, but no significant relationships were found. Since we make use of the three day travel diary of the MPN, the parameters refer to distances or trips per three days. The results show that there is a small, but significant negative effect of walking distance on BMI among non-obese people (β = -0.016, p = 0.024). This indicates that when people increase their walking distance per three days with 10 km, this results in a decrease of their BMI by 0.16 in the following year. For someone of 1.80 m tall, this translates to 0.52 kg of weight loss. A similar (negative) effect is not found for obese people.

The results show that the effect of active travel on BMI is not present for cycling. For cycling, a reverse effect is found among non-obese people. That is, an increase in the level of BMI in one year results in a decrease in bicycle use in the next year, both in travelled distances (β = -0.384, p = 0.021) and trips (β = -0.139, p = 0.005). No such effects are found in the obese group. Also between e-bike use and BMI no significant effects are found.

Several parameters relating to the relationships between bicycle use and BMI among obese people are close to being statistically significant at the 5% level with t-values close to 1.96. These parameters all have unexpected signs as they would imply that bicycle use leads to an increase in the BMI and an increase in the BMI leads to higher bicycle use.

Table 4.7. Cross-lagged parameter estimates RI-CLPM relation BMI and active travel (travelled distances in km per three days (left) and trips in three days (right)

Direction	Distance (km per three days)				Trips (per three days)			
	Non-obese (BMI<30)		Obese (BMI≥30)		Non-obese (BMI<30)		Obese (BMI≥30)	
	Est.	t-value	Est.	t-value	Est.	t-value	Est.	t-value
BMI → cycling	-0.384	-2.316	0.112	1.148	-0.139	-2.815	0.062	1.725
Cycling → BMI	-0.002	-0.649	0.029	1.854	-0.005	-0.351	0.085	1.882
BMI → E-bike	-0.045	-0.323	-0.004	-0.029	-0.017	-0.518	0.002	0.062
E-bike → BMI	-0.002	-0.614	0.000	0.006	-0.008	-0.362	-0.028	-0.432
BMI → Walking	0.081	1.005	-0.020	-0.324	-0.035	-0.737	-0.042	-0.958
Walking → BMI	-0.016	-2.258	0.010	0.354	-0.011	-0.755	-0.035	-0.522

Table 4.8 presents the cross-lagged parameter estimates of the RI-CLPMs on the relation between active travel and SRH. One statistically significant positive relationship is found between cycled distance and SRH (β = 0.003, p = 0.050), indicating that an increase in the travelled distance by bicycle in one year results in a more positive SRH in the next year. This is, again, a small effect. The other parameters related to cycling indicate that an improvement in SRH leads to an increase in bicycle use. These parameters are, however, not significant at the 5% level (β = 0.636, p = 0.072 for travelled distance and β = 0.174, p = 0.075 for number of trips). No significant relationships are found between SRH and the other active travel modes e-bike and walking.

Table 4.8. Cross-lagged parameter estimates RI-CLPM relation self-rated health (SRH) and active travel (travelled distances in km per three days (left) and trips in three days (right))

Direction	Distance (km per three days)		Trips (per three days)	
	Est.	t-value	Est.	t-value
SRH → cycling	0.636	1.852	0.174	1.800
Cycling → SRH	0.003	1.960	0.012	1.782
SRH → e-bike	-0.299	-1.058	0.015	0.241
E-bike → SRH	-0.001	-0.358	0.004	0.437
SRH → walking	-0.074	-0.452	-0.033	-0.355
Walking → SRH	-0.002	-0.597	-0.009	-1.183

The above-discussed cross-lagged parameter estimates indicate within-person effects. The RI-CLPM also provides estimates of the correlation between the random intercepts. These correlations indicate the association between the variables on the between-person level. Table 4.9 shows these estimated correlation coefficients between the random intercepts for each of the estimated models. In the multi-group models, the correlation between the random intercepts is estimated separately for each of the groups. Results are largely in line with the outcomes of the presented regression models. People with a more positive SRH make more use of the bicycle and travel more distance by foot compared to people with a more negative SRH. A higher BMI is associated with less bicycle use, both in the obese and non-obese group. For walking distance, there is only a significant negative correlation with BMI in the obese group. Interestingly, in the non-obese group, BMI is positively correlated with e-bike use, indicating that people with a higher BMI make more use of the e-bike in the non-obese group. This positive correlation is not observed in the obese group.

Table 4.9. Correlation coefficients between the random intercepts

Relation	Distance				Trips			
	Est.	t-value			Est.	t-value		
Perc. health - cycling	0.222	8.289			0.023	6.905		
Perc. health – e-bike	-0.017	-0.676			-0.100	-4.830		
Perc. health - walking	0.063	2.351			-0.017	-0.730		
	Non-obese (BMI<30)		Obese (BMI≥30)		Non-obese (BMI<30)		Obese (BMI≥30)	
	Est.	t-value	Est.	t-value	Est.	t-value	Est.	t-value
BMI - cycling	-0.153	-6.981	-0.285	-2.397	-0.118	-6.408	-0.323	-2.126
BMI – e-bike	0.065	3.231	-0.051	-0.523	0.083	4.789	-0.069	-0.969
BMI - walking	-0.033	-1.551	-0.231	-2.328	0.006	0.323	-0.092	-1.504

4.5 Discussion

From the analyses we find only limited evidence for the existence of causal effects between BMI and active travel. Contrary to previous studies, we find no significant effects in the generic models (i.e. where we do not distinguish between obese and non-obese people). Only in the multi-group models significant effects are found. Here, we find that walking has a small negative effect on BMI in a later year among non-obese people, while no evidence was found for the reverse effect. While the effect is small, this result is in line with studies concerning the relationship between active travel who did not consider reciprocal effects (e.g. Martin et al. (2015) and Flint et al. (2016)). Our results, however, contradict those obtained in the study of

Kroesen and De Vos (2020), who found that the level of BMI does have an influence on walking, while the reverse effect was not observed. This discrepancy in results could be related to the different ways in which walking is operationalised in the two studies. In the study of Kroesen and De Vos (2020), walking frequency is measured as the number of days that an individual walked for at least 10 minutes in the past 7 days. In the present study, more detailed information on the number of trips and travelled distances is available.

Our results with regard to the relationship between cycling and BMI are more in line with those obtained in studies focusing on bidirectional effects between physical activity and BMI. Similarly to Bak et al. (2004), Petersen et al. (2004), Mortensen et al. (2006) and Ekelund et al. (2008) we find that a change in BMI has a negative effect on cycling, while no effect of cycling on the BMI is found. However, the found effect is relatively small: for every point change in BMI, an individual will change his or her bicycle usage in three days in the inverse direction of the BMI change with 0.384 km or 0.139 trips. For an individual of 1.80 m tall, a point change in BMI translates to 3.24 kg. As it is expected that the share of overweight and obese people will increase in the near future (Pineda et al., 2018; Ward et al., 2019), these results do imply that, relatively speaking, bicycle usage could decrease in the future, *ceteris paribus*.

We found no significant effects between e-bike use and BMI. This implies that, contrary to the regular bicycle, e-bike use would not be affected by the expected increase in overweight and obesity rates. Although riding an e-bike requires less effort compared to a regular bicycle, several studies found that it may be considered a moderate intensive physical activity (Bourne et al., 2018). E-bike use thereby contributes to reaching physical activity guidelines. Therefore, if the use of the regular bicycle will indeed decrease in the future due to overweight and obesity rates, the e-bike may turn out to be a promising mode of transport that will allow people to maintain current ‘bicycle’ levels.

Based on findings from literature, we expected that the relationship between active travel and BMI would be stronger among obese people compared to non-obese people. However, we did not find any statistically significant effects among obese people. We did, however, find several parameters in an unexpected direction related to cycling and BMI among obese people that are statistically significant at the 10% (two-tailed) level with t-values greater than 1.645. These parameters imply that bicycle use among obese people leads to an increase in the BMI and an increase in the BMI leads to higher bicycle use. While not significant at the 5% level, we will discuss a number of possible explanations for these unexpected findings.

Since we are estimating many models and allowing a 5% error margin in each of these models, it is possible that we find unexpected effects by chance. The unexpected signs could also be related to the (in)stability of the BMI among obese people. Other studies report that weight is less stable among people with a high weight (Bangalore et al., 2017; Stevens et al., 2006). This is also true for our sample. The correlation of the BMI between years is higher among non-obese (correlation coefficients between 0.876 and 0.907) than obese (correlation coefficients between 0.662 and 0.802) people. These fluctuations in BMI, which may be unrelated to bicycle use, may have an effect on the model estimations that causes us to find this result by chance.

However, it is also possible that these unexpected effects actually do exists among obese people. The notions of moral licensing and moral cleansing can be identified as possible behavioural mechanisms that underlie the effects. Moral licensing is the subconscious phenomenon that moral behaviour can lead to engaging in immoral behaviour (Merritt et al., 2010), driven by mental accounting or ‘book-keeping’ processes. This may explain why an increase in cycling would result in an increase in the level of BMI. It is known that an increase energy expenditure due to physical activity is compensated to a certain extent by, for instance, a higher energy intake (Westerterp, 2010). It may be that the increase in cycling among obese people leads to

overcompensating, i.e. increasing the subsequent energy intake more than would be justified by the increase in energy expenditure. Moral cleansing refers to the phenomenon that people tend to show moral behaviour when an individual's self-perception has been compensated due to immoral behaviour (Jordan et al., 2011). Behaviour that led to an increase in the BMI (immoral behaviour) may lead to an increase in bicycle use (moral behaviour), explaining the positive effect of BMI on cycling.

For the relationship between active travel and SRH, we only found a significant positive effect of cycling distance on SRH. In other words, when people increase their travelled cycling distance in one year, they will rate their health more positively in the following year. This result is in line with studies that assessed the relationship between SRH and general physical activity (e.g. Hamer et al. (2012) and Haveman-Nies et al. (2003)). Although only significant at the 10% level, we also found a positive effect of SRH on both cycling distance and cycling trips. This is an interesting finding, as we found no previous studies considering this effect. The standardized parameters ($\beta = 0.047$ for cycling distance on SRH, $\beta = 0.039$ for SRH on cycling distance) indicate that the effect of cycling on SRH is stronger than the reverse effect. In line with Avila-Palencia et al. (2018), no relations between e-bike and SRH were found.

4.6 Conclusion

In this study, we assessed the bi-directional relationship between active travel, measured by both trips and distances with the bicycle, e-bike or walking, on the one hand, and two health outcomes, namely BMI and self-rated health (SRH), on the other hand. The results of the RI-CLPMs, based on three waves of data from the Netherlands Mobility Panel (MPN), highlight the importance of longitudinal analyses when estimating the relationship between active travel and health. While the cross-sectional regression models showed relatively strong relationships between active travel and the two health outcomes considered in this paper, most of the relationships do not appear to be present on the within-person level. We only find a small negative effect for walking distance on BMI for non-obese people. Furthermore, while most previous longitudinal studies only considered an effect of active travel on BMI, we found evidence for a negative reverse effect of BMI on cycling distance. For the relation between active travel and SRH we find a significant positive effect of cycling distance on SRH.

From a policy perspective, our results indicate that promoting active travel may only result in a slight decrease of BMI through an increase in walking. The reverse negative effect of BMI on cycling implies that policies aimed at decreasing overweight and obesity may have an effect on cycling levels. In light of increasing overweight and obesity rates, policies aimed at reducing the consumption of unhealthy foods and increasing physical activity levels are already in place (Ministry of Health, Welfare and Sport, 2019; World Health Organization, 2016). If these policies are effective in realizing a decrease in BMI, this may result in an increase of cycling rates.

A limitation of this study is that we used self-reported measures of active travel and health. The measures may therefore be biased, for instance due to rounding of travel times or under- and over-reporting weight and height (Rietveld, 2001; Stommel & Schoenborn, 2009). As explained before, such biased measurements are unlikely to lead to biased results in our study. However, objectively measuring active travel (e.g. with accelerometers) and BMI (e.g. with physical measurements of weight and height) may still result in more valid results. As we used data from the Netherlands Mobility Panel (MPN), three days of travel behaviour per wave are available. Three days may be too short to capture active travel. For instance, there may be respondents who primarily use active modes during weekends but were asked to report three weekdays.

Furthermore, the available measures of health (BMI and SRH) only give a limited reflection of one's health. For instance, while the amount and distribution of body fat are important health outcomes, BMI does not account for body composition (Wells & Fewtrell, 2006). Future research could include more objective measures of physical health, such as blood pressure, diabetes and amount of body fat. Besides physical health, including other health outcomes such as mental health, psychological well-being, vitality or sick days would be helpful understanding the relation between active travel and health.

Finally, the dataset that we used in this study was collected before the COVID-19 pandemic. The pandemic and all measures taken to reduce the spread of the virus greatly impacted people's lives. Insights from the Netherlands showed that while the total amount of trips and travelled distances dropped due to the coronavirus crisis, the popularity of roundtrips (e.g. a walking or cycling tour) gained in popularity (de Haas et al., 2020). It may be that the role of active travel in reaching physical activity guidelines may have changed during the coronavirus crisis (e.g. because people could not perform their usual physical activity as a result of measures taken to reduce the spread of the virus). It may therefore be that the relation between active travel and health has changed due to the coronavirus crisis (e.g. it may be that active travel became more important in weight maintenance if it became the primary source of physical activity). Such effects would be an interesting subject of future research.

5 Identifying soft-refusal in (longitudinal) travel behaviour surveys

This chapter is based on the following article:

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de Haas, M., Kroesen, M., Chorus, C., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (submitted). Didn't travel or just being lazy? An empirical study of soft-refusal in mobility diaries

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Abstract

In mobility panels, respondents may use a strategy of soft-refusal to lower their response burden, e.g. by claiming they did not leave their house even though they actually did. Soft-refusal leads to poor data quality and may complicate research, e.g. focused on people with actual low mobility. In this study we develop three methods to detect the presence of soft-refusal in mobility panels, based on respectively (observed and predicted) out-of-home activity, straightlining and speeding. For each indicator, we explore the relation with reported immobility and panel attrition. The results show that speeding and straightlining in a questionnaire is strongly related to reported immobility in a (self-reported) travel diary. Using a binary logit model, respondents who are predicted to leave their home but report no trips are identified as possible soft refusers. To reveal different patterns of soft-refusal and assess how these patterns influence the probability to drop out of the panel, a latent transition model is estimated. The results show four behavioral patterns with respect to soft-refusal ranging from a large class of reliable respondents who score positive on all three soft-refusal indicators, to a small 'high-risk' class of respondents who score poorly on all indicators. This 'high-risk' group also reports the highest immobility and has the highest attrition rate. The model also shows that respondents who do not drop out of the panel, tend to stay in the same behavioral pattern over time. The amount of soft-refusal expressed by a respondent therefore seems to be a stable behavioral trait.

5.1 Introduction

In travel behavior research, multi-year panels have been set up to understand the drivers of (changes in) travel behavior over time. Participants in these panels typically complete – on a regular basis (e.g., every year) – a (self-reported) multiple-day travel diary along with a questionnaire containing personal and psychographic information. The resulting data are ideally suited to model and understand the (causal) mechanisms behind travel behavior, and the changes therein over time at the individual level (see e.g. Scheiner et al. (2016) and de Haas et al. (2022b)).

To use the data effectively for this purpose, it is crucial that the data quality is guaranteed. One cause of poor data quality, which has received considerable attention in research, relates to (selective) attrition. In the context of travel behavior research, it has been shown that panel attrition is related to household income, household size, educational level and reported number of trips (Golob et al., 1986; Kitamura & Bovy, 1987).

However, next to attrition, there are other processes that may result in low data quality, which have received less attention in research. One such mechanism relates to the notion of soft-refusal, which describes the tendency of some respondents to refuse participation in a 'soft' way, e.g. by claiming they did not leave their house even though they actually did. Identifying these "soft refusers" is important, e.g., in the context of research that is focused on identifying vulnerable groups with actual low mobility. Obviously, having these vulnerable groups mixed with soft refusers complicates research efforts focused on questions related to this subject.

Next to wrongfully reporting to stay at home, two other sources of bias may be identified, namely straightlining and speeding, which have been extensively studied in general survey research (but not in a travel behavior context). Straightlining can be defined as the tendency to provide the same answer to every item in a grid (Struminskaya et al., 2015) and speeding as the tendency to complete the questionnaire in a (much) shorter time than average. These tendencies are often described as satisficing (Barge & Gehlbach, 2012; Krosnick et al., 1996) and can actually also be seen as instances of "soft-refusal"; respondents still participate but refuse in a soft way by minimizing effort and not providing accurate answers.

Against this background several relevant research questions can be formulated, namely to what extent do these instances of soft-refusal actually occur and to what extent are they correlated with reported immobility? Next to the relation with reported immobility, the present study will focus on the link between soft-refusal and attrition. Formulated specifically, to what extent are these soft-refusal indicators associated with attrition?

Being able to identify respondents who do not fill out surveys of travel diaries truthfully provides the option to increase data quality by removing these people from the sample. Given the multi-year context of a mobility panel, it is important to decide whether to remove only a single wave of data of these respondents, or to remove the respondent from the panel entirely (i.e., no longer inviting the respondent for following waves). Given the costs and efforts involved in recruiting new panel members, the first option is more desirable, but should only be chosen if it is likely that the respondent will behave better in future waves. To this end, this study also addresses the question whether being a soft refuser is a 'fixed state' over time, or whether respondents can shift to being a reliable respondent in a future wave.

The present study uses data from the Netherlands Mobility Panel (MPN) to study this research question. The MPN is a longitudinal household panel in which respondents yearly fill out an extensive questionnaire and report three days of travel behavior in an online travel diary (Hoogendoorn-Lanser et al., 2015). The methods presented in this study to identify soft-refusal make use of both the questionnaire and the travel diary. Based on the questionnaire, speeding

and straightlining will be studied as indicators of soft-refusal, while the questionnaire is used to directly identify respondents who wrongfully report no trips by predicting whether a respondent should leave their home on a given day. As such, the present study aims to contribute by presenting and testing new methods (to identify soft-refusal) and by empirically investigating to what extent soft-refusal may be present in multi-year mobility panels and how it relates to attrition. We wish to note that, while we focus on soft-refusal in multi-year mobility panels, many of our results have direct relevance for one-shot mobility diaries and travel surveys as well.

In the next section, previous studies on the link between response behavior and data quality are discussed. Results of these previous studies are used to specify the methods to identify soft-refusal in the present study. The methods to identify soft-refusal are in detail discussed in the method section, as well as the conceptual model to study soft-refusal over time. Next, the data is discussed followed by the results of the analyses. Finally, the results of the methods to identify soft-refusal are discussed followed by the results of our longitudinal analysis to study soft-refusal over time.

5.2 Previous research on response behavior in surveys

To achieve high data quality from (web) surveys, respondents should participate in a thoughtful way. In reality, respondents may try to lower their respondent burden by strategic behavior. Krosnick et al. (1996) applied the concept of satisficing[1] (the idea that people often expend the effort necessary to make a satisfactory or acceptable decision) on surveys to describe different strategies respondents may use to lower their response burden. They argued that, while some respondents may have an intrinsic motivation to provide high-quality data, many respondents may not be inclined to put a lot of effort into answering questions carefully. These types of respondents may take different strategies, for instance picking the first acceptable answer option or only superficially interpreting questions, resulting in sub-optimal answers. Two types of these strategies have been studied quite extensively, namely straightlining and speeding.

5.2.1 Straightlining and speeding

Couper et al. (2013) argue that grid questions can be distinguished between grids where straightlining is plausible and where straightlining is implausible. Plausible straightlining refers to a situation where straightlining may be a reasonable answer. They suggest that implausible straightlining occurs with behavioral questions, for which more natural variation exists, while attitudinal items are associated with plausible straightlining, as these are typically aligned with one another. Schonlau and Toepoel (2015) studied straightlining in three annual waves of a web survey. In line with the reasoning by Couper et al. (2013), they found a considerably higher amount of straightlining among grids for which straightlining is plausible compared to grids where this is implausible. Furthermore, they found that implausible straightlining is associated with younger age and that the amount of straightlining increases among respondents who participate in the panel for multiple waves.

Considering a shift towards web-only surveys in the past years, studying straightlining seems to have become more important. A study to compare data quality of telephone surveys to web surveys found that straightlining occurs more often in web surveys than in telephone surveys (Fricker et al., 2005). While most studies define straightlining as providing the same answer to

[1] In a travel behavior context, satisficing may also refer to an individual's decision strategy to choose an alternative (e.g., travel mode or trip route) that satisfies a minimum threshold as opposed to a maximizing strategy in which an individual strives to choose the alternative with the highest utility. To avoid confusion, satisficing strategies to the lower response burden in a survey will be referred to as soft-refusal in the remainder of this paper.

each question in the grid, Kim et al. (2019) compare five methods of measuring straightlining. The methods range from a simple nondifferentiation method (i.e. measuring the proportion of respondents using a single response category) to a scale point variation method (i.e. inferring the probability that a respondent differentiates answers). They concluded that while each of the methods measures a slightly different aspect of straightlining behavior, they are all highly correlated. It can be expected that straightlining may also be an issue in a travel behavior context, as travel behavior surveys often include attitudinal statements in the form of grid questions.

Another strategy respondents may use to lower their response burden is to speed through the survey. As argued by Tourangeau et al. (2000) respondents must go through four mental steps when answering survey questions. Respondents must comprehend the question, must retrieve relevant information from their memory, form a judgement based on the available information and finally they have to formulate an answer or select an answer category. Given the mental efforts involved in these processes, answering each question in a survey should take a certain amount of time for a respondent to be able to provide a meaningful answer. It is therefore assumed that respondents with very short response latencies provide low quality data compared to other respondents.

Several studies have presented evidence that speeding is indeed associated with poor data quality. For instance, Malhotra (2008) found strong primacy effects (choosing the first option) among low-educated respondents who speeded through the survey. Greszki et al. (2015) on the other hand, found that providing no answer or choosing the 'don't know' option was associated with response times below the time it should theoretically take to comprehend the question. In a travel behavior context, Chen et al. (2016) found that answering fast in a choice experiment leads to more random choice behavior (i.e. a larger variance of the random error term of the utility function). Furthermore, Zhang and Conrad (2014) showed that speeding is also related to straightlining as persistent speeders show a higher share of straightlining.

5.2.2 Response behavior and attrition

As travel behavior studies often include a (multiple-day) travel diary, some effects of soft-refusal may also be present in the recorded travel behavior. However, as the ground truth (the person's actual travel behavior) is usually unknown, it is very difficult to assess whether the reported travel behavior is (in)correct. Madre et al. (2007) did show that soft-refusal (respondents who incorrectly report to stay at home during the survey period) may be an issue in self-reported travel diaries. They suggested using a binary logit model to identify respondents who have a very high probability of leaving their home (based on sociodemographic characteristics), but who nonetheless reported to stay at home. Soft-refusal in a travel diary is a likely candidate strategy to ease response burden. No additional studies were found in a travel behavior context that assess the presence of soft-refusal and its effects on reported mobility. It can be hypothesized that respondents who show soft-refusal in a questionnaire, may also show satisficing behavior in the accompanying travel diary.

An issue specific to longitudinal surveys that influences data quality in multi-year mobility panels is attrition. As longitudinal surveys aim to monitor a sample for a longer period of time, attrition becomes a problem when it changes the composition of the sample or is related to the study outcome (i.e. it is non-random). Earlier studies have indeed shown that attrition is usually non-random and related to sociodemographic characteristics, such as educational level, income and household composition (e.g. (Golob et al., 1986; Gustavson et al., 2012; Tambs et al., 2009)). Specifically in a travel behavior context, it was found that attrition rates are higher among respondents who reported very few trips compared to respondents who reported more

trips (Kitamura & Bovy, 1987). This may be an indication that attrition itself can be used as an indicator of soft-refusal in the wave before dropping out.

5.2.3 Research contributions

While there is ample evidence that soft-refusal may have an effect on data quality, no study is available that assesses different indicators of soft-refusal in a travel behavior context and its relationship with reported travel behavior. Therefore, the main contribution of the present study is that it assesses the presence of soft-refusal in a longitudinal mobility panel and shows how soft-refusal is related to reported immobility. More specifically, we will assess three different methods to identify possible soft-refusal. First, similar to Madre et al. (2007), we will directly identify possible soft refusers in the travel diary by predicting out-of-home activity. People with a high model-implied probability of an out-of-home activity, but no observed out-of-home activity are identified as soft-refusers. The following two methods focus on response behavior in the questionnaire. We will identify the extent to which straightlining and speeding is present in the questionnaire and we will show how these behaviors are related with reported immobility in the travel diary. Next to these three methods, we will assess to what extent these indicators on soft-refusal are associated with attrition. Furthermore, as we focus on a longitudinal mobility panel, we will assess how soft-refusal develops over time among individuals. To do so, we will classify respondents into different response behavior classes based on the indicators of soft-refusal and study transitions between these classes over time using a Latent Transition Analysis (LTA).

5.3 Methods

In this section, we discuss different methods to identify possible soft refusers in a longitudinal travel survey and to assess soft-refusal over time. First, we discuss the three methods to identify soft-refusal, followed by the conceptual model to assess soft-refusal over time.

5.3.1 Methods to identify soft-refusal

To assess the presence of soft-refusal in longitudinal travel surveys, we study three different methods in which we make use of indicators that are available from the survey itself.

5.3.1.1 Method 1: predicting out-of-home activity

The first method which we use to identify respondents who possibly used a soft-refusal strategy, relies on a prediction of out-of-home activity. Using a binary logistic regression model, we calculate the probability that a respondent will leave their home on a given day. While there is obviously a random component in whether people leave their home on a given day, there are several indicators, especially on working days, that can be used to effectively predict whether people will leave their home or not. Indicators such as sociodemographic variables (e.g. age, work status and household composition), stated frequencies of the use of travel modes and number of working days per week are used in the model. This method is similar to the approach of Madre et al. (2007). If such a model predicts that there is a very high probability that an individual leaves their home on a given day, and if that individual nonetheless reports no trips, this could indicate soft-refusal.

Since (reported) immobility levels are different on weekdays, Saturdays and Sundays, three separate models for these different types of days are estimated. The models are limited in the sense that all reporting days are treated as independent observations while each respondent reports three days per wave in the MPN. This violation of the assumption of independent

observations is not considered a major issue in the present study, as the goal of these models is not to show to what extent certain factors influence out-of-home activity, but to identify respondents who do not report any trips while a high chance of out-of-home activity is predicted.

5.3.1.2 Method 2: straightlining

The next two methods to identify respondents who possibly used a soft-refusal strategy, makes use of indicators on how respondents behave when filling out a survey. Travel behavior surveys usually do not only consist of a travel diary, but also include one or more questionnaires to collect background information of the respondent. We assess whether straightlining is present in the survey. If a respondent straightlines one or more grid questions, this could indicate laziness or low commitment to the study. To determine whether respondents straightline, we use a simple nondifferentiation method as this is the most extreme form of straightlining and it is easy to apply. Furthermore, as discussed earlier, Kim et al. (2019) concluded that this simple method is highly correlated with more sophisticated measures of straightlining.

5.3.1.3 Method 3: speeding

As a third method we assess to what extent speeding in the questionnaire is present and how this is related to reported immobility. A difficulty when assessing whether a respondent is speeding, is determining a threshold value that is considered to result in a valid versus an invalid response. Zhang and Conrad (2014) calculated a threshold value by assuming that respondents should take at least 300 milliseconds per word to read a question. This method, however, does not account for differences in reading speed between respondents and neither for differences in difficulty of each question. Therefore, in the present study we compare response times of respondents to determine whether a respondent is speeding. A characteristic of many (travel behavior) surveys is that the length of the survey depends on several factors. These could either be characteristics of the respondents (e.g. age or device that is used to fill out the survey) or answers that people give on certain question (e.g. certain questions are only presented if respondents answered earlier questions in a specific way). To account for such differences in the length of the questionnaires for different respondents, we estimate a regression model that predicts survey time based on several indicators. The included indicators are all known to have an influence on fill out time of the survey (e.g., work status or device that is used to fill out the survey). To determine if a respondent is speeding, we use the ratio between predicted survey time from the regression model and actual survey time.

Both straightlining and speeding can be considered strategies to lower the response burden. Incorrectly reporting to stay at home a full day in the travel diary is also a way to lower the response burden. We therefore hypothesize that poor response behavior in the questionnaire (i.e. straightlining or speeding) is an indicator of response behavior in the travel diary. To test this hypothesis, we will assess to what extent straightlining and speeding in the questionnaire are related to reported immobility in the travel diary.

If respondents used a strategy to lower their response burden, this may indicate that they lost interest and might be more likely to drop out of the panel before the next wave. We will assess to what extent the indicators on soft-refusal are associated with attrition. This is done by comparing reported immobility of three different types of respondents; those who are identified as a possible soft refuser by the three methods, those who are not identified as a possible soft refuser but remain in the panel and those who are not identified with any of the three methods, but who did drop out of the panel. If it is possible to predict attrition based on indicators of soft-refusal, this would improve the refreshment of the panel since it would be known beforehand

which (socio-demographic) type of respondents should be recruited to fill in the gaps left by those participants who are likely to leave.

5.3.2 Method to study soft-refusal over time

To study soft-refusal behavior over time, we use a latent transition analysis. Within this model, it is assumed that at each time point the same set of latent classes can be defined that explain associations between the included indicators (Collins & Lanza, 2009). In the present study, we define the latent classes using the three indicators on soft-refusal we described in the previous section. As a result, the latent classes represent different behavioral patterns with respect to soft-refusal. For example, it may be expected that certain respondents perform well or poor on all indicators, but there may also be different behavioral patterns in which respondents score poor on certain indicators but well on others. Figure 5.1 shows the conceptualization of this model. At each time point, individuals are probabilistically assigned to the latent classes and the parameter estimates can be used to compute transition probability matrices.

To decide on the appropriate number of clusters, we estimate a 1- through 10-class model and use the Bayesian Information Criterion (BIC) and the relative reduction in L^2 to determine which model fits best as described by Magidson and Vermunt (2004). The BIC takes both model fit and parsimony into account. A model with a lower BIC is preferred. To determine the reduction in L^2, the L^2 of the 1-class model is used as a baseline measure of the total amount of association in the data. The reduction in L^2 of higher class models represents the association that is explained by the model. It is no longer justifiable to add an extra class to the model, if this results in a small relative reduction of L^2.

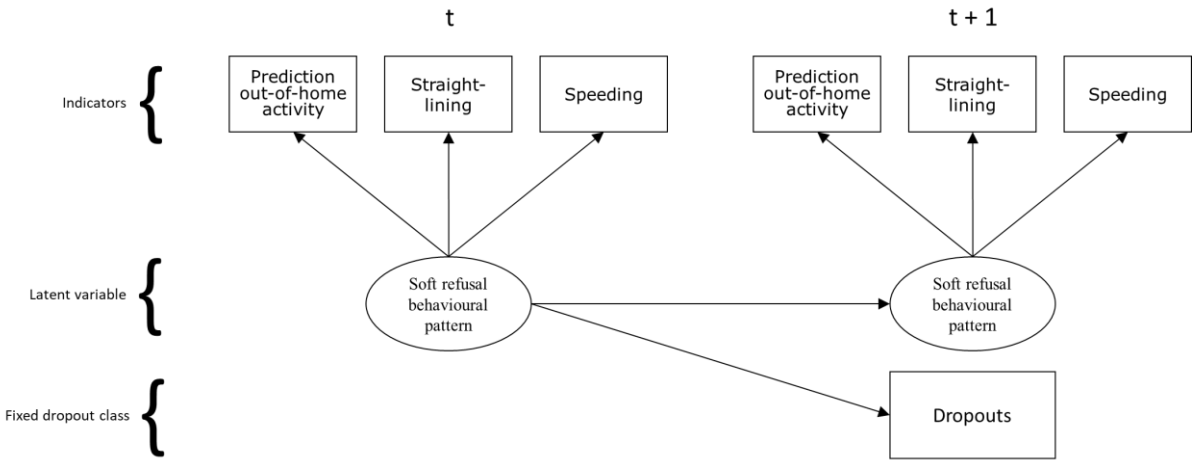


Figure 5.1 Conceptual model of the latent transition analysis

The transition matrices show to what extent people stay within the same class or shift to another behavioral pattern over time. Note that from the moment respondents drop out of the panel, information on soft-refusal is no longer available. This could bias the transition matrices, as attrition rates may be different between the different classes. Therefore, a separate class is added to the model to present respondents who dropped out. With this class included, the transition matrices will not only show transitions between behavioral patterns, but also the relation of a behavioral pattern with attrition.

5.4 Case study data

To test the different methods to identify soft-refusal and assess whether being a soft refuser is stable behavior over time or not, we make use of panel data from the Netherlands Mobility Panel (MPN). The MPN is an annual household panel that started in 2013 and consists of approximately 2,000 complete households. The MPN was set up to study the short-run and long-run dynamics in travel behavior of Dutch individuals and households and to assess how changes in personal- and household characteristics correlate with changes in travel behavior. To this end, household members of at least 12 years old are asked to complete a three-day travel diary each year and fill in an extensive questionnaire that includes questions on topics such as occupational status, use of different modes of transport and life events in the past year. Respondents are equally distributed over weekdays and have the same starting weekday each year. Furthermore, every household is asked to fill in a questionnaire about household related characteristics, such as information about household composition and ownership of means of transport. A more extensive description of the MPN can be found in Hoogendoorn-Lanser et al. (2015).

Data from the first seven waves of the MPN (2013 to 2019) are used. Although data from the eighth wave in 2020 is available, this wave is not included in the present study. In 2020, the COVID-19 pandemic has significantly impacted travel behavior. Because of governmental measures to reduce the spread of COVID-19 in the Netherlands, many people started working from home and many people were limited in their daily activities such as shopping and doing sports (de Haas et al., 2020). As a result, the reported level of immobility increased sharply as is shown in Table 5.1. As this study is focused on identifying people who wrongfully report to be immobile, using this wave of the MPN with a very different level of reported immobility compared to all other waves would unnecessarily complicate the study.

Table 5.1. Number of yearly respondents and reported immobility in the Netherlands Mobility Panel (MPN)

Year	# respondents	Reported immobility (%)	Year	# respondents	Reported immobility (%)
2013	3.996	16.4	2017	5.413	17.6
2014	5.466	17.0	2018	6.100	19.1
2015	3.915	17.3	2019	5.349	20.2
2016	4.208	18.3	2020	4.881	30.2

5.5 Results

In this section, we present the results of the three methods to identify soft-refusal and show the link with reported immobility. Next, we show how the three methods are correlated and study soft-refusal over time with the latent transition analysis.

5.5.1 Predicting out-of-home activity

The first method to identify possible soft refusers is based on a binary logit model that predicts the likelihood that an individual leaves their home on a given day. Table 5.2 shows the parameter estimates for the three separate models. The models include several sociodemographic variables (age, gender, education level, number of working days per week, number of days working from home per week, migration background and household composition) as well as information about travel behavior from the questionnaire (ownership of a car and bicycle and stated frequency of use of the car, bicycle, and walking). Finally, the

wave number is included to account for differences in immobility between years as well as an indicator on whether the respondent reported trips on the same day in another wave.

All included indicators are significant predictors of out-of-home activity in the model for weekdays. Discussing all parameters in detail is out of the scope of this study, but parameter estimates are in the expected direction. For instance, respondents who work more days per week have a higher chance of leaving their home on weekdays, while an increasing number of days working from home reduces that chance. Furthermore, respondents who indicate in the questionnaire to use the car, bicycle or walking more than four times per week have a higher chance of leaving their home on any day compared to people who state to use these modes with a lower frequency.

Table 5.2. Parameter estimates binary logit models to predict out-of-home activity

		Weekday		Saturday		Sunday	
		B	S.E.	B	S.E.	B	S.E.
Intercept		0.64**	0.09	0.84**	0.18	-0.09	0.15
Gender	Male	Ref.		Ref.		Ref.	
	Female	0.04	0.02	0.05	0.05	0.03	0.04
Age	12-17 years	1.06**	0.07	0.20	0.12	-0.03	0.10
	18-24 years	0.28**	0.05	0.24*	0.10	0.37**	0.09
	25-34 years	-0.20**	0.04	-0.07	0.08	0.00	0.07
	35-44 years	Ref.		Ref.		Ref.	
	45-54 years	0.16**	0.04	0.18*	0.08	0.03	0.07
	55-64 years	0.25**	0.05	0.22*	0.09	0.19*	0.08
	65-74 years	0.42**	0.05	0.59**	0.10	0.35**	0.09
	75+ years	0.33**	0.06	0.39**	0.12	0.29**	0.11
Education level	Low	0.00**	0.00	0.00**	0.00	0.00**	0.00
	Mid	0.10**	0.03	0.03	0.06	0.08	0.05
	High	0.31**	0.03	0.21**	0.07	0.22**	0.06
Origin	Native	Ref.		Ref.		Ref.	
	Foreign	-0.19**	0.04	-0.21**	0.08	-0.18*	0.07
Number of 12+ in household	1	0.00**	0.00	0.00*	0.00	0.00**	0.00
	2	-0.14**	0.03	-0.13*	0.07	-0.04	0.06
	3 or more	-0.27**	0.04	-0.22**	0.08	-0.28**	0.06
Number of 12- in household	0	0.00**	0.00	0.00	0.00	0.00	0.00
	1	0.14**	0.05	0.13	0.08	0.06	0.07
	2 or more	0.23**	0.05	0.02	0.08	0.06	0.07
Level of urbanization	Urban (1500+ inhabitants/km²)	Ref.		Ref.		Ref.	
	Sub-urban (1000-1500 inhabitants/km²)	0.07*	0.03	-0.02	0.06	-0.01	0.05
	Rural (less than 1000 inhabitants/km²)	-0.03	0.03	-0.06	0.05	-0.04	0.05
Working days/week	1	Ref.		Ref.		Ref.	
	2	0.12**	0.04	0.17*	0.08	0.16*	0.06
	3	-0.17**	0.05	-0.09	0.10	-0.10	0.08
	4	-0.52**	0.08	0.03	0.17	-0.07	0.14
	5 or more	-0.83**	0.10	-0.56*	0.22	0.19	0.21
	No job	-1.21**	0.09	-0.82**	0.21	-0.30	0.19
Working from home days/week	0	Ref.		Ref.		Ref.	
	1	0.12**	0.04	0.17*	0.08	0.16*	0.06
	2	-0.17**	0.05	-0.09	0.10	-0.10	0.08
	3	-0.52**	0.08	0.03	0.17	-0.07	0.14
	4	-0.83**	0.10	-0.56*	0.22	0.19	0.21
	5 or more	-1.21**	0.09	-0.82**	0.21	-0.30	0.19
Owns a bicycle	No	Ref.		Ref.		Ref.	
	Yes	0.22**	0.03	0.18**	0.05	0.19**	0.05
Car in the household	No	Ref.**	0.00	Ref.**	0.00	Ref.**	0.00
	1 or more cars	0.20**	0.04	0.08	0.08	0.17*	0.07

		Weekday		Saturday		Sunday	
		B	S.E.	B	S.E.	B	S.E.
Frequency of car use	More than 4 times/week	Ref.		Ref.		Ref.	
	1-3 times/week	-0.16**	0.03	-0.21**	0.06	-0.01	0.05
	Less than 1 times/week	-0.28**	0.04	-0.40**	0.07	-0.20**	0.06
Frequency of bicycle use	More than 4 times/week	Ref.		Ref.		Ref.	
	1-3 times/week	-0.30**	0.03	-0.28**	0.06	-0.28**	0.05
	Less than 1 times/week	-0.48**	0.03	-0.52**	0.06	-0.41**	0.05
Walking frequency	More than 4 times/week	Ref.		Ref.		Ref.	
	1-3 times/week	-0.06*	0.03	-0.03	0.05	-0.19**	0.05
	Less than 1 times/week	-0.18**	0.03	-0.25**	0.06	-0.26**	0.05
Reported trips same day in previous or following wave	No	Ref.		Ref.		Ref.	
	Yes	1.50**	0.03	1.46**	0.06	1.21**	0.04
	Did not participate in other years	0.88**	0.04	0.75**	0.07	0.65**	0.06
Wave number	1	Ref.		Ref.		Ref.	
	2	-0.20**	0.05	-0.30**	0.09	-0.08	0.08
	3	-0.32**	0.05	-0.45**	0.10	-0.26**	0.08
	4	-0.28**	0.05	-0.40**	0.10	-0.20*	0.08
	5	-0.10*	0.05	-0.31**	0.09	-0.02	0.08
	6	-0.38**	0.05	-0.41**	0.09	-0.09	0.08
	7	-0.31**	0.05	-0.30**	0.09	-0.15*	0.08

* $P \leq 0.05$, ** $P \leq 0.01$, Nagelkerke R Square: Weekday: 0.132, Saturday: 0.138, Sunday: 0.130

For each reporting day, the models can be used to calculate the probability that a respondent leaves his home. For weekdays this probability ranges from 22 to 98%, with a mean of 86%, while for Saturdays and Sundays this ranges from 17 to 96%, with means of respectively 79% and 67%. To identify respondents who might show soft-refusal, an arbitrary choice must be made on the cut-off value. In other words, how high should the predicted probability be to consider a respondent who does not report any trips as a potential soft refuser. A higher cut-off value will lower the number of false-positives, while increasing the number of false-negatives. In the present study, we chose a relatively high cut-off value of 90%, as we consider lowering false-positives more important than false-negatives.

In total, just over 5 percent of respondents are identified as a possible soft refuser in any of the three models, as shown in Table 5.3. The reported immobility in this table refers to the average immobility for the three reporting days (i.e., if a respondent reports no trips on one of their reporting days their level of immobility would be 33.3%). A result of the relatively high cut-off value of 90% is that only few respondents are identified as possible soft refusers on Saturdays and Sundays. The reported immobility of respondents who are identified as a possible soft refuser is considerably higher than that of respondents who are not identified as a possible soft refuser. However, since this method only identifies respondents who reported to stay at home on at least one of their three reporting days, the theoretical minimum level of reported immobility among the possible soft refuser group is 33.3%.

Table 5.3. Reported immobility for possible soft refusers based on the binary logit out-of-home activity model versus other respondents

	Potential soft refuser	Reported immobility possible soft refusers	Reported immobility other respondents
Weekdays	4.8%	52.2%	17.7%
Saturdays	1.2%	47.3%	21.0%
Sundays	0.0%	33.3%	23.2%
Total	5.3%	51.2%	17.6%

5.5.2 Straightlining

For the following two methods to identify possible soft refusers, we make use of indicators on how respondents filled out the survey. More specifically, we use indicators on straightlining and speeding. In the MPN, respondents are asked to fill out an extensive survey besides keeping a three-day travel diary. This questionnaire is sent out two weeks prior to the travel diary. In the even waves (2, 4 and 6), the questionnaire includes a relatively large number of grid questions. Depending on age and travel mode use, respondents fill out four to thirteen grid questions, with approximately 90% of respondents filling out at least eight grid questions. An indicator of measurement error is the amount of straightlined grid questions (Struminskaya et al., 2015). As discussed before, we consider a respondent to be straightlining when they provide the same answer to every item in the grid.

Just over half of respondents do not straightline any of their grid questions, while just over one third straightlines up to a quarter of their grid questions. It should be noted that straightlining part of the grid questions is not by definition an indicator of poor response behavior as certain grid questions focus on attitudes towards travel modes. Couper et al. (2013) argued that with these types of grid questions straightlining is plausible. For instance, people who are strongly oriented towards a certain travel mode may be very positive about all aspects of that mode, resulting in straightlining a grid question. We therefore assume that straightlining up to a quarter of the grid questions is plausible, while a higher share may indicate poor response behavior.

Table 5.4 shows the reported immobility in the travel diary related to the amount of straightlining in the questionnaire. Again, this level of immobility refers to the immobility of the three reporting days. Respondents are grouped together based on their share of grid questions they straightline to ease comparison. From the table it becomes clear that our hypothesis seems to be correct. Respondents who straightline more than a quarter of their grid questions report considerably more immobile days, with the level of reported immobility increasing with a further increase in the share of straightlining.

Table 5.4. Straightlining in the MPN and its relation with reported immobility

	Share of respondents	Reported immobility
0% straightlining	51.6%	14.7%
1% - 25% straightlining	35.0%	18.2%
25% - 50% straightlining	8.4%	25.9%
50% - 66% straightlining	2.4%	32.3%
>66% straightlining	2.7%	40.9%

The questionnaires of the uneven waves (2013, 2015, etc.) of the MPN only include a few grid questions, making this method less reliable for these uneven waves. However, since most respondents participate at least two waves in the MPN, it is technically possible to explore whether this indicator on straightlining from even waves (2014, 2016, etc.) predicts soft-refusal in a previous or subsequent uneven wave. It turns out that the amount of straightlining in a previous or subsequent wave is strongly related to reported immobility in uneven waves, as is shown in Table 5.5 (if respondents participated both the previous and subsequent wave, we took the average of straightlining in those waves).

Table 5.5. Relation between straightlining in previous or subsequent wave and reported immobility.

	Share	Reported immobility in subsequent wave
0% straightlining	45.3%	13.6%
1% - 25% straightlining	43.3%	17.3%
25% - 50% straightlining	7.9%	26.5%
50% - 66% straightlining	1.8%	30.6%
>66% straightlining	1.7%	39.6%

5.5.3 Speeding

The second indicator of response behavior in the questionnaire we use to identify soft-refusal is the time respondents take to fill out the survey. When a respondent fills out a questionnaire very fast, it becomes likely that this respondent does not fill out the survey thoughtfully. We estimated a regression model to predict the response time for each respondent. The predictors in the model are known to either influence speed directly (age and device that people use to fill out the survey) or change the length of the survey (age, work status, number of experienced life events and wave number of the MPN). Table 5.6 shows the parameter estimates of the regression model. Discussing all parameter estimates is outside the scope of this study, but the parameter estimates are in the expected direction. For instance, younger respondents have a lower response time, while respondents who experienced more life events have a higher response time. Furthermore, respondents who used a tablet to fill out the survey are slower compared to respondents who used a PC, but faster than respondents who used a smartphone.

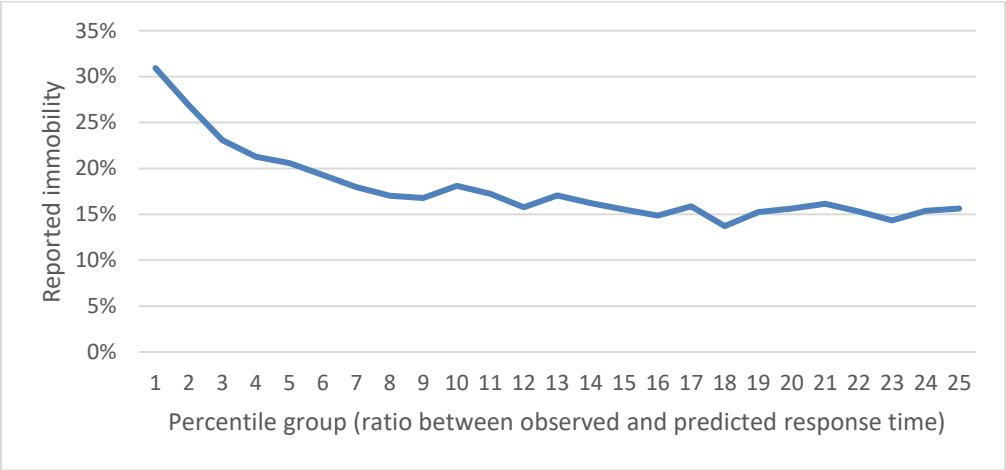
Table 5.6. Parameter estimates of regression model to predict response time

		B	S.E.			B	S.E.
Intercept		1271.53**	14.92	**Number of life events**	0	Ref.	
Age	12-14 years	-788.86**	19.08		1	79.48**	4.35
	15-17 years	-654.54**	18.60		2	116.72**	6.34
	18-19 years	-607.86**	19.17		3	141.80**	8.84
	20-24 years	-558.22**	16.18		4	170.56**	11.81
	25-29 years	-549.85**	15.41		5	243.74**	19.39
	30-34 years	-546.83**	15.22		6	300.97**	35.99
	35-39 years	-532.05**	15.08		7	352.69**	62.19
	40-44 years	-515.40**	15.09		8	686.89**	135.85
	45-49 years	-508.89**	14.90		10	-203.51	303.67
	50-54 years	-469.90**	14.77	**Number of ICT events**	0	Ref.	
	55-59 years	-373.17**	14.70		1	93.78**	5.33
	60-64 years	-347.85**	14.21		2	157.36**	7.75
	65-69 years	-265.92**	13.05		3	163.61**	12.77
	70-74 years	-177.55**	13.28		4	222.32**	16.45
	75-79 years	-86.62**	14.40		5	176.78**	36.74
	80+ years	Ref.			6	171.19**	57.49
Work status	Working	Ref.			7	143.37**	47.54
	No job	-60.39**	5.16	**Wave number**	1	38.43**	6.66
	Retired	-78.68**	8.98		2	265.95**	6.11
	Student	-39.07**	9.71		3	210.30**	6.63
	Other	24.80	20.15		4	296.72**	6.46
Device	Tablet	Ref.			5	528.77**	6.02
	PC	-55.60**	4.82		6	47.77**	5.90
	Mobile phone	48.75**	6.32		7	Ref.	

* $P \leq 0.05$. ** $P \leq 0.01$, Adjusted R-squared = 0.173

Using the parameter estimates, response times can be predicted for each respondent. By ranking respondents in groups based on their ratio between observed response time and predicted response time, a clear relation between speeding and reported immobility becomes visible. Respondents are ranked from the lowest ratio (faster than expected) to the highest ratio (slower than expected) in 25 percentile groups per wave. Figure 5.2 shows the average reported immobility per percentile group. The reported immobility is considerably higher among the first percentile groups compared to the other groups. The average ratio between observed response time and predicted response time in the first five percentile groups ranges from 0.35 to 0.60 (i.e., respondents in these groups are on average 1.67 to almost 3 times faster than expected). Starting from percentile group 17, respondents are slower than expected, but this does not seem to be related to reported immobility.

Figure 5.2. Relation between speeding in the questionnaire and reported immobility in the travel diary



5.5.4 Attrition

When respondents drop out of the panel, it is possible that they already lost interest in their final wave of participation. Kitamura and Bovy (1987) found that reporting low mobility is related to attrition. Table 5.7 shows the level of immobility for respondents in the MPN based on their starting year and number of waves they participated. Although there are some exceptions, for instance respondents who started in 2013 and participated 5 waves, the level of immobility in the final wave of participation is considerably higher than the wave(s) before that.

Table 5.7. Reported immobility in the MPN by starting year and number of participating waves

		Reporting year						
Start year	**# waves participated**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
2013	1	21.8%	-	-	-	-	-	-
	2	16.7%	20.6%	-	-	-	-	-
	3	17.7%	18.1%	24.7%	-	-	-	-
	4	13.3%	18.3%	16.7%	24.0%	-	-	-
	5	13.3%	16.2%	15.9%	21.1%	16.8%	-	-
	6	15.2%	15.6%	16.8%	20.8%	20.9%	20.3%	-
	7	12.1%	17.0%	15.2%	17.0%	16.2%	17.1%	23.8%
	8	12.7%	14.1%	14.8%	15.2%	14.0%	15.2%	16.6%
2014	1	-	20.9%	-	-	-	-	-
	2	-	15.7%	20.1%	-	-	-	-
	3	-	11.8%	11.7%	16.6%	-	-	-
	4	-	15.9%	14.3%	24.6%	26.8%	-	-
	5	-	14.7%	14.7%	17.6%	21.8%	19.0%	-
	6	-	18.5%	22.3%	21.2%	20.1%	23.6%	28.9%
	7	-	15.1%	15.2%	17.1%	15.2%	19.2%	19.0%
2015	*	-	-	-	-	-	-	-
2016	1	-	-	-	22.8%	-	-	-
	2	-	-	-	14.6%	13.7%	-	-
	3	-	-	-	15.0%	13.8%	18.8%	-
	4	-	-	-	16.8%	14.7%	19.2%	19.8%
	5	-	-	-	14.9%	15.8%	15.7%	18.8%
2017	1	-	-	-	-	21.1%	-	-
	2	-	-	-	-	14.0%	22.5%	-
	3	-	-	-	-	18.0%	17.1%	22.1%
	4	-	-	-	-	16.3%	17.9%	19.2%
2018	1	-	-	-	-	-	27.4%	-
	2	-	-	-	-	-	24.7%	30.1%
	3	-	-	-	-	-	23.1%	23.6%
2019	1	-	-	-	-	-	-	23.7%
	2	-	-	-	-	-	-	21.7%

*No new respondents were recruited in 2015

As described in the previous sections, the indicators of soft-refusal can be used to identify groups of respondents with a relatively high level of reported immobility. It may be that we can use the indicators on soft-refusal to predict attrition. If this is possible, we could use this information in the recruitment of new respondents, as we would know beforehand which respondents will likely dropout. Table 5.8 shows the reported immobility of different groups of respondents based on attrition and identification as a possible soft refuser with the three methods we discussed before. For this table, we consider respondents as possible soft refusers if they either are identified in the binary logit out-of-home activity model, straightline more than 25% of their grid questions or are in the first five percentile groups regarding the ratio between observed and predicted response time.

Table 5.8. Reported immobility of respondents based on attrition or identification as a possible soft refuser

Dropped out after wave	Identified as possible soft refuser with either of the three methods	Reported immobility	# respondents
No	No	11.9%	18,429
	Yes	27.1%	8,163
Yes	No	17.5%	5,371
	Yes	31.7%	2,484

From the table it is clear that reported immobility is highest amongst respondents who are identified by any of the three methods we discussed before. The lowest reported immobility can be found among respondents who do not drop out and are not identified as a potential soft refuser by any of the three methods. Compared to this group, the reported immobility of respondents who are not identified by any of the three methods as a soft refuser, but who did drop out is considerably higher. This may indicate that attrition in itself is also an indicator of possible soft-refusal in the final wave of participation. To test this hypothesis, a linear regression model is estimated to predict reported immobility using the indicators on soft-refusal and the information of attrition as predictors. Table 5.9 shows the parameter estimates of this model. As expected, all indicators on soft-refusal are significant predictors of reported immobility. In addition, the model confirms that attrition itself is also an indicator of possible soft-refusal, as it is a significant predictor of reported immobility in the previous wave.

Table 5.9. Parameter estimates of model to predict reported immobility based on indicators of soft-refusal and information on attrition

	B	S.E.
Constant	0.86**	0.00
Possible soft refuser based on straightlining	-0.12**	0.00
Possible soft refuser based on speeding	-0.06**	0.00
Possible soft refuser based on predicting out-of-home activity	-0.12**	0.01
Respondent drops out after wave	-0.03**	0.00

* $P \leq 0.05$. ** $P \leq 0.01$, Adjusted R-squared = 0.067

5.5.5 Correlation between indicators of soft-refusal

Figure 5.3 shows how the different indicators on soft-refusal, including information on attrition, overlap each other in a Venn diagram. Respondents who are not identified by any of the methods and who do not drop out (53% of respondent-years) are not shown in this diagram. From the Venn diagram it becomes clear that three quarters of the respondents that may be a soft refuser are only identified by one of the four indicators. Approximately 21% is identified by two indicators as a possible soft refuser and just over 3% by three or four indicators. Hence, there is some overlap between the indicators, but correlations are not that strong. This in turn suggests that each indicator to some extent measures a separate aspect of soft-refusal.

While the Venn diagram visualizes the correlation between the different methods to identify potential soft refusers, it only shows this in a binary way (i.e. respondents are flagged by an indicator or not; it does not show exactly how they score on this indicator). There may be groups within the MPN with similar behavioral patterns in terms of these indicators. The Venn diagram does not show these underlying behavioral patterns and how people transition between these patterns over time. In the next section, these behavioral patterns and transitions between them over time are studied more in-depth using a Latent Transition model.

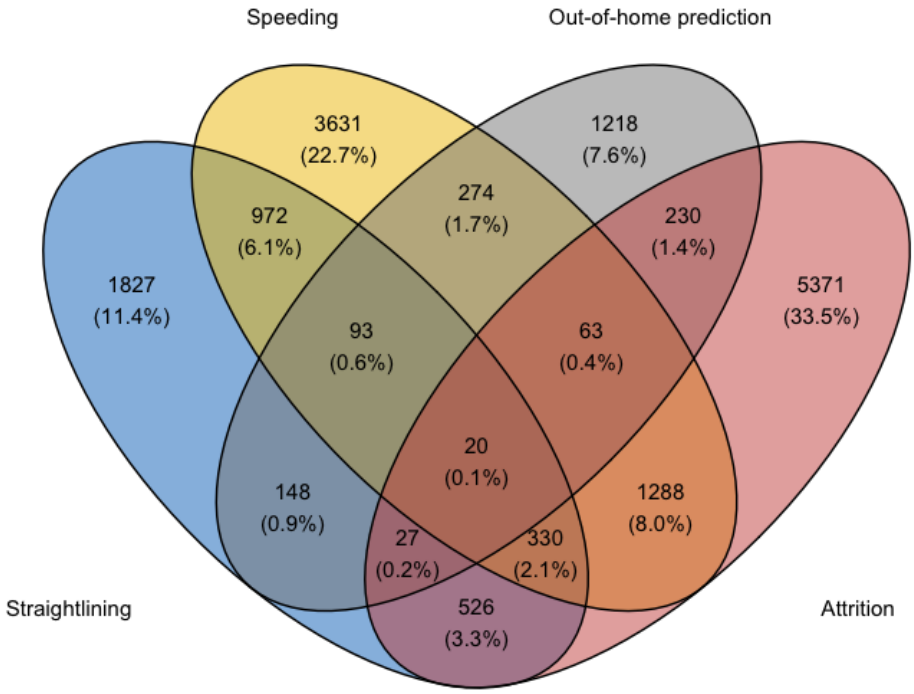


Figure 5.3 Venn diagram of MPN respondents who are identified as a possible soft refuser (n =16,018)

5.5.6 Behavioral classes with respect to soft-refusal

Table 5.10 shows the profiles of the five latent classes in the Latent Transition Analysis. It should be noted that only the even waves of the MPN (2014, 2016 and 2018) are used in the estimation. As discussed, only these waves include enough grid questions to reliably determine whether respondents are straightlining. As explained in the Method section, the BIC and reduction in L^2 were used to determine the number of classes. While the BIC suggests that a 6-class model fits the data best, the relative reduction in L^2 after the 5-class model is small (<0.2%). Furthermore, the classification error of the 5-class model is considerably lower than that of the 6-class model (15.2% vs 22.4%). Therefore, the 5-class model was chosen. Overall, the five classes are well-interpretable.

The first class (‘Low risk’, 39% of the sample) includes respondents with the lowest risk of showing soft-refusal, as they are rarely identified by any of the indicators on soft-refusal. Almost all of them straightline a maximum of 25% of grid questions, they have the lowest share of flags from the binary logit out-of-home activity model and are mostly slower or as fast as expected when filling out the survey. Respondents in this class also show the lowest level of reported immobility. In terms of sociodemographics, this class is consistent with the sample average, with a slightly higher share of high educated people.

Respondents in the second class (‘Speeders’, 20% of the sample) often do not straightline, similar to the first class. However, they are flagged more often in the out-of-home activity model and they are often faster than expected when filling out the survey. Their reported level of immobility is higher than respondents in the first class. Compared to the first class, there are slightly less elderly in this group. Correlated with that, there are more respondents with a paid job and respondents are more often part of a household with children compared to the first class.

Table 5.10. Profiles of the five latent classes in the Latent Transition Analysis (MPN 2014, 2016, 2018)

Class*		LR	SP	SL	HR	DO	Overall**
Size (%)		39	20	9	5	28	-
Size corrected for the dropout class (%)		54	27	12	6	-	-
Indicators							
Straightlining	0% straightlining	66	52	9	2	0	51
	1-25% straightlining	31	42	42	21	0	35
	25-50% straightlining	2	6	31	30	0	9
	50-66% straightlining	0	0	10	18	0	2
	>66% straightlining	0	0	8	28	0	3
	Dropped out	0	0	0	0	100	
Binary logit out-of-home activity (%)	Not flagged	95	93	94	93	0	94
	Flagged	5	7	6	7	0	6
	Dropped out	0	0	0	0	100	
Speeding (predicted vs observed) (%)	>3 times as fast	0	0	0	7	0	1
	2-3 times as fast	0	12	0	45	0	6
	1.25 - 2 times as fast	18	69	20	45	0	34
	1.25 times slower - 1.25 times faster	46	18	46	2	0	35
	>1.25 times slower	36	2	33	0	0	24
	Dropped out	0	0	0	0	100	-
Attrition	In panel	100	100	100	100	0	-
	Dropped out	0	0	0	0	100	-
Inactive covariates							
Reported immobility (%)		14	19	18	33	20	17
Gender (%)	Male	46	46	46	50	46	46
	Female	54	54	54	50	54	54
Age (%)	12-24 years	16	18	20	31	28	18
	25-44 years	29	32	28	32	29	30
	45-65 years	36	35	34	27	33	35
	65+ years	19	15	18	10	11	17
Education level (%)	Low	28	29	37	49	37	31
	Mid	37	38	39	34	37	37
	High	35	33	24	17	26	32
Work status (%)	Paid work	53	56	51	47	53	53
	No job	3	3	4	4	4	3
	Retired	18	14	16	9	10	16
	Student	13	15	15	23	22	15
	Other	13	12	15	17	11	13
Household composition (%)	Single	20	16	21	14	11	19
	Adult household	29	28	27	18	20	28
	Household with children	50	55	51	66	67	52
	Other	1	1	1	3	1	1

*LR: Low risk, SP: Speeders, SL: Straightliners, HR: High risk, DO: Dropouts
**This column shows the overall mean without the dropout class

The third group ('Straightliners', 9% of the sample) are respondents with an above-average share of straightlining. Just over 90% straightline at least one of their grid questions, with approximately 50% straightlining more than 25% of their grid questions. They score similar as the first class on the indicators of the out-of-home activity model and speeding. The reported level of immobility in this group is higher than the first class, but lower than the other two classes. This group differs clearly from the first (low risk respondents) and second (speeders) group in education level, as highly educated people are underrepresented.

The fourth and smallest class (‘High risk’, 5% of the sample) is clearly a high-risk group in terms of soft-refusal. This class has the highest share of straightlining and speeding and the share of respondents who are flagged by the out-of-home activity model is similar to that in the third class. The reported level of immobility in this class is almost double the average. This class also has a distinct sociodemographic profile. Young people are overrepresented in this class and as a result there is a high share of less educated people, a high share of students and a high share of respondents living in a household with children.

The fifth class (‘Dropouts’, 28% of the sample) represents respondents who dropped out of the panel. Similar to the high-risk class, young people and people from a household with children are overrepresented in this class. This indicates that the attrition rate among young respondents from households with children is higher than average.

5.5.7 Soft-refusal over time

Besides the different behavioral patterns and their profiles, the latent transition analysis allows to examine how respondents shift between patterns over time. Table 5.11 shows the probabilities for respondents in each class to either stay in the same class, or transition to another class over time. The first thing that stands out, is that the probability to transition to the dropout class is very similar for the first three classes (the low risk respondents, speeders and straightliners). Only when respondents are identified as possible soft refusers on multiple indicators, this is predictive for attrition, as can be seen from the higher probability for the high-risk group to drop out.

When respondents do not dropout, they tend to stay in the same class over time, as can be seen from the diagonal. There is only a small probability that respondents transition to another behavioral class. If they do, we see that the low risk group primarily transition to the speeder group and vice versa, while the straightliners primarily transition to the high-risk group and vice versa. In other words, speeders may transition to a more reliable class, while straightliners may transition to a worse class in terms of soft-refusal. This implies that straightlining is a better indicator of poor response behavior than speeding. This makes sense intuitively, as one has to make a conscious choice to straightline grid questions (i.e. if a respondent straightlines more than a plausible share, this has to be done on purpose), while speeding could be plausible behavior, for instance because a respondent is a fast reader compared to other respondents.

Table 5.11. Transition probability matrix five class latent transition analysis

		Class* [t-1]				
		LR	SP	SL	HR	DO
Class* [t]	LR	0.56	0.06	0.00	0.00	0.00
	SP	0.02	0.51	0.00	0.02	0.00
	SL	0.01	0.03	0.51	0.08	0.00
	HR	0.00	0.00	0.07	0.36	0.00
	DO	0.41	0.39	0.42	0.55	1.00

*LR: Low risk, SP: Speeders, SL: Straightliners, HR: High risk, DO: Dropouts

5.6 Conclusion and discussion

We presented three different methods to identify possible soft-refusal in a longitudinal travel behavior panel, based on: 1) predicting out-of-home activity 2) straightlining, and 3) speeding. We used these methods to explore soft-refusal and attrition in a multi-year mobility panel. All methods seem to be able to identify respondents with poor response behavior in a travel behavior context (i.e. a suspiciously high level of reported immobility). While the first method

(binary logit out-of-home activity model) is directly aimed at identifying reporting days on which respondents incorrectly report no trips, it was found that also speeding and straightlining in a questionnaire are strongly related to reported immobility in the travel diary. Similar to Kitamura and Bovy (1987) we found that attrition is correlated with reported immobility. Furthermore, we found that attrition itself is an additional indicator of reported immobility in the final wave of participation. In other words, the three presented methods likely do not capture all soft-refusal.

While the presented methods all seem to identify respondents who have a higher probability of wrongfully reporting to stay at home, this points at an important limitation to this research. Since the ground truth is often not known in a travel behavior panel, there is no possibility to statistically test the effectiveness and reliability of the presented methods in identifying true soft refusers. While it would be easy for travel behavior panels to include a question to directly ask whether respondents reported their true travel behavior, this information would probably also be biased as soft refusers might use this question to justify their reported immobility. As a result of the ground truth being unknown, it may be difficult to decide when a respondent is considered to score poorly on a certain indicator (i.e. how fast should a respondent be to be speeding too much and what percentage of straightlining is plausible and/or acceptable).

Due to the inability to test effectiveness and reliability of the methods, it is not recommended to use just a single method to identify soft refusers as this will likely result in a high number of false positives, i.e. respondents who are wrongfully identified as a soft refuser. While soft refusers may bias a data set, removing true respondents will also introduce a bias. Since the indicators on soft-refusal in this study are (strongly) related to reported immobility, there is a risk of wrongfully removing respondents who have a low level of immobility. Because people with a low mobility level may be part of a vulnerable group of society (especially if this low level of mobility is involuntarily), the costs of removing false positives may be higher than keeping false negatives in the dataset. Using a combination of indicators will lower the chance of wrongfully identifying respondents as soft refusers, see for example how being flagged by several indicators at once appears to be a strong indicator of subsequent attrition, compared to just a single flag.

The latent transition analysis showed that there are four distinct behavioral patterns in terms of soft-refusal behavior (plus a fifth class to represent dropouts). The largest class consists of respondents who are overall not identified as a possible soft refuser, followed by a class who seem to be speeding and a class with a higher share of straightlining. While their level of reported immobility is higher than the first class, there are only a few differences in their sociodemographic profiles. Only the fifth class (the high-risk soft-refusal class with a very high level of reported immobility) has a distinct sociodemographic profile. Knowing a priori which type of respondents have a higher risk of showing soft-refusal provides the possibility to account for this by oversampling these groups. In the case of the MPN, that would be young and less educated people.

From the transition analysis we found that only when respondents are identified as possible soft refusers on multiple indicators (the high-risk class), the attrition rate is higher. Furthermore, if respondents do not dropout, they tend to stay in the same class over time. This implies that keeping respondents from the high-risk class in the panel will mainly result in these respondents providing the same poor data quality in subsequent measurements. One could therefore argue to remove these respondents entirely from the panel. However, in the specific case of the MPN, removing a single respondent results in removing the entire household from the panel. Since most respondents from the high-risk class are part of a multi-person household, removing them would simultaneously remove more reliable respondents from the panel.

The extent of the impact that soft refusers will have on analyses with the data depends on the type of analysis. In light of longitudinal analyses (i.e., studying travel behavior changes), the finding that soft refusers from the high-risk class are likely to stay in that class over time can be considered a positive finding. Because they will likely be a soft refuser in all their waves, no (or only few) travel behavior changes will be observed (since they will likely always report a low level of mobility). While this may lead to an underestimation of effects, including soft refusers in longitudinal analyses will probably have a limited impact on the results. When doing cross-sectional analyses, the impact may be greater. Especially when doing research on low-mobility groups, soft refusers may (strongly) bias the results. However, also the high-risk class will likely include false positives. Removing this group entirely from the analyses, may also bias the results. However, being able to identify respondents with a high-risk of being a soft refuser allows to study the effect of this group on the results (e.g. comparing results with and without these respondents included). This seems to be a relatively safe way to deal with potential soft-refusers in the data.

5.7 Future research

From the results, some recommendations for future research can be given. First, future research could focus on finding the ground truth in mobility panels. As already discussed, directly asking respondents whether they reported their true travel behavior will likely result in biased answers from soft refusers. A possible option would be to have respondent self-report their travel behavior and simultaneously passively collect the travel behavior (e.g., with a GPS tracker, or a smartphone app). This research should also study the impact of passively collecting data on the self-reporting of travel behavior (respondents may report more accurate data if they know the ground truth is known). Being able to compare self-reported and passively collected data would provide the possibility to test the effectiveness and reliability of the methods and help in determining thresholds for the methods e.g., what is the maximum allowed share of straightlining.

Studying the link between the soft-refusal indicators and underreporting of trips may be another interesting avenue for future research. The present research focuses mainly on the link between the soft-refusal indicators and reported immobility. Reporting no trips at all can be considered the most extreme form of underreporting trips. It may be that the indicators on soft-refusal are also related to less extreme forms of underreporting, i.e., reporting only a part of trips.

A third direction for future research is to study if, and how, these soft refusers could be motivated to transition from the high-risk class towards a more reliable class. If it turns out soft-refusal is mainly the result of a lack of interest, the options to motivate these respondents are probably limited. However, if this is not the case, knowing how to motivate this specific group of soft refusers (e.g. with other types of incentives, or with more interaction) would help in solving (part of) the soft-refusal problem.

6 The effects of the COVID-pandemic on travel behaviour

This chapter is based on the following article:

de Haas, M., Faber, R., & Hamersma, M. (2020). How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. *Transportation Research Interdisciplinary Perspectives, 6*, 100150. doi: https://doi.org/10.1016/j.trip.2020.100150

Abstract

COVID-19 has massively affected the lives of people all over the world. This paper presents first insights in current and potential future effects of the virus and the Dutch government's 'intelligent lockdown' on people's activities and travel behaviour. Findings are based on a representative sample of about 2500 respondents from the Netherlands Mobility Panel (MPN). We show that approximately 80% of people reduced their activities outdoors, with a stronger decrease for older people. 44% of workers started or increased the amount of hours working from home and 30% have more remote meetings. Most of these workers report positive experiences. Students and school pupils, however, are mostly not happy with following education from home. Furthermore, the amount of trips and distance travelled dropped by 55% and 68% respectively when compared to the fall of 2019. So-called 'roundtrips' (e.g. a walking or cycling tour) gained in popularity. People are currently more positive towards the car and far more negative towards public transport. Changes in outdoor activities seem to be temporal, with over 90% of people who currently reduced their outdoor activities not expecting to continue this behaviour in the future after corona. However, 27% of home-workers expect to work from home more often in the future. In addition, 20% of people expect to cycle and walk more and 20% expect to fly less in the future. These findings show that the coronavirus crisis might result in structural behavioural changes, although future longitudinal analyses are needed to observe these possible structural effects.

6.1 Introduction

In Wuhan, China, an outbreak of pneumonia was detected in December 2019. It has since been identified as a novel and contagious coronavirus, which is now named COVID-19 (Zhu et al., 2020). After spreading around the world at an alarming rate, the World Health Organization (WHO) declared COVID-19 as a pandemic on the 11th of March 2020 (WHO, 2020). Governments are taking unprecedented measures to limit the spread of the virus with the aim of eventually containing this pandemic. As such, COVID-19 has massively affected the lives of people all over the world.

Countries have taken drastic measures to contain the outbreak. In Europe, several countries, such as France and Italy, have implemented national lockdowns, limiting all non-essential travel. Other countries, such as Sweden, were less strict and still allowed for people to visit bars, restaurants or go to school. In the Netherlands, the government implemented its so-called 'intelligent lockdown'. At the time of this study, people were urged to leave their homes as little as possible and work from home. Furthermore bars, restaurants, schools, gyms and 'contact professions' were closed and visiting people in nursing homes was not allowed. Even though people were urged to stay home, they were still allowed to move around freely as long as they kept a distance of 1.5m to others. This instruction was strictly enforced (within the limits of available police forces) and offenders were fined 390€.

The societal impacts of both the virus and the measures taken to reduce its spread are severe. The circumstances result in a unique situation in which people have had to change their daily life radically, often within the span of days or weeks. People's activity patterns, the way they work and how they travel are three facets of daily life that have changed drastically. From both a research and policy point of view, it is important to assess how people respond to these externally induced changes and how these immediate impacts might lead to structural behavioural changes.

Research has shown that people are creatures of habit. Daily travel behaviour particularly depends on habit and routine (Schönfelder & Axhausen, 2010). Therefore, changes in behaviour do not occur often. However, several studies have shown that there are certain events in people's life course that trigger change in travel behaviour (Müggenburg et al., 2015; Schoenduwe et al., 2015). Schäfer et al. (2012) describe these life events as 'windows of opportunity' to change people's habitual routines. Earlier research has for instance shown that changing jobs leads to a mode shift towards the car (Oakil et al., 2011) and that people tend to shift to a travel pattern in which mainly car and walking trips are made (de Haas et al., 2018; Scheiner & Holz-Rau, 2013). Other research shows that not only travel patterns, but also activity patterns are less stable after such events (Hilgert et al., 2018). Besides changing behaviour themselves after certain life events, research has also shown that people are more susceptible to interventions after these events (Anable, 2013; Verplanken & Roy, 2016). The current lockdown situation may be a similar 'game changer' having comparable effects on behaviour as life events, with the exception that it occurs for society as a whole and that it is externally induced.

Breaking habits without an external (life) event is shown to be difficult. Dean (2013) showed that the length of time required to create new habitual behaviour depends on the type of new behaviour one wants to learn. Forming habits for relatively simple activities, such as drinking a glass of water with breakfast, is much easier than forming habits for more difficult activities, such as incorporating an activity like jogging into a daily pattern. Furthermore, Sigurdardottir et al. (2013) revealed the importance of both positive and negative experiences; for example, it was easier for people to make cycling part of their daily routine if they had more positive experiences with cycling when they were young. Trying out new activities can help in adopting new habits, as this experience may show that obstacles that were initially envisioned (for

instance that cycling requires too much effort or is unsafe) turn out to be untrue (Strömberg & Karlsson, 2016). As people in the Netherlands (and many other countries) now have to follow directives to stay at home, many are now forming experiences with new behaviour. These experiences might affect future behaviour, long after the virus itself is no longer a threat. People might for instance prefer to work from home in the future, now that they have experienced what it is like to work from home.

Experiences with these new types of activities and ways of travelling and external factors related to COVID-19 and governmental measures could have an influence on people's attitudes as well. The relationship between attitudes and travel behaviour has been studied extensively and it has been shown that attitudes indeed play a role in mode choice behaviour (Gärling et al., 1998; Paulssen et al., 2014). The influence of attitudes on mode choice behaviour was found to be particularly strong in cases where habit is weak (Verplanken et al., 1994). This is particularly interesting in the light of the current COVID-19 situation, as many people are forced to, at least temporarily, break their habits. It may be expected that attitudes have changed as a result of COVID-19. People might for instance have a more negative attitude towards shared travel modes, due to the fear that they might become infected with the virus when using these modes. If this change in attitudes turns out to be a structural, it might have structural effects on travel behaviour. For instance, people might structurally shift from public transport to car for commuting. Such a shift could have negative consequences in terms of both sustainability and accessibility. To understand possible effects of COVID-19 and the lockdown on travel behaviour in a future without the disease insights are needed into how people are experiencing its current effects and how these experiences relate to travel behaviour and attitudes.

Governments worldwide are facing challenges for the future with regard to their transport system. The high popularity of motorized transport comes with a number of issues such as increased congestion, damage to the environment and human health due to emissions, and reduced liveability of cities. In the EU, road transport is responsible for ≥70% of all CO_2 transport emissions and up to 30% of small particulate emissions in the EU (Alonso Raposo et al., 2019). Furthermore, it is expected that urbanization rates will further increase in the future, with an expected share of 70% of people worldwide living in urban areas by 2050 (The World Bank, 2019). This will not only put more pressure on the transport system as transport demand will increase, it also means that more people will be affected by its negative side effects such as congestion and emissions. To deal with these challenges, governments are looking to not only change the transport system itself, but also the behaviour of its users. In this light, it is important to monitor the temporal changes in travel behaviour due to the coronavirus crisis and assess whether these will result in structural behavioural changes.

This study aims to explore how the coronavirus and related measures affect people's daily behaviour and attitudes in terms of activity patterns, work, education and travel patterns. It discusses the current situation, the changes in daily mobility compared to the situation before the corona virus, and people's expectations for the future. The findings are based on longitudinal data from a representative sample of approximately 2500 Dutch citizens from the Netherlands Mobility Panel (MPN). Using such data makes it possible to study intrapersonal (behavioural) changes. The longitudinal data is combined with additional (partly retrospective) questions to better understand the current behaviour and future expectations. This way, we gain a broad picture of the actual and expected impact on daily travel related behaviour on the shorter and on the longer term.

6.2 Research framework & methods

This study will assess the extent to which the COVID-19 virus and the measures taken by the Dutch government influence people's daily life in terms of activity patterns, work, education, and travel now and potentially in the future after the coronavirus crisis. In this section, the research methods and data collection are presented.

6.2.1 Research framework

Using literature on the relation between external events and behavioural change, a research framework is developed to structure the data collection and data analysis of this research. The aim of this framework is to show how the coronavirus might have affected people's current behaviour, as well as how it might structurally affect future behaviour. In the framework, two separate drivers of behavioural change associated with COVID-19 are distinguished. The first is the impact of the coronavirus crisis on the personal situation. This encompasses, for instance, a change in work situation as businesses are closed as well as the fear of becoming or actually being infected with the virus. The second category are governments measures taken to reduce the spread of the virus, which in the Netherlands at the time of data collection consisted of a so-called 'intelligent lockdown', which was further explained in the introduction.

Both the personal impact of the virus and the government's measures as a result of COVID-19 are likely to have led to changes in behaviour and preferences associated with this behaviour. Preferences here are defined as a broad concept and may for instance be influenced by attitudes or the way people experience certain behaviour. From previous studies it is known that attitudes play a role in determining people's travel behaviour (Bohte et al., 2009). Preferences may directly be influenced by COVID-19 as people might, for instance, prefer to avoid places where keeping 1.5m distance to others is difficult, such as public transport. Preferences may also be influenced through experiences with new behaviour. For example, a negative experience with grocery shopping outdoors in the current situation may result in a lower preference for outdoor shopping. Given that a bi-directional relation between attitudes and behaviour seems to exist (Kroesen et al., 2017), such a negative experience with grocery shopping in itself might again affect this behaviour. Social demographics might mediate these relationships; for example, older people might react differently to the impacts of COVID-19 than younger people.

Both behavioural change itself and preferences towards this behavioural change (as a result of how this new behaviour is experienced) might have an effect on people's expectations of future behaviour (after the corona situation) (Ajzen, 1991; Dean, 2013; Sigurdardottir et al., 2013). People are suddenly confronted with new behaviour, which is, in many cases, different from their 'normal' habits. This may be a trigger for structural behavioural change to take place. When experiences with the current (changed) behaviour are more positive, it is more likely to be reflected in positive expectations regarding continuing the behaviour in the future (Strömberg & Karlsson, 2016). Therefore, we expect a direct relation between people's expectations about their current behaviour, such as their current way of working, and their expectations about future behavioural change. The relationships hypothesized above are graphically presented in Figure 6.1.

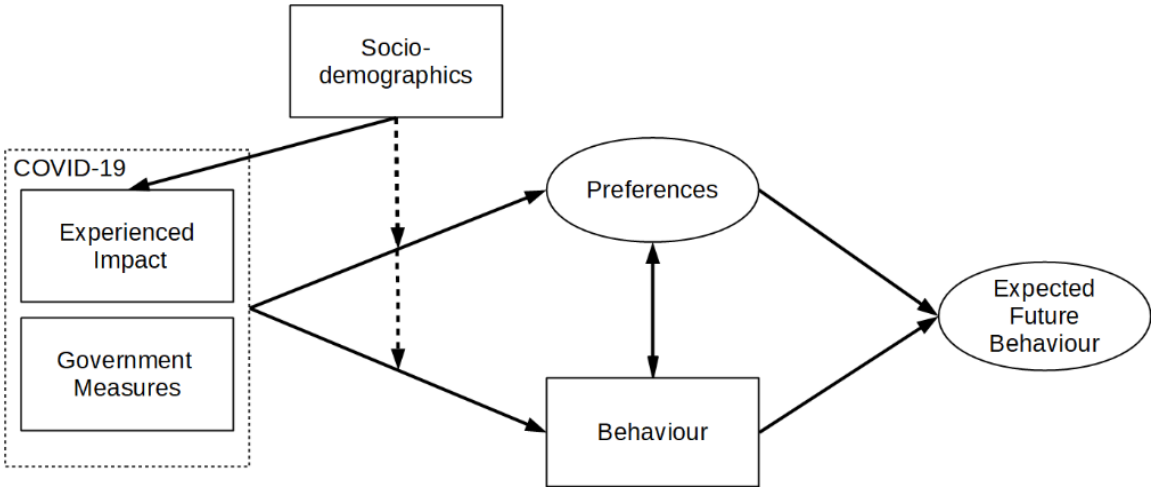


Figure 6.1. Research framework of the impact of COVID-19

This presented research framework could be applied to many research fields, but the interest of this paper is to analyse the effects of COVID-19 on personal mobility in the Netherlands. Mobility here is seen as a derivation from activity patterns. To study this, three relevant categories influencing mobility are identified: outdoor activities, work and education, and travel behaviour. If our outdoor activity patterns change, then our mobility demand will change as well. This research studies both general outdoor activities, like grocery shopping and social contacts, and the more specific activity of work or education. COVID-19 has undoubtedly changed the behaviours and experiences of these activities, if not due to the direct impact of the virus itself then due to the government's measures taken to reduce the spread of the virus. Activity patterns and the current situation of work and education influence people's travel patterns. In addition, preferences for certain travel modes could have changed which also may influence people's travel pattern. The main interest here is to what extent and how people have travelled and what their experiences are. The mode of transport, travelled distances, and attitudes towards modes are particularly relevant here.

It should be stressed that it is not the goal of the present study to test the hypothesized relationships in the framework. The framework has been used to identify topics of interest and to both structure the data collection and data analysis of this research.

6.2.2 Methods

6.2.2.1 Data

To capture behaviour changes, either longitudinal or retrospective data are required. In the present study both types of data are included using the Netherlands Mobility Panel (MPN). The MPN is an annual household panel that started in 2013 and consists of approximately 2000 complete households. Each year, household members of at least 12 years old are asked to complete a three-day travel diary and fill in an extensive questionnaire that includes questions on topics such as work, outdoor activities and (attitudes towards the) use of different modes of transport. Furthermore, every household is asked to fill in a questionnaire about household related characteristics, such as information about household composition and ownership of means of transport. More information about the MPN can be found in Hoogendoorn-Lanser et al. (2015).

For the purpose of the present study, a representative sample of 2800 panel members from the MPN were asked to keep a travel diary for three consecutive days in the week between

27 March and 4 April 2020. A questionnaire was distributed to this group as well. The research framework (Figure 6.1) has been the basis for the data collection for this study. By comparing people's behaviour before the situation with corona and during the situation with corona, behavioural changes are measured. In addition to that, questions are posed about people's experiences with their behaviour in the current situation. Finally, people have been asked about their expectations for their future behaviour after the corona situation.Thereby, the questionnaire included both retrospective and forward-looking questions. It consists of three core components: the first focusing on people's occupation, the second on people's outdoor activities, and the third on people's travel patterns.

The response to the survey amounted to 2296 completed diaries and 2494 completed questionnaires – a net response of 82% and 89% respectively. As respondents already participated in the MPN before, their (travel) behaviour in a time with COVID-19 can be compared directly to their (travel behaviour) before the pandemic. Table 6.1 shows the composition of the sample. In this table, data from the 2019 wave of the MPN are used. The population statistics for some variables, such as occupation, have been affected considerably by COVID-19. The sample used in this study is thus a fairly representative subset of the Dutch population before COVID-19. There is a small underrepresentation of young people and an overrepresentation of people with a high level of education. For the analyses data is weighted on both sociodemographic- and geographical factors.

Table 6.1. Sample composition

Variable	Levels	Sample (%)	Population[1] (%)
Gender	Male	48.6	49.5
	Female	51.4	50.5
Age (years)	12-25	12.1	17.0
	25-44	28.3	28.5
	45-64	35.0	33.1
	65+	24.6	21.3
Main occupation	Unemployed	39.9	40.4
	Employed in public sector	6.9	6.0
	Employed in private sector	39.0	38.9
	Self-employed or entrepreneur	5.7	7.3
	Student	8.6	7.2
Education	Low	24.1	25.1
	Medium	38.5	40.9
	High	37.4	33.9
Urban Density (inhabitants/km2)	<500	7.8	7.8
	500-1000	21.3	21.6
	1000-1500	16.3	15.6
	1500-2500	31.8	30.3
	>2500	22.9	24.6
Household composition	Single	22.2	20.7
	Multiple adults	49.0	46.1
	Family with child <=12	18.8	21.3
	Family with child >12	9.9	11.8

[1]: Population statistics taken from 2019 (MOA, 2019). They therefore refer to the situation before the corona crisis.

6.2.2.2 Analyses

Given the urgent need for information on the impacts of the corona virus on society, the present article will discuss the main findings of the data collection in a mostly descriptive way. Where relevant the effects on experiences, behaviour, and expectations are broken down by

background characteristics, such as age or region. Furthermore, this research uses the longitudinal structure of the data to enable a direct comparison between behaviour measured in the fall of 2019 and behaviour measured during the early stages of the coronavirus crisis in late March and early April of 2020. Retrospective questions are used for these comparisons in some cases where prior information was not recorded in the fall of 2019. These comparative analyses are complemented by a chi-square test, to give an indication of the significance of the differences. To interpret the results, the assumption is made that many of the changes in behaviour between the two measurement periods are a consequence of the coronavirus crisis. However, there may be other reasons for the differences in behaviour between the two periods for individuals, such as changes in weather or life events.

6.3 Results

In this section we discuss the main findings of the study. We start with a few main insights on how people experience the current coronavirus crisis in the Netherlands. More detailed findings are presented in a structure that is based on the framework presented before and the three main themes of outdoor activities, work and education, and travel patterns.

As experiences with the current situation are very subjective, a number of questions regarding impact on both the personal situation and society in general were included in the survey. Generally speaking, the majority of people (>90%) indicate that they think the current crisis will have large, long-term impacts on society. Fewer people (about 50%) perceive a negative impact on their personal situation. Younger people more often experience a negative impact on their personal situation, which contrasts to the initial expectations that the more vulnerable group of elderly people would be most affected (χ^2 (5, N = 2492) = 15.271, p = .001). This can be explained by the fact that this group used to be more active in terms of participating in activities such as sports and going out before the coronavirus. In addition, they are more likely to be affected in terms of work (more flexible and temporary contracts) and education.

On average about 35% of people are afraid to become infected with the virus. Here a clear age effect is observed as well, but now the number increases with age. Only one in five younger people (<25 years) are afraid of becoming infected, while a majority of people older than 65 are afraid (χ^2 (1, N = 2492) = 95.230, p = .001). There are no clear regional differences. About 6% of the respondents think that they have already been infected by the coronavirus. This number is a bit higher in the southern provinces of the Netherlands, which makes sense given that this area of the Netherlands has a higher infection rate as determined by the number of positive tests (RIVM, 2020). We should stress that these findings purely reflect the experience of respondents and may not reflect true infection numbers.

6.3.1 Outdoor activities

Our findings show that the coronavirus crisis has resulted in people of all age groups in the Dutch population to be less active outdoors (Figure 6.2). For example, where in September 2019 15% of the respondents did their groceries outside of their home at least four times per week, this number dropped to about 8% in late March/early April 2020. Especially the number of times that people shop outdoors or visit other people has dropped since the coronavirus reached the Netherlands. Respectively, around 85% and 90% of the people indicate that they do these activities less often.

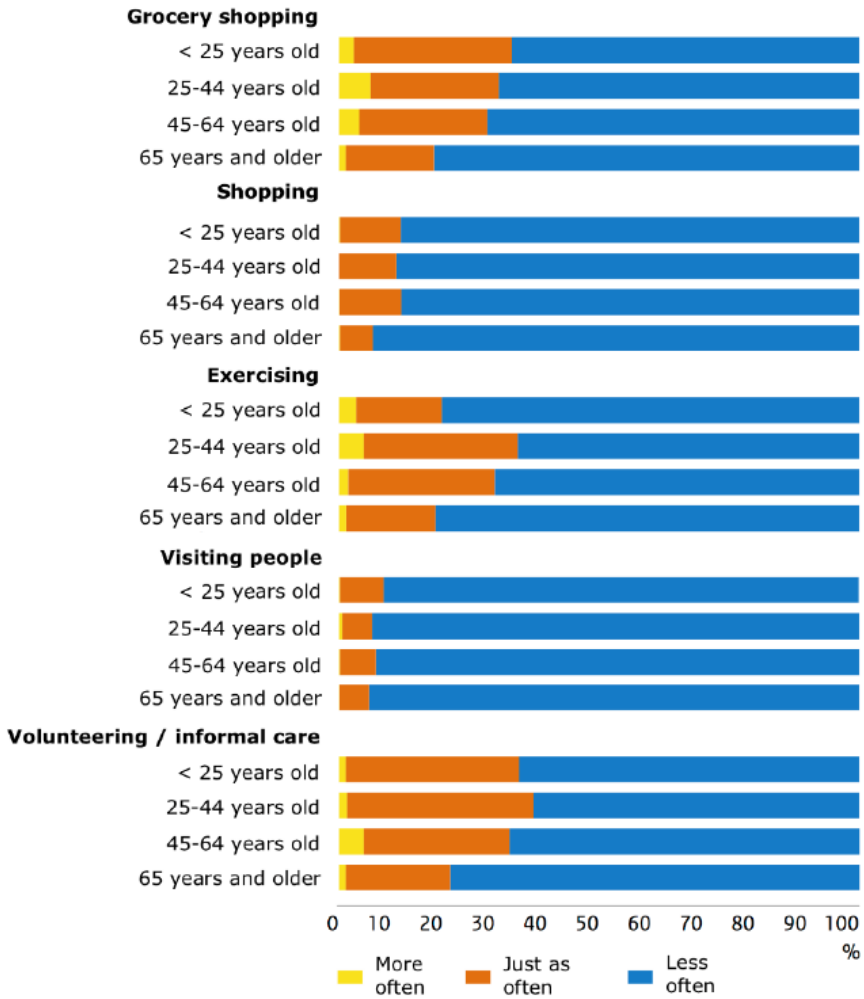


Figure 6.2. Change in outdoor activities since coronavirus crisis, per age group

Older people in particular are much less active than before the crisis (Chi-square tests: grocery shopping χ^2 (2, N = 2492) = 36.411, p = .000, shopping χ^2 (2, N = 2492) = 13.078, p = .001, exercising χ^2 (2, N = 2492) = 28.876, p = .000, volunteering χ^2 (2, N = 2492) = 37.606, p = .001, visiting people not significant). The fact that elderly people are more afraid of becoming infected with the new virus might play a role in this. With regard to outdoors exercise, a large decrease can also be observed for the youngest age group, which might be explained by the fact that this group was the most active before the coronavirus.

Given the fact that the southern provinces of the Netherlands were more affected by the coronavirus than the northern part when our data was collected, it was expected that people in the southern provinces would show a larger drop in outdoor activities as a result of the government's appeal to stay at home as much as possible. On the 31st of March, halfway through our fieldwork, the most heavily affected province in the south ('Noord-Brabant') had almost 7 times more confirmed cases of COVID-19 per inhabitant compared to the least affected province in the north ('Friesland') (RIVM, 2020). However, no clear regional pattern was found, which seemed to indicate that people seem to adjust their behaviour to the situation irrespective of the amount of people infected in their surroundings. The finding that 90% of respondents indicate that the appeal by the government to stay at home is the main reason for the reduction in their outdoor activities is a further confirmation of this explanation. The second most reported reasons, that people do not want to go outside due to the virus itself (reported by about 80% of people) however would seemingly contradict this explanation. Older people (65

years or older) are more likely to name this reason, which makes sense given the fact that they are more afraid of being infected.

More in-depth experiences were collected for two types of outdoor activities, namely grocery shopping and social visits to other people. With regard to doing groceries, a positive finding is that most people (about 80%) experience sufficient possibilities for getting their groceries in the current situation. Perhaps surprisingly, older people are a bit more positive compared to other age groups (χ^2 (4, N = 2376) = 10.312, p = .035). Despite having sufficient access to groceries, most people experience grocery shopping as unpleasant in the current situation. Interestingly, this applies to both grocery shopping outdoors as well as ordering groceries online. By ordering groceries online one avoids a visit to the supermarket, and the associated risk of becoming infected. However, the capacity for delivery of online ordered groceries has turned out to be insufficient to accommodate the sudden increase in demand. Therefore, waiting times were long. This might explain why people experience online grocery shopping as unpleasant. Most respondents then also report that digital solutions for grocery shopping are not a sufficient replacement for physical shopping. As could be expected, especially older people are less positive in this respect, while people aged 25-44 are most positive (χ^2 (4, N = 1814) = 46.437, p = .000). In addition, people in urban areas seem to be a bit more positive compared to people in less urban areas (χ^2 (4, N = 1814) = 21.223, p = .000); perhaps because possibilities for digital grocery shopping are more prevalent in urban areas.

With respect to social visits to other people, the findings show that about 40% of people were not happy about the possibilities for social interaction at the time in which the fieldwork was conducted. The group of people that were still happy with the possibilities for social contact is of about the same size; the rest is neither positive nor negative. No differences are found between age groups or household composition (single households, couples or families). Older people however are currently less comfortable with physical meetings (χ^2 (4, N = 2302) = 15.826, p = .003). Digital alternatives for social interaction were considered to be more convenient than physical meetings for all age groups. Nevertheless, people also indicate that they do not consider digital or online social interaction as a full replacement for physically meeting people.

Although almost all people report fewer outdoor activities, people expect to go back to their behaviour from before the coronavirus when the threat of the virus has subsided. The vast majority of people (>90%) do not expect that the current changes in outdoor activities will continue after the coronavirus crisis (Figure 6.3). This is not entirely unexpected, as it was found that a considerable group of people do not have positive experiences with their current activity patterns. Especially with regard to visiting people, most respondents expect to go back to their previous behaviour. However, people who consider digital solutions to be full replacements of physically meeting people are more likely to expect to also visit fewer people in the future (χ^2 (16, N = 2269) = 391.996, p = .000). The same holds for grocery shopping outdoors for people who are happy with doing their groceries online (χ^2 (16, N = 1354) = 148.590, p = .000) or who think online grocery shopping is a full replacement of outdoors grocery shopping (χ^2 (16, N = 1521) = 143.498, p = .000).

Interestingly, among the people who reported more outdoor activities during the pandemic, expectations about keeping to the new behaviour are higher than people who showed a decrease in outdoor activities. This however entails a small percentage of the total population.

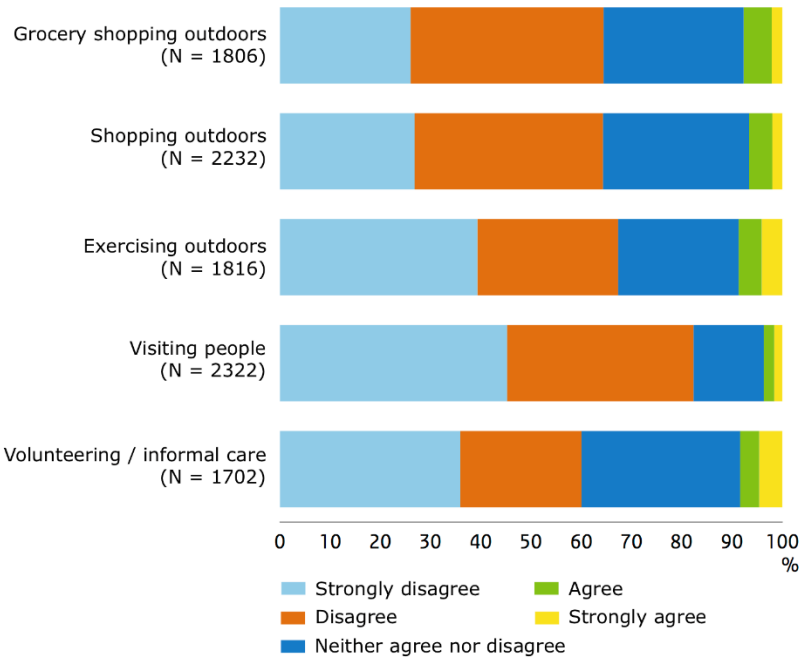


Figure 6.3. Opinion on the statement "I also expect to do fewer outdoor activities after the corona situation compared to the situation before corona."

6.3.2 Work and education

The coronavirus crisis and the government's measures also have a large impact on people's work and educational situation. Schools are closed and people are urged to work from home whenever possible. Furthermore, certain businesses closed completely, such as bars, restaurants, hotels and 'contact professions'. Restaurants were, however, still allowed to open for take-away or delivery services. At the time of our survey, approximately half of the workers indicated that their work situation had changed. Only a small part (1%) lost their job or went bankrupt. Most changes relate to a change in working times (24%) or a reduction in working hours (16%). Approximately 10% of people indicated that they temporarily stopped working. Another part (8%) of workers reported an increase in their working hours. Especially entrepreneurs and employees with a flexible contract are affected by the coronavirus crisis. Entrepreneurs report more changes to their work situation compared to non-entrepreneurs (χ^2 (1, N = 1873) = 13.349, p = .000), and people with a flexible contract reported more changes compared to people with a contract for a fixed number of hours (χ^2 (4, N = 1873) = 150.859, p = .000)). The most important reason for people to temporarily stop working is that their company closed down, followed by receiving less work from their clients or employer. The latter is also the most important reason for people to have decreased their working hours. Note that this information pertains to the week where data was collected. This situation can drastically change, depending on the length of time during which the economy has to be partly shut down to control the spread of the virus.

Aside from the aforementioned changes to employment, number of hours worked, and work schedules, people report changes on how they did their work. Approximately 44% of workers reported that they either started to work from home or increased the hours that they are working from home. In 2019, 6% of respondents reported to work almost all their hours (>75%) from home. This figure sharply increased to 39% in the current situation. Currently, more than half (54%) of all workers work from home at least a part of the week. Physical meetings are also less common, with 30% of workers reporting an increase in remote meetings (for instance by

videoconferencing). Since schools and universities were completely closed nearly all students and pupils need to follow education from their homes. These changes have resulted in a sizeable drop in the number of commuting and education trips, which causes a big change in our mobility system. Estimating the entirety of this impact is outside of the scope of this study, but one thing to look at is which people are more likely to work from home and how they commuted before. One expectation here is that people who normally commute by public transport are more likely to have increased the number of hours they work from home since people were urged to avoid public transport as much as possible. Indeed, results show that this share is, with 69%, significantly higher among workers who usually commute by public transport (χ^2 (1, N = 1425) = 35.655, p = .000).

A somewhat surprising and very relevant finding is that people are in general positive about the changes in the way they have to work. Figure 6.4 shows people's experiences with working from home. Over 60% of people who work from home indicate that this is easy for them. Even more people have a good place to work from home (65%) and sufficient digital facilities (85%). It should be noted that the latter is not surprising as the Netherlands has the highest share of households having an internet connection (98%) in the EU (Eurostat, 2020), while over 90% of households owning a computer (Statistics Netherlands, 2018a). Roughly 40% of the people who worked from home said that they considered themselves as an experienced home-worker before the coronavirus crisis hit the Netherlands. The majority (58%) are thus forming completely new experiences with working from home.

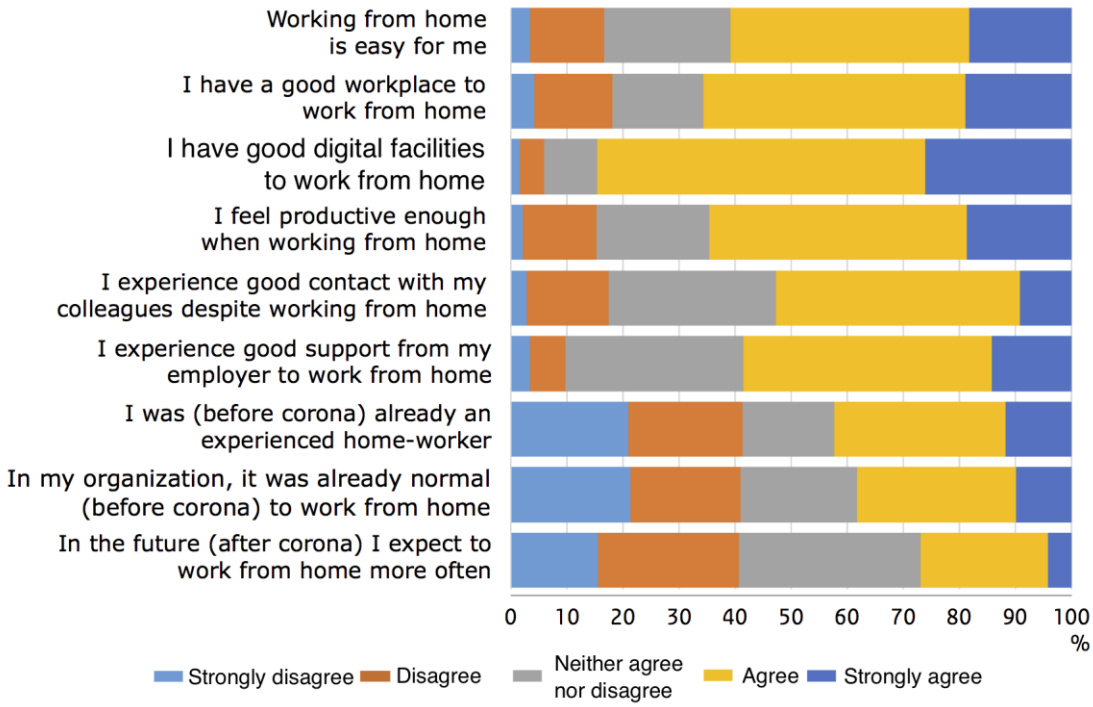


Figure 6.4. Experience with working from home

Similarly to experiences with working from home, over 60% of people who are now having more remote meetings have had positive experiences, with 42% of people considering remote meetings just as productive as physical meetings (Figure 6.5). While just over half of these people (55%) consider remote meetings to be suitable for most types of appointments, almost two thirds (64%) think these types of meetings are particularly suitable for consultation with direct colleagues. For most people, remote meetings are new to them, as only one in five (21%) indicated that remote meetings were already normal within their organization before corona.

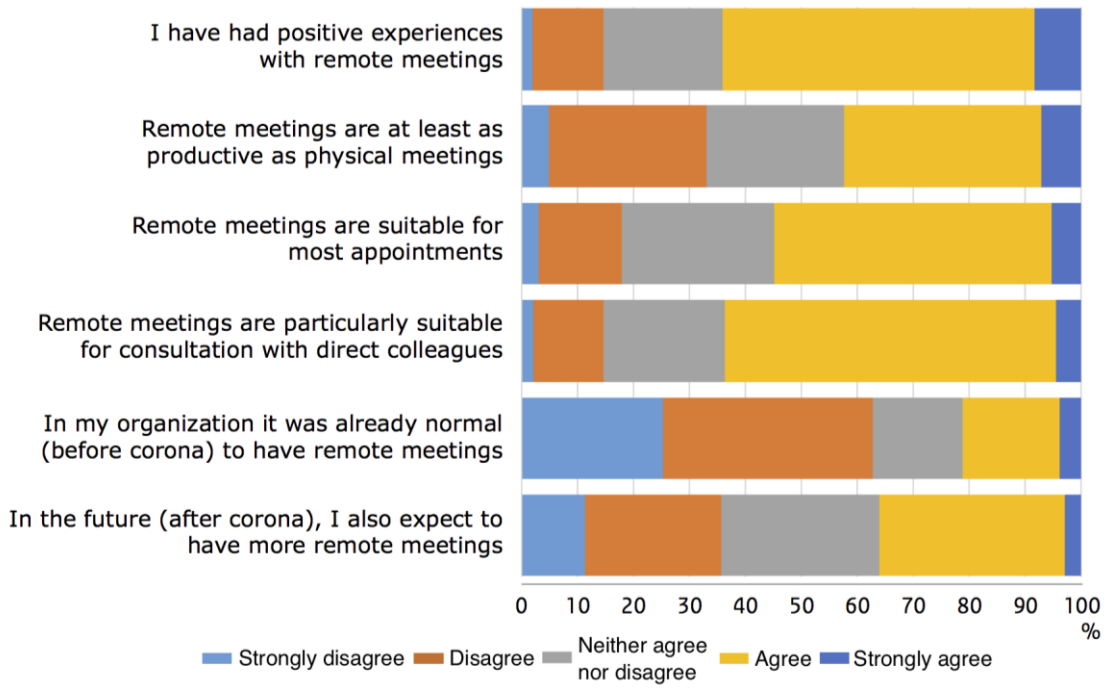


Figure 6.5. Experience with (more) remote meetings

There are some differences between sectors here (difference in working more from home between sectors χ^2 (5, N = 1427) = 164.686, p = .000, difference in increase in remote meetings between sectors χ^2 (5, N = 1427) = 114.751, p = .000). In the sector 'Automation and IT' the number of people working from home increased by the greatest amount. In Healthcare and in Retail, relatively few people have started working from home. Experiences with both working from home and remote meetings also differ per sector, with people from the sector 'Automation and IT' being most positive (difference in experience with working from between sectors χ^2 (20, N = 828) = 49.010 , p = .000, difference in experience with remote meetings between sectors χ^2 (20, N = 451) = 34.443, p = .023). Strikingly people working in the section Education are much less positive, even though they have started to work from home at an only slightly lower rate compared to Automation and IT.

Alongside those in the workforce, younger people are also experiencing major changes in their daily routine as schools and universities had to close down. Students and school pupils are therefore forced to follow lessons at home. Compared to people who work, they are not as positive on their new way of education (Figure 6.6). Only one in three students and school pupils (34%) experiences home education as pleasant. While most have a good working place (76%) and sufficient digital facilities (89%), only slightly more than half (53%) can concentrate on their study or school work.

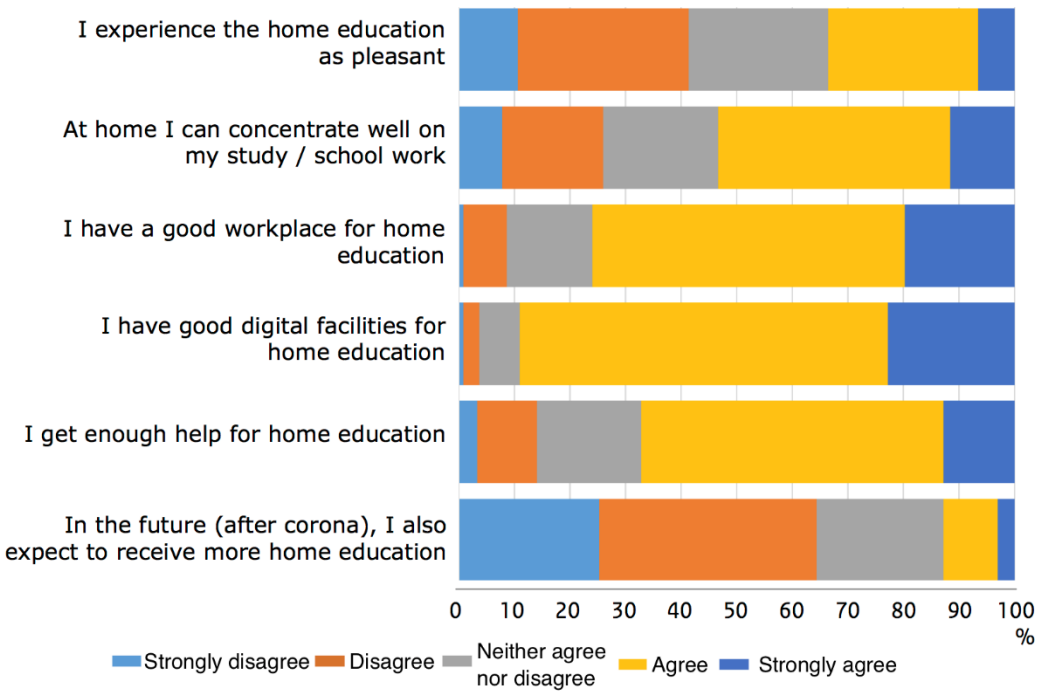


Figure 6.6. Experience with home education

While the vast majority (>90%) of people do not expect that current changes in outdoor activities will continue in the future after corona (as discussed in section 6.3.1), this turns out to be different for the new way of working. Over a quarter (27%) of people who currently work (more) from home expect to work more from home in the future after corona compared to the situation before corona. For remote meetings 36% expect to do this more often in the future. For people who indicated to have positive experiences with working from home or remote meetings, expectations to continue this behaviour in the future are higher (working from home χ^2 (16, N = 869) = 153.774, p = .000, remote meetings χ^2 (16, N = 460) = 150.803, p = .000). If these expectations are realized into actual behaviour, this could result in a significant change within the mobility system, resulting from the structural decrease in the number of commuting and business trips. An important factor in realizing the expectation into actual behaviour is whether employers will allow their employees to also work more from home or have remote meetings in the future.

Expectations of the students and school pupils who are currently following education from their homes are much more moderate. Only 13% of them expect to follow education from home more often after corona than they did before corona. This can be explained by the overall less satisfying experience with home education. While not included in the questionnaire, another important reason for this is likely to be the lack of social interactions with their fellow students or classmates. Finally, students and pupils might have less say over whether they follow their education from home or not, as their schools and universities play a large part in this decision.

6.3.3 Personal travel patterns

The final category of interest are the personal travel patterns and how these have changed because of corona, how people experience their current patterns, and what they expect to do in the future. Findings show that people stay at home for an entire day much more often (with corona) compared to our measurement in September 2019 (without corona). In September 2019,

about 20% of the people stayed home on an average day. In our survey of March and early April 2020, respondents reported no trips in their travel diaries on 50% of the days. Not having to leave home for work or education, the government's appeal to stay at home and the fear of being infected when leaving their home are likely to play an important role in this sharp increase. People who are afraid to become infected stay at home significantly more often compared to people who are not afraid to become infected (53% versus 48%, χ^2 (1, N = 6589) = 16.257, p = .000)

The total number of trips and travelled distance in three days (as the MPN includes a three-day travel diary, these figures are reported for three day aggregates) has then also dropped considerably, with 55% and 68% respectively. The average amount of trips dropped from 8.0 trips to 3.6 trips per three days. All travel modes are affected by this decrease in overall mobility. However, with only a 14% decrease, walking trips are affected the least. The total travelled distance dropped from 94 km to 30 km in three days. The average distance travelled per trip has dropped as well from around 12 to 8 km per trip. Similar to what was observed in outdoor activities and work and education, no clear regional relationship seems to be present.

Relatively speaking, the use of public transport and car as passenger show the largest decrease. For public transport, more than 90% fewer trips are reported, whereas almost 80% fewer car trips as passenger are reported. As a result, the mode shares of these modes in terms of trips also show a considerable drop. By contrast, the share of walking has almost doubled. Figure 6.7 shows the modal split in trips from the travel diaries of September 2019 and the travel diaries of the wave in March and April 2020. This significant drop in public transport use is not unexpected as both the government as well as public transport operators urged people to only travel by public transport if highly necessary. Furthermore, students and people with a higher education, both groups that are generally more likely to be able to study or work from home, often used public transport before the coronavirus crisis.

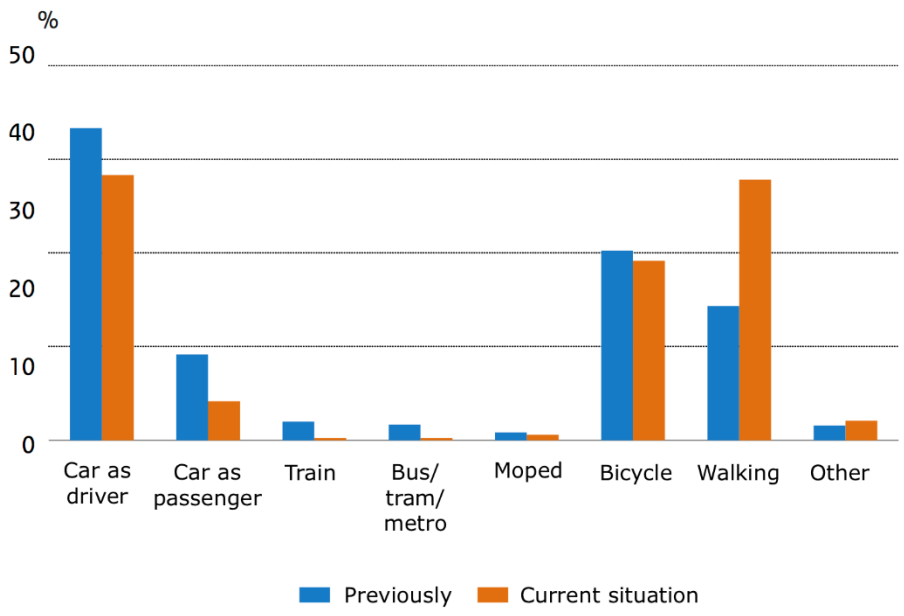


Figure 6.7. Share of travel modes in current situation with corona (in trips)

Because of changes in daily activities, the relative importance of different travel purposes has also changed. While most trip motives show a decrease in share (Figure 6.8), the share of commuting trips is comparable to the situation before the corona virus, meaning that the relative decrease in number of commuting trips is comparable to the overall decrease in number of trips.

Furthermore, only the shares of (grocery) shopping and touring/walking show a significant increase in share, with the share of touring/walking almost quadrupling. It should be noted that touring/walking is the only trip motive with an increase in absolute number of trips.

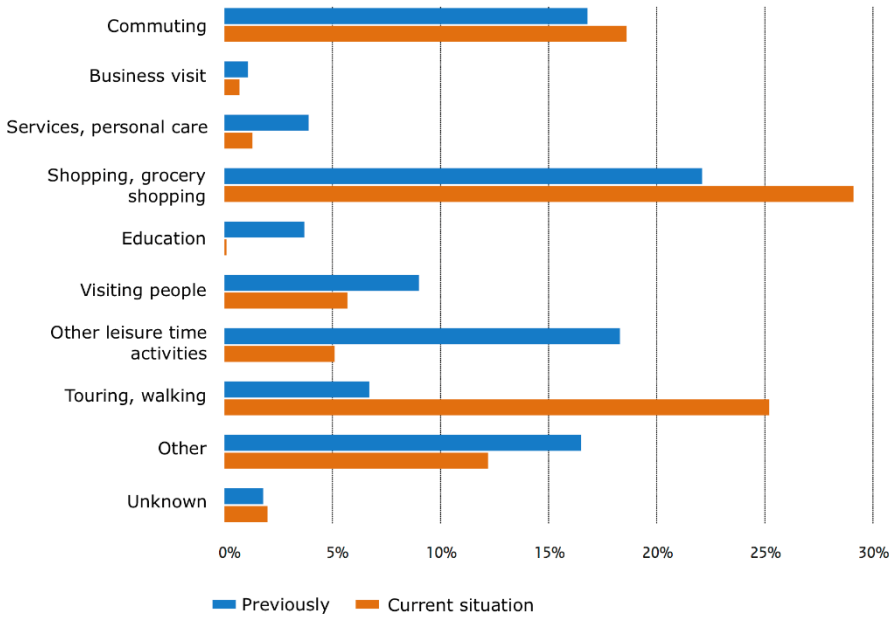


Figure 6.8. Share of trip motives in number of trips

This sharp increase in the share of touring/walking is strongly related to an increase in number of so-called 'roundtrips' (e.g. trips where the destination is the same as the origin, like walking the dog or cycling for recreational purposes). Whereas before the coronavirus crisis approximately one in fifteen trips (7%) was such a roundtrip, this has increased to one in four trips (25%) in the 2020 wave. Absolutely speaking, the number of roundtrips increased by over 70%. Especially the number of cycling and walking tours increased as this is currently the most important reason for a roundtrip. Before the coronavirus crisis, the most important reason for a roundtrip was to walk the dog.

This increase in tours by either foot or bicycle also has an effect on the average trip distance with these modes. While the overall average trip distance decreased from approximately 12 to 8 km, both cycling and walking show an increase in average trip distance. The average distance of a cycling trip has increased by 30%, from 3.3 to 4.3 km per trip. The length of walking trips increased even more with 83% from 1.2 to 2.2 km per trip. This is a result of the increase in relative importance of roundtrips, as we know from previous measurements of the MPN that roundtrips are generally longer in distance compared to more utilitarian trips.

It may be expected that the current situation not only has an effect on travel behaviour, but also a direct effect on attitudes and preferences towards travel modes. As attitudes were already measured in the MPN, effects of the coronavirus crisis on these attitudes can be assessed. Figure 6.9 clearly shows that especially attitudes towards public transport have changed considerably. People were already the least positive about public transport before the coronavirus. In the new measurement these attitudes however dropped even further, as less than 10% of people have a positive attitude towards train, bus, tram or metro. Besides public transport, there is a noticeably increase in the number of people who are very positive towards the car. Attitudes towards the bicycle and walking have not changed. These changes in attitudes are also reflected in the fact

that almost all people (88%) indicate that they currently prefer to use individual modes (like car of bicycle) over public or shared modes of transport. People who are more afraid to become infected have a stronger preference for individual modes compared to people who do not fear of becoming infected (χ^2 (4, N = 2443) = 71.811, p = .000). Whereas 71% of people who are afraid to become infected currently strongly prefer individual modes, only 54% of people who are not afraid say the same.

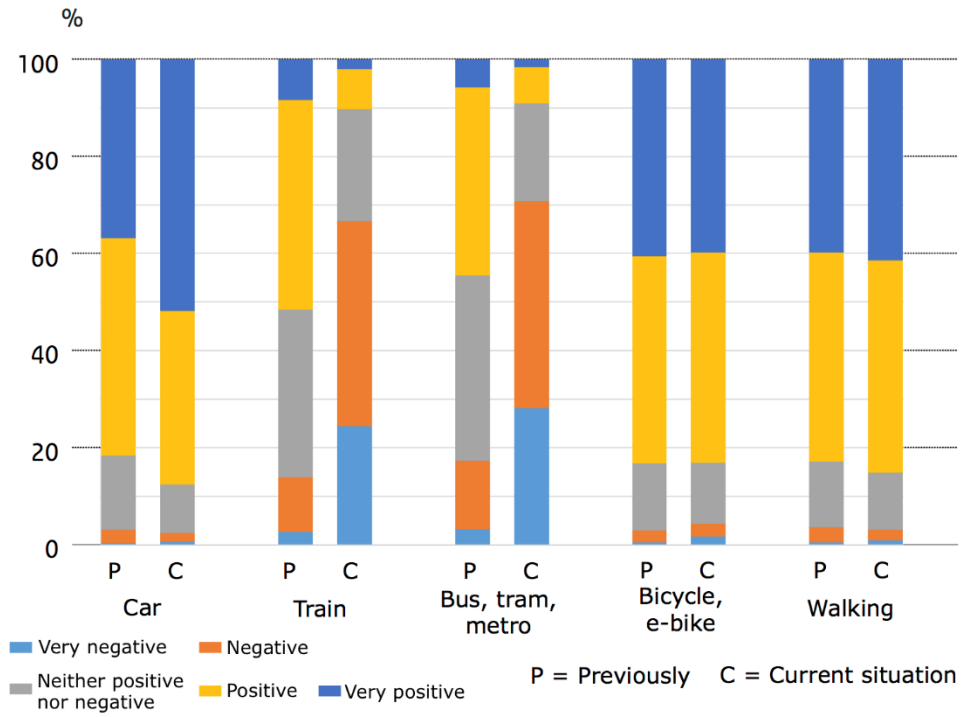


Figure 6.9. Attitudes towards travel modes in situation with corona

Evidently, both travel patterns and attitudes towards travel modes have changed, at least temporarily, due to the coronavirus crisis. The question whether these temporal effects will result in structural behavioural changes remains. Especially the observed changes in attitudes towards travel modes might partly be temporal, as they will partly revert to the pre-corona values when shared transport modes are considered to be safe again. People generally do not expect that the current situation will largely affect their use of travel modes in the future, as approximately 80% of people think they will use all travel modes just as much in the future after corona as they did before corona (Figure 6.10). Others think their mode choice use will change. For public transport there is a larger group thinking they will decrease their use, whereas for the private car more people think they will increase their use. These differences are however less strong than the expectations for the active modes walking and cycling. For cycling, 20% thinks they will increase their use as opposed to 3% who expects a decrease. For walking this is 21% and 5%, respectively. A possible explanation for this expected increase of walking and cycling are the current (positive) experiences. People may find the increase in walking and cycling tours to be a positive experience, which may result in the intention to also do this more often in the future. These effects are measured relatively shortly after the coronavirus reached the Netherlands, so long-term (economic) effects of the crisis were yet very unclear. The aforementioned expectations might change as a result from changes in expectations with regards to the economic effects of corona in the longer term.

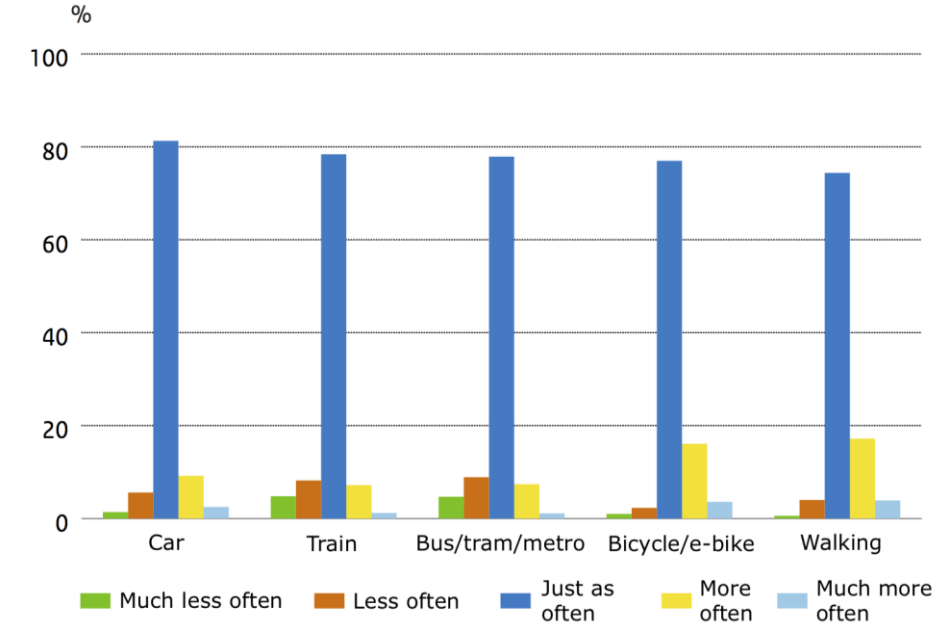


Figure 6.10. Expected use of modes of transport in the future after corona compared to the situation before corona

The impact of the coronavirus pandemic on international travel is even larger than on daily regional mobility. Due to international travel restrictions many airlines have to keep large parts of their fleet grounded. Results from our survey show that 21% of people who have flown before expect to reduce their amount of air travel in the future after corona. Approximately 5% expects an increase in air travel. There seems to be a clear relationship between age and expectations for the amount of air travel in the future as older people expect a stronger decrease (χ^2 (4, N = 1615) = 123.967, p = .000). While just under 16% of people under 65 years old expect to decrease their air travel, 43% of people 65 years or older do. This might be related to the fear to become infected with COVID-19. As the current pandemic showed that being abroad during the outbreak of a pandemic could for instance lead to problems returning home, it might be that older people do not feel comfortable to be dependent on aviation to return home. Another explanation might be that this is the result of older people expecting to fly less because of their age, irrespective of COVID-19.

6.4 Discussion

The main rationale behind this study is that COVID-19 (and the government's policies to stop the spread of the disease) will not only have an effect during the pandemic, but may also have structural, long-lasting effects on travel behaviour and people's mobility. The findings presented in this paper provide some first evidence for this hypothesis. We show that there are major immediate changes in outdoor activities, work and travel behaviour due to COVID-19 and related governmental measures. We also show that people expect that some of these changes will last into a future without an active pandemic, as about 30% of people expect to work more from home, 20% to cycle and walk more and fly less in the future after the coronavirus crisis. Our findings contribute to the literature on life-events, indicating that certain events in someone's life (e.g. relocating to a new home) could have both immediate and structural behavioural effects (Müggenburg et al., 2015; Schäfer et al., 2012; Schoenduwe et

al., 2015). Studying COVID-19 from this angle might prove fruitful, allowing researchers to embed their studies of this new and unique phenomenon into this branch of literature.

However, there are still some uncertainties with respect to our findings regarding potential structural changes. First, whether people will structurally change their behaviour will probably depend on the longevity of the crisis and its economic repercussions. Currently, it is unknown how long government measures will be in place and how they will affect our economy on the longer term. An economic recession may lead to higher unemployment rates, affecting both commuting mobility as well as travel budgets of people for non-commuting trips. Furthermore, as long as people need to keep a distance of 1.5m to others, capacity of public transport will be considerably lower forcing people to stay home or search for alternatives.

Secondly, our method relies on people's self-reported experiences and expectations. People's expectations do not always result in actual behavioural intentions in the future (Ajzen, 1991). These intentions and future behaviour in itself are also influenced by people's ability to change their behaviour irrespective of others. In reality, this ability depends on external factors such as the employer, educational institutions, public transport operators, and others. To what extent people actually change their behaviour and behavioural intention in the future thus remains to be seen. Future measurements are needed to alleviate this concern.

This research has several implications for policy makers. For example, many of the observed changes in behaviour would not have been possible without ICT. People resort to digital solutions for grocery shopping or social contacts, or e-conferencing to work from home. However, this increased importance of ICT in daily activities may have some negative effects in light of the so-called digital divide (Selwyn, 2004). For people who do not have access to these ICT tools or do not own the necessary skills to use them this shift to ICT may result in being unable to participate in these daily activities. In turn, this could lead to some forms of social exclusion (Lucas, 2012). In addition, the present research showed that experiences with these ICT solutions are not always positive. For social contacts for instance, the group that considers digital social contacts as a full replacement for face-to-face contacts is just as large as the groups that does not. The same goes for home-workers. While the majority of workers indicate to have good digital facilities, there is a smaller group without sufficient digital facilities to work from home. For policy makers it is important to address the issue of digital divide that may become larger with an increasing reliance on ICT and address the apparent shortcomings of available ICT solutions to facilitate behavioural changes that rely on ICT.

Furthermore, the results show an immediate shift towards more sustainable behaviour as overall travel decreased, which can be seen as a positive side effect of the government's policies to reduce the spread of the coronavirus. In addition, we observe an increased interest in cycling and walking. On the other hand, when looking at the remaining trips only a fraction of public transport use remains while the relative importance of the car changed only minimally. The latter development does not indicate more sustainable behaviour in the present situation. Policy makers should be aware of the increased preference for individual travel modes as well as the more negative attitude towards public transport because of the corona crisis.

In sum, the extent to which COVID-19 and related governmental measures will have long term positive effects on sustainability needs to be seen. The finding that one in five people expect to walk and cycle more and fly less and over a quarter of home-workers expect to work from home more often in the future after the coronavirus crisis could have positive outcomes in terms of sustainability and health. Nevertheless, people also expect to make as much use of the car and to go back to the same amount of outdoor activities as before the crisis, which would have no positive sustainability impacts in itself. It probably also depends on accommodating policies by national and regional governments (e.g. to stimulate working from home and active mode use

when returning to (a new) normal) whether or not behavioural changes will be structural. From a sustainability perspective, the current exogenous shock might be seen as a window of opportunity for policy makers to realise these desired behavioural changes. On the other hand, the governmental urge to restrict public transport use could result in a (structural) shift from public transport to car. Given these uncertainties, it is important for governments to actively follow the changes in mobility behaviour and the impacts of governmental actions.

6.5 Conclusion

This study aimed to explore to what extent the coronavirus and related governmental measures to reduce the spread of the virus in the Netherlands impact people's daily mobility behaviour and may result in structural behavioural changes. The findings are based on a combination of longitudinal data complemented with (partly retrospective) questions on behaviour, attitudes, and preferences during the coronavirus crisis from a representative group of approximately 2500 Dutch citizens aged 12 years and older who are part of the Netherlands Mobility Panel (MPN).

The Dutch government introduced an "intelligent lockdown", a lighter version of a full lock-down. At the time of this study, people were urged to leave their homes as little as possible and work from home. Furthermore bars, restaurants, schools, gyms and 'contact professions' were closed and visiting people in nursing homes was not allowed. Even though people are urged to stay inside of their home, they are still allowed to move around freely as long as they keep a distance of 1.5m to others. Despite these relatively mild measures, when compared to many other European countries, impacts on all studied aspects relating to mobility are found to be very large.

Our findings show that at the time of the data collection (March/April 2020) approximately 80% of people reported less activities outside of their home. Older people in particular are much less active than before the crisis. Although most people still experience enough possibilities for grocery shopping, roughly 40% of people are unhappy with the restricted possibilities for social interaction. Digital solutions are generally not considered to be a full replacement for meeting people physically. Roughly half of the (previously) employed people faced a change in their work situation such as working less hours or at different times. Furthermore, people and businesses have been able to experience working from their home and remote meetings. Most people report positive experiences with this new way of working. Students and school pupils, however, are mostly not happy with following education from home.

Changes in outdoor activities, work and education as well as the virus itself have impacted people's travel patterns. The amount of trips and distance travelled are reduced by 55% and 68% respectively when compared to the fall of 2019. The use of public transport is impacted the most with a decrease of over 90% of trips. So-called 'roundtrips' gained in popularity. Currently, one in four trips is a roundtrip such as a walking or cycling tour. Besides use of travel modes, attitudes have also changed. A larger share is very positive towards the car, while people's attitudes towards public transport have taken a drastic turn for the worse. This is also reflected in the fact that 88% of people currently prefer individual modes compared to public or shared modes of transport.

In addition, we provide first indications that the drastic shock to daily life may have some structural effects on our mobility even when the immediate threat of the virus has subsided. For outdoor activities, more than 90% of people who currently reduced their outdoor activities do not expect that they will continue to reduce their outdoor activities in the future. However, our results indicate that the coronavirus crisis might have permanently altered the way we work and

travel. More than a quarter of home-workers expect to work from home more often in the future after the coronavirus crisis. For workers who currently have more remote meetings, just over a third expect to continue to hold more remote meetings in the future. Similarly, some structural changes on the way we travel are expected. Roughly 20% of people expect to cycle and walk more in the future. A similar share of people with air travel experience expect to decrease their air travel in the future. These findings show that the coronavirus crisis might turn out to be an external event forming a window of opportunity for behavioural change.

As discussed before, future research could follow-up on this study in several ways. First, there is a need for longitudinal measurements in the future, enabling researchers to measure how expectations, experiences, and behaviour change over time. This allows studying whether people's expectations with regard to changes in activities and travel behaviour will result in actual structural behavioural change after the coronavirus crisis. Second, more in-depth qualitative studies can be applied to better understand how and why people's behaviour is changing because of the coronavirus crisis. Third, the results of this study can be embedded in the broader field of how policies can stimulate desired behavioural shifts (and deter undesired behavioural shifts). For instance, more insight is needed in the role of ICT in behavioural changes. Next to the required ICT developments and policies to facilitate behavioural change, these studies should focus on how it can be ensured that also people without access to the ICT tools or without the required digital skills can still participate in activities that have largely shifted to ICT solutions. Finally, there is a need for international comparison. The coronavirus will have different effects for different countries, based on the amount of cases, governmental policies, and previous behavioural trends. Given the international nature of the coronavirus crisis and the interconnectivity of the globalised world, international studies are needed to further research possible structural effects of this crisis and understand which policies might have caused them.

7 Conclusions and recommendations

In this thesis, I answered several substantive questions related to travel behaviour change on an individual level. I primarily made use of data from the Netherlands Mobility Panel (MPN) as these data offer (new) possibilities to study these kinds of questions. I specifically focused on topics that will help policy makers understand how travel behaviour changes and provide them with knowledge to promote travel behaviour change towards a more sustainable mobility system. I showed how life events influence travel behaviour, how the e-bike may promote a shift towards sustainable travel, how health and active travel are related, how soft-refusers in mobility panels can be identified and lastly, I addressed the effects of the COVID-19 pandemic on travel behaviour. In this chapter, I summarize the conclusions of each of the studies, draw some general conclusions on the use of longitudinal data and discuss policy implications. Finally, I reflect on the studies and present recommendations for future research.

7.1 Conclusions

7.1.1 Conclusions study 1: The effect of life evens on daily travel patterns

The first study aimed to answer the following research question:

How do life events (e.g. having a baby or moving house) interact with previous behaviour in shaping new behavioural patterns?

In the first study, we estimated latent class- and transition models using the first three waves (2013-2015) of MPN data to reveal different travel patterns and assess the effect of life events and other exogenous variables on transitions between these travel patterns. The latent class model identified six different meaningful and distinguishable travel patterns: a strict car class, a car and bicycle class, a bicycle class, a car and walk class, a low mobility class and a public transport class.

With a latent transition model we studied transitions between these travel patterns over time. The transition analysis confirms findings by other studies (e.g. Chorus and Dellaert (2012) and

Gärling and Axhausen (2003)) that travel behaviour is inert. In addition, unimodal travellers show a higher probability of remaining in the same travel pattern, compared to multimodal travellers, regardless of any life events. Furthermore, all identified travel patterns show a very low probability of transitioning towards the public transport travel pattern. To answer our research question, we assessed the interaction between the transitions between travel patterns and six life events (change in number of adults living in the household, birth of a child, changing jobs, stop working, starting or changing an educational programme and a residential move).

For a decrease in the number of adult household members, public transport users are most strongly affected. They show a strong increase in the probability to transition to a more car dependent travel pattern. Furthermore, people with a low mobility travel pattern before this event show an increased probability to adopt the bicycle travel pattern. After an increase in the number of adults within the household fewer effects are found in terms of changes between travel patterns. This finding is in line with other studies (e.g. Beige and Axhausen (2012) Oakil et al. (2011)).

The overall effect of changing jobs is a shift towards a more car-dependent travel pattern. While the probability to adopt a strict car travel pattern increases, the probability to adopt (or remain with) the car and walk pattern decreases. Only for people with a public transport class it was found that their probability to transition to a more car-dependent class decreases. It has to be noted that for the public transport class some unexpected results were found, as the probability to adopt a low mobility travel pattern increases after changing job. When people stop working opposite effects are found, as car-dependency tends to decrease. This is the only life event for which we found that strict car users have a higher probability to adopt another travel pattern, mainly a car and bicycle pattern or a low mobility pattern. People with a car and bicycle travel pattern show more transitions towards the bicycle class (and thereby reducing their car use) after the stop working. Public transport users mainly show an increase in the adoption of the low mobility travel pattern, while people from the remaining travel patterns (car and walk and low mobility) become more inert and tend to keep the same travel pattern.

The effects of a residential move is also different for people with different travel patterns. This life event has little effects on people with more unimodal travel patterns (the strict car and the bicycle pattern). While people with a car and bicycle class show an increase in the probability of becoming a strict car user, people from the car and walk pattern shows a strong increase in the probability of adopting a low mobility or public transport travel pattern. One explanation of finding these different effects could be that a residential move is included as a single variable, while it can be expected that the effect of moving from a rural area to an urban area will have a different effect than a move from an urban tot a rural area or move to an area with the same level of urbanization, something that was also shown by Clark et al. (2014) and Prillwitz et al. (2006). It was, however, found that over 85% of the respondents moved to an area with the same level of urbanization, which makes it difficult to explicitly model the effects of a change in the level of urbanization.

After the birth of a child, all classes show an increasing probability of becoming a strict car user. All classes also show an increase in the probability of becoming a member of the car and walk class, in accordance with results found by Scheiner and Holz-Rau (2013). Apparently, people see the car as one of the few suitable means of transport with a baby. This might indicate that people are not well informed about the possibilities of travelling by bicycle or public transport with a baby.

The start or change of education increases the probability of becoming a public transport user for most classes. This is an expected result, since students are provided with a free public

transport card in the Netherlands. The low mobility class shows the greatest changes. The probability of remaining in the low mobility class decreases from 69% to only 17%.

Overall, we can conclude that changes in travel patterns occur more often after a life event, while the effects can be different dependent on the travel pattern before the life event. In general, unimodal travellers are less affected by life events than multimodal travellers. Since changes in travel behaviour occur more often after a life event, this may indicate that these events are 'windows of opportunity' for policy makers to change travel behaviour.

7.1.2 Conclusions study 2: The e-bike: a new technology that may promote a shift towards sustainable travel

In this second study, we answered the following two research questions:

1. *To what extent does the use of the e-bike substitute the use of other modes on an individual level?*
2. *Which homogenous groups are present within the e-bike population and how do these groups develop over time?*

To answer the first research question, we made use of five waves of the MPN (2014-2018). A Random Intercept Cross-Lagged Panel Model (RI-CLPM) was estimated to assess substitution effects between travel modes on a within-person level. The results show that overall, that the e-bike only has a significant substitution effect on the conventional bicycle. This result contrasts results obtained in previous studies, as they often conclude that the e-bike not only substitute the conventional bicycle but also the car and public transport (e.g. Jones et al. (2016) and Kroesen (2017)).

Substitution effects turn out to be dependent on trip motive, as different results were found when estimating separate models for different trip motives. When only assessing commuting trips, the results show the e-bike not only substitutes the conventional bicycle, but also the car. Apparently, for commuting trips people see the e-bike not only as a replacement for the conventional bicycle but also for the car. For both leisure and shopping trips, the e-bike turns out to only be a significant substitution for the conventional bicycle.

Although the main interest in this study is on the substitution effects of the e-bike, the study also provided insight in substitution effects between other modes. For commuting the car acts as a substitute for the train, while the conventional bicycle stimulates walking and walking stimulates train use. For leisure trips, there are substitution effects of the car on the conventional bicycle and BTM on walking. Furthermore, there is a positive effect of walking on car use. A possible explanation of this somewhat unexpected effect may be that people use the car to drive to a destination where people make a leisure walking tour (e.g. a forest). For leisure trips, walking substitutes the e-bike to a certain extent and BTM substitutes the conventional bicycle. Lastly, train use for leisure purposes has a positive effect on the number of walking trips.

Our finding that the e-bike is only substituting the conventional bicycle at a general level (i.e., combining all trip purposes), raises the question whether the e-bike has a positive effect on the environment, road congestion and health. Although there are no emissions while using the e-bike, there are charging-related emissions, making the e-bike less environmentally friendly compared to the conventional bicycle (Otten et al., 2015). With regards to health, several studies have shown that using an e-bike can be regarded as physical activity, but the level of intensity is lower compared to a conventional bicycle (Bourne et al., 2018).

To answer the second research question, five years (2013-2017) of the Dutch national travel survey (OViN) were used to estimate a latent class model. Groups within the e-bike population

were revealed using five socio-demographic variables (gender, age, education level, work status, household composition). The analysis showed that we can distinguish five meaningful groups.

The first and largest class (53% of the sample) represents the retired older leisure users. This group is comprised of the traditional e-bike users, with virtually everyone in this group aged 65+. This group's average age is 72 years old. Consequently, nearly everyone in this group is retired. This user group primarily uses e-bikes for leisure or shopping purposes.

The second class (20% of the sample) represents the middle-aged full-time working people. These users are considerably younger than those in the first class, with an average age of around 53 years old. Most of the people in this group have full-time jobs (78%), which is also reflected in the relatively high share of work-related trips in this group.

The third class (14% of the sample) represents mostly female and relatively older leisure users. This third group consists primarily of women aged between 50 and 65 years old. This group consists almost equally of people with part-time jobs and people who are primarily homemakers. Similar to the first class, this group mainly uses e-bikes for leisure or shopping purposes.

The fourth class (11% of the sample) represents the younger part-time working women with children. This group is largely comprised of women. With an average age of 46 years old, this group is relatively young compared to the previous groups, with most of the people in this group having part-time jobs. Notably, over 80% of the people in this group reside in households consisting of two adults (partners) with children. This group uses e-bikes for work-related trips, as well as for leisure and shopping purposes.

The fifth and smallest class (1% of the sample) represents students and pupils. This group largely consists of teenagers: 94% of this group is aged 12 to 20 years old. Given this group's young average age, the group includes a high proportion of lower educated people. Moreover, 90% of the people in this group are high school or college students, which is also reflected in the fact that people in this group frequently use e-bikes for education-related purposes.

As we used five years of data from the national travel survey, we can compute the absolute sizes of the five groups for each of the five years. Between 2013 and 2017, the total number of e-bike owners in the Netherlands grew from approximately 1.2 million to over 2 million people, an increase of 74% as shown in Figure 7.1. The two groups with the oldest users, the first and third group, show a slower growth rate of 50 and 39% respectively. As a result, the shares of these two groups (compared to all e-bike owners at one point in time) declined over the years. While the first group had a share of just over 56% in 2013, the share in 2017 was just under 49%. The share of the third group decreased from 15% to 12%. For the other three user groups, a higher growth rate is visible. These three groups all more than doubled in five years. Relatively speaking, the younger part-time working women with children (group 4) is growing the fastest.

Although no data is available after 2017, it is not expected that these trends will suddenly change. Therefore, it is expected that the three younger groups (group 2, 4 and 5) will keep growing at a higher rate. As these groups use the e-bike primarily for commuting or education, the shares of these trip purposes will keep growing. Furthermore, it is likely that substitution effects will become more evident due to these trends. If more people start using the e-bike for commuting, it is likely that the substitution effect that e-bike trips have on car trips can also be observed on the general level.

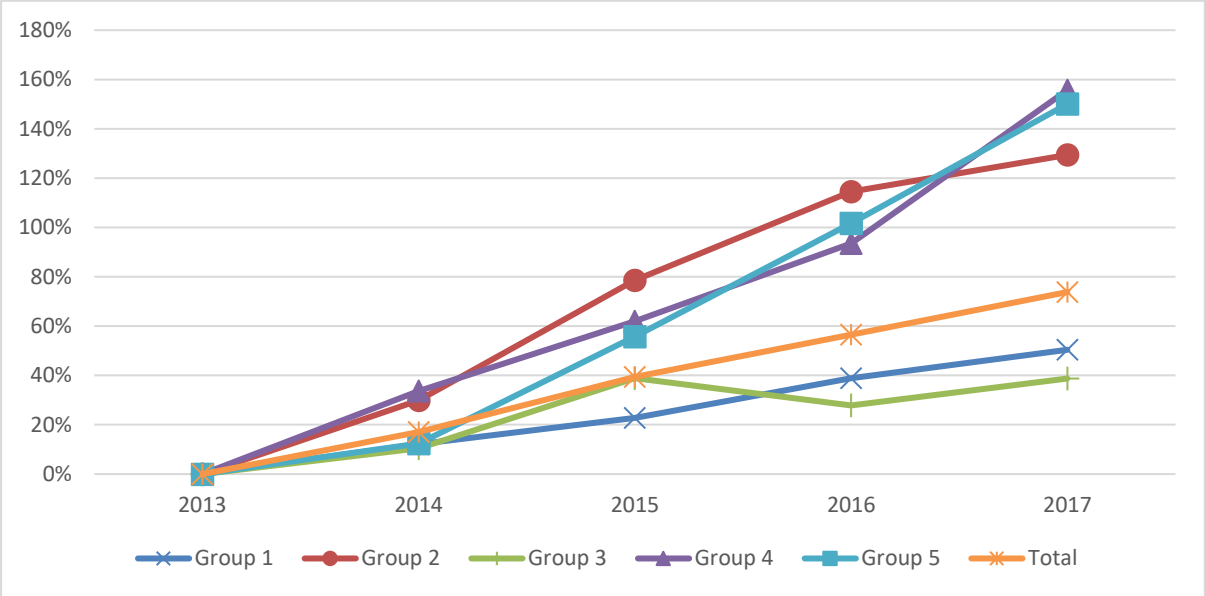


Figure 7.1. Growth of e-bike user groups compared to 2013

7.1.3 Conclusions study 3: Active travel and increasing overweight and obesity rates

In the third study we answered the following research question:

To what extent do active travel (bicycle, e-bike, walking) and health (body-mass index (BMI) and self-rated health (SRH)) influence each other over time?

To answer this question, we started with an initial assessment of the relationships between active travel and the two health outcomes (BMI and SRH) by estimating multivariate linear regression models for travelled distances and number of trips with active modes. In this study, we made use of three years of data from the MPN (2017 – 2019). While these regression models do not show how active travel and health influence each other time, they do show how active mode use is different between people with different BMIs and SRH while controlling for relevant variables.

The regressions models show that there is a clear relation between the two health outcomes and active travel. People who are overweight or obese make fewer trips and travel less distance by bicycle. For instance, while people in our sample make 1.4 cycling trips over a distance of 3.9 km in three days on average, obese people make on average 0.56 fewer trips and cycle 1.47 km less compared to people with a healthy weight. Similar relationships are found between the BMI and walking, with the only difference that overweight people do not make significantly fewer trips on foot compared to people with a healthy weight.

While these results suggest that, in line with literature, people with a higher BMI make less use of active modes, this does not hold for the e-bike. Obese people make more trips by e-bike compared to people with a healthy weight. The difference in travelled distances is not statistically significant, indicating that the extra trips on e-bike by obese people are likely to be relatively short trips. This difference in e-bike use raises the question whether obese people make more use of the e-bike because of their weight (since the e-bike provides them with a relatively easy method of active travel) or that the e-bike use contributes to a higher weight (because the physical intensity might be lower compared to a non-electric bicycle).

To assess whether active travel and health influence each other over time, we estimated twelve separate RI-CLPMs resulting from the combination of two indicators of active travel (distances

and trips) with three active modes (bicycle, e-bike and walking) and two health outcomes. The results show that there is a small, but significant negative effect of walking distance on BMI among non-obese people. This result indicates that when people increase their walking distance per three days with 10 km, this results in a decrease of their BMI by 0.16 in the following year. For someone of 1.80 m tall, this translates to 0.52 kilogram of weight loss. A similar (negative) effect is not found for obese people.

The effect of active travel on BMI is not present for cycling. For cycling, a reverse effect is found among non-obese people. That is, an increase in the level of BMI in one year results in a decrease in bicycle use in the next year, both in travelled distances and trips. No such effects are found in the obese group. Also between e-bike use and BMI no significant effects are found.

Between active travel and SRH only one statistically significant positive relationship is found for the effect of cycled distance on SRH , indicating that an increase in the travelled distance by bicycle in one year results in a more positive SRH in the next year.

In conclusion, our results indicate that promoting active travel may only result in a slight decrease of BMI through an increase in walking. The reverse negative effect of BMI on cycling implies that the increasing overweight and obesity rates may have a negative effect on cycling levels. Formulated positively, if policy makers succeed in reducing obesity levels (e.g. through better diet), the results indicate this may increase levels of active travel.

7.1.4 Conclusions study 4: Identifying soft-refusal in (longitudinal) travel behaviour surveys

In the fourth study we answered the following research questions:

1. *How can soft-refusal be identified in (longitudinal) travel surveys and to what extent is soft-refusal correlated with reported immobility?*
2. *To what extent is soft-refusal behaviour constant over time?*

We presented three different methods to identify possible soft-refusal in a longitudinal travel behavior panel, based on: 1) predicting out-of-home activity 2) straightlining, and 3) speeding. We used these methods to explore soft-refusal and attrition in a multi-year mobility panel. All methods seem to be able to identify respondents with poor response behavior in a travel behavior context (i.e. a suspiciously high level of reported immobility). While the first method (binary logit out-of-home activity model) is directly aimed at identifying reporting days on which respondents incorrectly report no trips, it was found that also speeding and straightlining in a questionnaire are strongly related to reported immobility in the travel diary. Similar to Kitamura and Bovy (1987) we found that attrition is correlated with reported immobility. Furthermore, we found that attrition itself is an additional indicator of reported immobility in the final wave of participation. In other words, the three presented methods likely do not capture all soft-refusal.

Due to the inability to test effectiveness and reliability of the methods (as the ground truth is unknown), it is not recommended to use just a single method to identify soft refusers as this will likely result in a high number of false positives, i.e. respondents who are wrongfully identified as a soft refuser. A considerable share of MPN respondents who were identified as possible soft refusers, were only identified by a single method, as shown in Figure 7.2. While soft refusers may bias a data set, removing true respondents will also introduce a bias. Since the indicators on soft-refusal in this study are (strongly) related to reported immobility, there is a risk of wrongfully removing respondents who have a low level of immobility. Because people with a low mobility level may be part of a vulnerable group of society (especially if this low

level of mobility is involuntarily), the costs of removing false positives may be higher than keeping false negatives in the dataset. Using a combination of indicators will lower the chance of wrongfully identifying respondents as soft refusers.

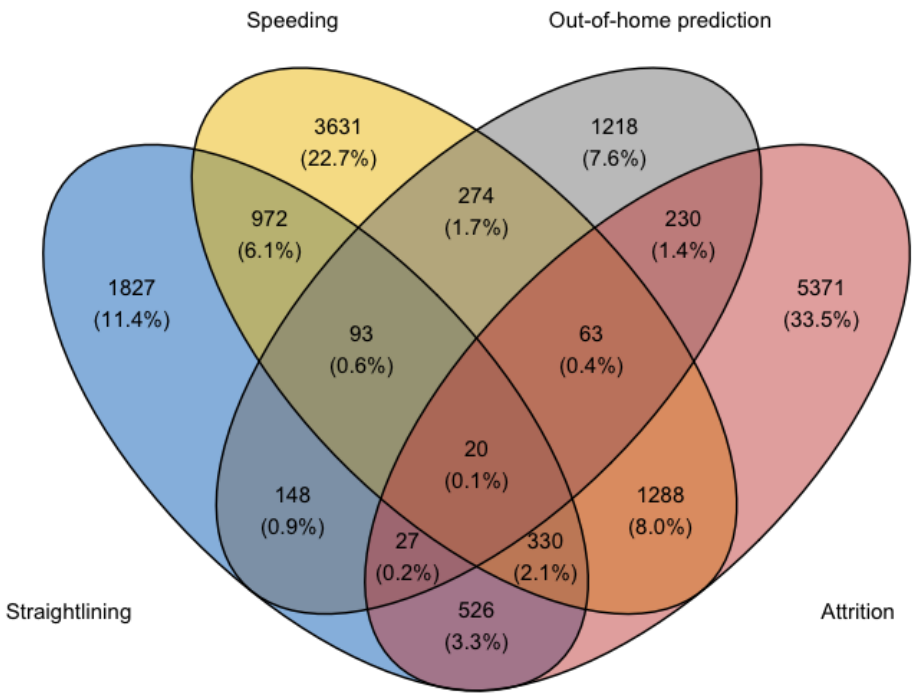


Figure 7.2. Venn diagram of MPN respondents who are identified as a possible soft refuser (n =16,018)

While the Venn diagram visualizes the correlation between the different methods to identify potential soft refusers, it only shows this in a binary way (i.e. respondents are flagged by an indicator or not; it does not show exactly how they score on this indicator). A latent transition model was estimated to reveal different behavioral patterns with respect to the soft-refusal indicators and study transitions between these patterns over time. This analysis showed that there are four distinct behavioral patterns in terms of soft-refusal behavior (plus a fifth class to represent dropouts). The largest class consists of respondents who are overall not identified as a possible soft refuser, followed by a class who seem to be speeding and a class with a higher share of straightlining. While their level of reported immobility is higher than the first class, there are only a few differences in their sociodemographic profiles. Only the fourth class (a high-risk soft-refusal class with a very high level of reported immobility) has a distinct sociodemographic profile. Knowing a priori which type of respondents have a higher risk of showing soft-refusal provides the possibility to account for this by oversampling these groups. In the case of the MPN, that would be young and less educated people.

From the transition analysis we found that only when respondents are identified as possible soft refusers on multiple indicators (the high-risk class), the attrition rate is higher. Furthermore, if respondents do not dropout, they tend to stay in the same class over time. This implies that keeping respondents from the high-risk class in the panel will mainly result in these respondents providing the same poor data quality in subsequent measurements. One could therefore argue to remove these respondents entirely from the panel. However, in the specific case of the MPN, removing a single respondent results in removing the entire household from the panel. Since most respondents from the high-risk class are part of a multi-person household, removing them would simultaneously remove more reliable respondents from the panel.

7.1.5 Conclusions study 5: The effects of the COVID-pandemic on travel behaviour

In the final study we answered the following research question:

How do the COVID-pandemic and the measures to reduce the spread of the virus change activities, work and travel behaviour in the Netherlands?

This study presented first insights on the impacts of COVID-19 and the related governmental measures to reduce the spread of the virus in the Netherlands. To answer the research question, we invited a representative sub-sample of the MPN (approximately 2,500 respondents) to participate in an additional measurement including a questionnaire and the three-day travel diary. Since these respondents were already a member of the MPN before the pandemic, we had reliable measurements of this exact same group of individuals regarding experiences, preferences and behaviour pre-pandemic. To structure data collection and analysis, we developed the research framework as shown in Figure 7.3.

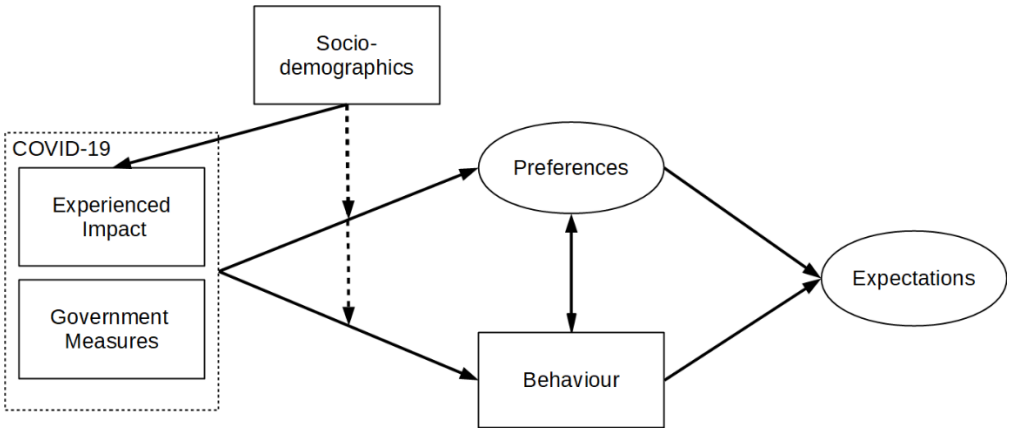


Figure 7.3. Research framework of the impact of COVID-19

While this research framework could be applied to many research fields, the interest of our studied was on the effects of COVID-19 on personal mobility in the Netherlands. We consider mobility to be a derivation from activity patterns. We identified three relevant categories of activities that may have been influenced by the pandemic and as a result have an effect on mobility: outdoor activities, work and education, and travel behaviour.

The results showed that approximately 80% of people reduced their activities outdoors. Older people in particular were much less active than before the crisis. Although most people still experienced enough possibilities for grocery shopping, roughly 40% of people were unhappy with the restricted possibilities for social interaction. Digital solutions were not considered to be a full replacement for meeting people physically. Roughly half of the (previously) employed people faced a change in their work situation such as working less hours or at different times. Furthermore, people and businesses had been able to experience what it's like to work from home and have remote meetings. Most people reported positive experiences with this new way of working. Students and school pupils, however, were mostly not happy with following education from home.

Changes in outdoor activities, work and education as well as the virus itself impacted people's travel patterns. The amount of trips and distance travelled were reduced by 55% and 68% respectively when compared to the fall of 2019. The use of public transport was impacted the most with a decrease of over 90% of trips. So-called 'roundtrips' gained in popularity. One in four trips was a roundtrip such as a walking or cycling tour. Besides use of travel modes, attitudes also changed. A larger share was very positive towards the car, while people's attitudes

towards public transport took a drastic turn for the worse. This was also reflected in 88% of people currently preferring individual modes rather than public transport.

The shock to daily life that the pandemic caused may have some structural effects on our mobility. While more than 90% of people who reduced their outdoor activities at the time of our study did not expect this behaviour would continue in the future, more people expect structural changes for the way we work and travel. More than a quarter of home-workers expected to work from home more often in the future after the pandemic. For workers who had more remote meetings, just over a third expected to also do this more often in the future. Similarly, some structural changes on the way we travel can be expected. Roughly 20% of people expected to cycle and walk more in the future. A similar share of people with air travel experience expected to decrease their air travel in the future.

In short, the pandemic and the measures to prevent the spread of the virus have a major impact on the activities we do, the way we work and our travel behaviour. In light of the first study of this thesis, we could consider the pandemic a 'life event' with the exception that it occurs for society as a whole and that it is externally induced. The present study gives first indications that the pandemic may have structural impacts on our travel behaviour, although more research is needed to confirm this.

7.2 General conclusions on using longitudinal travel behaviour data

All of the presented studies made use of data from the Netherlands Mobility Panel (MPN). The availability of longitudinal data allows researchers to uncover mechanisms underlying travel behaviour change. As many travel behaviour surveys are of a cross-sectional nature, they do not allow tracking the same individuals through time. While cross-sectional studies show how travel behaviour changes among the population and how several trends in society (e.g. the increasing popularity of the e-bike, or the COVID-19 pandemic) impact travel behaviour on an aggregated level, we need longitudinal data to explain these trends based on changes that take place on an individual level. Using cross-sectional data to explain travel behaviour changes can result in drawing wrong conclusions about the strengths and direction of effects. For instance, cross-sectional data are suited to show how e-bike use is related to car use, but based on these data, it is not possible to determine whether e-bike use affects car use or vice versa on an individual level. To do so, longitudinal data are needed. The studies presented in this thesis highlight several other benefits of using longitudinal data over cross-sectional data.

First of all, the study on the relation between health and active travel showed the importance of considering bidirectional effects. Most previous studies on this relationship only considered the effect of active travel on health, while our study showed that there are also reverse effects. Studies (not only related to health and mobility) should at least address the question whether bidirectional effects may exist. This highlights the importance of having longitudinal data, because the direction of effects cannot be determined based on cross-sectional data as we need several measurements of the same individuals over time.

Secondly, the study on health and active travel also showed that is important to distinguish between within-person and between-person effects. The cross-sectional regression models I discussed in that study showed relatively strong relationships between active travel and the two health outcomes considered in the study (BMI and self-rated health (SRH)). However, from the longitudinal analyses I found that most of these relationships do not appear to be present on the within-person level. Based on the cross-sectional analyses the effects between health and travel behaviour would have been largely overestimated.

Furthermore, having a panel with willing-to-cooperate participants in place offers the possibility to study additional topics that are not covered in the regular questionnaires relatively easily. As a lot of information is already known about the respondents (not only their sociodemographic profile, but also their travel behaviour), this allows us to focus specifically on this additional topic, resulting in less time-consuming and complex questionnaires. This possibility is especially highlighted by events such as the COVID-19 pandemic. As the MPN was already in place before the pandemic started, it was possible to quickly start an additional measurement and show the effects of the pandemic by comparing behaviour from this additional measurement with behaviour that was recorded in pre-pandemic measurements.

Although this thesis shows that panel data offers several additional possibilities compared to cross-sectional data, this does not mean that cross-sectional surveys should not be conducted anymore. It mainly shows that panel studies and cross-sectional studies have different goals and that they should be used for their intended goals. For instance, since panel studies are relatively costly to operate (e.g. due to a more complex recruitment process and efforts needed to keep respondents in the panel), panels are often smaller in terms of sample size compared to cross-sectional studies. As a result, cross-sectional studies are better suited to draw statistics about yearly mobility on an aggregated level and observe trends on an aggregated level. To explain these trends based on travel behaviour changes on an individual level, panel data is needed. Therefore, an ideal situation is to both have a large-scale (repeated) cross-sectional travel behaviour survey and a travel behaviour panel available.

This thesis also shows that there are some challenges when using data from a (longitudinal) travel behaviour survey. The study on identifying soft-refusal shows that a (small) part of respondents will apply a strategy when participating to a (travel behaviour) survey to ease their response burden (i.e. soft-refusers) which may bias the data. Since the ground-truth is usually not known, these strategies may go unnoticed when processing the raw data from the survey. As a result, at least a part of these soft-refusers remain in the data that are used for research. It is important that researchers are aware of the presence of soft-refusers in their data and put effort into identifying these respondents.

7.3 Policy implications

Policy makers are faced with many challenges (e.g. increased congestion and negative effects on human health due to emissions) to keep their countries and cities accessible, attractive, safe and liveable. The solution to these challenges does not only lie in changing the mobility system itself, but also (and maybe even more) in changing the behaviour of its users. The results in this thesis have several policy implications which I will discuss in this section.

First of all, policy makers should realize that travel behaviour is, on average, relatively inert. In line with previous studies, I found that travel patterns do not change very often and can be considered as habitual. Therefore, the effectiveness of policies aimed at changing travel behaviour may be limited if they are not targeted at specific groups of people. However, there are certain moments when changes in travel behaviour occur more often. I showed that travel patterns change more often after people experience a life event (e.g. birth of a child, or moving house). Apparently, these life events are moments when people reconsider their (travel) behaviour. These life events can therefore be considered as windows of opportunities for policy makers to change travel behaviour. It is likely that people are more susceptible to policy interventions on such moments when they are reconsidering their travel behaviour.

How policy makers can act on life events, depends on the type of life event. While policy makers can be aware of the occurrence of certain life events due to these life events including

interaction with the government, other events may not include this direct interaction with the government. For instance, after people move house, they have to register their new address at the (new) municipality. This moment can directly be used by policy by, for instance, offering free public transport for a limited time, increasing the chance that these people will adopt a travel pattern that included public transport. For other life events, there is no direct interaction with the government and policy makers have to other ways to reach these people. For instance, to act on the life event of changing jobs, policy makers could encourage employers to promote sustainable commuting among their (new) employees.

Another point to learn for policy makers from the study on the effect of life events is that while changes do occur more often after these life events, these changes are not always in the desired direction from a policy point of view. For instance, after the birth of a child or changing jobs, people more often switch to car dependent travel patterns. So, while life events may present windows of opportunities to change travel behaviour, there is also a risk of travel behaviour becoming less sustainable if policy makers do not act on these life events.

From the study on user groups of the e-bike and effects on travel behaviour, some implications for policy makers can also been drawn. As policy makers are striving to promote sustainable travel, the uptake of the e-bike may present an opportunity to further increase active and sustainable travel. From the study, we learned that there are five different user groups of the e-bike with distinct sociodemographic profiles. Apparently, people with these profiles are open to using an e-bike. To effectively promote the e-bike, policy makers could target people with a similar profile who do not own an e-bike yet.

A group that especially deserves attention, is the working population. While on a general level only a substitution effect on the conventional bicycle is observed, I found significant substitution effects of the e-bike on car use for commuting trips. Therefore, policy makers should aim to promote e-bike use among the working population as this will likely result in some mode shift from car to e-bike. In the Netherlands, policy makers already acted on this by implementing a tax measure that allowed employers to provide their employees with a lease-e-bike more easily. Other options to make e-bike use more attractive for commuting are, for instance, by increasing the travel allowance for active commuting, or by making other modes less attractive (e.g. by pricing car use).

The study on health and active travel indicates that policy makers may also be able to promote active travel with policies that are not directly linked to mobility. While the results show that promoting active travel may only result in a slight decrease of BMI through an increase in walking, the reverse negative effect of BMI on cycling implies that policies aimed at decreasing overweight and obesity rates may have an effect on active travel. In light of increasing overweight and obesity rates, policies aimed at reducing the consumption of unhealthy foods and increasing physical activity levels are already in place (Ministry of Health, Welfare and Sport, 2019; World Health Organization, 2016). If these policies are effective in reducing obesity rates, this may result in an increase of cycling. The results of this study also highlight the importance that policy makers of different departments work together as their policy goals may be intertwined.

Although the study on identifying soft-refusal in travel behaviour surveys is mainly of interest for researchers, policy makers should take some lessons from this research. One of the reasons of doing this study was to have the ability to distinguish people who truly show low mobility from people who are wrongly reporting to have a low level of mobility. From a policy point of view, people with a (involuntarily) low level of mobility are an important group, as there may be a risk of social exclusion due to having limited mobility options. Policy makers should be aware of the presence of soft-refusers in travel behaviour surveys. Without correctly identifying

these soft-refusers, there is a risk that (both policy makers and researchers) draw wrong conclusions about how many people experience transport poverty and who these people are.

This research on the effects on the COVID-19 pandemic shows that many of the observed changes in behaviour would not have been possible without ICT. For instance, people resort to digital solutions for grocery shopping or social contacts. However, the study also showed that experiences with these possibilities are not always positive. For social contacts for instance, the group that consider digital social contacts as a full replacement for face-to-face contacts is just as large as the groups that does not. The same goes for home-workers. While the majority of workers indicate to have good digital facilities, there is a smaller group that apparently do not have sufficient digital facilities to work from home. For policy makers it is important to address these apparent shortcomings of available ICT solutions to facilitate behavioural changes that rely on ICT.

Furthermore, the results showed an immediate shift towards more sustainable behaviour as overall travel decreased, which can be seen as a positive side-effect of the governmental measures to reduce the spread of the coronavirus. On the other hand, when looking at the remaining trips only a fraction of public transport use remained while the relative importance of the car changed only minimally. This does not indicate more sustainable behaviour. It is likely that the level of mobility will recover, at least partly, once the pandemic ends or governmental measures are lifted. How the pandemic will structural change travel behaviour will probably also depend on accommodating policies by national and regional governments. Policy makers should therefore aim to design policies that accommodate a lower level of mobility, or more sustainable travel (e.g. to stimulate working from home and active mode use when returning to (a new) normal).

7.4 Reflections and further research

The presented studies in this thesis provided new insights in travel behaviour change. However, many more questions on how travel behaviour changes remain. In this section I will reflect on the presented studies and give recommendations for further research. In the study on the effects of life events on travel behaviour I estimated a latent transition model to show how people shift between travel patterns after several life events. An important drawback of latent transition analysis is the fact that it requires a large sample to reveal significant effects. One of the characteristics of life events is the fact that they do not occur regularly. Since six different travel patterns were identified, the transition matrix consisted of 36 cells (6 initial clusters x 6 future clusters). Because travel behaviour is inert, most people will remain in the same class. As a result, only a limited number of observations is available to compute the off-diagonal probabilities. This is probably the main reason that I only found a limited number of significant effects. As the MPN is continuing the coming years many more observations of life events (and transitions between travel patterns) will be present in the data. It is therefore recommended that this study is repeated using more waves of panel data.

For a number of life events unexpected results or results that are difficult to interpret are found. One important reason for this is probably the fact that a number of life events have different underlying events. For instance, an increase in the number of adults in the household could be because partners started living together, or just because a child turned 18. The first event will probably have a larger effect than the other. To fully understand how life events change travel behaviour and how these life events can be used to promote sustainable behavioural changes, the effects of life events should be studied in more detail. To be able to distinguish more detailed life events, data from more waves are needed. If more data are available, a distinction could be made between, for instance, moving from rural areas to urban areas and vice versa, changing

from a full-time to a part-time job and vice versa, stop working due to retirement and due to involuntarily losing a job et cetera.

Another possible explanation for finding unexpected results is that the effect of life events may be different depending on other factors than the travel pattern before the event. A more recent study by Olde Kalter et al. (2021b), also using data from the MPN, focused on the effects of childbirth, moving home or a new job on travel behaviour among young adults (18-39 years). While there are some key differences between the analyses (e.g., Olde Kalter et al. (2021b) use structural equation models to study the effects of life events on the several trip modes separately instead of considering the entire travel pattern and they use trip frequencies from the questionnaire instead of the trip diaries) part of the results are in line with my study, such as childbirth resulting in an increase in car use. Contrary to my study, they found that moving home results in an increase of bicycle use whereas I concluded that people with a strict bicycle travel pattern are not affected a lot by moving home while people who have a car and bicycle travel pattern tend to shift towards a more car-dependent travel pattern. While these differences could be the result in differences in type of analysis and how mode use is operationalized, it could also be an indication that effects of life events are different among young adults compared to older people. Another indication for this was found in the study by Jin et al. (2020). They showed that the effects of life events are stronger if these events happen earlier in life. It would be interesting to assess whether these apparent interactions between the effects of life events and age (and other socio-demographics) can also be observed when considering the complete travel patterns.

Since I only had three waves of MPN data available at the time of the study on life events, I did not have the possibility to include effects with longer lags than one year or lead effects. It is possible that life events do not only impact travel behaviour on the short term (1 year), but also after a longer time. It could, for instance, be that after a residential move people change their travel behaviour on the short term, but change this behaviour again on the long term as they start to adopt new habits. Including effects with longer lags than one year could reveal such behaviour. Similarly, including lead effects could show whether people anticipate on life events. Modelling lead effects or effects with a longer time lag than one year would require the sample to consist of respondents who participated at least three consecutive waves. Revealing these effects is necessary to determine the best timing of a policy intervention to change travel behaviour when the life event occurs.

Since the e-bike theoretically has great potential to replace many car trips, more studies on this relatively new mode of transport are needed. In the study on the e-bike, I showed that the e-bike substitutes the car for commuting trips. A limitation of that study is that it is unknown why people purchased an e-bike. This is important to know as it has an impact on the potential of the e-bike in terms of substitution effects. It could, for instance, be the case that the respondents that show a decrease in car use due to using the e-bike for commuting already had the desire to reduce their car use for commuting. If people only substitute the car by e-bike if they have this desire, promoting the e-bike among current non-users may have lower usage levels and substitution effects than expected by policy makers. It is therefore crucial to study motivations behind purchasing an e-bike. In general, it can be hypothesized that those who bought an e-bike in ‘early’ years (when the e-bike was relatively expensive) use it more regularly than those who might choose to buy an e-bike in future years (possibly stimulated by monetary incentives from the government). The reason for this hypothesis, is that early adopters willing to spend a considerable sum of money on an e-bike, will most likely have done so based on the expectation that they will frequently and intensively use the e-bike for their personal travel. In contrast, those who currently do not own an e-bike but might be lured into buying one in future years as

they get cheaper (possibly aided by tax-incentives), will be likely to use it less often than those early adopters – otherwise they would have bought one already when prices were higher.

Furthermore, I found that there are five different user groups of the e-bike that are different from each other in terms of sociodemographic and in terms of their purpose for using the e-bike. As these groups differ from each other, it may be argued that the substitution effects are also different for each of these groups. While the latent class analysis (LCA) to reveal these user groups made use of data from the Dutch national travel survey, the MPN includes the same indicators, making it possible to include MPN respondents in the LCA in order to identify to which user group each respondent belongs. Unfortunately, since the MPN is relatively small in sample size compared to the national travel survey, the number of respondents per user group is currently too low to model substitution effects per user group. However, if e-bike ownership is developing at the same rate the coming years, the number of e-bike users within the MPN will also grow allowing for the estimation of the RI-CLPM per user group. It is very relevant for policy-making to understand the effects of the e-bike within different user groups, as this allows targeting policies that promote the e-bike at specific groups where the e-bike is most likely to reduce car use.

Next to substitution effects, it is possible that the e-bike also results in trip generation or visiting locations further away. For instance, it may be that people change the location of certain activities (e.g. shopping) to a location further away when they discover that they can easily cover longer distances with an e-bike compared to a conventional bicycle. Similarly, people may increase the frequency that they undertake certain activities (e.g. leisure trips). It would be relevant to study whether these effects are indeed present. If it turns out that the e-bike indeed results in more time travelling in an active way, this could mean that the e-bike has positive effects on health even though it mainly substitutes the conventional bicycle.

A general limitation of all studies using panel data from the MPN is that they rely on self-reported measures of travel behavior. These measures may be biased due to, for instance, rounding of travel times or over- or underestimating distances (Rietveld, 2001). If we assume that reporting errors are somewhat constant over time (i.e. an individual will always make similar errors when reporting his or her travel behaviour) these errors will not bias a study on changes in travel behaviour over time. However, especially in light of the study on health and active travel this is an important point to address. In this study, also measures on health may be biased, as respondents may under- or over-report their weight and height (Stommel & Schoenborn, 2009). While it is unlikely that such biased measurements lead to biased results (e.g. because we can assume that reporting errors in travel behaviour are not dependent on health status and vice versa), the validity of the results will probably be improved if we would objectively measure active travel (e.g. with GPS and/or accelerometers) and BMI (e.g. with physical measurements of weight and height). Not only would we have more precise measurement, this would also allow us to account for differences in intensity while walking or cycling (e.g. some people walk or cycle at a faster pace than others and some people may always use the e-bike with a higher level of support from the electric motor)

Another limitation of the study on health and active travel is that the available measures on health in the MPN (BMI and self-rated health (SRH)) only give a limited reflection of one's health. For instance, while the amount and distribution of body fat are important health outcomes, BMI does not account for body composition (Wells & Fewtrell, 2006). Future research should include more objective measures of physical health, such as blood pressure, diabetes and amount of body fat. Besides physical health, including other health outcomes such as mental health, psychological well-being, vitality or sick days is necessary to understand the relation between active travel and health.

In the study on health and active travel, I only found limited effects between BMI, SRH and active travel. The study is, however, entirely based on data that was collected before the COVID-19 pandemic started. In many countries, as well as the Netherlands, the pandemic included several periods in which many activities, including sports, were not possible due to (partial) lockdowns. Simultaneously, our fifth study on the effects of the pandemic on travel behaviour showed that the number of roundtrips sharply increased. As roundtrips are usually made on foot or by bicycle, it may be that using active modes became a more important source of physical activity during the pandemic (as many other types of physical activity were not possible). As such, it may be that the effects between active travel, BMI and SRH became stronger during the pandemic (e.g. it may be that active travel became more important in weight maintenance if it became the primary source of physical activity). It would be an interesting avenue for further research to study these links again, based on data that was collected during several periods of the pandemic.

In the study on soft refusal, I presented several methods to identify respondents who have a higher probability of wrongfully reporting to stay at home. However, an important limitation of this research is that there is no possibility to statistically test the effectiveness and reliability of the presented methods in identifying true soft refusers since the ground truth is not known. As a result of the ground truth being unknown, it may be difficult to decide when a respondent is considered to score poorly on a certain indicator (i.e. how fast should a respondent be to be speeding too much and what percentage of straightlining is plausible and/or acceptable). Further research could focus on finding the ground truth in mobility panels. While it would be easy for travel behavior panels to include a question to directly ask whether respondents reported their true travel behavior, this information would probably also be biased as soft refusers might use this question to justify their reported immobility. A possible option would, for instance, be to have respondents self-report their travel behavior and simultaneously passively collect the travel behavior (e.g., with a GPS tracker, or a smartphone app). This research should also study the impact of passively collecting data on the self-reporting of travel behavior (respondents may report more accurate data if they know the ground truth is known). Being able to compare self-reported and passively collected data would provide the possibility to test the effectiveness and reliability of the methods and help in determining thresholds for the methods (e.g., what is the maximum allowed share of straightlining).

Another limitation of the study on soft-refusal is that I mainly focused on the link between soft-refusal indicators and reported immobility, while these indicators may also be related to underreporting of trips. Reporting no trips at all can be considered the most extreme form of underreporting trips, while it may be that the indicators on soft-refusal are also related to less extreme forms of underreporting, i.e., reporting only a part of trips. Further research should study these links.

From the study on soft-refusal, we learned that being a soft-refuser is rather constant over time. Since the MPN is a household panel, removing specific household members is not desirable. A more desirable solution would be to have these soft-refusers transition to a more reliable behavioral pattern in terms of soft-refusal. Further research is needed to study possibilities to achieve this. If it turns out soft-refusal is mainly the result of a lack of interest, the options to motivate these respondents are probably limited. However, if this is not the case, knowing how to motivate this specific group of soft refusers (e.g. with other types of incentives, or with more interaction) would help in solving (part of) the soft-refusal problem.

The study on soft-refusal also raises the question whether researchers should still rely on self-reported data while there are many possibilities to track respondents automatically. As the majority of people own one or more devices that allow tracking (e.g. a smartphone, smartwatch

or activity tracker), shifting towards more passive data collection methods may be promising as it solves some of the problems of self-reported data. For instance, there is no risk of underreporting trips (on the condition that these devices are carried around the whole day) and respondents do not have to estimate travel times and distances. Furthermore, these data may offer new possibilities compared to self-reported studies, such as studying the relation between the built environment and route choice or travel speeds.

However, collecting data completely passive (i.e. with no additional input from the respondent) will not result in data that is suited to study travel behaviour changes. Without input from respondent's, a lot of context information that is needed to explain travel behaviour changes is missing. For instance, information on the individual itself (e.g., socio-demographic characteristics, ownership of transport modes and events that happened in this person's life) and additional info on the recorded trips (e.g. is the respondent the driver or passenger, is this person travelling with others, what specific car is used, is this person using an e-bike or normal bicycle) are needed to uncover the mechanisms underlying travel behaviour change. Therefore, a more viable option seems a more hybrid form, in which trips are recorded automatically (e.g. through GPS), but the respondent's still has to fill out a survey and provide additional information about the recorded trips.

While the use of more advanced data collection seems promising, these new methods also come with new challenges. For instance, the quality and precision of the data may differ between different devices (e.g. different brands or different operating systems). For data to be suited to study travel behaviour changes, it is important that the data is comparable over time and therefore the way the data is collected has to remain constant over time. However, since operating systems of these devices are constantly in development, any changes may impact the data collection. Also, algorithms used with these new data collection methods (e.g. to determine when a trip starts or stops, or when a respondent transfers to another mode) may also be changed over time to improve their accuracy. As a result, it is possible that data is not comparable over time and thereby less suited to study behavioural changes.

In conclusion, there are some clear advantages of using new technologies to (semi-) automatically collect travel behaviour data, but there are also several challenges still to overcome. As these new technologies seem promising, researchers should keep working on improving these methods and solve their shortcomings. For existing panels such as the MPN, switching to another mode of data collection is not an option as the data before and after switching modes would be incomparable. When setting up a new panel, incorporating some of these new technologies to automatically record travel behaviour should at least be considered. In this case, it is important to incorporate it in such a way that it can be expected that the data is comparable over time and not impacted by changes in, for instance, the operating system's or algorithms. An option worth exploring would be to automatically record all trips, but to have respondents validate, and if necessary correct, all recorded trips, the used trip modes and trip motives.

The study on the effects of the COVID-pandemic on travel behaviour was one of the first studies that showed these effects based on panel data. The results showed that the changes in outdoor activities, work and travel behaviour could be, to a certain extent, of a structural nature. Since the study was published, many other studies also showed strong reductions in overall travel in, both in the Netherlands and in other countries (see e.g. Beck and Hensher (2020), (Olde Kalter et al., 2021a), Molloy et al. (2021) and Shakibaei et al. (2021)). More recently, studies show that the pandemic will probably result in a structural lower level of commuting (Beck & Hensher, 2022; Currie et al., 2021), while a structural positive effect may be expected for leisure and maintenance travel (Balbontin et al., 2022; Chen & Steiner, 2022). Recent measurements

with the MPN show that in the Netherlands, expectations regarding working from home and teleconferencing after the pandemic have been very stable between April 2021 and May 2022, indicating that the increased levels of working from home and teleconferencing are likely to remain in the future (de Haas et al., 2022a).

However, an important limitation of studies on the effects of the COVID-pandemic on travel behaviour is that they are based on data when restrictions still applied, or that they rely on people's self-reported experiences and expectations. It is well-known people's expectations are not always turned into actual behavioural intentions in the future (Ajzen, 1991). This might also be influenced by people's ability to change their behaviour irrespective of others. In reality, this ability depends on external factors such as the employer, educational institutions, public transport operators, and others. Further research should study the extent that people actually structurally change their behaviour when all restrictions have been lifted for a longer time and how this relates to expectations people had during the pandemic.

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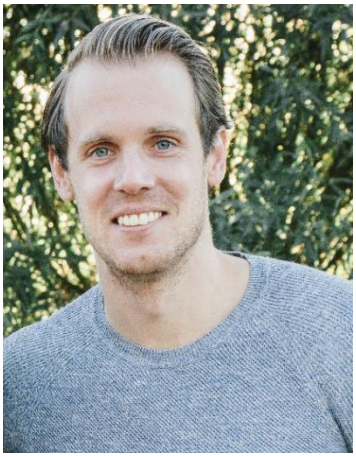
About the author



Mathijs de Haas was born in Haarlem on the 4th of February 1991. After finishing his high school, he joined the Delft University of Technology to follow the bachelor's program Systems Engineering, Policy Analysis, and Management.

In 2013 he finished his BSc program and took a gap year to travel through Asia. In 2014, he started with the MSc program Transportation, Infrastructure and Logistics at the Delft University of Technology. To write his master thesis, he got an internship at The Netherlands Institute for Transport Policy Analysis (KiM), a research institute that is part of the Dutch Ministry of Infrastructure and Water Management. After graduating, he remained at KiM to work as a researcher, with a main focus on person mobility.

After a year of working at KiM, he was offered the opportunity to pursue a PhD as an external PhD student at the Delft University of Technology. In January 2018 he officially started with his PhD.

His research interests are person mobility, active modes (cycling and walking), and analyzing changes in travel behavior using advanced statistical methods.

Author's publications

Journal articles

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de Haas, M., Kroesen, M., Chorus, C., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (submitted). Didn't travel or just being lazy? An empirical study of soft-refusal in mobility diaries

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