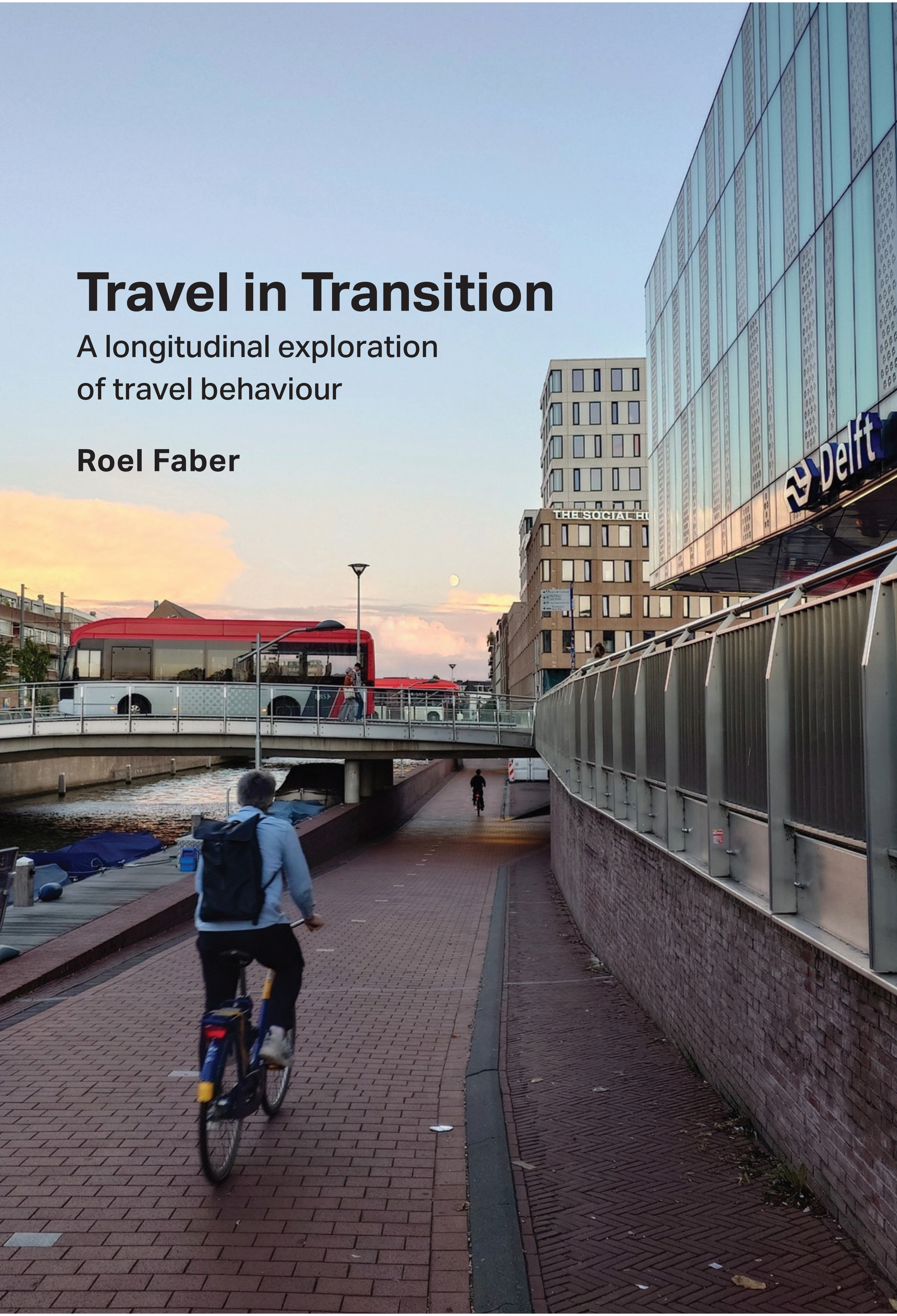
# Travel in Transition

## A longitudinal exploration of travel behaviour

**Roel Faber**



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Roel Faber

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## A longitudinal exploration of travel behaviour

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by

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’If I have seen farther it is by standing on the shoulders of giants’, wrote Isaac Newton in 1675. Although I have no delusions about how my research would compare to Newton’s scientific contributions, I do think the famous quote is not entirely complete.

More than any metaphorical giants, my research is supported immeasurably by all the ordinarily-sized people who are close to me. Without their support and encouragement through the difficult times, as well as their celebrations and cheers when things went well, there would not have been a dissertation for you to read.

I thank them all for their support.

Roel Faber, 27 May 2026, Haarlem

*- Misschien, zegt Qviqstad, is de tijd nabij, dat men computers kan construeren die intelligenter zijn dan de menselijke hersens, zelfs die van de grootste geleerden. (...) Dan wordt de wetenschap een sport. Zoiets als schieten met pijl en boog op een folkloristisch feest, of roeien, of snelwandelen.*

*- Of schaken, zegt Arne.*

*- O nee, schaken niet, want dan zijn er al lang computers die niemand verslaan kan. Of je kunt alle mogelijke combinaties opzoeken in een soort logaritmetafel die door computers is berekend. Alles is tegen die tijd uitgerekend. Goed schaken zou dan een kwestie van geheugen worden.*

*Nee, schaken gaat eruit.*

*Je vraagt je wel af waarmee de mensen zich dan nog zullen amuseren.*

Nooit Meer Slapen (1966), door W.F. Hermans

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# Summary

Travel behaviour and the transport system is a familiar topic for everyone: to participate in activities, we all need to travel to specific locations, such as the office address, the supermarket, or a friend's house. Our travel behaviour is an accumulation of many decisions: from daily choices, such as which supermarket to visit and whether to use the car or the bicycle to do so, to less common decisions, such as whether to accept a new job, change the number of days one works per week, or move to a new place.

The field of travel behaviour research studies how and why people make these decisions. As the nature of the decisions varies wildly, as do the underlying mechanisms, the field is very diverse and multi-disciplinary.

This dissertation uses longitudinal data and statistical modelling techniques to delve deeper into the causal mechanisms that underlie decision-making processes within the realm of travel behaviour. The dissertation aims to contribute to three established research lines in travel behavior research:

1. The possible effects of working from home on travel behaviour
2. Travel-related attitudes, and their relations with travel behaviour
3. The effects of exogenous shocks or levers on travel behaviour

In the first two lines, the direction and strength of the key causal relationship is a subject of academic debate. The present thesis aims to contribute to these lines by using panel data and advanced modelling techniques. The third research line adopts a different approach, namely, establishing the direction of causality by using exogenous variables (the weather and life events). This helps us to provide further information on the strength of these effects and how they differ between different groups or between different travel modes.

**The effects of working from home on travel behaviour**

<u>Study 1: The effect of the COVID-19 pandemic on working from home and travel behaviour</u>

The onset of the COVID-19 pandemic resulted in unprecedented societal changes and government interventions around the world, drastically altering daily routines. In the Netherlands, the government initially implemented targeted restrictions aimed at reducing transmission of the virus, whilst preserving some degree of personal freedom.

Understanding how activity patterns, work, and travel behaviour changed in the short-term is critical for assessing both the immediate impacts of the pandemic on travel behaviour and the potential for longer-term societal changes.

The results show drastic reductions in travel. Between 80% and 90% of respondents reported a reduction in activities, with particularly strong effects among older adults and for recreational purposes such as social visits and shopping. Work and education were moved online, as 44% of the workforce and a large proportion of students were forced to participate remotely in these activities. The aforementioned changes resulted in large reductions in trip frequency (down 55%) and distance travelled (down 68%), with public transport suffering the largest drop in usage. Even though many of these changes were perceived as temporary, a substantial group anticipated longer-term adoption of new behaviours: 27% of workers expected to work from home more post-pandemic, 20% foresaw increased active transport, and a similar percentage expected reduced air travel. The findings underline the impact of COVID-19 and associated policy measures on Dutch mobility and activity behaviour, revealing both immediate disruptions and the seeds of longer-term change.

Study 2: The relations between working from home and travel behaviour

Understanding the relationships between working from home (WFH) and travel behaviour is critical to assessing the potential long-term effects of the increases in working from home during the COVID-19 pandemic on travel behaviour. Using longitudinal data collected both before and during the pandemic, the interactions between working from home and time spent on travelling are studied.

The analysis reveals that increases in WFH hours lead to significant decreases in commute travel time, both before- and during the pandemic. The effect is larger during the pandemic. For non-commute (leisure) travel time, there is some evidence of complementary effects before the pandemic as WFH increases leisure travel time, but these effects are diminished or absent during the pandemic. The strongest reduction in travel time is found among public transport commuters, who were much more likely to substitute commute trips by working from home than those commuting by car or bicycle.

These results confirm a strong effect between increases in working from home and reductions in commute travel time, which is most pronounced for public transport users. The effects during the pandemic are stronger than they were before the pandemic, and we theorize that the 'before'-effects are more likely to align with effects after the pandemic (which we did not estimate). Furthermore, we observed complementary effects before the pandemic as well as positive between-person effects, possibly indicating the existence of rebound effects.

Study 3: The long-term effects of the increase of working from home on travel behaviour

Building upon the results from the two previous studies, we investigated how long-term increases in working from home (WFH) and teleconferencing, brought about by the COVID-19 pandemic, are expected to influence travel demand in the Netherlands.

Findings reveal that only about half of the Dutch workforce has jobs suitable to remote work, primarily among office- and managerial workers with higher education levels. For this group, the increase in WFH and teleconferencing is predicted to lead to a substantial reduction in commute trips, with estimated decreases in commutes ranging from 4% to 26% across the different modes. The expected decline in usage is strongest for public transport commutes, with train commute trips projected to fall by 14–26% and bus/tram/metro commutes by 10–19%.

Car commutes are expected to fall by 7–15%. Business travel is also projected to decrease, by 2–22% depending on mode. The uncertainty range is higher, due to having less available data.

Total travel demand however is not expected to fall as much as commute/business travel, because some of the non-made trips are compensated for by increases in travel for other purposes: a complementary effect that reduces the net decrease in overall travel demand. Long-term increases in working from home and teleconferencing will therefore have a lasting, but relatively moderate negative effect on commute and business travel, particularly during peak hours. Public transport will be affected most severely, which could potentially affect the viability of transit provision if not offset by other demand.

**Travel-related attitudes, and their relations with travel behaviour**

Study 4: The role of travel-related reasons for location choice in residential self-selection

This study addresses the mechanism of residential self-selection (RSS). RSS is a theoretical mechanism, stating that the impact of the built environment on travel behaviour is weaker than bivariate correlations suggest, because travel-related attitudes influence both the built environment and travel behaviour and therefore at least partially account for the bivariate relationship. In this study, we seek to empirically disentangle the roles of general travel attitudes versus specific travel-related location reasons within the context of RSS.

The results suggest that the travel-related location reasons are stronger predictors for built environment location than travel mode attitudes and that the directions of causality between attitudes, travel-related location reasons, the built environment, and travel behaviour often run in both directions. Substantively, our findings indicate that public transport use is most strongly affected by the built environment (after controlling for both stated reasons and attitudes), while car and bicycle use are hardly affected.

This chapter therefore provides empirical support for a conceptual distinction between general travel mode attitudes and specific travel-related reasons for choosing a location in the residential self-selection process. Both constructs are important, but they serve distinct roles: location reasons shape where people choose to live, while attitudes are more closely related to actual travel.

Study 5: Investigating changes in within-person effects between attitudes and travel behaviour during the COVID pandemic

As we have seen previously, the relationships between travel mode attitudes and travel behaviour are empirically estimated to be bi-directional. We investigate this finding in more depth, by estimating the (bi-directional) relationships between travel mode attitudes and travel behaviours across five main transport modes (car, train, bus/tram/metro, bicycle, walking), with a particular focus on how these relationships may have changed during the COVID-19 pandemic. Furthermore, we make a clear distinction between general between-person correlations, using the stable differences between individuals, and within-person effects, using the development of attitudes and behaviours within individuals over time.

The results show significant bi-directional within-person effects between attitudes and behaviour. Positive changes in attitudes towards a specific mode increase the likelihood of greater usage of that mode in the subsequent period, and increased usage also feeds back into more positive attitudes. However, the effect sizes for within-person relationships are systematically smaller than those produced by models which do not allow for this separation, suggesting that much of the observed association is due to stable differences between individuals rather than intra-individual effects. During the COVID-19 pandemic, the structure of these relationships is altered, with temporary disruptions in the strength or direction of attitude-behaviour links, especially for public transport modes. The temporal instability is most pronounced between 2020 and 2021, paralleling substantial pandemic-related changes in both attitudes and travel opportunity structures.

Study 6: Investigating generational differences in travel mode attitudes using latent growth curve trajectories

Understanding how attitudes towards travel modes evolve over the life course and across generations is important for forecasting future travel behaviour. In this study, we model growth trajectories in attitudes towards car use and public transport.

For both public transport and car attitudes, three latent growth classes were identified. For public transport, the growth curve as a function of age was U-shaped: younger and older adults were more positive, while middle-aged adults (minimum attitude at roughly 43 years old) were less positive. For the car, the pattern was inverted U-shaped, peaking at around age 39. Generational differences in class membership were present but less substantial than the age effects. Notably, Generation Z appeared more likely to belong to the group with high positive car attitudes, contradicting narratives of generational car aversion.

Modelling the growth of travel mode attitudes reveals age, cohort and period effects, with relatively small generational differences. There is a non-linear relationship between age and attitudes towards both the car and public transport. The COVID-19 pandemic had a significant but mostly temporary impact on both. The structure and timing of attitude change observed in this chapter provide a foundation for improved forecasting of travel behaviour and inform future research aiming to differentiate age, cohort, and period effects in attitudinal dynamics. Growth models represent a promising advance for understanding—and ultimately anticipating—future trends in the psychological drivers of mobility.

**The effects of exogenous shocks or levers on travel behaviour.**

Study 7: Inferring modality styles by revealing mode choice heterogeneity in response to weather conditions

This study examines how modality styles - meaning the general patterns in individuals' use of different transport modes - moderate the influence of the weather on daily mode choice. It does so by synthesizing the literature on modality style heterogeneity and that on weather sensitivity to assess the variation in mode responsiveness to daily weather across different modality styles.

The results show that three distinct modality styles exist: car mostly, multimodal, and bike+car. 'Car mostly' individuals show relatively low sensitivity to adverse weather. By contrast, the more multimodal other classes are more sensitive, with increased use of car or public transport alternatives on adverse weather days. The influence of the weather on travel is heterogeneous, being stronger among multimodal and active-mode users than it is for car users, with implications for both academic modelling and practical planning under future weather variability.

Study 8: Estimating the effects of life events and changes in mobility tool ownership on mode choice behaviour

This chapter explored the effect of life events (such as changes in employment status and household composition) and mobility tool ownership (e.g., car or bicycle ownership) on mode choice. While life events are often assumed to induce significant behavioural shifts, this chapter investigates the relative influence of such changes compared to changes in the ownership of key mobility tools, using a dynamic, longitudinal approach.

The model identifies two latent classes: 1) a car-dependent modality style and 2) a multi-modal modality style. The transition probabilities between these two modality styles show that, compared to life events (such as a change in household size or employment status), changes in mobility tool ownership exert a much stronger effect on modality style transitions. In particular, acquiring a car substantially increases the likelihood of joining (and remaining in) car-oriented modality styles. This effect is to some degree irreversible, as the effect of losing a car is substantially smaller. Furthermore, buying an electric bicycle is particularly effective in creating a shift towards a multimodal modality style, increasing the probability of using bicycles (including for longer trips) and reducing sensitivity to travel time and distance.

**Conclusions and practical implications**

Some overarching conclusions can be drawn from the combined results of the above studies. These main conclusions are given below for each section, together with their practical implications.

*1. The effects of working from home on travel behaviour*

The first conclusion that can be made is that working from home has had a stronger effect on the use of public transport than on the use of any other mode. There are two reasons why this is the case. First, people who commute by public transport are more likely to work in jobs that are well-suited to working from home. Second, commuting travel is a relatively larger proportion of public transport use than for any other mode. The second conclusion is that working from home does not only result in a reduction of commute travel, but also in an increase of leisure travel.

As a result of these conclusions, it is doubtful whether increases in working from home behaviour have resulted in net-positive effects on the mobility system. For the public transportation system, working from home has led to drastic reductions in overall travel demand. Furthermore, the variability of this travel demand has increased as working from home has concentrated on Wednesdays and Fridays, leaving hyperpeaks on the Tuesdays and Thursdays. These two phenomena are a threat to the profitability of the public transport network and the ability of transit operators to properly invest in high-quality public transport operations.

*2. Travel-related attitudes, and their relations with travel behaviour*

We find that the causal relationship between travel-related attitudes and travel behaviour are bi-directional, and furthermore that the between-person correlations between these two concepts are much larger than the within-person effects. These conclusions seem to indicate that travel-related attitudes do not provide a fruitful pathway for policy makers seeking to change people's travel behaviour. Leaving aside the difficulty of changing attitudes in the first place and presupposing that some policies are effective at changing people's travel attitudes towards certain modes, there are still only very weak effects of these changes in travel-related attitudes on their travel behaviour. Another conclusion of the work is that the differences in travel-related attitudes between newer and older generations seem to disappear after controlling for the effects of people's age. There has been some speculation about younger generations having less favourable attitudes towards the car, but this seems to first and foremost an age-related effect. Policy makers thus should not rely on some innate force driving newer generations to more easily accept car-free lifestyles.

*3. The effects of exogenous shocks or levers on travel behaviour*

The final overarching conclusion is that the travel behaviour of more multi-modal travellers is more sensitive to exogenous variation. Modality styles which revolve around the use of only the car are relatively inert and it is difficult to get people within these lifestyles to use the car less often. A key pathway for policy makers seeking to reduce overall car use therefore is to prevent or delay the switch towards these car-based modality styles. A specific example that seems to offer some potential is the electric bicycle, which resulted in more overall use of the bicycle and a smaller chance to switch towards car-based modality styles. Most likely other policies aimed at increasing the utility of other modes and/or decreasing the utility of the car will have similar effects.

# Samenvatting

Mobiliteit is een onderwerp waarmee iedereen persoonlijke ervaring heeft: om aan activiteiten deel te nemen, moeten we allemaal naar bepaalde locaties reizen, zoals kantoor, de supermarkt of het huis van een vriend. Mobiliteit en reisgedrag zijn dan ook het resultaat van vele beslissingen: van dagelijkse keuzes, zoals welke supermarkt je bezoekt en of je daarvoor de auto of de fiets gebruikt, tot minder frequente beslissingen, zoals het aannemen van een nieuwe baan, het aanpassen van het aantal werkdagen per week of het verhuizen naar een andere woonplaats.

Het onderzoeksveld van mobiliteit en reisgedrag bestudeert hoe en waarom mensen deze beslissingen nemen. Omdat de aard van deze beslissingen sterk varieert, en de onderliggende mechanismen dat ook doen, is het onderzoeksveld zeer divers en multidisciplinair.

Dit proefschrift maakt gebruik van longitudinale data en statistische modelleertechnieken om dieper in te gaan op de causale mechanismen die ten grondslag liggen aan besluitvormingsprocessen binnen het domein van de mobiliteit. Het proefschrift beoogt bij te dragen aan drie gevestigde onderzoekslijnen binnen dit domein:

1. De mogelijke effecten van thuiswerken op reisgedrag
2. Attitudes en hun relatie met reisgedrag
3. De effecten van exogene schokken of hefbomen op reisgedrag

In de eerste twee onderzoekslijnen zijn de richting en sterkte van de belangrijkste causale relaties onderwerp van academisch debat. Dit proefschrift draagt bij aan deze onderzoekslijnen door gebruik te maken van paneldata en geavanceerde modelleertechnieken. De derde onderzoekslijn hanteert een andere benadering, namelijk het vaststellen van de richting van causaliteit door middel van exogene variabelen (zoals weer en levensgebeurtenissen). Dit helpt om meer inzicht te krijgen in de sterkte van deze effecten en hoe ze verschillen tussen groepen mensen of tussen bepaalde vervoerswijzen.

**De effecten van thuiswerken op reisgedrag**

Studie 1: Het effect van de COVID-19-pandemie op thuiswerken en reisgedrag

Het begin van de COVID-19-pandemie leidde tot ongekende maatschappelijke veranderingen en overheidsmaatregelen wereldwijd, waardoor dagelijkse routines drastisch werden gewijzigd. In Nederland voerde de overheid aanvankelijk gerichte maatregelen in om de verspreiding van het virus te beperken, terwijl een zekere mate van persoonlijke vrijheid behouden bleef. Inzicht in hoe activiteitenpatronen, werk en reisgedrag op korte termijn veranderden, is cruciaal voor het beoordelen van zowel de directe effecten van de pandemie op reisgedrag als de potentiële langetermijnveranderingen in de samenleving.

De resultaten tonen aanzienlijke afnames in reisgedrag. Tussen de 80% en 90% van de respondenten rapporteerden een afname in activiteiten, met bijzonder sterke effecten onder ouderen en voor recreatieve doeleinden zoals sociale bezoeken en winkelen. Werk en onderwijs werden grotendeels online voortgezet, aangezien 44% van de beroepsbevolking en een groot deel van de studenten gedwongen werd deze activiteiten op afstand uit te voeren. Deze veranderingen resulteerden in een sterke daling van het aantal verplaatsingen (-55%) en de afgelegde afstand (-68%), waarbij het openbaar vervoer de grootste daling in gebruik kende. Hoewel veel van deze veranderingen als tijdelijk werden beschouwd, verwachtte een aanzienlijk deel van de respondenten blijvende gedragsveranderingen: 27% van de werknemers verwachtte na de pandemie vaker thuis te werken, 20% voorzag meer actief vervoer, en een vergelijkbaar percentage verwachtte minder te vliegen.

De bevindingen onderstrepen de impact van de COVID-19-pandemie en de bijbehorende beleidsmaatregelen op de Nederlandse mobiliteit en activiteitenpatronen, en tonen zowel directe verstoringen als de kiemen van langdurige verandering.

Studie 2: De relatie tussen thuiswerken en reisgedrag

Inzicht in de relaties tussen thuiswerken en reisgedrag is essentieel om de mogelijke langetermijneffecten van de toename in thuiswerken tijdens de COVID-19-pandemie op reisgedrag te kunnen bepalen. Met behulp van longitudinale gegevens, verzameld zowel vóór als tijdens de pandemie, zijn de relaties tussen thuiswerken en reistijd onderzocht.

De analyse toont aan dat een toename in het aantal thuiswerkuren leidt tot significante afnames in reistijd voor woon-werkverkeer, zowel vóór als tijdens de pandemie. Het effect is sterker tijdens de pandemie. Voor niet-woonwerkverkeer (vrije tijd) is er vóór de pandemie enig bewijs voor complementaire effecten, waarbij meer thuiswerken samenhangt met meer vrijetijdsreizen, maar deze effecten zijn tijdens de pandemie verminderd of afwezig. De sterkste reductie in reistijd wordt gevonden onder forenzen die normaal met het openbaar vervoer reizen. Zij zijn vaker gaan thuiswerken dan mensen die met de auto of te fiets naar het werk gingen.

Deze resultaten bevestigen een sterke relatie tussen meer thuiswerken en minder reistijd voor woon-werkverkeer, vooral onder ov-gebruikers. De effecten tijdens de pandemie zijn sterker dan ervoor; vermoedelijk zullen de 'voor'-effecten beter overeenkomen met de effecten na de pandemie (die niet zijn geschat). Daarnaast werden vóór de pandemie complementaire effecten en positieve correlaties tussen personen waargenomen, wat mogelijk op reboundeffecten wijst.

Studie 3: De langetermijneffecten van de toename in thuiswerken op reisgedrag

Voortbouwend op de voorgaande studies is onderzocht hoe de langdurige toename van thuiswerken, veroorzaakt door de COVID-19-pandemie, naar verwachting de vervoersvraag in Nederland zal beïnvloeden.

Uit de resultaten blijkt dat slechts ongeveer de helft van de Nederlandse beroepsbevolking werk heeft dat geschikt is voor thuiswerken, dit zijn voornamelijk kantoormedewerkers en leidinggevenden met een hoger opleidingsniveau. Voor deze groep leidt de toename in thuiswerken tot een aanzienlijke daling in woon-werkverkeer, met verwachte afnames tussen 4% en 26% afhankelijk van de vervoerswijze. De grootste daling wordt verwacht bij openbaar vervoer: treinritten voor woon-werk dalen met 14–26% en bus/tram/metroritten met 10–19%. Autoritten nemen naar verwachting af met 7–15%.

De totale vervoersvraag daalt echter minder sterk, omdat sommige niet-gemaakte ritten worden gecompenseerd door meer reizen voor andere doeleinden – een complementair effect dat de netto-afname beperkt. Langdurige toename van thuiswerken en teleconferencing zal dus een blijvend, maar voor de meeste vervoerwijzen relatief gematigd negatief effect hebben op woon-werkreizen. Het effect zal naar verwachting het grootst zijn tijdens de spitsuren. Het openbaar vervoer zal het hardst worden geraakt, wat gevolgen kan hebben voor de financiële haalbaarheid van ov-exploitatie als deze vraag niet op een andere manier kan worden gegenereerd.

**Reisgerelateerde attitudes en hun relatie met reisgedrag**

Studie 4: De rol van reisgerelateerde motieven bij locatiekeuze in residentiële zelfselectie

Deze studie behandelt het mechanisme van residentiële zelfselectie (Residential self-selection; RSS). RSS stelt dat de invloed van de bebouwde omgeving op reisgedrag zwakker is dan bivariate correlaties suggereren, omdat reisgerelateerde attitudes zowel de keuze van woonomgeving als het reisgedrag beïnvloeden, en dus ten minste gedeeltelijk de waargenomen correlaties verklaren. In deze studie proberen we empirisch het onderscheid te maken tussen algemene reisattitudes en specifieke reisgerelateerde locatiekeuzemotieven binnen de context van RSS.

De resultaten suggereren dat reisgerelateerde locatiekeuzemotieven sterkere voorspellers zijn van de bebouwde omgeving dan houdingen ten aanzien van vervoerswijzen, en dat de causale relaties tussen attitudes, locatiekeuzemotieven, de bebouwde omgeving en reisgedrag vaak in beide richtingen lopen. Verder tonen de resultaten aan dat ov-gebruik het sterkst wordt beïnvloed door de bebouwde omgeving (na correctie voor zowel motieven als attitudes), terwijl auto- en fietsgebruik nauwelijks worden beïnvloed.

Deze bevindingen bieden empirische steun voor een conceptueel onderscheid tussen algemene reisattitudes en specifieke locatiekeuzemotieven in het RSS-proces. Beide concepten zijn belangrijk, maar vervullen verschillende functies: locatiekeuzemotieven bepalen waar mensen wonen, terwijl attitudes nauwer samenhangen met het daadwerkelijke reisgedrag.

Studie 5: Veranderingen in binnen-persoonseffecten tussen attitudes en reisgedrag tijdens de COVID-pandemie

De relaties tussen reisattitudes en reisgedrag zijn bi-directioneel: beide concepten beïnvloeden elkaar. In deze studie wordt dit verder onderzocht door de bidirectionele relaties tussen reisattitudes en reisgedrag te schatten voor vijf hoofdvervoerswijzen (auto, trein, bus/tram/metro, fiets, lopen), met bijzondere aandacht voor veranderingen tijdens de COVID-19-pandemie. Daarbij wordt onderscheid gemaakt tussen algemene correlaties tussen personen (stabiele verschillen tussen individuen) en effecten binnen het individu (veranderingen binnen individuen in de tijd).

De resultaten tonen significante bi-directionele binnen-persoonseffecten tussen attitudes en gedrag. Positieve veranderingen in attitude ten opzichte van een vervoerswijze verhogen de kans op meer gebruik van die modaliteit in de volgende periode, en omgekeerd zorgt meer gebruik voor een positievere attitude. De groottes van deze effecten zijn echter kleiner dan in modellen zonder de scheiding tussen binnnen-persoonseffecten en tussen-persoonscorrelaties, wat suggereert dat veel van de waargenomen samenhang voortkomt uit stabiele verschillen tussen personen in plaats van effecten binnen het individu.

Studie 6: Generatieverschillen in reisattitudes via latente groeicurven

Inzicht in hoe attitudes ten opzichte van vervoerswijzen zich ontwikkelen over de levensloop en tussen generaties is belangrijk voor de voorspelling van toekomstig reisgedrag. In deze studie worden groeitrajecten gemodelleerd voor attitudes ten opzichte van autogebruik en openbaar vervoer.

Voor zowel ov- als auto-attitudes worden drie latente groeiklassen geïdentificeerd. Voor ov is de relatie met leeftijd U-vormig: jongeren en ouderen zijn positiever, terwijl volwassenen (minimum rond 43 jaar) minder positief zijn. Voor de auto is het patroon omgekeerd: een omgekeerde U, met een piek rond 39 jaar. Generatieverschillen in klassenlidmaatschap zijn aanwezig, maar beduidend kleiner dan leeftijdseffecten. Opvallend is dat Generatie Z eerder tot de groep met hoge positieve auto-attitudes behoort, wat gangbare veronderstellingen dat jongere generaties minder autogeneigd zijn tegenspreekt.

Deze groeimodellen tonen leeftijds-, cohort- en periode-effecten met relatief kleine generatieverschillen. De COVID-19-pandemie had een significante maar grotendeels tijdelijke invloed op beide attitudesets. De waargenomen patronen vormen een basis voor betere voorspellingen van toekomstig reisgedrag en verdere studies naar de dynamiek van attitudes.

**De effecten van exogene schokken of hefbomen op reisgedrag**

Studie 7: Modality styles en weersgevoeligheid

Deze studie onderzoekt hoe modaliteitspatronen – algemene patronen in het gebruik van verschillende vervoerswijzen – de invloed van het weer op de dagelijkse vervoerskeuze modereren. Door literatuur over modaliteitspatroon-heterogeniteit en weersgevoeligheid te combineren, wordt geanalyseerd hoe sterk de reactie op dagelijkse weersveranderingen verschilt tussen verschillende reizigerstypes.

De resultaten tonen drie onderscheidende modaliteitspatronen: ’voornamelijk auto’, ’multimodaal’, en ’fiets+auto’. Personen in de categorie ‘voornamelijk auto’ zijn relatief ongevoelig voor slecht weer. Multimodale groepen reageren sterker, met meer gebruik van auto of ov tijdens dagen dat het weer slecht is. De invloed van het weer is dus heterogeen en sterker bij multimodale en actieve gebruikers dan bij automobilisten, met implicaties voor modellering en beleid onder toekomstige klimaatvariabiliteit.

Studie 8: De effecten van levensgebeurtenissen en veranderingen in bezit van mobiliteitsmiddelen op vervoerskeuze

Deze studie onderzoekt het effect van levensgebeurtenissen (zoals veranderingen in werkstatus of huishoudsamenstelling) en veranderingen in bezit van mobiliteitsmiddelen (zoals auto of fiets) op vervoerskeuze, met behulp van een dynamische longitudinale benadering.

Het model identificeert twee latente klassen: 1) een autogericht modaliteitspatroon en 2) een multimodaal modaliteitspatroon. Veranderingen in het bezit van mobiliteitsmiddelen hebben een veel sterker effect op de kans van het ene naar het andere patroon te wisselen dan levensgebeurtenissen. Vooral het aanschaffen van een auto vergroot de kans om in een autogerichte stijl te geraken of daar te blijven. Dit effect is deels onomkeerbaar, omdat het verlies van een auto een beduidend kleiner effect heeft. De aanschaf van een elektrische fiets daarentegen bevordert een verschuiving naar multimodaliteit, met meer fietsgebruik (ook voor langere afstanden) en minder gevoeligheid voor reistijd en afstand.

### Conclusies en praktische implicaties

Er kunnen enkele overkoepelende conclusies worden getrokken uit de resultaten van de bovenstaande studies.

*1. De effecten van thuiswerken op reisgedrag*

Thuiswerken heeft een sterker effect gehad op het gebruik van het openbaar vervoer dan op enig ander vervoermiddel. Dit komt enerzijds doordat ov-forenzen vaker werk hebben dat geschikt is voor thuiswerken, en anderzijds doordat woon-werkverkeer een groter aandeel vormt van het totale ov-gebruik. Daarnaast leidt thuiswerken niet alleen tot minder woon-werkverkeer, maar ook tot meer vrijetijdsverplaatsingen.

Het is dan ook twijfelachtig of de toename van thuiswerken een netto positief effect heeft op het mobiliteitssysteem. Voor het ov heeft het geleid tot forse dalingen in de vraag, en de spreiding van die vraag is toegenomen doordat veel mensen juist op woensdag en vrijdag thuiswerken, met pieken op dinsdag en donderdag. Deze verschuivingen vormen een bedreiging voor de betaalbaarheid en de kwaliteit van het ov-systeem.

*2. Reisgerelateerde attitudes en hun relatie met reisgedrag*

De causale relatie tussen reisattitudes en reisgedrag blijkt beide richtingen op te gaan. De stabiele verschillen tussen personen zijn bovendien veel groter dan de effecten binnen het individu. Dit suggereert dat het beïnvloeden van attitudes geen effectieve beleidsstrategie is om reisgedrag te veranderen. Bovendien verdwijnen vermeende generatieverschillen in attitudes grotendeels wanneer rekening wordt gehouden met leeftijdseffecten. Beleidsmakers zouden dus niet moeten vertrouwen op een 'natuurlijke' transitie naar autovrije levensstijlen bij jongere generaties.

*3. De effecten van exogene schokken of hefbomen op reisgedrag*

Ten slotte blijkt dat het reisgedrag van multimodale reizigers gevoeliger is voor externe invloeden. Auto-gedomineerde mobiliteitspatronen zijn bovendien relatief inert. Een belangrijk beleidsinzicht is daarom dat het voorkomen of vertragen van de transitie naar zulke autogerichte patronen cruciaal is voor het beperken van autogebruik. Als mensen eenmaal zo'n patroon hebben ontwikkeld is het heel lastig dit patroon te doorbreken. De elektrische fiets blijkt hierbij een mogelijk middel te zijn, doordat deze het fietsgebruik verhoogt en de kans op een overstap naar een auto-gedomineerd mobiliteitspatroon aanzienlijk verkleint.

# Chapter 1

# Introduction

*Wetenschap is de titanische poging van het menselijk intellect*
*zich uit zijn kosmische isolement te verlossen*
*door te begrijpen!*

*Science is the colossal pursuit of the human intellect*
*to liberate itself from its cosmic solitude*
*by means of understanding!*

Prof. Nummedal in 'Nooit meer slapen' by W.F. Hermans

## 1.1 Background and societal relevance

Travel behaviour research is a multidisciplinary branch of science, studying how and why individuals (and groups of individuals) make travel-related decisions. Examples of such decisions are the choice of travel mode, whether to travel at all, when to travel, and where to travel to. These decisions are very common, to the point that most people make them multiple times every day. That makes it very easy to relate the scientific study to personal anecdote – sometimes frustratingly so, when the two do not appear to align.

Typically, such disagreements arise from conflicts related to policy makers' societal objectives. Two main societal objectives within the realm of travel behaviour and mobility are accessibility and sustainability. Accessibility can be defined as the 'extent to which the land-use and transportation systems enable groups of individuals to reach activities or destinations' (Geurs & van Wee, 2004, p. 128). Following Geurs and van Wee (2004), four components of accessibility can be defined: the land-use component, the transport component, the temporal component, and the individual component. Examples of policies aimed at improving accessibility are highway expansions, land-use management aimed at decreasing distances between residential and activity areas, and public transport subsidies. Sustainability is a broad concept, with many different definitions. The definitions in use in the Dutch government (CBS, 2025; PBL, 2025) stem from the United Nations (Brundtland-Commission, 1987, p. 41): "meeting the needs of the present without compromising the ability of future generations to meet their own needs". In the context of travel behaviour research, sustainable policies are aimed at reducing greenhouse-gas emissiond, energy usage, and the use of scarce resources. Examples of such policies are subsidies for the electrification of vehicles, bicycle policies aimed at a mode shift from the car towards the bicycle, and taxes on greenhouse-gas emissions.

In practice, these societal objectives are, at least to some extent, at odds with one another, as policies aimed at improving one objective often negatively affect the other. For example, enforcing stringent parking restrictions will lead to reduced levels of accessibility by car. The resulting reductions in car use reduce greenhouse gas emissions, thereby improving the sustainability of the transport system. There is a trade-off between the goals relating to (perceptions of) accessibility and those relating to sustainability. Even if there is no such conflict between these different objectives, there can be a clash between various groups within one objective. Again, using our previous example of parking restrictions, such policies might reduce car-based accessibility in favour of bicycle-based accessibility if parking spaces are turned into bike lanes. In effect, this improves the accessibility of people who mostly use the bicycle at the expense of people who mostly use the car. The indirect effects of such policies can be much more complicated, but the above outlines some of the trade-offs that policy makers deal with in this area.

In the face of the upcoming transitions to the mobility system, as a result of climate change legislation and an increasing shift from a mobility and accessibility-based approach towards a general welfare-based approach, policy makers face the difficult challenge of realising sustainability objectives set forth by the Paris Climate Agreement (UNFCCC, 2016) and the Dutch Klimaatakkoord (Klimaatberaad, 2019), without reducing the (perceptions of) accessibility to unacceptable levels. This dilemma can be summarized as follows: *How can we make the mobility system more sustainable, without harmfully reducing the (perception of) the levels of accessibility of the different parts of the population.*

To effectively deal with this dilemma, policy makers need insights into the workings of the mobility system. By understanding how policy levers might affect different parts of the mobility system, more accurate trade-offs between the policy objectives can be made. This is the key link between the policy makers' dilemma – and the political perspective – and the scientific perspective. By providing policy makers with a wider base of scientific knowledge on behavioural mechanisms within transportation the scientific study of travel behaviour enables, at least in theory, better-informed decision making on the part of policy makers.

## 1.2 An overarching theme: longitudinal data and causality

In the search for information that can be used by policy makers to make better-informed policy decisions, researchers often seek to answer inherently causal questions:

- Will introducing congestion pricing result in a reduction in car use?
- Does stimulating working from home result in a reduction of road congestion?
- Will decreasing the price of public transport result in decreases in road congestion?

A proper answer to the questions framed above would in principle demand that the researcher establishes a causal relation from an intervention or treatment (congestion pricing, working from home, public transport price decrease) on an outcome of interest (car use, road congestion, road transport). Policy makers want to know that implemented policies actually affect the intended outcome. The causal nature of these questions put the researcher who seeks to answer them in some difficulty, as causality is notoriously difficult to establish.

The study of causality is an entire field of itself, so the below can only be seen as a brief introduction to this particular field of study. More information can be found in McHugh (2023), Graham (2025) and Pearl (2009). Typically, in order to establish causality, the following conditions need to be met:

1. There is a theory establishing a causal mechanism between the independent variable, or the cause, (X) and the dependent variable, or the effect, y.
2. There is an empirical correlation between X and y.
3. Changes in X temporally precede changes in y.
4. There are no confounding variables explaining the relationship between X and y.

Meeting these conditions and thus establishing a causal connection between two variables is not an easy task. The most difficult are the third and fourth conditions. Using cross-sectional data, which is measured at one point in time, researchers cannot empirically establish temporal precedence. Only theoretical notions can be used to establish this precedence, for example in the case of clearly exogenous variables (such as gender or age). The use of such exogenous variables can thus allow for further causal probing. In the absence of these external variables and the resulting restrictions on the temporal order, longitudinal data is necessary to establish temporal precedence. The fourth condition states that there can be no confounding variables explaining the relationship: in other words, that the established correlation is not spurious. As it is impossible to exhaustively include all possible confounding variables in a model, this condition is very difficult to fully meet. In practice, meeting this condition depends on the inclusion of at least those variables which are known to play an important role in the causal relationship under question.

One method is seen as the golden standard when it comes to establishing a causal relation: the use of experimental designs. In the natural sciences, like physics or chemistry, scientists are able to control the circumstances, allowing for careful manipulation of the experimental set-up in order to study causal effects. They can create experiments where, for example, they first allow a certain chemical reaction to occur and measure some objective indicator they are interested in, like the speed at which one of the chemicals is dissolved. They can then add different chemicals, change the temperature or the pressure, and see if these changes have any meaningful effect on the speed of the reaction. All other variables can be held constant. In doing so, they are able to meet both the third and fourth conditions stated above.

Such experimental control is more difficult in sciences that concern human behaviour. Experimental designs do exist, and they are commonly used in the field of medicine and psychology, for example to establish the effect of certain treatments on health-related outcomes. In such experimental designs, also called randomized control trials, participants are carefully grouped into multiple groups, with varying treatment plans. Often, some of these groups are offered no treatment but rather a placebo. In a simple example, their health is then measured both before the treatment has begun and after it has concluded and the difference is compared across the various groups. Other examples can be seen in the digital world, where digital companies can carefully control digital interactions, for example to test whether certain web designs are more successful than others at harnessing engagement.

Due to practical and ethical issues, such experimental designs are uncommon in the field of travel behaviour research. As a result, the main method used in the past decades to take steps towards establishing causal relations in this field is the use of observational longitudinal data. Rather than using experimental designs, researchers observe large groups of people over a sufficient tract of time. This method improves upon cross-sectional observational methods by allowing for an empirical test of temporal precedence (condition 3). As the same set of variables is observed multiple times for every individual, empirical models can be used to test whether changes in X at the first measurement affect values of y at the following measurements, or whether changes in y affect later values of X.

Furthermore, the use of multiple measurements for one individual allows the researcher to disentangle between-persons from within-persons effects. By using multiple measurements for each individual, we can calculate the average value for a respondent. These averages can then be compared across individuals to get between-persons correlations between variables. The deviations from the average can be used to calculate within-persons effects, for example to investigate if a lower-than-average score on X results in a lower-than-average score for y in the following measurement. This will be explained in more detail in section 1.4.2. One benefit of this approach is that it controls the estimated within-person effects for all time-invariable differences between individuals. In this way, many possible confounders are taken care of, resulting in more confidence that all relevant confounders are included in the model (condition 4). The second benefit is that in many cases, the practical implications of a relationship depend on the existence of within-person effects as they rely on policies that change some circumstances or characteristics of some individual, which should then result in changes in the outcome variable within that individual.

## 1.3 Substantive sections

As mentioned above in Section 1.2, the dissertation concerns studies that use either longitudinal data or external stimuli to provide further insights into several causal relationships in the area of travel behaviour research. Aside from this common thread throughout the dissertation, there are further substantive and methodological links between the chapters. Substantively, the dissertation is divided into the following three research lines:

1. The relations between working from home and travel behaviour
2. Travel-related attitudes, and their relations with travel behaviour
3. The effects of exogenous shocks or levers on travel behaviour

The first two of these research lines were chosen because the direction and strength of the key causal relationship (respectively that between working from home and travel behaviour for the first section and the relationship between attitudes and travel behaviour for the second section) is a subject of academic debate. Using longitudinal data and advanced modelling methods, we push the boundary of knowledge concerning causal directions and effects in these fields. As a result, the thesis clearly contributes to the scientific literature in these sections by providing a deeper understanding of the causal mechanisms in question. The third section in contrast uses a different approach: by using exogenous variables (the weather and life events) the direction of causality is more clearly defined. This helps us to provide further information on the strength of these effects and how they differ across different groups or between different travel modes. These sections are introduced in more detail below.

### 1.3.1 The relations between working from home and travel behaviour

Since the 1970s, working from home has been seen as an alternative to commuting, meaning that increasing working from home behaviour could be a promising policy instrument to diminish the problem of congestion. Considering the policy dilemma sketched above, working from home seems to be an ideal solution at first glance: we reduce commuting behaviour, congestion, vehicle miles driven (VMD), and greenhouse-gas emissions. This does not seem to come at the cost of accessibility, as physical access is replaced by a digital form of access. This substitution between physical and digital accessibility is a growing trend due to digitalisation (Andreev et al., 2010).

However, the story is more complicated. Previous research has shown that people who work from home actually travel more than people who do not(Elldér, 2020). There are three plausible theoretical explanations for this finding: first, that people who work from home use their saved travel time for other travel purposes (Caldarola & Sorrell, 2022; Milakis & van Wee, 2018). Second, that people who work from home accept longer commutes (Wöhner, 2022), and third, that unrelated differences between people who work from home and people who do not work from home explain the difference in travel behaviour (Elldér, 2020). Note that there is a key difference between the first two and the last explanation. If the first two explanations are true, then there are indirect positive causal effects from working from home on commute travel, thereby negating the primary negative effect of a reduction in commute frequency due to working from home. The third explanation however does not rely on such causal effects.

This debate rose to the forefront of the travel behaviour research community because of the COVID-19 pandemic, which resulted in an unprecedented spike of working from home behaviour. The temporary effects of this spike are of course interesting, but the main question of interest is whether there would be any structural uptake of working from home after the pandemic would be over, and, if so, what the structural effects of this uptake on our travel behaviour would be. This section contains three chapters:

Chapter 2: the effect of the COVID-19 pandemic on working from home and travel behaviour

The COVID-19 pandemic has resulted in a very large shock to travel behaviour, both as a result of the pandemic itself and of contact-restricting measures enacted by governments worldwide. These unprecedented circumstances quickly led to questions revolving around both the short- and long-term changes in travel behaviour as a result of the pandemic. This was particularly true at the start of the pandemic, when uncertainty was at a maximum. In this first chapter of this section, we show descriptively how the pandemic and the measures taken to reduce its spread have affected our travel behaviour, with a special focus on the effects induced by mandatory working from home. We show both the direct short-term changes as well as the expectations for the future, as recorded at the start of the pandemic in March and April 2020.

Chapter 3: the relations between working from home and travel behaviour

Due to the large and sudden increase in working from home due to the pandemic, as shown in Chapter 2, the travel behaviour research community and policy makers were left wondering what the possible effects on travel behaviour could be. As stated above, the causal mechanisms between working from home and travel behaviour are complex. In particular, we were still unsure whether the relationship between working from home and travel behaviour was net negative or net positive: whether working from home thus results in a net increase or decrease in travel. In the second chapter of this section, we use a panel dataset to uncover the relations between time spent on work, either at home or at the office, and time spent on travel, where we distinguish commute travel from leisure travel. As a result of this analysis, we further improve our understanding of the relations between work from home and travel behaviour.

Chapter 4: Estimating post-pandemic effects of working from home on travel behaviour

In the third study, we combine both pieces of knowledge to provide an estimation for the (causal) effect that working from home will have on the mobility system in the post-pandemic world. This estimate is very relevant, even now that the pandemic has been over for multiple years. In the Netherlands travel behaviour has substantially changed in the pandemic years, but it is not entirely clear why this is the case. By estimating the effects of working from home, we can more accurately attribute the remaining difference to other effects.

### 1.3.2 Travel-related attitudes, and their relations with travel behaviour

The relations between attitudes and behaviour have been a very popular subject of study in the field of travel behaviour research (De Vos, 2022), following popular psychological theories such as the Theory of Planned Behaviour (Ajzen, 1985, 1991). Following on from this theory, attitudes are typically seen as antecedents of travel behaviour (Van Wee et al., 2019). Furthermore, they are mostly found to have strong correlations with behaviour. Combining these two statements, one would surmise that there is a strong causal effect of attitudes on travel behaviour, and subsequently, that policy makers can try to steer our behaviour by designing policies aimed at changing our attitudes through, for example, information campaigns.

However, again, the matter is not so simple. Around a decade ago a research line in the travel behaviour research literature started, which has been empirically testing the relations between travel-related attitudes and travel behaviour (Kroesen et al., 2017). In particular, this stream has tested the direction of causality between the two concepts. The vast majority of the studies that have done so have found a bi-directional effect (De Vos, 2022): behaviour affects attitudes just as attitudes affect behaviour. These insights are relatively fresh, and therefore there is still much to explore. In this dissertation, we provide three chapters looking into travel-related attitudes and their relations with travel behaviour.

Chapter 5: The role of travel-related reasons for location choice in residential self-selection

First, we study the relations of travel mode attitudes and travel-related reasons for location choice in the context of residential self-selection. Summarised succinctly, residential self-selection is a notion where demographics, travel preferences, and residential preferences underlie both the decision where to live and our travel behaviour (Cao et al., 2009; Næss, 2009). As a result, the direct effect between the residential built environment and travel behaviour can be explained, at least to some extent, by travel and residential preferences (Guan et al., 2020). Thus, the observed difference in travel behaviour between people living in various residential neighbourhoods cannot solely be attributed to a direct effect of the built environment on travel behaviour, as there are many confounding variables. In this chapter, we explicitly distinguish between travel-related attitudes and travel-related reasons for location choice, following an article by Ettema and Nieuwenhuis (2017). Previously, the different roles played by general travel-related attitudes and more specific travel-related reasons for location choice were not well understood. Using a combination of cross-sectional and longitudinal models, we investigate how these concepts are related to travel behaviour. We postulate that travel-related reasons for location choice have a stronger effect on the built environment characteristics whereas travel-related attitudes are more strongly tied to our travel behaviour.

Chapter 6: Investigating changes in within-person effects between attitudes and travel behaviour during the COVID-19 pandemic

Second, we expand on the bi-directional testing of the causality between travel-related attitudes and travel behaviour. We extend this literature in two ways. Previously, there have been no studies that jointly investigate the relationships between attitudes and travel behaviour across the various travel modes. As a result, the total effect of attitudes on travel behaviour might have been underestimated, due to the focus on effects within a travel mode. The effects of attitudes with respect to other modes on the use of one travel mode has been somewhat overlooked.

Furthermore, in most previous studies, no effective distinction was made between within-person effects and between-person correlations (De Vos, 2022; Olde Kalter et al., 2021). This distinction is important, as policies aimed at affecting travel behaviour through travel-related attitudes are dependent on the existence of within-person effects (De Vos, 2022). As a result of not making this distinction, the within-persons effects between attitudes and travel behaviour might have been overestimated. In this chapter, we use a model that integrates travel behaviour and travel-related attitudes of five main travel modes (car, local public transport, train, bicycle, and walking). Furthermore, we use longitudinal data and an advanced model to separate within-person effects from between-person correlations.

Chapter 7: Latent growth curve trajectories for travel mode attitudes during and after the COVID-19 pandemic

Finally, we take a different approach and focus on the changes over time within travel-related attitudes themselves, rather than studying the relationship between attitudes and travel behaviour. This chapter does not focus on the (causal) effects between attitudes and travel behaviour, but it does study the time dynamics involved in travel-related attitudes. Given that we know that attitudes are strongly related to travel behaviour, increasing our understanding of travel attitudes themselves might prove an effective avenue towards further use of attitudes in travel behaviour practice. More substantively, we use a growth modelling approach to study the effects of age, calendar year, and generations on travel-related attitudes. Differences in attitudes between generations are relatively poorly understood, although concepts such as 'peak car' seem to presuppose that younger generations hold less favourable views of the car than older generations. By accounting for the effects of age in the model and using a decade of attitude-related data, we can empirically estimate the differences in attitudes between various generations.

### 1.3.3 The effects of exogenous shocks or levers on travel behaviour

The final section of the dissertation focuses on understanding the mechanism behind behavioural change by studying the effects of exogenous shocks. A common problem in research on travel behaviour research is that of endogeneity, where the temporal and causal order between the dependent and independent variables is unclear. We have seen examples of this problem before when studying the relationship between attitudes and behaviour. Using attitudes as pure antecedents of behaviour is problematic, as attitudes themselves are affected by travel behaviour as well and should thus be treated as an endogenous variable in the model.

In the above sections, we have used longitudinal data to overcome this problem, as longitudinal data allows us to model causal structures that contain loops. Another solution is to use variables which are clearly exogenous, thereby simplifying the causal structure. By studying the changes in travel behaviour that are induced by changes in these external variables, we are able to improve our understanding of travel behaviour.

Chapter 8: Inferring modality styles by revealing mode choice heterogeneity in response to weather conditions

The first chapter of this section studies the effects of the weather on travel behaviour, where we ask the question which types of travellers are more or less sensitive to the weathers' influence. In the chapter, we use the weather as an exogenous shock, postulating that more monomodal travellers, who are likely to have stronger travel habits, are less sensitive to exogenous shocks. Conversely, multi-modal travellers are then more sensitive to exogenous shocks. By using the weather, which is a clearly exogenous variable, we are able to estimate modality styles and the sensitivity of these modality styles to exogenous variation more generally. En passant, we improve upon the growing literature on the effects of the weather on travel behaviour, where the heterogeneity of this effect is not yet well understood.

Chapter 9: Estimating the effects of life events and changes in mobility tool ownership on mode choice behaviour

The final chapter included here uses a latent transition choice model to study the effects of life events and changes in mobility tools on our mode choice behaviour. Here we have two types of shocks: life events, which are relatively more exogenous to travel behaviour, and changes in modality styles, which are more endogenous. In this chapter, we explicitly account for time dynamics in the modelling approach, enabling us to draw stronger causal conclusions than would be possible otherwise. Substantively, we use the mode choice modeling approach to test the direction and size of the effects of life events and changes in mobility tool ownership on mode choice. By accounting for time dynamics, we can for example see the difference in effects between gaining access to a mobility tool and losing access to the same tool.

### 1.3.4 Substantive synthesis

Above we have introduced three substantive research topics which we study in this dissertation. In Figure 1.1, we have grouped the chapters of the dissertation according to their substantive topic.

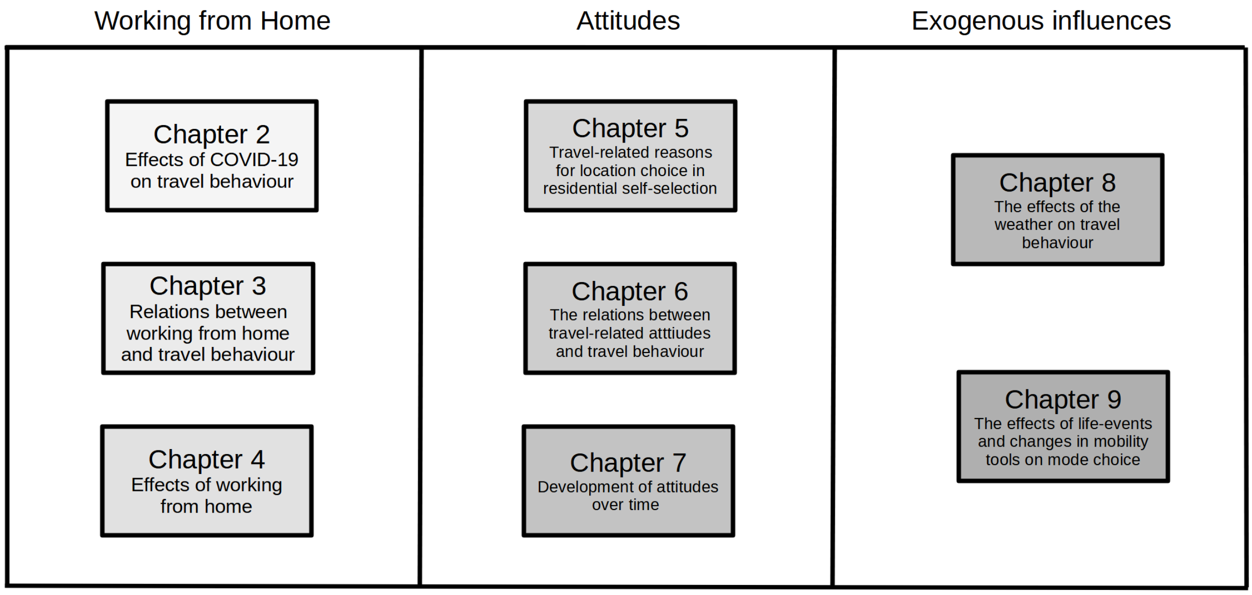


*Figure 1.1: The substantive connections between the various chapters in this dissertation*

## 1.4 Methodological Congruency

In the above introduction of the chapters of this dissertation, the chapters have been divided into three sections based on the substantive subjects studied in each chapter. Aside from these substantive connections between the chapters, there are also strong methodological links that tie the dissertation together. The biggest such link is the use of the same primary data source for all chapters: the Netherlands Mobility Panel. The second link is the use of statistical models that leverage the presence of panel data to gather insights that would not be achievable with cross-sectional data.

### Research data: the Netherlands Mobility Panel

The Netherlands Mobility Panel (MPN) is an annual household panel, with data collection starting in 2013 and which consists of approximately 2,000 complete households (Hoogendoorn-Lanser et al., 2015). The MPN was set up to study both the short- and long-run dynamics in travel behaviour of Dutch individuals and households and to assess how changes in personal and household characteristics are related to changes in travel behaviour. The different constituent elements of the MPN are shown in Figure 1. Respondents are recruited from the Verian NIPObase Online Access Panel (OAP). Respondents for this larger OAP are recruited based on register data from Statistics Netherlands (CBS) and voluntary sign-up is impossible.

After agreeing to participate in the MPN, households are asked to complete several questionnaires and a travel diary every year. This fieldwork always occurs between the months of September and November. First, the primary contact person within each household, termed the gatekeeper, fills out a household questionnaire in which they report information on the household composition, ownership of means of transport and mobility tools and detailed information on the cars in the household. Next, all household members of at least 12 years old 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. We have summarized the above information in Figure 1.2.

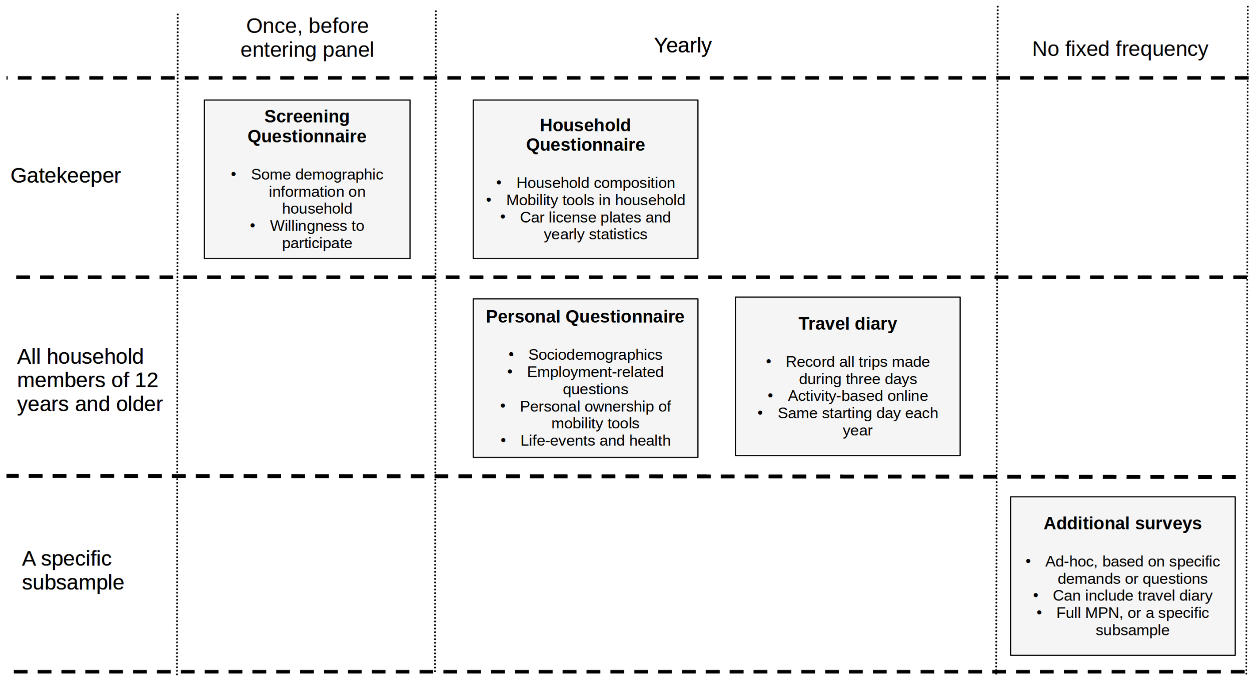


*Figure 1.2: Design of the MPN*

Besides the yearly questionnaires and the three-day travel diary, the MPN explicitly offers the possibility to study specific topics by means of additional questionnaires or by repeating the three-day travel diary throughout the year. This possibility allows for the creation of a rich dataset with relatively little effort, as all additional collected data can be linked to data from the regular yearly waves on an individual level.

This dissertation uses nearly all facets of the MPN: both the travel diary and the set of questionnaires, data collected between 2013 and 2023, data collected during the regular main waves and data collected using additional surveys carried out throughout the COVID pandemic.

### Modelling Techniques

Aside from the shared use of data from the MPN, which unifies all chapters of this dissertation, there are also commonalities between the chapters in the use of certain statistical methods. In particular, two distinct families of methods are applied in multiple chapters:

1. Structural Equations Modelling
2. Discrete Choice Modelling

Three chapters use separate methods, which we will quickly introduce here as well. But first, we start by introducing the two methods above and how they are applied within this dissertation.

**Structural Equations Modelling**

Structural Equations Modelling is a modelling approach with its roots in psychology, sociology and economics, which has been widely adapted in many fields. At its core, it is a combination of factor analysis (Spearman, 1904; Thurstone, 1931) and path analysis (Wright, 1934). Combining these two methods leads to some core benefits of structural equation modelling over other regression techniques (Joreskog, 1970). SEM enables the researcher to simultaneously estimate multiple relationships, incorporate latent variables, and account for measurement error. A structural equation model consists of two main components: the structural model, which links the various constructs together, and the measurement model, which models the measurement of the constructs based on one or multiple indicators. In this dissertation, we use longitudinal structural equation models. Such models use multiple measurements of the same construct over time to estimate the relationships between multiple variables over time. By explicitly incorporating the time-component in the model, an important hurdle to establish causal relationships can be overcome. A common problem in cross-sectional models is that the direction of causality cannot be tested empirically: instead, theoretical assumptions are needed to establish the direction of the causal structure used in the model. Given two variables $X$ and $Y$, each measured at the same time using cross-sectional data, there is no statistical difference between estimating the causal relationship $X \rightarrow Y$, the relationship $Y \rightarrow X$, or a correlation between the two variables. The modeller has to decide on the assumed causal structure based purely on theoretical notions. Longitudinal data can solve this problem.

To illustrate, we assume that two variables X and Y are both measured at three consecutive timepoints. Using the cross-lagged panel model (CLPM), which was used as the workhorse model in the study of (Granger) causality in longitudinal correlational data (Hamaker et al., 2015), bi-directional relationships between two or more variables over time can be estimated, as well as auto-regressive relationships. These auto-regressive relationships are supposed to control for the stability of a variable over time. The model thus empirically estimates whether the effects of X on Y are stronger than the reciprocal effects of Y on X. The differences between the cross-sectional model and a longitudinal model are visualized in Figure 1.3

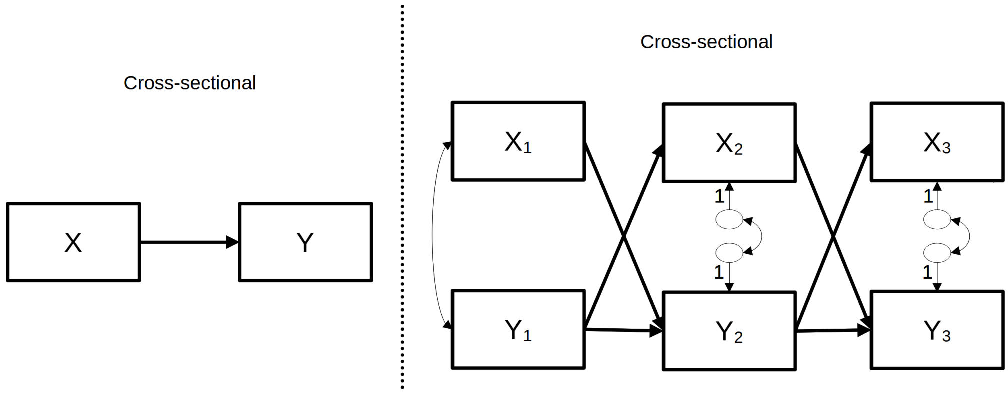


*Figure 1.3: Graphical view of a cross-sectional and longitudinal model*

The CLPM itself was then also critiqued (Hamaker et al., 2015) on the basis that it does not incorporate within-person stability within the model. Accordingly, the CLPM assumes that the score for each variable for every person varies over time around the same sample mean. This is problematic if stable between-person differences exist, which is often the case in observational data. (Hamaker et al., 2015) therefore introduce the random intercept cross lagged panel model (RI-CLPM), where random intercepts are added to account for stable, time-invariant, differences between individuals. The random intercept structure thus captures the between-person differences, allowing the regressive structure to specifically capture within-person effects. The coefficients can then be interpreted as within-individual carry-over effects, where a positive estimate for example indicates that a higher score at one observation is likely to be followed by another higher score at the next observation. The differences between a CLPM and RI-CLPM are visualized in Figure 1.4.

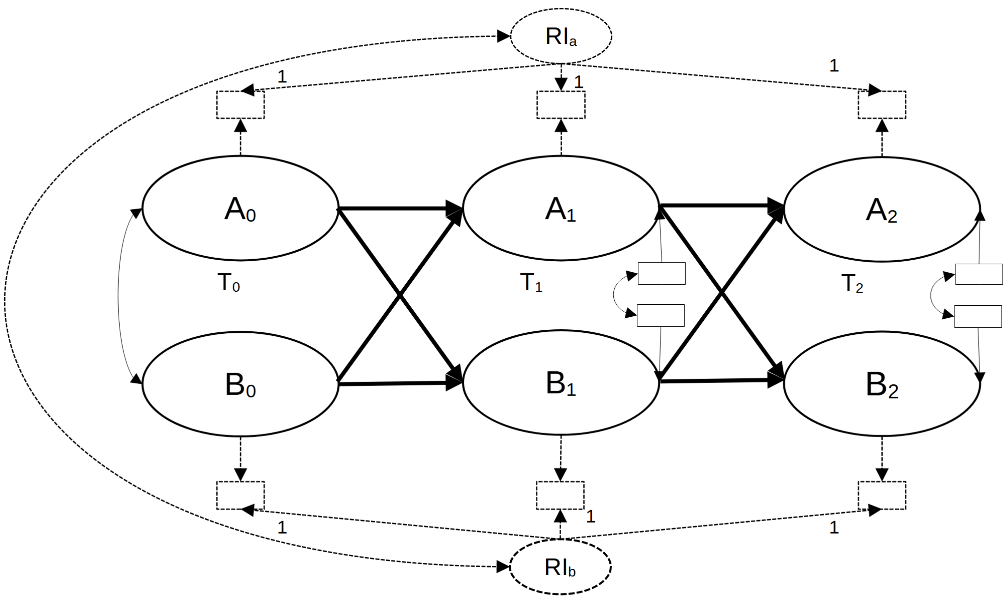


*Figure 1.4: Graphical view of the CLPM and RI-CLPM, where the additions of the RI-CLPM are dashed*

In the dissertation, we will make use of both cross-sectional and longitudinal structural equation models. We estimate both CLPM's and RI-CLPM's and show the differences between the two.

**Choice Modelling**

Choice Modelling is one of the most employed methods in the field of travel behaviour research since its inception in the 1960s and 70s (McFadden, 1974, 2001). Stated succinctly, choice modelling concerns the statistical modelling of the choice of some alternative i by a decision maker n from a discrete set of alternatives J, each having certain attributes. Based on random utility maximization theory, discrete choice models often assume that the decision maker chooses the alternative that maximizes their utility. From the point of view of the analyst, this total utility $U_{n,}$ can be decomposed into a known or structural part $V_{n,i}$ and an unknown part $\varepsilon_{n,i}$ as stated in equation 1.1.

$$U_{n,i} = V_{n,i} + \varepsilon_{n,i} \tag{1.1}$$

The analyst can then model the structural or known part of the utility $V_{n,i}$ in a manner of their own choosing. Often, this model uses a so-called linear-in-parameters expression based on known attributes X and a set of parameters $\beta$, as follows in equation1.2:

$$V_{n,i} = \beta X_{n,i} \tag{1.2}$$

By assuming that the unknown part is independently and identically distributed extreme value for each alternative, the probability $P_{n,i}$ that the decision maker chooses alternative i from a set of alternatives i, .., j can be described in a closed-form solution as follows in equation 1.3:

$$P_{n,i} = \frac{e^{V_{n,i}}}{\sum_j e^{V_{n,j}}} \tag{1.3}$$

This closed-form solution has the necessary properties ascribed to probabilities: $P_{n,i}$ will always fall in the range between 0 and 1, and the sum of all probabilities equals one.

Since its inception, this basic form of the choice model has been extended in many ways by allowing for more flexible specifications of the error term, arguing that the classic MNL-error term is too rigid to capture choice behaviour accurately. This is not the place to delve deeper into these many extensions, but the reader is referred to Train (2009) for an extensive overview. In this dissertation, both chapters on choice modelling make use of the latent class choice model formulation, which is why I will describe this model here in a bit more detail.

The latent class choice model is one possible way to investigate heterogeneity in the population with respect to the effect of the attributes on utility. In the MNL-model formulated above, each decision maker n is assumed to value certain attributes equally. In real-life applications, this assumption is often problematic. Some groups of people might value travel time more, other groups place more emphasis on reducing costs. For practical purposes, it can be very important to find a) whether there is heterogeneity and b) what the sources of this heterogeneity are. The latent class choice model solves this problem by assuming that there are multiple distinct groups or classes within the population, such that the value ascribed to certain attributes is the same within the classes but can be different across the classes (Greene & Hensher, 2003; Magidson & Vermunt, 2004).

Mathematically, this is achieved by allowing for a discrete mixed distribution of some or all of the estimated parameters $\beta$, such that these values of $\beta$ are conditional on the class s. The final probability that decision maker n chooses alternative i is then the mixed probability over all classes, as in equation 1.4.

$$P_n(i \mid \beta) = \sum_{s=1}^{S} \pi_{n,s} P_n(i \mid \beta_s) \tag{1.4}$$

The class-membership probabilities $\pi_{n,s}$ can themselves be modelled using a class-membership function. This allows the researcher to not only identify discrete segments in the population, but also which characteristics influence the probability of belonging to certain segments. Typically, the class-membership function is specified as a logit function, using both constants $\delta_s$ and a function $g$ of a vector of parameters $\gamma_s$ and a corresponding vector of characteristics $z_n$, as in equation 1.5.

$$\pi_{n,s} = \frac{e^{\delta_s} + g(\gamma_s, z_n)}{\sum_{l=1..S} e^{\delta_l} + g(\gamma_l, z_n)} \tag{1.5}$$

**Other methods**

Aside from structural equations modelling and (discrete) choice modelling, three chapters of this dissertation use other methods, which are unique to these chapters. Chapter 2 mostly uses descriptive analyses of data collected at the start of the COVID-19 pandemic. Chapter 4 uses linear regression models to calculate the expected decrease in travel behaviour as a result of increases in working from home. Chapter 7 uses a growth modelling approached. As each chapter uses a different method, there is no overarching introduction necessary. The detailed information for each method is already fully present within each chapter.

### Synthesis of research methods

The above introduces the main methods used in each chapter of the dissertation. In a similar vein to Figure 1.1, which visually summarized the substantive connections between the chapters, we have visually summarized the methodological connections in Figure 1.5 below.

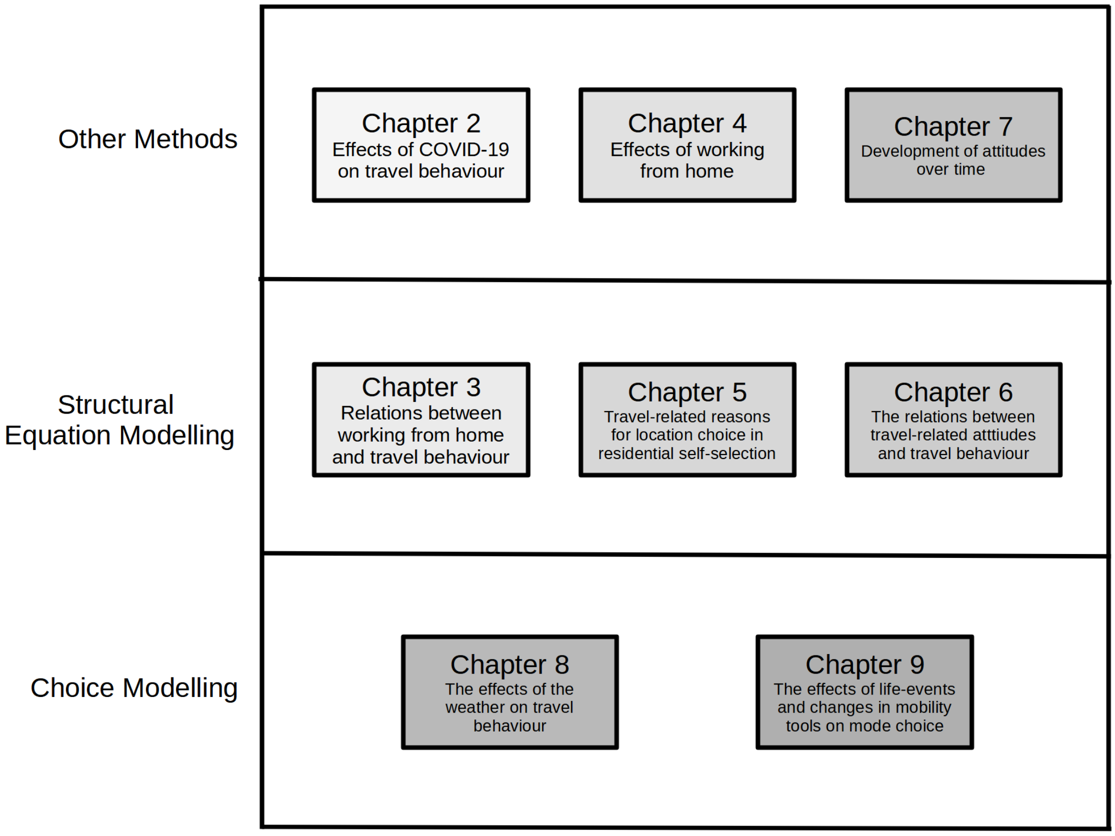


*Figure 1.5: Methodological connections in this dissertation*

## 1.5 Combining substantive and methodological perspectives

As introduced above, this dissertation is tied together in both substantive and methodological ways. It is of course no coincidence that the two figures denoting these different ties use a different axis to sort the chapters. Combining both figures leads to a two-dimensional grid, which can again be filled in using the chapters in the dissertation. This provides a quick and comprehensive overview of the various chapters in this dissertation and the way in which they form a comprehensive story.

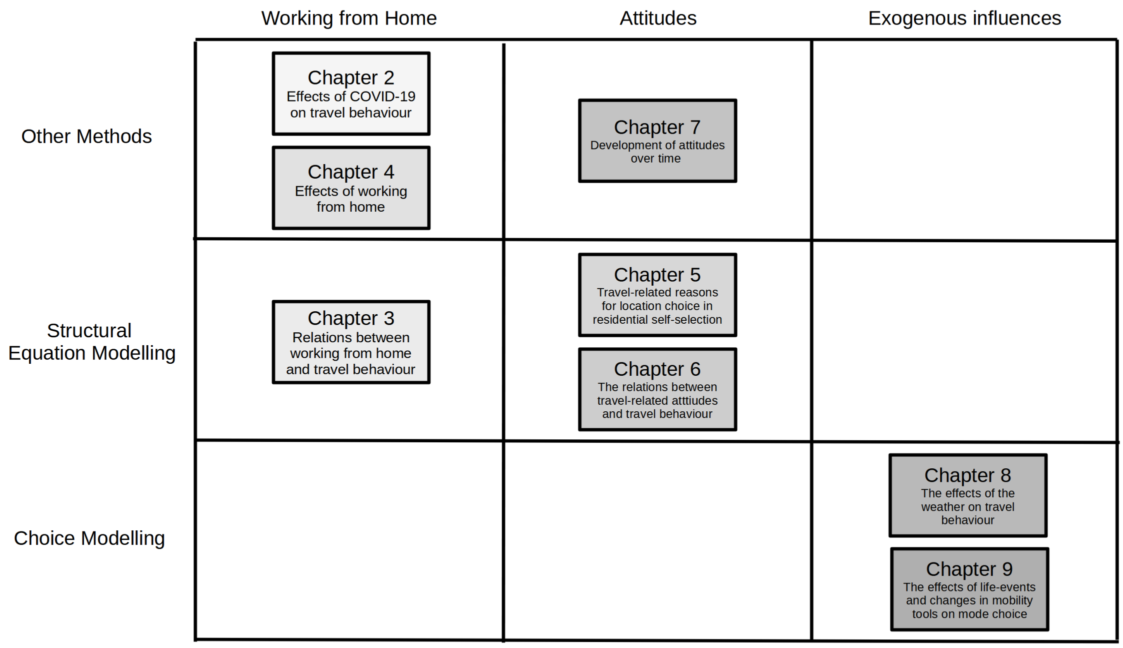


*Figure 1.6: Methodological connections in this dissertation*

Using Figure 1.6, we can quickly sketch the outline of the dissertation. The first three chapters (Chapters 2 through 4) focus on the relationship between working from home and travel behaviour. Chapters 2 and 4 both use 'other' methods, but chapter 3 uses a structural equation modelling approach. The next three chapters, chapters 5 through 7, zoom in on the relations between attitudes and travel behaviour. Both Chapters 5 and 6 use different forms of structural equation models, whilst Chapter 7 uses growth modelling as the main research method. Finally, Chapters 8 and 9 discuss different ways in which exogenous variables influence our travel behaviour. Both chapters use discrete choice models.

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# Chapter 2

# How COVID-19 changed activities, work and travel behaviour: evidence from longitudinal data in the Netherlands

This chapter is based on 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. 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.*

## 2.1 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 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, 2016). 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 (M. C. 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 (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 more than 70% of all CO2 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.

## 2.2 Research Framework and 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.

### 2.2.1 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; 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 et al., 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 2.1.

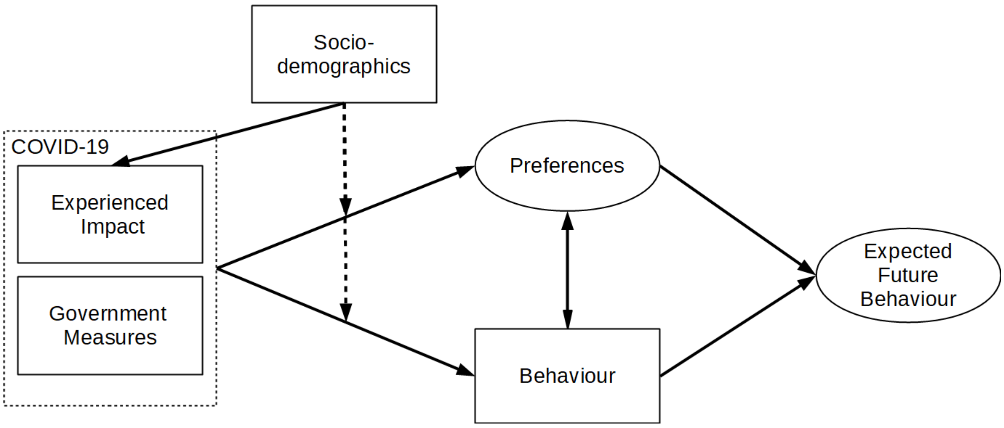


*Figure 2.1: Research framework of the impact of COVID-19*

The 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 hypothesised 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.

### 2.2.2 Methods

#### 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 2,000 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 2.1) 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 2,296 completed diaries and 2,494 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 2.1 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 descriptive analyses, the data is weighted on both sociodemographic- and geographical factors.

**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.

## 2.3 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

| 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/km$^2$) | $< 500$ | 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 $\leq 12$ | 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.

*Table 2.1: Sample distribution of the pure-stayer sample, the cross-sectional participants of the 2019 wave, and the population.*

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, a large majority of people (more than 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 ($\chi^2$ (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 ($\chi^2$ (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.

### 2.3.1 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 2.2). 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.

Older people in particular are much less active than before the crisis (Chi-square tests: grocery shopping $\chi^2$ (2, N = 2492) = 36.411, p = .000, shopping $\chi^2$ (2, N = 2492) = 13.078, p = .001, exercising $\chi^2$ (2, N = 2492) = 28.876, p = .000, volunteering $\chi^2$ (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 ($\chi^2$ (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

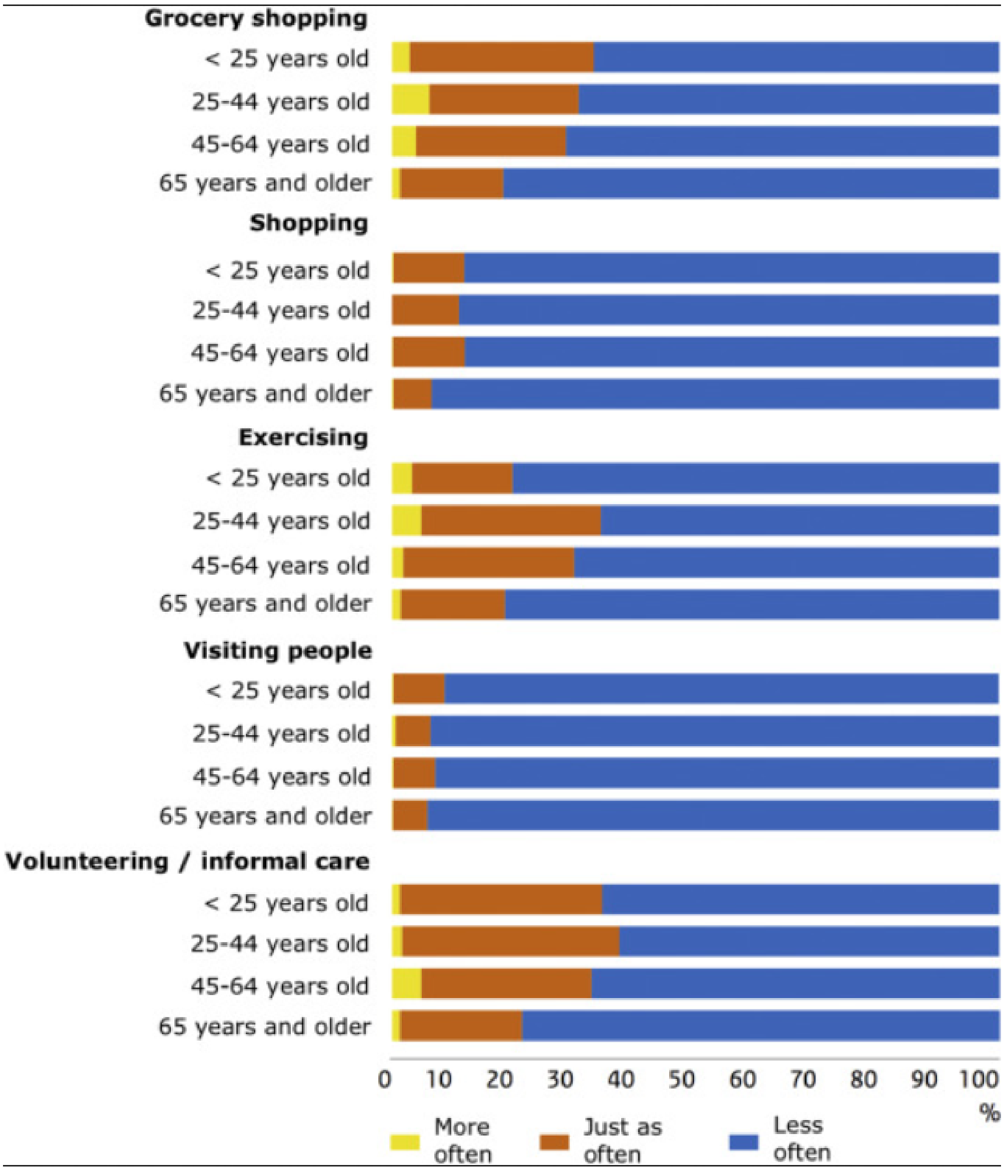


*Figure 2.2: Change in outdoor activities since coronavirus crisis, per age group*

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 ($\chi^2$ (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 ($\chi^2$ (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 ($\chi^2$ (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 (more than 90%) do not expect that the current changes in outdoor activities will continue after the coronavirus crisis (Figure 2.3). 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 ($\chi^2$ (16, N = 2269) = 391.996, p = .000). The same holds for grocery shopping outdoors for people who are happy with doing their groceries online ($\chi^2$ (16, N = 1354) = 148.590, p = .000) or who think online grocery shopping is a full replacement of outdoors grocery shopping ($\chi^2$ (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.

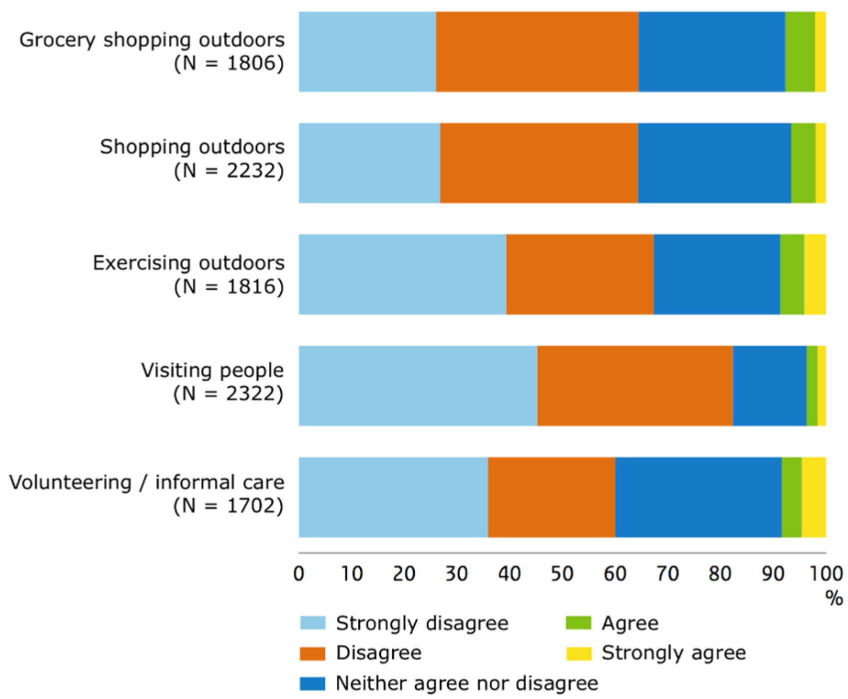


*Figure 2.3: Opinion on the statement "I also expect to do fewer outdoor activities after the corona situation compared to the situation before corona."*

### 2.3.2 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 ($\chi^2$ (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 ($\chi^2$ (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 at least 75% of their working hours 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 ($\chi^2$ (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 2.4 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, 2018). 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.

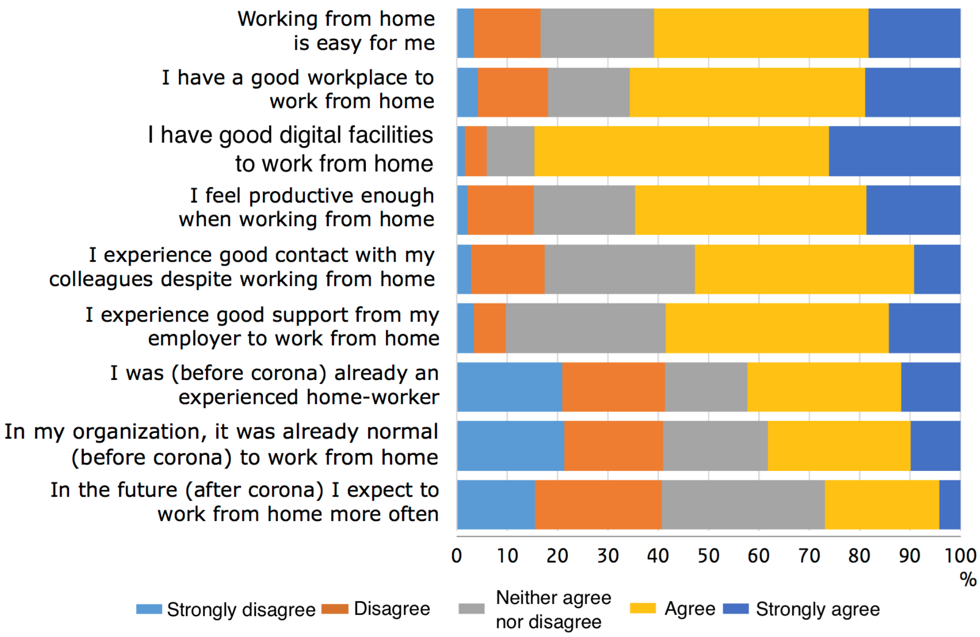


*Figure 2.4: Experience with working from home*

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 2.5). 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.

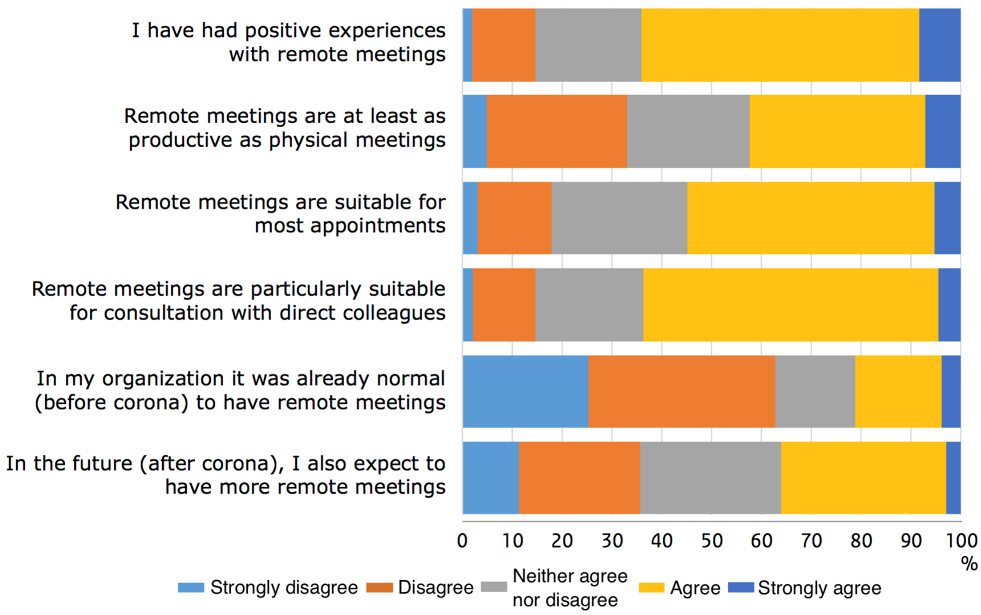


*Figure 2.5: Experience with (more) remote meetings*

There are some differences between sectors here (difference in working more from home between sectors $\chi^2$ (5, N = 1427) = 164.686, p = .000, difference in increase in remote meetings between sectors $\chi^2$ (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 $\chi^2$ (20, N = 828) = 49.010 , p = .000, difference in experience with remote meetings between sectors $\chi^2$ (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 2.6). 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.

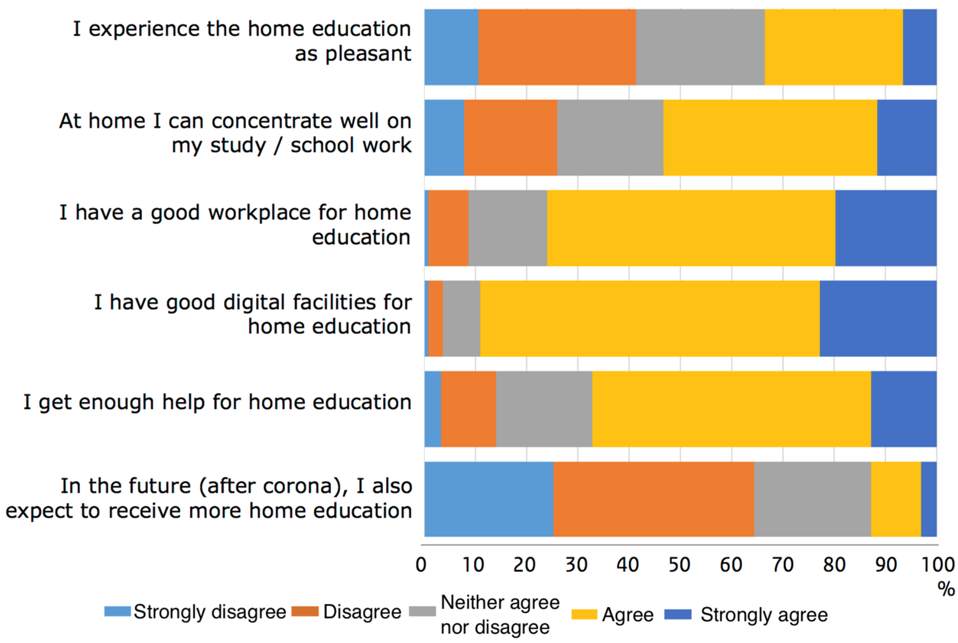


*Figure 2.6: Experience with following education at home*

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 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 $\chi^2$ (16, N = 869) = 153.774, p = .000, remote meetings $\chi^2$ (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.

### 2.3.3 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%, $\chi^2$ (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 2.7 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.

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 2.8), 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,

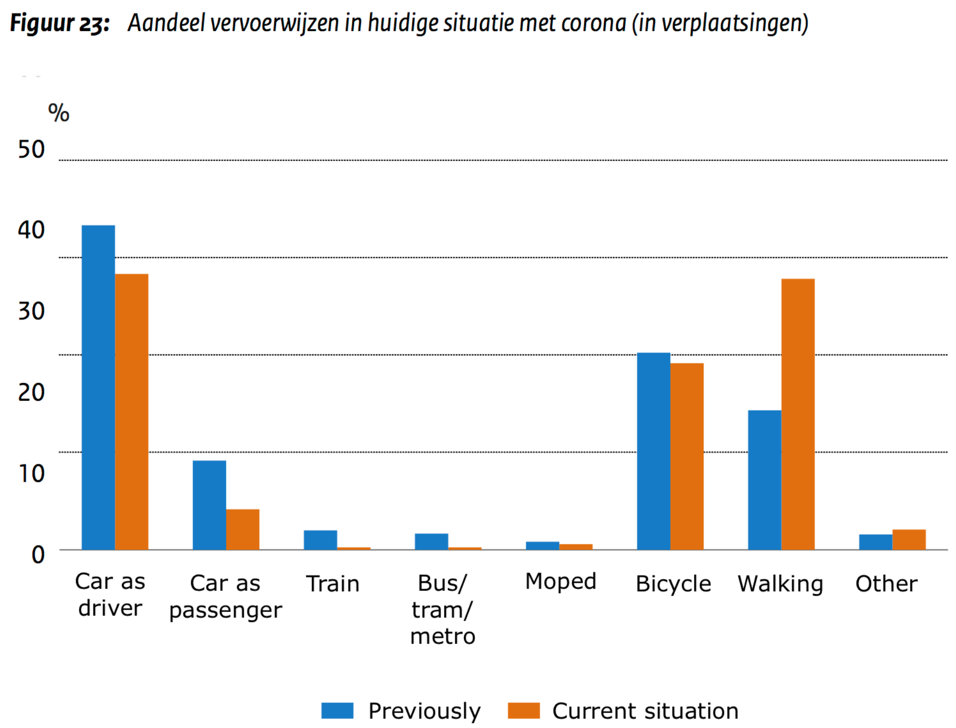


*Figure 2.7: Share of travel modes in current situation with corona (in trips)*

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.

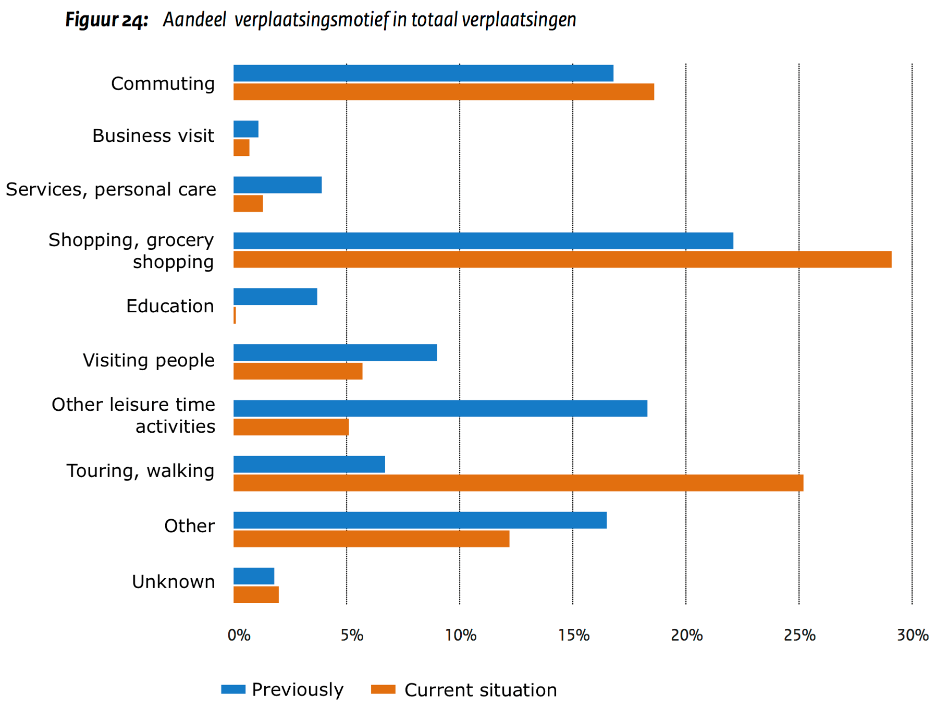


*Figure 2.8: Share of trip motives in number of trips*

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 2.9 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 ($\chi^2$ (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.

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 2.10). 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

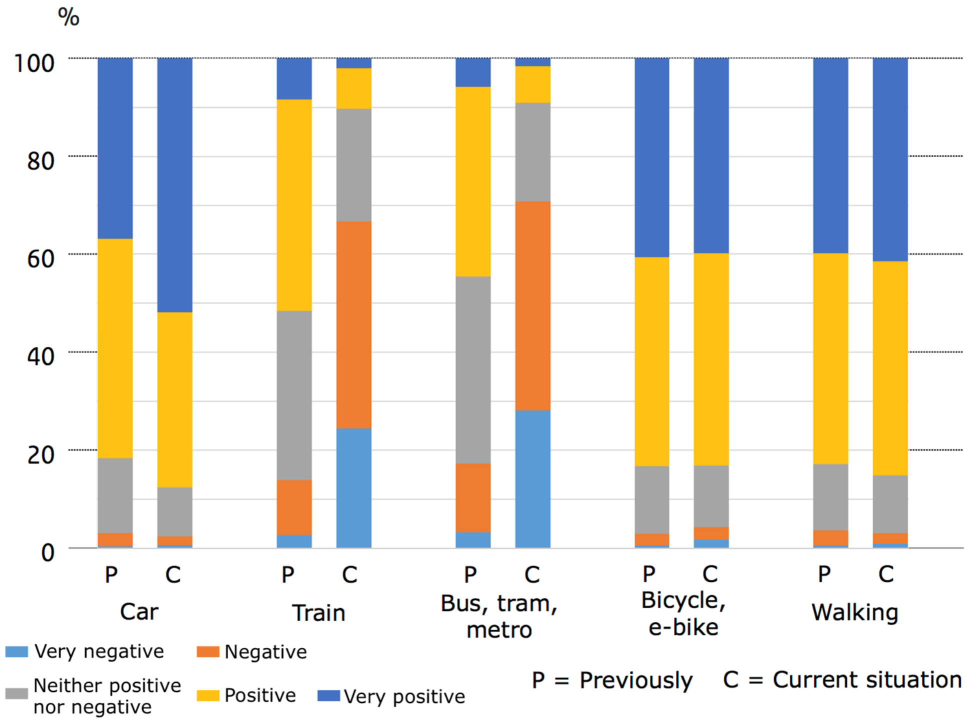


*Figure 2.9: Attitudes towards travel modes in situation with corona*

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.

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 ($\chi^2$ (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.

## 2.4 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

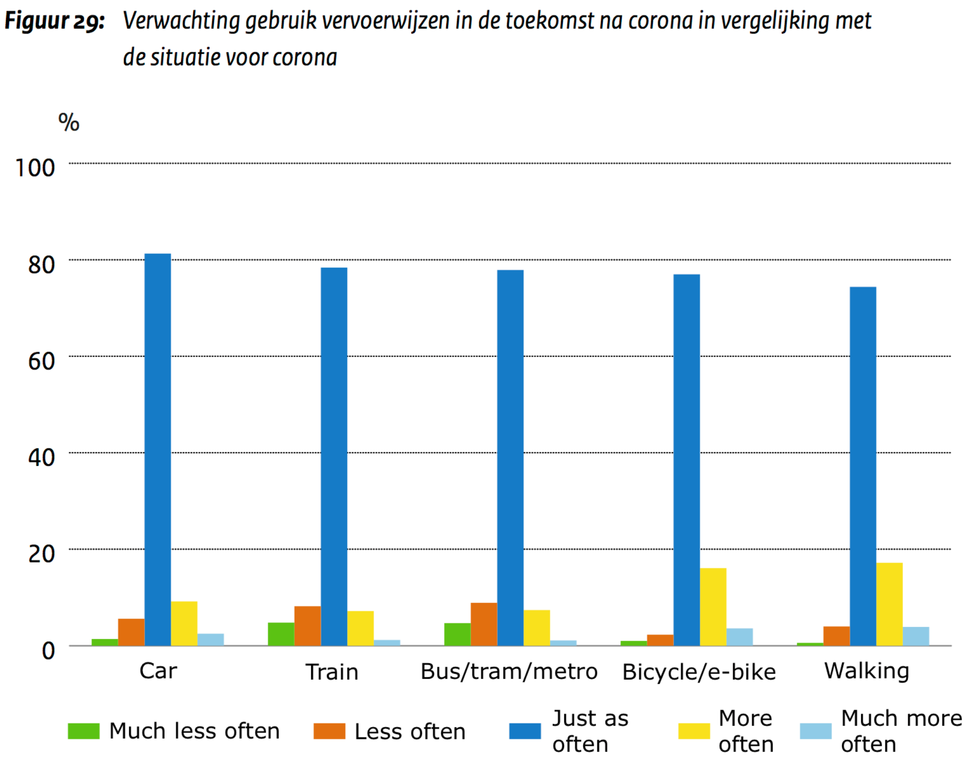


*Figure 2.10: Expected use of modes of transport in the future after corona compared to the situation before corona*

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.

## 2.5 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.

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# Chapter 3

# The relations between working from home and travel behaviour: a panel analysis

This chapter is based on Faber, R. M., Hamersma, M., Brimaire, J., Kroesen, M., & Molin, E. J. (2023). The relations between working from home and travel behaviour: a panel analysis. *Transportation*, *51*(6), 2173–2197. https://doi.org/10.1007/S11116-023-10401-4/TABLES/8

Abstract:

*Policies to increase the amount of time people spend working from home were widely used during the COVID-19 pandemic. Since research suggests that the resulting increase in working from home will outlast these policies themselves, policymakers want to understand the relations between working from home and travel behaviour. We apply longitudinal modelling techniques to estimate the relations between working from home and travel behaviour using panel data from the Netherlands Mobility Panel spanning the years 2017 through 2021. This allows us to separate between-persons and within-persons relations and effects and to see whether these effects changed during the pandemic. We find a negative effect of working from home on commute travel time both before and during the pandemic and a positive effect on leisure travel time only before the pandemic. The sizes of these effects remained roughly similar during the pandemic, although the extent to which working from home affected commute travel time increased during the pandemic. The net effect of working from home on travel time is negative, indicating that working from home policies could be used to reduce travel time. The results also show that some of the relationships between working from home and travel behaviour have changed during the pandemic. As a result, policymakers and transport operators should be careful when estimating future travel demand based on extrapolations of relationships found only before or during the pandemic.*

## 3.1 Introduction

Ongoing developments in information and communication technologies have enabled more people to effectively work from home in the last few decades. This trend is not new, and visions of empty highways because of drastically reduced commuting demand were discussed as early as the 1970s and 1980s (Kraut, 1989; Olson, 1983). These visions however did not come to fruition for decades, until the COVID-19 pandemic. In the wake of the COVID-19 pandemic, many governments enforced a work-from-home mandate in some form (Shibayama et al., 2021). This policy led to, or coincided with, a sharp decline in travel demand (Beck & Hensher, 2020; de Haas et al., 2020; Molloy et al., 2021).

In many countries, including the Netherlands, the policies intended to reduce the spread of COVID-19 have been scaled down in the spring and summer of 2022. Subsequently, total travel demand increased again. However, the increase in working from home appears to outlast the original measures of the government (Jain et al., 2022), as a substantial share of employees and employers alike have discovered its benefits (Shortall et al., 2022). For policymakers and transport planners, who are interested in a prediction of travel demand in the future, this raises the question what the effects of working from home on travel demand will be in the post-pandemic future. To answer this question, the relationship between working from home and travel behaviour needs to be understood well.

The literature on this relationship shows that people who work from home effectively substitute their commute to work with digital communication technologies, reducing the demand for travel. However, it is not clear what effect this has on the time spent travelling for other purposes. Past research has indicated that people who work from home spend more time on non-commute travel, a phenomenon referred to as complementarity (Elldér, 2020). In addition, working from home can have the longer-term effect that people decide to accept longer, but less frequent trips, for example, by relocating or changing jobs (Mokhtarian et al., 2004).

However, these general findings do not provide a clear and convincing answer to questions relating to the relationship between working from home and travel behaviour. First, there is no consensus about the relative size of the substitution and the complementary effects: in essence, whether an increase of working from home results in an increase or decrease of total travel demand. In general, earlier studies find a net substitution effect (Mokhtarian et al., 1995), whereas more recent studies find a more balanced or even net complementary effect (Elldér, 2020). A possible reason for this discrepancy is the difference in study design. Earlier studies often used relatively small panel samples, based on specific projects or pilots, while more recent studies use larger, cross-sectional travel survey data. The upside of the latter approach is the greater power the larger samples have to generalize findings to the population, but the downside is that the cross-sectional data makes it difficult to disentangle within-person (causal) effects – and the direction of these effects – from between-person (correlational) relationships. This study combines the main benefits of both approaches previously used in the literature: the larger sample size and greater generalizability of the larger cross-sectional studies and the ability of panel data to disentangle within-person from between-person effects. This combination is the first contribution of this study to the literature. To separate the within-person from between-person relationships we use a random intercept cross-lagged panel model (RI-CLPM; Hamaker et al. (2015)), which we apply to data from the Netherlands Mobility Panel (MPN), a large panel travel survey.

A second contribution stems from the unprecedented change in working from home behaviour that has been seen since the outbreak of the COVID-19 pandemic. These changes make extrapolating the results from pre-pandemic studies to the post-pandemic world problematic, for two reasons: 1) a new cohort of people started working from home during the pandemic and 2) people worked many more hours from home during the pandemic than they did before the pandemic. Studies that only collect data during the pandemic can be of help, but they too can not fully solve this problem as the behaviour during this period is inevitably intertwined with the broader effects of the pandemic. To connect the pre-pandemic and post-pandemic studies then, the solution is to analyse the behaviour during both tracts of time. Doing so is the second contribution of this paper to the literature, as we use data collected both before and during the COVID-19 pandemic. We apply the RI-CLPM to data collected between 2017 and 2021. This effectively gives us two wave-pairs collected fully before the pandemic (2017 to 2018 and 2018 to 2019) and two wave-pairs collected partly during the pandemic (2019 to 2020 and 2020 to 2021), which allows us to test whether the pandemic resulted in a change to these within-persons relations.

The insights of this study help provide policymakers, road authorities, and public transport operators with better predictions for the effects of working from home on travel behaviour. These predictions affect both relatively short-term decisions, such as public transport operational schedules, as well as longer-term decisions, such as road infrastructure investments. Thus, more insights into the relations between working from home and travel behavior are necessary both during the more short-term transition from the pandemic to the post-pandemic 'normal' and the long-term predictions of how working from home will shape travel demand in the more distant future. Furthermore, it may help policymakers and employers in evaluating the effects policies related to working from home on travel behaviour.

In Section 3.2, an overview of the literature on working from home and travel behaviour is provided, culminating in a conceptual model. In Section 3.3, the methods and data are introduced and described. Section 3.4 contains the results from the estimated model, and the conclusion and discussion can be found in Section 3.5.

## 3.2 Literature Overview

This section contains an overview of the literature on the relations between working from home and travel behaviour. First, an overview of different conceptual relations between working from home and travel behaviour is shown, followed by a more in-depth look at these identified relations. Then we summarise the literature on the effects of COVID-19 on working from home and travel behaviour.

### 3.2.1 Conceptualising the relationship between working from home and travel behaviour

The relationship between working from home and travel behaviour has been studied since at least the early 1970s, when Nilles (1976) proposed it as a solution to reduce commute travel in the face of the oil crisis (He & Hu, 2015). With the rapid increase in information and communication technologies, working from home has become a more feasible solution for a greater part of the population in the decades since (Harpaz, 2002; Siha & Monroe, 2006). Despite seeing an (albeit relatively small) increase in working from home in developed nations in the decades between the 1970s and 2019, total time spent travelling remained relatively constant during the same time as well (Kasraian et al., 2018; Susilo & Maat, 2007). It appears thus that until the COVID-19 pandemic, the effect of working from home on travel behaviour was relatively small, at least for the population as a whole.

This small or non-existing effect can partly be explained by the relatively low rate of adoption of working from home, but also partly by the complex relationship between working from home and travel behaviour. For one, the literature suggests that there is a bi-directional relationship between working from home and travel behaviour (Mokhtarian et al., 2004). Part of this relationship is due to self-selection effects, as people who choose to work from home, and thus have the option to do so, have different travel behaviour habits than people who do not choose to do so (He & Hu, 2015). Another part is due to a relationship between commute distance and working from home, where people with a longer commute distance seemingly choose to work from home more often (de Vos et al., 2018; Zhu, 2012). These issues make it impossible to estimate the unbiased effects of working from home on travel behaviour without controlling for endogeneity (He & Hu, 2015). One of the best ways of doing so is using panel studies, which however are rare in the literature. One application of a panel by De Vos et al. (2018) uses a fixed-effects model to account for time-invariant confounders to separate within- and between-person effects. They find that people who work from home are willing to accept a 5% longer commute. This effect size is smaller than the 11.7% longer commute they found using an OLS model which does not account for time-invariant confounders.

Further complicating the matter is the fact that the effect of working from home on travel behaviour is not as straightforward as it may seem at first glance (Mokhtarian, 1990; Salomon, 1986; Zhu, 2012). Certainly, by replacing a physical (travel) commute with a digital telecommute, working from home causes people to make fewer commute travel trips. This effect is referred to as the substitution effect, where the use of ICT substitutes for physical travel (Andreev et al., 2010). However, the lack of a physical commute saves time, which can be used for travelling for other purposes (Elldér, 2020). If this is the case, working from home also generates new trips, an effect referred to as complementarity (Andreev et al., 2010).

A theoretical explanation for this complementary effect can be found in the theory of constant travel time budgets (Ahmed & Stopher, 2014; Milakis & van Wee, 2018), which states that people like to spend, on average, roughly the same amount of time (per day) for travelling. On a societal level, the existence of constant travel time budgets would mean that people balance travel time spent on commuting and travel time spent on leisure . If the theory turns out to be true, then if one goes down, the other will go up. In other words, reduced commute travel resulting from working from home will result in a rebound effect (Caldarola & Sorrell, 2022; Hostettler Macias et al., 2022; Rietveld, 2011). These rebound effects might result from the within-person complementary generation of leisure travel described above as the complementary effect, but also from between-person effects. Examples of potential mechanisms are reduced crowding and congestion leading to induced demand, greater availability of household cars to other people in the household, and longer-term decisions regarding the distance between the workplace and the residence (Rietveld, 2011; Wöhner, 2022).

The relationships discussed in this section are graphically summarized in the conceptual model for this study, which is given in Figure 3.1. We discussed that there are two distinct effects of working from home on travel behaviour: a negative effect on commute travel, referred to as substitution, and a positive effect on leisure travel, referred to as complementarity. One possible mechanism behind these substitution and complementary effects is that of a constant travel time budget, which should then also be observed for other reasons that are not related to working from home.

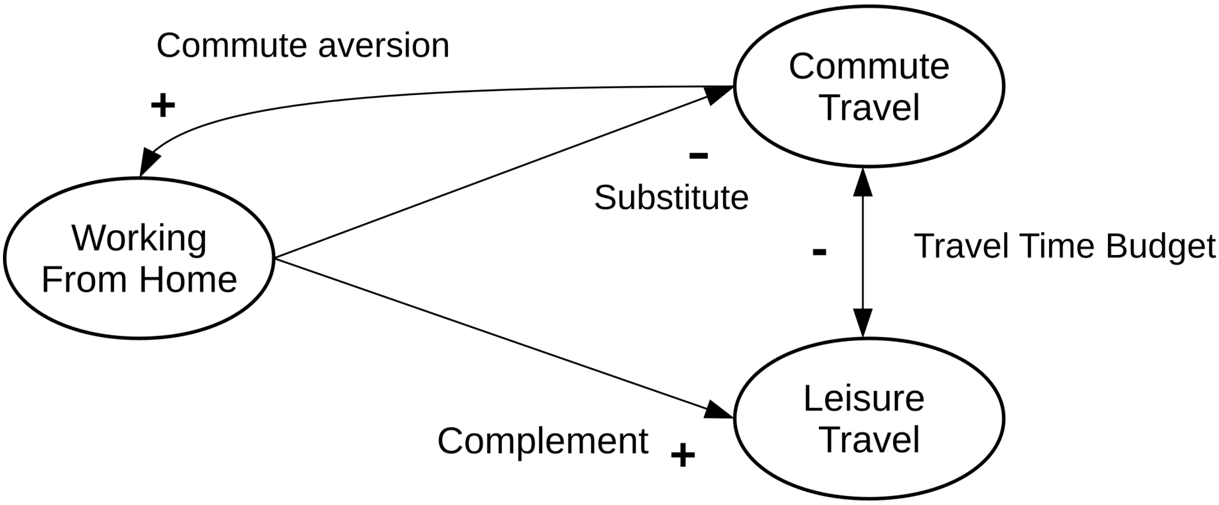


*Figure 3.1: The conceptual model used in this study*

It is important to point out here that the conceptual model is an overview of the relationships between working from home and travel behaviour that are expected to exist, based on the overview of the literature. As will be clarified later in the discussion of the research method and the operational model, we empirically test all possible relationships between the concepts in this conceptual model. The conceptual model thus serves as a theoretically underpinned base for further analyses in this study – both how they are set up and how they are interpreted.

### 3.2.2 The effects of working from home on travel behaviour

In this subsection, we will provide an overview of the literature discussing the various relationships visualized in Figure 3.1. We will start by looking at the effects of working from home on travel behaviour, and whether there is a net substitution or complementary effect. We will then dive into the literature on travel time budgets.

#### Net substitution or net complementarity

The complex conceptual relations between working from home and travel behaviour make it difficult to adequately assess the relative size of the effects that working from home has on travel behaviour. Earlier review studies show that in total, working from home reduces travel demand and thus that the substitution effect is stronger than the complementary effect (Andreev et al., 2010; Mokhtarian, 1991).

Several more recent studies indicate that people who work from home travel either a greater total distance or make more trips than people who do not work from home (de Abreu e Silva & Melo, 2018; He & Hu, 2015; Zhu, 2012; Zhu et al., 2018). Elldér (2020) found that people who work a full day from home travel a smaller distance, but that people who work from home for part of the day travel more often and for longer distances. Caldarola and Sorrell (2022) found a similar effect: working from home is associated with greater distances travelled up to a certain point (working from home 3 or more days a week), where they travel less. Wöhner (2022) finds that people who telework travel a similar distance as people who do not. All the above studies find that working from home is related to making fewer commute trips, but more non-commute trips. Summarising then, many recent studies find that people who work from home travel more than people who do not, suggesting that the complementary effect is at least similar in size to the substitution effect.

#### Between-persons vs within-persons effects

This raises the question why there is such a difference between the general findings of the earlier and later studies: research design or a real underlying change in the effects over time. There is a striking difference in research design between many earlier and many later studies. Earlier studies typically used data collected from smaller sample sizes, collected specifically around one or multiple projects where people increased the amount of time they would work from home. Later studies more often use data from general travel surveys, generally consisting of larger sets of respondents that are meant to be representative of a region or country (Elldér, 2020). Earlier studies often collected longitudinal data (from before and after people started working from home), whereas later studies used cross-sectional data. These later studies then cannot disentangle between-persons from within-persons effects. Another drawback of using general travel surveys is that the measurement of working from home is often not so precise: respondents for example indicate that they work from home ‘regularly’ or ‘sometimes’. Elldér (2020) showed that using more precise measurements, such as when people telework and for how many hours, leads to different results with stronger substitution effects. They posit that more recent studies typically use less precise measurements of working from home, which is one explanation for the difference in results between earlier and more recent studies.

### 3.2.3 The disruption of the COVID-19 pandemic

The COVID-19 pandemic has had a profound impact both on working from home and travel behaviour. This impact is the result of two related effects: the fear of the pandemic causes people to travel less often, and government mandates aiming to curb the spread of the virus have severely affected people’s ability to employ activities outside of their homes.

#### Effects on working from home

Research shows that the amount of time people worked from home increased during the COVID-19 pandemic in many countries, all over the world (Beck & Hensher, 2020; de Haas et al., 2020; Downey et al., 2021; Kolarova et al., 2021; Rafiq et al., 2022; Yilmazkuday, 2020; Zhang, 2021). This is the result of policies by many national governments, which aimed to inhibit the transmission of the virus by reducing contacts between people both at work and whilst travelling to work. This sudden development contrasts the gradual growth of working from home over the past decades (Mokhtarian, 2020; Stiles & Smart, 2021). Many people started working from home during the pandemic and discovered its benefits and drawbacks for the first time (Reiffer et al., 2022). This means that people were generally not able to self-select into work circumstances that allowed them to work from home, but rather were either forced to do so or suddenly found themselves able to (Ecke et al., 2022). The effects of working from home for these new groups of people can be vastly different to those found before the pandemic, which is based on a much narrower group (Kramer & Kramer, 2020; Reiffer et al., 2022). Finally, studies find that a substantial number of people that started working from home have been content with this change in their life and expect to work from home post-pandemic as well (Shortall et al., 2021). This means that increased levels of working from home will have a lasting impact on working from home, even after the pandemic and the associated measurements are no longer a driving force behind working from home adoption.

#### Effects on travel behaviour

Simultaneously, activity-travel patterns changed drastically during the pandemic as well. In general, commuting travel decreased (Beck & Hensher, 2020; Beck et al., 2020; de Haas et al., 2020; Shamshiripour et al., 2020). This decline was most substantial for public transport use (Beck & Hensher, 2020; de Haas et al., 2020), which can at least partly be explained by the increase in working from home. Studies indicate that working from home has a relatively strong negative effect on public transport use (Bohman et al., 2021; Currie et al., 2022; Downey et al., 2022; Sweet & Scott, 2022), due to the finding that former public transport commuters are commonly able to work from home. Some studies also report a shift towards travel for leisure purposes, especially those made on foot or a bicycle (Campisi et al., 2022; Christidis et al., 2022; de Haas et al., 2020; Zhang, 2021). These changes can only partially be explained by the increase in working from home: other contact-reducing measures (up to and including lockdowns) and the general fear of being infected with the disease of course played a much larger role as well.

## 3.3 Research Methods

This section describes the data and methods used to investigate the relations visualized in the conceptual model. The data panel is described first, followed by the operationalisation of the concepts into variables. Then descriptive statistics of the data are presented, followed by a description of the research method. Finally, the section culminates in the specification of the final model, descriptions of model estimation and an operational model.

### 3.3.1 Data and Sampling

To investigate the relationship between working from home and travel behaviour, we use data from the MPN, a longitudinal household panel that consists of a 3-day travel diary and a set of questionnaires (Hoogendoorn-Lanser et al., 2015). Respondents for the MPN are recruited from an invite-only internet access panel (IAP), the Kantar NIPObase panel. Respondents for this larger IAP are recruited using register data, and it is not possible to sign-up to become a member of this IAP. Members from this larger IAP are recruited to participate in the MPN based on their socio-demographic characteristics, which ensures that the MPN itself tracks the population distribution on these variables. For example, if younger people are underrepresented in the MPN, then in the next wave more young people are invited from the larger IAP. Between 30% and 50% of respondents accept this initial invitation to participate in the panel. Response rates for the respondents within the panel vary between 85% to 90% for each yearly wave.

We use five waves of data from the MPN, spanning the years 2017 through 2021. Effectively, this gives us three waves of data collected before the COVID-19 pandemic and two waves collected during the COVID-19 pandemic. Each wave is collected in the Fall of each year. During the pandemic years of 2020 and 2021, COVID-19 the government recommended that people work from home when able. Furthermore, COVID-19 cases were rising during both years as we transitioned from relatively carefree summers to winters with prolonged lockdowns. In 2020, stricter measures were introduced during the fieldwork period. In 2021 measures were slightly relaxed halfway through, but the increase in measures culminating in a lockdown only started after the fieldwork period was over. The timing of the MPN measurements is visualized together with the COVID-19 hospital admissions and the Oxford CGRT Stringency Index (Hale et al., 2021) in Figure 3.2.

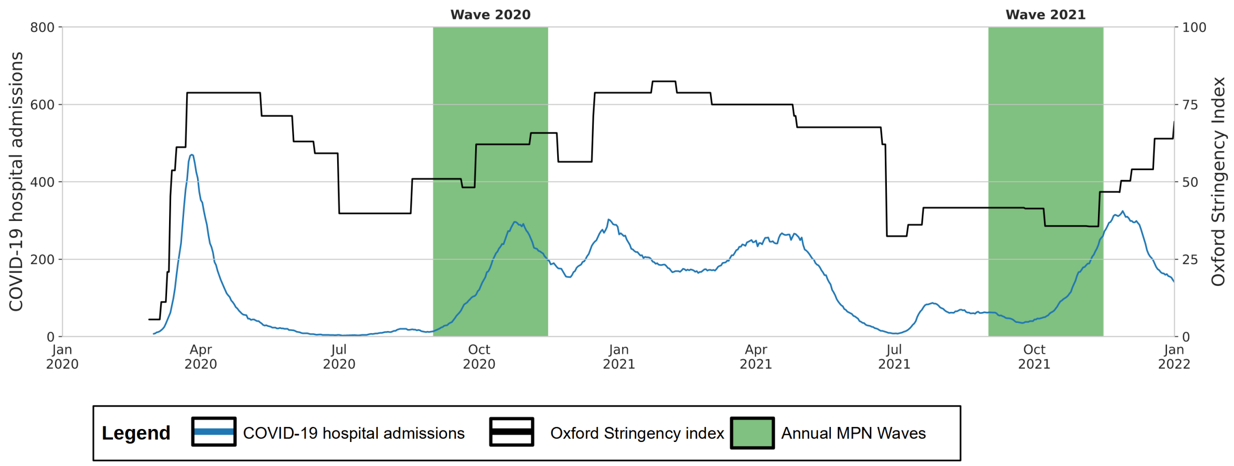


*Figure 3.2: Fieldwork period for the MPN waves visualized with COVID-19 hospital admissions and Oxford Stringency Index*

Since we are interested in the relationship between work and travel behaviour in this study, we only use MPN respondents that worked at least 16 hours per week during each wave. Furthermore, we use a pure-stayer sample of respondents who fully participated in all five waves. The use of a pure-stayer sample allows us to more directly compare the effect sizes found before and during the pandemic, as they are based on data generated by the same people. The final pure-stayer sample consists of 1100 respondents. A possible drawback of using a pure-stayer sample is the potential of non-random dropout, which could lead to a skewed data set. To test whether this is the case, we give a distribution of socio-demographic characteristics for both the pure-stayer sample and the cross-sectional sample of the 2019 MPN wave in Table 1. These can be compared to their distribution in the population, which are based on data registers produced in cooperation with Statistics Netherlands by the Dutch Marketing, Research, and Analytics organization (MOA Expertise Center, 2023).

| | | Study Sample (pure stayer) | Cross-sectional Sample (2019 wave) | Population (18+ years old with gainful employment) |
|---|---|---|---|---|
| Gender (%) | Male | 52 | 50 | 54 |
| | Female | 48 | 50 | 46 |
| Age (Years) | 18-29 | 8 | 15 | 17 |
| | 30-39 | 31 | 27 | 23 |
| | 40-49 | 25 | 26 | 25 |
| | 50-59 | 27 | 24 | 25 |
| | 60+ | 9 | 8 | 9 |
| Education (%) | Low | 11 | 14 | 14 |
| | Medium | 38 | 40 | 43 |
| | High | 52 | 46 | 43 |
| Net Personal Income (€/month) | Low (< 2000) | 32 | 38 | 45 |
| | Modal (€2000 to €3000) | 46 | 43 | 35 |
| | High (> 3000) | 22 | 19 | 20 |
| Urban Density (addresses/m$^2$) | < 500 | 7 | 9 | Not available |
| | 500-1000 | 20 | 21 | |
| | 1000-1500 | 17 | 18 | |
| | 1500-2500 | 33 | 32 | |
| | > 2500 | 23 | 20 | |
| Household type (%) | Single | 26 | 20 | Not available |
| | Adult household | 39 | 44 | |
| | Kids < 13 | 29 | 28 | |
| | Kids > 13 | 7 | 8 | |

*Table 3.1: Sample distribution of the pure-stayer sample, the cross-sectional participants of the 2019 wave, and the population.*

This comparison between the socio-demographics of the pure-stayer sample and the cross-sectional sample, given in Table 3.1, shows that drop-out is indeed higher in some subgroups, leading to a slightly skewed sample. In particular, younger people (younger than 29 years) seem to drop out more often. This leads to an underrepresentation of this group in our final sample compared to the population. Both the cross-sectional and the pure-stayer sample also contain a slight overrepresentation of higher-educated, higher-income groups.

### 3.3.2 Operationalisation

The main interest of this research is to:

a. determine the direction and size of the (causal) relations between working from home and travel behaviour

and

b. find whether these effects changed during the COVID pandemic. To find the bidirectional (causal) relations between working from home and travel demand we need to include four variables within each wave.

First, we include the weekly number of hours worked from home and the weekly number of hours worked in total. These two variables allow us to capture the effect of working more from home, whilst controlling for the effects of simply working more. Effectively, we need to separate increases in working from home that result from a simple increase in the total number of hours worked and increases that result from a shift from hours worked in a separate work location (for example an office) to hours worked from home. These variables are measured using a questionnaire, where respondents are prompted to answer how many hours on average they worked in total in the last few weeks. Afterwards, they distribute these hours over the location where they worked, giving us the weekly number of hours spent working from home. This information is recorded for a general week during the fieldwork period, but respondents do not specify on which specific days they worked from home.

For travel behaviour, we distinguish two types of travel. The first is commute travel, which we define as travel to move to and from the work location. Second, we distinguish leisure travel, which we broadly define as all travel that is not made specifically either for work (= either commuting or business travel) or educational purposes. We operationalise travel behaviour as the time spent travelling for either commuting or leisure purposes during the 3-day observational period of the MPN. We choose to use travel time, as opposed to travel distance, since we assume that people base their decisions on changes in travel time. In other words, we expect that the time saved by commuting less because of working from home is the most tangible benefit felt by people who work from home and that it is this saved up time they might spend on travelling for other purposes. This is also the main thought behind the theory of constant travel time budgets, which we can tie into our research in this way.

We extend the model beyond these four variables in two ways. First, we include the number of weekend days that are included in a respondent's travel diary allotment. MPN respondents keep 3-day travel diaries, where the allotted weekdays are kept stable across waves. Some respondents then have 1 or 2 weekend days in these allotted days, whereas others have none. We need to control for these differences to get more accurate between-person relations. Second, we want to allow for some form of heterogeneity with respect to travel modes in the model. This adds information that is highly relevant to policymakers, road operators, and transit planners. To do so, we add the most often used commute mode in the last pre-pandemic wave (2019). This allows us to obtain information on the extent to which commute demand for the various modes has been affected by working from home due to the pandemic. The commute mode is operationalised using two dummy variables: people who commuted by public transport and people who commuted by car. The reference group then consists of all people who commuted by other travel modes.

### 3.3.3 Data description

In this section, we describe and inspect the data. Means, medians, standard deviations and serial correlations for the four time-variant variables are given in Table 3.2.

| | | 2017 | 2018 | 2019 | 2020 | 2021 |
|---|---|---|---|---|---|---|
| **Hours worked per week** | Mean | 35 | 35 | 35 | 35 | 35 |
| | Median | 36 | 36 | 36 | 36 | 36 |
| | SD | 8.9 | 8.6 | 8.5 | 8.4 | 8.0 |
| | Serial correlation[1] | - | 0.81 | 0.85 | 0.81 | 0.85 |
| **Hours WFH per week** | Mean | 3 | 3 | 3 | 12 | 10 |
| | Median | 0 | 0 | 0 | 4 | 3 |
| | SD | 6.3 | 6.8 | 6.5 | 15 | 13 |
| | Serial correlation[1] | - | 0.66 | 0.75 | 0.40 | 0.77 |
| **Commute travel time (hours / 3 days)** | Mean | 1.30 | 1.27 | 1.23 | 0.67 | 1.30 |
| | Median | 1.00 | 0.92 | 0.80 | 0.17 | 1.00 |
| | SD | 1.43 | 1.43 | 1.47 | 1.07 | 1.43 |
| | Serial correlation[1] | - | 0.50 | 0.58 | 0.29 | 0.41 |
| **Leisure travel time (hours / 3 days)** | Mean | 1.98 | 2.15 | 2.03 | 1.73 | 1.98 |
| | Median | 1.45 | 1.62 | 1.57 | 1.20 | 1.45 |
| | SD | 1.95 | 2.12 | 1.95 | 1.90 | 1.95 |
| | Serial correlation[1] | - | 0.36 | 0.35 | 0.35 | 0.44 |

1: Year-on-year serial correlation. That is, the correlation within one variable of the given year with the previous year

*Table 3.2: Means, medians, standard deviations and serial correlations for the time-variant variables*

The mean, median and standard deviation values of all variables are stable in the three pre-pandemic years. This stability disappears when comparing both 2020 and 2021 to the years before the pandemic, especially for the number of hours worked from home and commute time travelled. The average number of hours worked from home substantially increased in the year 2019/2020, before levelling off at an average of 10 hours worked per week in 2021. Both commute and leisure travel time decreased: from 74 minutes per 3 days for commute travel in 2019 to 40 minutes in 2020 and from 122 minutes per 3 days for leisure travel to 104 minutes. The decrease in commute travel time thus was much more substantial than the decrease in leisure travel time.

Another way of showing the stability of the variables over time is by looking at the serial correlation of each variable. The serial correlation refers to the correlation between the measurements at timepoint t and the measurements at the previous timepoint t-1. These correlations are relatively stable for the number of hours worked in total and leisure travel time throughout the sampling period. However, there is a very strong decrease in the serial correlation between 2019 and 2020 for the number of hours worked from home and commute travel time compared to the serial correlation before the COVID-19 pandemic. This shows that the COVID-19 pandemic disrupted both the hours worked from home and commute travel time, but not the total hours worked and leisure travel time.

| | Hours worked | Hours WFH | Commute travel time | Leisure travel time |
|---|---|---|---|---|
| Hours worked | 1 | *0.31* | *0.13* | *-0.041* |
| Hours WFH | **0.26** | 1 | *-0.24* | *0.040* |
| Commute travel time | **0.20** | **-0.068** | 1 | *-0.11* |
| Leisure travel time | **-0.035** | **0.057** | **-0.18** | 1 |

Bivariate correlations in the lower left (**bold**) are from the pooled 2017-2019 data; correlations in the upper right (*italic*) are from the pooled 2020-2021 data

*Table 3.3: Correlations between time-variant variables*

Finally, we can get a first appreciation for the relations between the variables by studying the bi-variate correlations between the time-variant variables for both the years before and the years during the COVID-19 pandemic, which are given in Table 3.3.

As expected, based on the conceptual model, the correlation between working from home and commute travel is negative both before and during the COVID-19 pandemic. The magnitude of the correlation is much larger during the pandemic than it was before the pandemic. The correlation of hours worked from home and leisure travel time is small, but positive – again in line with the expectation set out in the conceptual model – and did not change in magnitude nearly as much. The correlations between commute and leisure travel time are negative, and the correlations between working and working from home are positive.

### 3.3.4 Method and model specification

To determine the longitudinal relations between the variables, we use a random-intercept cross-lagged panel model (RI-CLPM), which is an extension of the cross-lagged panel model (CLPM; Finkel (2011)). The CLPM is an often-used model to study panel data used to empirically test the bidirectional effects between multiple concepts that are measured over time. To do so, the CLPM specifies auto-regressive relationships, which are supposed to control for the stability of a variable over time. The cross-lagged relationships between the constructs are then supposed to represent the causal processes between the variables. As pointed out by Hamaker et al. (2015), this approach assumes that the score of each variable for every person varies over time around the same sample mean. This assumption is problematic, as most variables do contain stable differences between individuals. For example, some individuals will persistently work more hours per week than others across all measurements, which is ignored by the CLPM.

Hamaker et al. (2015) therefore argue that researchers should not only control for temporal stability across the sample, but also for the time-invariant stability of each variable on the level of the individual. Doing so effectively separates within-person effects over time from constant between-person differences. This is achieved by including random intercepts, which account for the trait-like, time-invariant stability of the variables. The random intercepts thus capture the between-persons differences, allowing the (auto)-regressive structure to specifically capture within-person effects. The resulting auto-regressive coefficients can then be interpreted as within-individual carry-over effects (Mulder & Hamaker, 2020), meaning that a positive effect indicates that a higher (or lower) than expected score is likely to also have a higher (or lower) than expected score during the next observation, where the expected score is based on the average, trait-like, score per respondent. Similarly, the cross-lagged effects represent that an individual with a higher-than-expected score on one variable also has a higher-than-expected score on the other variable in the next measurement. These effects are directional and since they represent within-individual changes, they can be more correctly assumed to represent causal processes on the within-individual level than parameter estimates from CLPMs. The RI-CLPM also allows us to estimate the correlations between the random intercepts, which can be interpreted as the general between-person relations between the concepts associated with each of the random intercepts in question (Mulder & Hamaker, 2020).

The main methodological challenge in this study is that we need to account for the disruption caused by the COVID-19 pandemic, which can be termed a ‘regime change’ and threatens the ability to draw causal inferences from the model (Zyphur et al., 2019). We must find a solution for the resulting disruption to the stable, trait-like differences between individuals. Earlier we saw in Table 2 that the serial correlations for working from home and commute travel time were much lower between the years 2019 and 2020 than they were before the pandemic. This provides a challenge, as the random intercepts in a RI-CLPM typically assume that there are stable differences between individuals across the duration of the study by fixing all factor loadings of the random intercept to one (Hamaker et al., 2015). The pandemic makes this a problematic assumption, especially for working from home and commute travel time. A potential solution is to remove the constraint on the factor loadings for the measurements during the COVID-19 pandemic (Hamaker et al., 2015; Zyphur et al., 2019) and to let the model estimate factor loadings separately for both measurements. We test this specification against the typical specification with fixed factor loadings to determine which provides the best fit to the data.

Furthermore, we are interested in answering the question whether this regime change resulted in changes to the within-person effects during the COVID-19 pandemic compared to before the pandemic. We can do so by estimating a model where the lagged parameters are constrained to be the same over the whole duration over time and testing it against a model where we relax this constraint. We will thus test a model with only one set of parameters for the entire duration of the study against a model with two sets of parameters, one for the lagged effects before the pandemic (2017 $\rightarrow$ 2018 $\rightarrow$ 2019) and one for the lagged effects during the pandemic (2019 $\rightarrow$ 2020 $\rightarrow$ 2021). Again, we can test which model best fits the data. If the latter model fits best, then we can say that the within-person relations changed during the pandemic.

Finally, we add two extensions to the model discussed by Mulder and Hamaker (2020), both relating to the incorporation of time-invariant predictors of the time-variant variables. Time-invariant variables are stable over time, and in this model specification we expect them to have affected the time-variant variables. The first extension is the use of the number of weekend days as a predictor of the random intercepts. Effectively, this controls the trait-like stability of the variables for the differences in our measuring instrument that assigns a different number of weekend days to the respondents. Second, we regress the time-variant variables for the waves during the pandemic on the commuting mode used in the last wave before the pandemic. This gives us additional insight into the effects of working from home on the use of different travel modes.

| Model | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Description | CLPM; Equality constraint | RI-CLPM; Equality constraint | RI-CLPM; Two sets of parameters | RI-CLPM; 2 RI Factor loadings relaxed | RI-CLPM; All RI factor loadings relaxed |
| Degrees of freedom | 192 | 182 | 166 | 162 | 158 |
| Df difference | - | 10 | 16 | 4 | 4 |
| Chi-square | 1339 | 653 | 487 | 428 | 423 |
| Chi-square difference (test) | - | 686 (p < 0.001) | 166 (p < 0.001) | 60 (p < 0.001) | 4.8 (p = 0.308) |
| CFI | 0.902 | 0.960 | 0.973 | 0.977 | 0.977 |
| RMSEA | 0.074 | 0.049 | 0.042 | 0.039 | 0.039 |
| SRMR | 0.077 | 0.068 | 0.056 | 0.038 | 0.037 |
| AIC | 109113 | 107958 | 107824 | 107772 | 107775 |
| BIC | 108624 | 108497 | 108443 | 108411 | 108434 |

*Table 3.4: Goodness-of-fit statistics for the five structural equation models*

### 3.3.5 Model estimation

In this section, we first compare the model fit of several models introduced above to see which model provides the best fit to the data. As introduced in section 3.4 above, we estimate five different models:

1. A RI-CLPM with equality-constrained lagged parameters where the variance and covariance of the random intercepts are constrained to zero. This effectively is a CLPM.
2. As in 1, but without the constraints on the variance and covariance of the random intercepts
3. Removing the equality constraints on the lagged parameters, instead estimating two sets of parameters. One before the pandemic, and one during the pandemic.
4. Removing the constraints on the factor loadings of the 2020 and 2021 measurements of working from home and commute travel time
5. Removing the constraints on the factor loadings of the 2020 and 2021 measurements of all four variables.

All models are estimated using the R-package Lavaan (Rosseel, 2012). The goodness-of-fit statistics, as given by Hooper et al. (2008), are displayed in Table 3.4.

The CLPM fits relatively poorly to the data with a chi-square value of 1339 (df = 192, p = 0.000) and unsatisfactory RMSEA, SRMR, and CFI scores. The RI-CLPM (model 2) provides a much better fit to the data based on these criteria. The equality constraint on the lagged parameters is relaxed in the step to model 3. This relaxation again results in a large increase in model fit and is to be preferred based on all goodness-of-fit indicators. For model 4, the factor loadings of the random intercepts pertaining to the COVID-19-influenced measurements of working from home and commute travel time are no longer constrained. This again results in a relatively large increase in model fit, with a very good model fit as indicated by the CFI (0.977), RMSEA (0.039), and SRMR (0.038). The final step to model 5, where the factor loadings of all measurements during the pandemic were no longer constrained proves to be less effective. Model 5 is not to be preferred over model 4 based on the Chi-square difference test and the AIC and BIC values.

## 3.4 Results and Discussion

This section describes and interprets the empirical results from the estimated model fitted to panel data in the Netherlands. The section is structured around the expected relations from the conceptual model given in Section 3.2. First, the results relating to the effects of working from home on both commute and leisure travel time are interpreted. Then, the effects of travel time on working from home and the relations between the two travel time variables are discussed. Finally, we discuss the stability of the variables and take a brief look at the effect of commuting by different modes.

As described in Section 3.3.4, the RI-CLPM estimates two different effects: the within-person directional effects, which vary over time, and the between-person correlations, which do not vary over time. Both sets can be analysed together to attain a comprehensive overview of the relationships between working from home and travel behaviour.

### 3.4.1 The effects of working from home on travel time

The relationship between working from home and travel time is interpreted using both the within-person and between-person coefficients estimated in the RI-CLPM. First, we will look at the within-person estimates. The unstandardized within-individual effects between the four time-variant variables, as well as the effect of the time-invariant predictor, are given in Table 3.5. As explained in Section 3.3.4, the auto-regressive coefficients can be interpreted as within-individual carry-over effects and the cross-lagged coefficients represent that an individual with a higher-than-expected score on one variable also has a higher-than-expected score on the other variable in the next measurement.

We find negative unstandardized effects from working from home on the travelled commute time both before the pandemic (-0.022) and during the pandemic (-0.023). This effect did not change during the pandemic compared to before the pandemic. We find a positive unstandardized effect of working from home on leisure travel time before the pandemic (0.013), which however nearly disappeared during the pandemic. These estimates provide evidence for the existence of both substitution and complementary effects.

| Independent variables | Dependent variables<br>Effects before COVID-19 pandemic (2017 – 2019) | | | | Effects during COVID-19 pandemic (2019 – 2021) | | | |
|---|---|---|---|---|---|---|---|---|
| | Work hours | WFH hours | Commute time travelled | Leisure time travelled | Work hours | WFH hours | Commute time travelled | Leisure time travelled |
| **Time-variant variables** | | | | | | | | |
| Work hours | 0.407*** | -0.062** | 0.003 | -0.019** | 0.241*** | -0.111 | 0.008 | -0.010 |
| WFH hours | 0.019 | 0.645*** | -0.022*** | 0.013* | -0.008 | 0.403*** | -0.023*** | 0.004 |
| Commute time travelled | -0.033 | -0.327*** | 0.212*** | 0.044 | -0.197* | -1.615*** | 0.159*** | 0.106** |
| Leisure time travelled | -0.019 | -0.109* | 0.029* | 0.063** | -0.171** | -0.492*** | 0.020 | 0.104*** |
| **Time-invariant predictors** | | | | | | | | |
| PT Commuter[a] | | | | | 0.855* | 8.458*** | -0.165 | -0.075 |
| Car Commuter[a] | | | | | 0.352 | -0.551 | 0.067 | -0.081 |

In this and following tables, *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$
a. reference: all other travel modes as main commute mode

*Table 3.5: Unstandardized within-individual effects between time-variant variables*

| | Hours worked at home | Commute travel time | Leisure travel time |
|---|---|---|---|
| Hours worked | 0.403*** | 0.432*** | -0.062 |
| Hours worked at home | | 0.180** | 0.183*** |
| Commute travel time | - | | -0.141** |

*Table 3.6: Correlations between random intercepts*

The latter effect however is only found to be statistically significant before the pandemic. Both before and during the pandemic we can conclude that the substitution effect appears to be stronger than the compensatory effect.

However, it is important to realize that standardized estimates can still change drastically, even if the unstandardized estimates are relatively stable. This is the case if the distribution of the variables changes over time. We saw in Section 3.3.3 that the standard deviation for working from home increased during the COVID-19 pandemic, whereas the standard deviation for commute travel time decreased. Since we saw that the unstandardized parameter remained nearly constant, we can conclude that the standardized parameter estimates of the effect of working from home on travel time increased during the COVID-19 pandemic. It increases from -0.110 (2018 to 2019) to -0.132 (2019 to 2020), to -0.249 (2020 to 2021). So even though the unstandardized effect barely changed at all during the same period, the variation in working from home had a larger influence on the variation in commute travel time during the pandemic than it did before the pandemic. In other words, changes in working from home were a greater driver of changes in commuting travel time during the pandemic than before the pandemic.

The above interpretation of the within-person effects can be complemented by an analysis of the between-person relations, which are estimated by the RI-CLPM as the correlations between the random intercepts. These correlations represent the time-invariant relations between the variables across the respondents. Table 3.6 contains the correlation coefficients between the four random intercepts.

The positive correlation (0.403) between the number of hours worked and the number of hours worked at home for example indicates that people who work more hours also work more hours from home. Similarly, people who work more also tend to commute more (correlation = 0.432). So far, these findings are not very surprising.

However, that changes when we turn our attention to the relations between working from home and travel time. We see a relatively strong and significant correlation between the number of hours worked from home and commute travel time (0.180). This finding contrasts the negative within-person effects of working from home on commute travel time discussed above. This means that people who work more hours from home in general travel more time for commuting. However, variations within the individual have an effect in the opposite direction: a higher-than-expected score for working from home results in a lower-than-expected score for commute travel time in the next measurement. Similarly, we also note the fairly large and positive correlation between working from home and leisure travel time (0.183), which stands in contrast with the fairly small within-person effect of working from home on leisure travel time, which was even insignificant during the COVID-19 pandemic.

The key takeaway then is that the within-persons and between-persons relations between travel time and working from home differ from one another. This implies that research methods which are unable to separate within-persons from between-persons effects will, to varying extents, over-estimate the size of the complementary effect and underestimate the size of the substitution effect. This would explain the difference between the more recent findings, based on cross-sectional studies, that working from home will lead to an increase in travel and the less recent findings, based on panel studies, that working from home leads to a decrease in travel, as discussed in Elldér (2020). This explanation complements the finding in Elldér (2020) itself, where the author poses that the difference in measurement of working from home between earlier and later studies explains the difference in outcomes. Both results together suggest that future researchers studying the effects of working from home on travel demand should both use more direct measurements of working from home and ideally use methods that can separate between-person from within-person differences.

### 3.4.2 Travel Time Budgets and effects on work and work from home

Based on the theory of constant travel time budgets, we expected a negative relationship between commute and leisure travel time. However, the model estimates either insignificant or positive within-person effects between these two variables. One explanation might be that as people move through life, they go through life events that increase mobility in general. Furthermore, the effect during the pandemic likely reflects a temporary unwillingness to travel due to underlying concerns about the virus. Turning our attention to the between-person correlations between the two travel time variables, however, we do find a negative relationship between commute and leisure travel time. This means that people who spend more time travelling for leisure purposes, in general, spend less time commuting. Again, the within-persons and between-persons effects seem to differ markedly. These findings would suggest that the theory of constant travel time budgets works on the between-person level, but not necessarily on the within-person level. Reduced commute travel (either due to increases in working from home or not) thus could lead to other people travelling more, but not necessarily to increases in leisure travel within the individual. This is a useful finding to keep in mind, as it seems to indicate that rebound effects (Caldarola & Sorrell, 2022; Hostettler Macias et al., 2022; Rietveld, 2011) at least partly occur between-persons. For the effectiveness of working-from-home policies, this would indicate that some of the reduced travel demand resulting from the net substitution effect within the individual, as discussed above, will be offset by increased travel demand from other persons.

We also find some effects of commute and leisure travel time on working from home. We find sizeable negative within-persons effects from commute time on working from home (-0.327 before the pandemic, -1.615 during). As explained in Section 3.2, we initially expected a positive effect here, as people with longer commutes net a larger gain by working from home more often. However, we operationalised commute travel time as the total amount of time travelled for commuting purposes, which does not necessarily encompass the amount of time travelled per commute. During the pandemic, we also find significant negative within-person effects of both commute and leisure travel time on working hours. This suggests that people that start to travel less, will then work fewer hours in the following year. There is no clear theoretical explanation for these findings. Perhaps the model is picking up certain life events that more frequently occurred during the pandemic, which results in changes to both the travel- and work-related variables.

### 3.4.3 Stability and Mode use heterogeneity

The sizes of the auto-regressive parameters also differ between the estimates before and during the pandemic. For all variables, these parameters were smaller during the pandemic than they were before the pandemic. This indicates a smaller carry-over effect from one measurement to the next of the behaviour seen, which indicates less stable behaviour. This makes sense, as we concluded earlier that the COVID-19 pandemic resulted in changes to both work- and travel behaviour.

Finally, we also included the main commuting mode as recorded during the last measurement before the pandemic (September 2019) as a time-invariant predictor of the variables in the following waves during the COVID-19 pandemic. Public transport commuters differed statistically from all other commuters in terms of the number of hours they work from home. People whose most often used commuting mode before the pandemic was public transport were far more likely to work from home during the pandemic (roughly 8,5 hours more per week compared to the reference group, which was non-car, non-public transport commuters). This confirms earlier findings that the shift to working from home was especially large for public transport commuters (Bohman et al., 2021; Currie et al., 2021; Downey et al., 2022).

## 3.5 Conclusion

In this study, we set out to:

1. separate the within-person from between-person relations between working from home and travel behaviour using panel data and
2. find whether the within-person relations changed during the COVID-19 pandemic. To do so, we estimated a random-intercept cross-lagged panel model using panel data collected both before and during the pandemic.

The results show that people who increase the amount of time they spent working from home reduce their commute travel. We also find a smaller, positive effect of working from home on leisure travel time before the COVID-19 pandemic, although it is only statistically significant if we accept a 10% threshold. Both before and during the pandemic, the within-person negative effect of working from home on commuting travel time is greater than the positive effect on leisure travel time. The net effect of working from home on the amount of time people spent travelling thus seems to be negative both before and during the pandemic. This finding contradicts most of the more recent literature on the effects of working from home on travel behaviour, where people who work from home are generally found to travel more than people who do not (Caldarola & Sorrell, 2022; Wöhner, 2022). We do find positive between-person relations between working from home and both commute and leisure travel time. We postulate therefore that the difference between these findings at least partly result from our panel design, and that separating the within-person and between-person relations offers new insights into the relations between working from home and travel behaviour.

Turning our attention to the differences in the relations between working from home and travel behaviour before and during the pandemic, we see that the effect of an additional hour worked from home on commute travel time was relatively stable. However, the extent to which commute travel time is determined by working from home sharply rose during the pandemic. This is the result of both a smaller variance in commute travel time and a larger variance in working from home. The extent to which working from home determines commute behaviour after the pandemic will in our expectations be somewhere in-between the pre-pandemic and post-pandemic relationships. We base this expectation on the indications that post-pandemic levels of working from home will be lower than during the pandemic, but higher than before the pandemic (Currie et al., 2021; Shortall et al., 2022).

Based on the literature, we expected that the complementary effect could partly be explained by the theory of constant travel time budgets, which states that people on average spend a similar, constant amount of time on total travel. If this is the case, then we would also find negative direct relations between commute and leisure travel time. We do indeed find a negative between-persons relation between commute and leisure travel time. This indicates that people who spend more time travelling for commuting spend less time travelling for leisure purposes. However, we find small but positive within-persons effects. This would indicate that the mechanism behind the theory of constant travel time budgets works on the between-person level, for example, due to negative between-persons feedback loops as a result of congestion or crowding. This would also indicate that research into the effectiveness of working-from-home policies on reducing total travel time should also rebound effects from people who do not work from home (Rietveld, 2011). However, our within-person findings could be biased, either because people in a panel only get older and thus go through certain life events that might make them more or less mobile in general, or due to COVID-19 resulting in some people travelling less in general due to the threat of the virus.

Finally, we find that PT commuters were much more likely to work from home more hours per week than non-PT commuters. Working from home has thus affected public transport commute travel time much more than travel time for the other modes. This finding is in-line with more descriptive analyses of the adoption and use of working from home because of the pandemic (Beck & Hensher, 2020; de Haas et al., 2020) and studies showing that commuting demand for public transport will be most strongly affected (Bohman et al., 2021; Currie et al., 2021; Sweet & Scott, 2022).

These conclusions have implications for policymakers, road authorities, and public transport operators. First, we do find that working from home reduces commute travel time. Working from home thus seems to be an effective strategy for policymakers to reduce peak-hour travel (which is largely based on commute travel) and thus congestion on roads and crowding in public transport. Critically, this recommendation depends on the assumption that our findings relating to travel time translate to decreases in travel distance. This might not necessarily be the case. We also find some evidence for between-persons rebound effects, which would also dampen the effectiveness of these policies. The within-person increase in leisure travel (found only before the COVID-19 pandemic) can also partly compensate for the reduced commute travel, but this shift will probably lead to a more spread-out activity pattern across the day and thus smaller peaks in travel demand. This finding is in line with expectations of the effects of the pandemic on travel behaviour in the literature (van Wee & Witlox, 2021). It is important to note that working from home is only one of many factors affecting travel behaviour and that relevant actors should not overestimate its effects compared to all other factors that influence travel demand, such as broader economic or socio-demographic factors. Since the extent to which working from home determined commute travel time was much greater during the pandemic than it was before the pandemic, policymakers and transport operators should be careful when extrapolating the apparent influence of working from home on travel behaviour that we've seen during the pandemic to the post-pandemic future.

Following some limitations of the present study, future research is needed to further understand the relationship between working from home and travel behaviour. A few specific points to address are mentioned below. First, this study uses data from before and during the pandemic to set expectations for future relations between working from home. The pandemic is not yet fully over, and it will be especially important to keep doing research into the relations as the world transitions out of the pandemic. Second, our study only partly addressed the heterogeneity of the impact of working from home concerning travel modes. More in-depth studies into the varying effects of working from home on especially public transport and active mode use would be a valuable addition. We did not account for other types of heterogeneity either, resulting in single estimates for the relations between working from home and travel time. There are at least two more interesting sources of heterogeneity to explore. First, studies could investigate potential differences between types of people, such as rural versus urban inhabitants or high-income versus low-income groups. Second, studies could explore whether there are differences between people who started to work from home during the pandemic and people who already worked from home before the pandemic started. This study used travel time to explore the relationship between working from home and travel behaviour: it would also be interesting to explore the effects on travel distance or number of trips using research methods that exploit the power of panel data. The last limitation of this study that we want to highlight here is that the effects are calculated using fixed timespans of one year between measurement waves. The effects of working from home are expected to vary over time, with people for example making different long-term decisions due to working from home. Hence, estimating the effects of working from home on travel behaviour using different spans of time could be a promising avenue for future research as well.

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# Chapter 4

# Estimating post-pandemic effects of working from home on travel behaviour

This chapter is based on Faber, R. M., Hamersma, M., de Haas, M., Krabbenborg, L., & Hoen, A. (2023). Estimating post-pandemic effects of working from home and teleconferencing on travel behaviour. *European Journal of Transport and Infrastructure Research*, *23*(1), 33–62. https://doi.org/10.18757/EJTIR.2023.23.1.6733

Abstract:

*Like in many other countries, the Dutch government instructed people to work from home where possible during the COVID-19 pandemic to halt the transmission of the virus. This policy seems to have resulted in a structural increase in working from home and teleconferencing that will outlast the pandemic. However, the longer-term effects on travel behaviour are still unclear. Making use of panel data collected using the Netherlands Mobility Panel, this paper has two main aims. First, it analyses developments in working from home and teleconferencing since COVID-19. Second, it estimates the expected post-pandemic effects on travel behaviour. The results show that compared to before the pandemic, the average number of hours that people work from home has doubled and roughly two-thirds of respondents indicate that they teleconference more often. We estimate that structural, post-pandemic increases in working from home and teleconferencing will result in a negative effect on distances travelled by train (-3% to -9%), by bus, tram, and metro (-1% to -5%) and car (-1 to -5%). The estimated effect on the distance travelled by bicycle (-2% to 0%), and walking (0% to +1%) is smaller or even positive, due to people making more complementary trips for other purposes when working from home. When interpreting these results, we should keep in mind that due to various other factors, such as population growth, total travel demand will still grow in the near future.*

## 4.1 Introduction

During the years 2020 through 2022, governments worldwide took measures to stop the spread of the novel coronavirus SARS-COV-2 (Brauner et al., 2020; Haug et al., 2020). Many governments advised, urged, or compelled people to work from home where possible (Brauner et al., 2020). Suddenly, many employees and employers were forced to experiment with working from home during the pandemic. As a result, use of telecommunication software and especially teleconferencing rose sharply. Simultaneously, the levels of congestion and of peak-travel crowding in public transport decreased substantially (Beck & Hensher, 2020; de Haas et al., 2020).

The instruction to work from home as much as possible was an important measure during the pandemic in The Netherlands as well. Based on measurements using the Netherlands Mobility Panel (MPN; Hoogendoorn-Lanser et al. (2015)), we observed a substantial increase in working from home and teleconferencing after implementation of these measures, especially in the first months of the COVID-19 pandemic (Hamersma et al., 2021). The total number of trips and distance travelled in the Netherlands reduced by 55% and 68% respectively at the beginning of the pandemic when compared to the fall of 2019 and the use of public transport was affected the most with a decrease of over 90% of trips (de Haas et al., 2020).

These substantial initial effects raise the question to what extent working from home and teleconferencing will affect travel behaviour after the pandemic is over. These structural effects of working from home on travel behaviour can be juxtaposed with the temporary effects of working from home on travel behaviour that occurred during the pandemic. These temporary effects will only turn structural when people decide to work from home more often than they did before the pandemic, even if there are no longer any temporary reasons directing them to do so, such as COVID-19 infections or work-from-home directives.

As of the year 2023, it seems evident that an increase in working from home and teleconferencing will be a structural change in the post-pandemic world (see for example, Beck and Hensher (2020), Beck et al. (2020), de Haas et al. (2020), and Olde Kalter, La Paix Puello, and Geurs (2021). This change will likely affect post-pandemic travel behaviour, which could potentially have consequences for the accessibility and sustainability of the transport system (van Wee & Witlox, 2021), where we define accessibility as the extent to which people are able to access destinations to participate in activities or exchange goods (Miller, 2018) and for sustainability we follow the narrow, environmental definition given in Zhao et al. (2020), which mostly refers to reducing both unwanted emissions and the use of depletable materials.

There is comparatively less in-depth information in the literature on the size of the expected structural, post-pandemic, effects of working from home and teleconferencing on travel behaviour. Studies show that there probably will be a negative structural effect on commuting travel (Currie et al., 2021), that there might be a positive structural effect on leisure and maintenance travel (Balbontin et al., 2022; Chen et al., 2022), and that the negative net effect is likely to be strongest for public transport (Ceccato et al., 2022; Ton et al., 2022).

The main contribution of this paper then is to provide estimates of the size of the post-pandemic effect of working from home and teleconferencing on travel behaviour for all main modes of personal travel. To present these estimates, this paper will provide the answer to two questions that will guide our analyses:

- What will the structural, post-pandemic increase in working from home and teleconferencing be?
- What effects will these increases have on post-pandemic travel behaviour?

As a result, we will first present developments in working from home and teleconferencing since the start of the pandemic and the expected structural change after the pandemic is over. Then, we will calculate the effects of these changes on travel behaviour in the Netherlands. These results will be based on quantitative analyses of data collected with the Netherlands Mobility Panel (MPN) and the National Travel Survey of the Netherlands (ODiN).

In the remainder of this paper, we first provide an overview of the literature on post-pandemic effects of working from home and teleconferencing on travel behaviour in Section 4.2. Then, we provide a conceptualisation of the relationships between COVID-19, changes in working from home, teleconferencing and travel behaviour that we use as the framework of this paper in Section 4.3. Afterwards, we provide an overview of data and methods used for our analyses in Section 4.4. Section 4.5 then presents our results: first the developments in working from home and teleconferencing, followed by the expected effects on travel behaviour. Section 4.6 finally contains the discussion and conclusion.

## 4.2 Literature Overview

This section will provide an overview of the existing literature on the structural effects of working from home on travel behaviour, after the COVID-19 pandemic will be over. To select papers for the overview, we queried the scholarly database Scopus on the 20th of November 2022 with the following query:

*“TITLE-ABS-KEY((covid-19 OR coronavirus OR corona) AND (”Work* from home” OR telecommut* OR teleconf*) AND (travel OR transport* ) AND (effects OR results OR quantitativ*))”*

Of the 56 resulting documents, 15 papers were included. The main criterion used to include papers is that the papers should discuss the effects of working from home on travel behaviour after the pandemic. Most papers that were not selected either only discussed the effects of the pandemic on travel behaviour and/or working from home separately, or only discussed the relations or effects during the COVID-19 pandemic. The documents were then forward snowballed, meaning that we looked at the papers that cited a document in the original selection.

Within a manuscript, up to three levels of headings may be used, not including the title of the manuscript. The first two levels are numbered, the third is not, but is typed in Italic. Figures, tables and mathematical expressions are numbered throughout the manuscript, not by section.

### 4.2.1 Working from home is here to stay after the pandemic will be over

The analysed papers overwhelmingly state that working from home is here to stay, as a substantial part of the people that increased the amount of time they worked from home during the pandemic state that they continue to work from home more after the pandemic than they did before it began. In the United States, roughly 40-50% of all workers expect to work from home at least a few times per month according to (Salon et al., 2022), which corresponds to a large majority of the adults that have the option to do so (Javadinasr et al., 2022). In a study in 20 European cities, roughly half of the respondents worked from home more often than they did before the pandemic (Christidis et al., 2022). In the Netherlands, roughly one-third of the working population expect to increase their working from home after the pandemic compared to before the pandemic (Olde Kalter, Geurs, & Wismans, 2021).

Some papers raise the point that not everyone is able to work from home (Bohman et al., 2021). In studies in Europe and North-America, roughly half of the population was not able to work from home at all (Bohman et al., 2021; Javadinasr et al., 2022; Paul & Taylor, 2022; Salon et al., 2022). When designing policies that provide an advantage to people who work from home then, policy makers should be aware that these advantages will have distributional effects. Combined with the finding that the group that can work from home often consists of more highly educated and higher-income people (Bohman et al., 2021; Olde Kalter, Geurs, & Wismans, 2021), such policies are likely to mainly benefit people who are already relatively well-off. This shows that policy makers should also focus on people who are not able to work from home and how they are affected by any policies related to this topic (Paul & Taylor, 2022).

### 4.2.2 Working from home will result in less commuting, but more leisure travel

In studies that analyse the structural effects of the COVID-19 pandemic as a whole on travel behaviour, working from home is often one of the primary drivers of structural differences in behaviour between the pre- and post-pandemic periods (Bohman et al., 2021; Christidis et al., 2021, 2022; Salon et al., 2022; Xu et al., 2022).

Studies show that working from home will have an expected negative effect on post-pandemic commute travel. Kogus et al. (2022) estimate a reduction of 6.5% and 8.7% commuting trips due to working from home in Israel and Czechia respectively. Javadinasr et al. (2022) expect that car commuting trips will go down by 9% and public transport commuting trips by 31% in the United States. An increase of 15% in working from home would result in a decrease of distance travelled by train of 8.3% in Switzerland (Manser et al., 2022). In Melbourne, decreases of commuting between 5% and 12.4% are expected, with larger decreases occurring in the inner region of the city (Currie et al., 2022).

Some studies also find expected increases in leisure travel. Christidis et al. (2021) assume based on an European survey that 50% of all avoided commute trips are replaced by retail or recreational trips instead. Campisi et al. (2022) find that people who spend more time working from home are more likely to travel for leisure purposes. They therefore emphasize that research should not only focus on the effects of working from home on commuting. Balbontin et al. (2022) find that people who work more from home make more shopping and recreational trips.

### 4.2.3 Strongest negative effect on public transport use

The effect of working from home varies over the various transport modes. All papers that have studied the effects of working from home on multiple travel modes seem to agree that public transport will be affected the most (Bohman et al., 2021; Currie et al., 2022; Downey et al., 2022; Javadinasr et al., 2022; Sweet & Scott, 2022). There are two principal reasons for this finding. First, people who can effectively work from home tend to use public transport to commute to their jobs more often. Second, commuting is a relatively large component of public transport use in many countries.

One often-reported finding is that people have shifted modes away from shared modes towards private ones (Bohman et al., 2021). This shift could exacerbate negative effects of working from home on the demand for shared transport modes such as public transport (Christidis et al., 2022; Paul & Taylor, 2022) and it could lead to increase use of less sustainable modes of transport such as the private car (Bohman et al., 2021; Christidis et al., 2021; Currie et al., 2022; Downey et al., 2022). This could lead to an increase in the use of the private car, despite potential negative effects of working from home on its use (Ceccato et al., 2022), although some studies find that the effect of working from home is large enough that a net-negative effect on car use can be expected (Olde Kalter, Geurs, & Wismans, 2021).

Simultaneously a few studies report a shift towards the active modes of cycling and walking (Campisi et al., 2022; Currie et al., 2022; Downey et al., 2022), which could have benefits for the sustainability and accessibility of the transport system.

## 4.3 Conceptual Framework

In this section, we introduce and discuss the framework we used to guide the analyses in this paper. The framework consists of a set of relationships between working from home, teleconferencing and travel behaviour and is presented graphically in Figure 4.1. The framework is not meant as a complete conceptual model of working from home and its many antecedents and effects. Rather, it forms the basis of our analyses of the effects of working from home and teleconferencing on travel behaviour.

This study will primarily focus on the continuous arrows in the framework, whereas the dashed arrows are kept in mind when interpreting our results. We distinguish and analyse impacts of working from home and teleconferencing on trips and distances (4.3.1), mode use (4.3.2) and the spread of travel over the day and the week (4.3.3). On the longer term, we expect relationships between travel and working from home & teleconferencing to occur (4.3.4), which we discuss, but do not analyse in-depth, in this paper. Similarly, the shorter-term effects on travel behaviour might also result in reverse effects on working from home, which we also do not discuss in-depth in this paper. Finally, we aim to provide some first insights into the potential effects of the travel behaviour changes on policy goals of the government with respect to travel behaviour, focusing mainly on the implications for accessibility and sustainability (4.3.5).

Below, we provide some explanations and references to literature that we used to conceptualize the framework.

### 4.3.1 Effects on trips and distances

We categorize the possible effects of working from home on the number of trips and travelled distance as follows (Andreev et al., 2010; Elldér, 2020; Salomon, 1986):

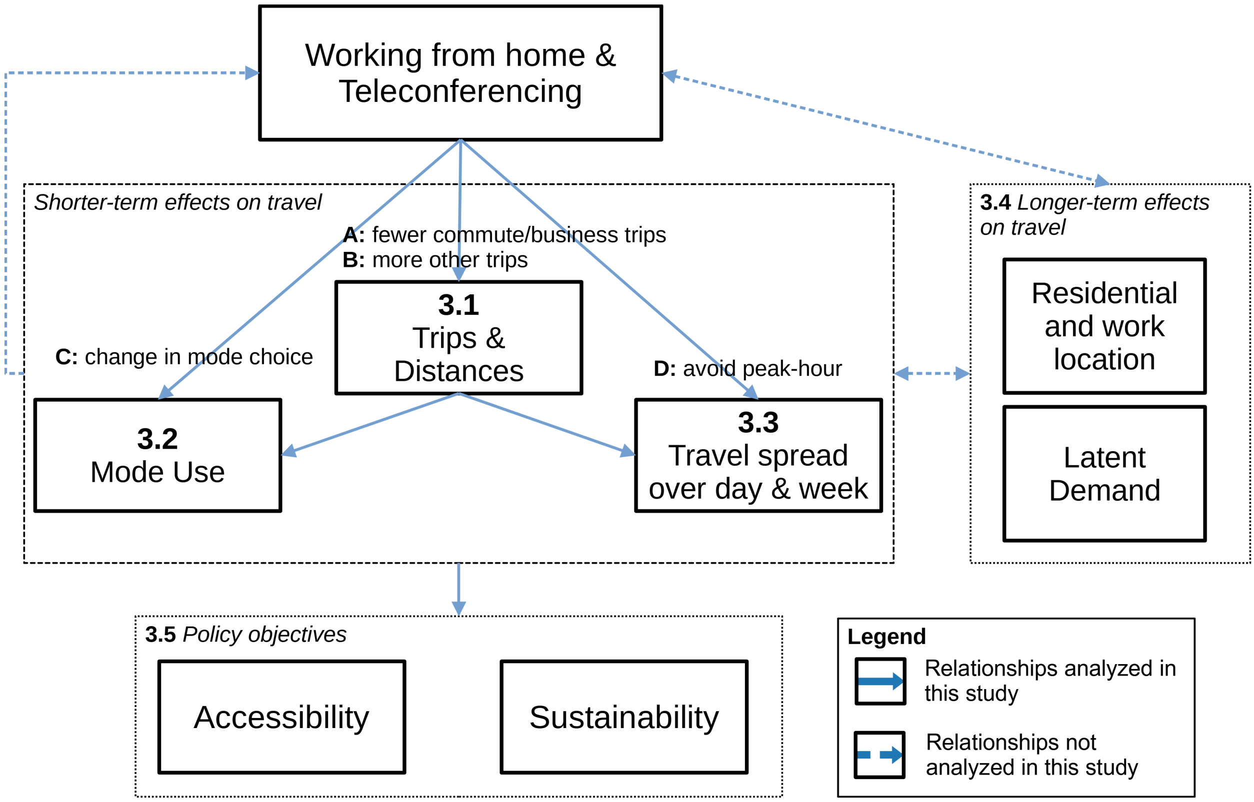


*Figure 4.1: Framework used to guide the analyses in this paper*

A. People travel less for commuting and business purposes, leading to reductions in trips and distances travelled. This is known as the substitution effect.

B. Because they save time, people travel more for other purposes. This results in an increase in trips and distances travelled. This is known as the complementary or complementation effect.

The net effect of working from home is the sum of the substitution effect and the complementary effect. As discussed earlier in Section 4.2 as well, recent research shows that the substitution effect is probably a little stronger, especially for people who work at home all day (Caldarola & Sorrell, 2022; Elldér, 2020). Nevertheless, the complementary effect should not be underestimated and could cause a smaller decrease in the number of trips than can be assumed based purely on the substitution effect (He & Hu, 2015; Kim et al., 2017). The existence of the complementary effect, especially in terms of travel time, could also be analysed in terms of a constant travel time budget (Ahmed & Stopher, 2014). Research into working from home and teleconferencing should be careful not to use a scope that is too narrow, by only focusing on the effects of working from home on commute and business travel.

### 4.3.2 Effects on mode use

Changes in working from home and teleconferencing could cause changes in mode use based on three separate effects:

A./B. People will travel less for commute and business trips, and they will likely travel more for other trips. Because travellers often use other means of transport for these purposes, the total use of the different transport modes will change as a result (Olde Kalter, Geurs, & Wismans, 2021).

C. Although less likely, people could also use different modes for the trips they do make.

- For commuting and business trips, they might use the train more often because of the possibility to work remotely during the trip
- For leisure trips, they might walk more often than they did before COVID-19 as more trips are made in the vicinity of the residential location during the working day (Lachapelle et al., 2018).

We expect that the effects A and B, which are based on making fewer or more trips for specific purposes, are likely stronger than possible mode choice effects.

### 4.3.3 Effects on spread of travel

Changes in the spread of travel can occur because of: A/B. Fewer utility trips and more leisure trips can lead to a different distribution of trips over the week. They can also cause traffic to shift during the day, from peak to off-peak hours (Stiles & Smart, 2021). D. The digital possibilities to work from home or meet via teleconferencing might partly eliminate the need to travel during rush hours and enable travellers to delay the commute or business trip from peak to off-peak (Stiles & Smart, 2021; Su et al., 2021).

### 4.3.4 Longer-term changes in travel behaviour

In the longer term, we may observe additional effects. Working from home and teleconferencing can influence the work and residential location choices (Mokhtarian et al., 2004). For example, saving travel time is often a key factor behind the decision whether to start or continue working at home (Mokhtarian & Salomon, 1994); working from home thus makes it possible to live further away from the work location. Hensher et al. (2021) for example indicate that working from home may be a stimulus that increases suburbanization. Additionally, the changes in travel behaviour of the people who do work from home or teleconferencing may also induce changes in behaviour of other people. For example, if people who work from home will reduce their commute travel, that would reduce congestion. People who do not work from home will probably then be enticed by the faster average travel time on the road network to make more trips, make longer trips, or change their travel time to peak-hours. We refer to this potential phenomenon as latent demand in Figure 1.

### 4.3.5 Implications for policy objectives

Working from home can result in less commuting travel. This could potentially have a positive influence on the performance of the road network by reducing congestion. Furthermore, the increased uptake of working from home and teleconferencing might result in greater digital accessibility of these activities, as the digital alternatives become more accepted by employees and employers. However, the loss of public transport use might result in reduced transit service. This could be problematic for the accessibility of the transport system, in particular for people who are unable to work from home and depend on the public transport system to get them to and from critical activities such as work.

Regarding sustainability, working from home and teleconferencing can reduce the commuting trips by people who work from home. This could lead to reductions in total commute travel distance. However, people who work from home might also decide to accept longer commute distances per trip as total commute travel time throughout the week would then remain stable (Cerqueira et al., 2020), undoing some of the advantages. Furthermore, any sustainability benefits depend on the extent to which these trips might be compensated for by other, complementary travel and to the travel modes used for commuting. Nevertheless, literature seems to suggest that the net effect of working from home on sustainability is positive (see for instance Hamersma et al. (2021), Krasilnikova and Levin-Keitel (2022), Moglia et al. (2021), and van Lier et al. (2014).

## 4.4 Research Methods

In this section, we describe the research methods and data used to study the relationships described above. First, all data sources are described in section 4.4.1. Then the main steps of the analysis procedure are described in section 4.4.2. This is followed by an operationalisation of the main variables and a description of the final sample in section 4.4.3. Finally, the regression models are described in section 4.4.4.

### 4.4.1 Description of data sources

An important data source for our analyses is the Netherlands Mobility Panel (MPN; Hoogendoorn-Lanser et al. (2015)). The MPN is a household panel that has been running since 2013 and consists of approximately 2000 complete households each year, corresponding to roughly 5000 respondents. Respondents are recruited from the Kantar NIPObase internet access panel in the Netherlands. This internet access panel recruits its respondents and does not allow for people to register themselves. New respondents for the MPN are recruited amongst the Kantar Access Panel yearly to account for panel dropout.

Every year in the fall, 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 the use of different modes of transport. Furthermore, one person per household answers questions related to household characteristics, such as household composition and ownership of means of transport. In between the annual measurements, it is possible to use the panel for additional studies.

To study the impact of COVID-19 on activities and travel behaviour, we prompted a subsample of the panel to fill out a questionnaire and a three-day travel diary at six moments since the start of the COVID-19 pandemic. The subsample was drawn from the sample of MPN respondents who fully participated in the last two annual waves of the MPN at the time, which were the 2018 and

2019 waves.

This subsample consisted of 2750 respondents for the first COVID-measurement. The response rate of each measurement was roughly 90% for the questionnaire and between 80 and 85% for the travel diaries. These high response rates result from the fact that the subsample only uses respondents that already participated in earlier MPN waves. We invited people with a complete questionnaire for the following measurements. To increase the number of respondents and correct for skewed panel dropout, we invited 733 new respondents in the measurement of January 2021. These 733 respondents were also recruited from the group of MPN respondents that fully participated in the 2018 and 2019 annual waves. The net response rate for our last measurement of May 2022 was 1743 completed diaries and 1930 completed questionnaires.

We used weights to ensure the subsample would be broadly representative for the Netherlands, based on socio-demographic characteristics such as gender, age, educational and vocational background, location, and household composition. Including the regular annual measurements in the fall of 2020 and 2021, we did 8 measurements among this selection of respondents so far during the COVID-19 pandemic in the Netherlands. The time of these measurements and the course of the pandemic in the Netherlands are given in Figure 4.2. The yearly waves are highlighted in green, the additional COVID-19 measurements are highlighted red. The blue line represents the 7-day rolling average of hospital admissions of COVID-19 patients.

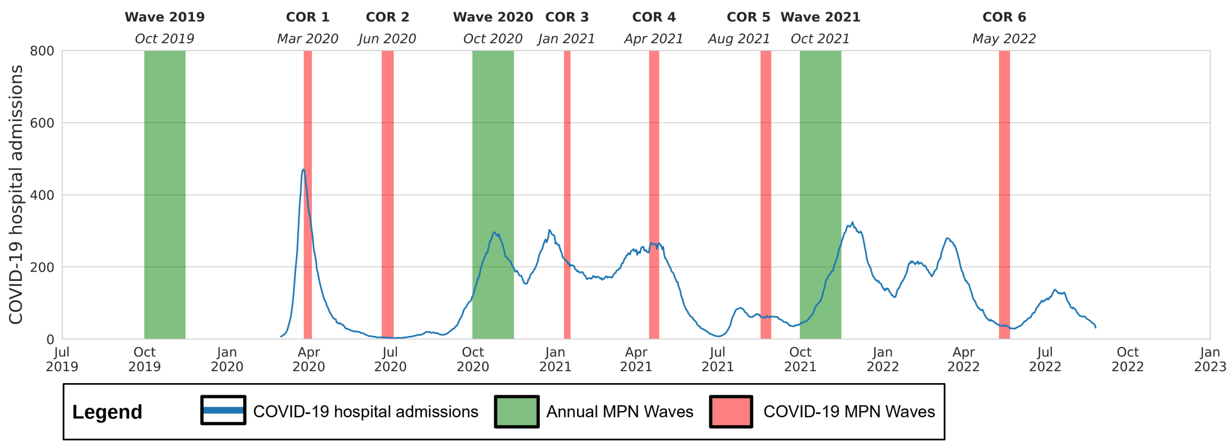


*Figure 4.2: MPN measurements in relation to COVID-19 pandemic*

The second dataset we use to estimate impacts on travel demand is the National Travel Survey of the Netherlands (called Onderweg in Nederland; ODiN). This cross-sectional individual survey is administered yearly by Statistics Netherlands, who use national registers to invite respondents. Respondents keep a 1-day travel diary and answer a shorter survey (compared to the MPN). In total, the ODiN contains 53 380 respondents, with a response rate of around 28% (CBS, 2022). As opposed to the MPN, the travel diaries are spread out throughout each calendar year, with respondents being assigned to a specific day of the year. Compared to the MPN, this dataset is much larger, but does not encompass information on working from home and lacks a longitudinal panel structure. In addition, there is no data available yet about 2022, when COVID-19 measures were lifted in the Netherlands. However, this dataset can be used to scale our findings up to the national level more accurately.

A comparison of the main differences between the three data sources is given in Table 4.1, as well as a very short summary of the main use of each datasource in this paper.

| | MPN annual wave | MPN COVID subsamples | ODiN |
|---|---|---|---|
| **Sampling unit** | Household | Individual | Individual |
| **Travel-diary** | 3 days. Collected annually around October | 3 days. Collected at multiple phases of the pandemic in roughly 2-week waves | 1 day. Collected year-round |
| **Information on working from home** | Both current and expectations | Both current and expectations | None |
| **Longitudinal?** | Yes | Yes | No |
| **Nr. Of respondents** | ±2500 households; ±5000 individuals | Between 1750 and 2750 respondents | Roughly 50.000 respondents |
| **Representative for the Dutch population** | Broadly representative based on 8 socio-demographic indicators | Broadly representative based on 8 socio-demographic indicators | Representative and weighted to national level by Statistics Netherlands |
| **Main purpose(s) in this paper** | - Use pre-pandemic travel diaries to calculate effects of working from home on travel for specific mode and purpose combinations | - Describe developments in working from home during the COVID-19 pandemic<br>- Use questionnaire to calculate effects of working from home and teleconferencing on travel per individual | - Scale up effects on travel behaviour within mode and purpose to effect on total travel demand<br>- Calculate effects on travel distances and travel times |

*Table 4.1: Comparison of the data sources used in this study*

### 4.4.2 Analysis procedure

In this paper we give two separate types of quantitative results, corresponding to the sub-questions we identified in the introduction:

1. 1. Descriptive statistics of developments in working from home, teleconferencing, and travel behaviour during the COVID-19 pandemic.
2. 2. Calculations of expected effects of working from home and teleconferencing on travel behaviour after the pandemic.

This section will first present the different steps of the analysis procedure. The descriptive analysis is based fully on data from the MPN. We use the panel to describe developments in working from home and teleconferencing since the start of the COVID-19 pandemic until May 2022. These results are presented in section 5.1. Because of the panel design of the MPN, we can make comparisons using the same set of respondents across measurements both before and during the COVID-19 pandemic. We pay attention both to developments in actual behaviour and to the intended behaviour after the pandemic. We show some differences between subgroups of the sample. In addition, we use descriptive insights based on the MPN to complement our calculations in section 5.2.

The calculations of the effects of working from home and teleconferencing on travel behaviour are based on a combination of data from the MPN and ODiN. The idea is that we use the MPN to calculate mode- and purpose-specific effects of both working from home and teleconferencing. These calculations are based on people's intended working from home and mobility behaviours after the pandemic, as the last available measurement (May 2022) is very much within a transitionary phase right after the government scaled back most COVID-related measures. In this phase, behaviours have not yet stabilized into what might be called a post-pandemic 'new normal'. To map these mode- and purpose-specific effects to national travel behaviour, we then use the relative shares of such trips from the National Travel Survey ODiN. For example, if we find a reduction of 10% in commuting trips for the train using MPN-based modelling, we use the share of commuting trips for train travel in 2019 based on ODiN ( 40%) to calculate an effect of roughly -4% (= 10% * -40%) on total train travel.

A graphical summary of this process is given in Figure 4.3.

In the first step of the calculations, we try to determine the effects of working from home and teleconferencing on commute and business trips per person. To this end, we estimate two sets of regression models: one to estimate the effects on commute travel, and one to estimate the effects on business travel.

In the second step, we use the individual-level expected changes based on the regression models and combine them with travel diary information from before the pandemic to estimate the expected change in commute and business trips per mode. Effectively, we weigh the expected individual-level changes by the pre-pandemic travel behaviour of these individuals to calculate trip-level changes. For example, if people with a higher expected change in working from home travelled more by public transport for commuting before the pandemic, then public transport will be affected by working from home to a greater extent.

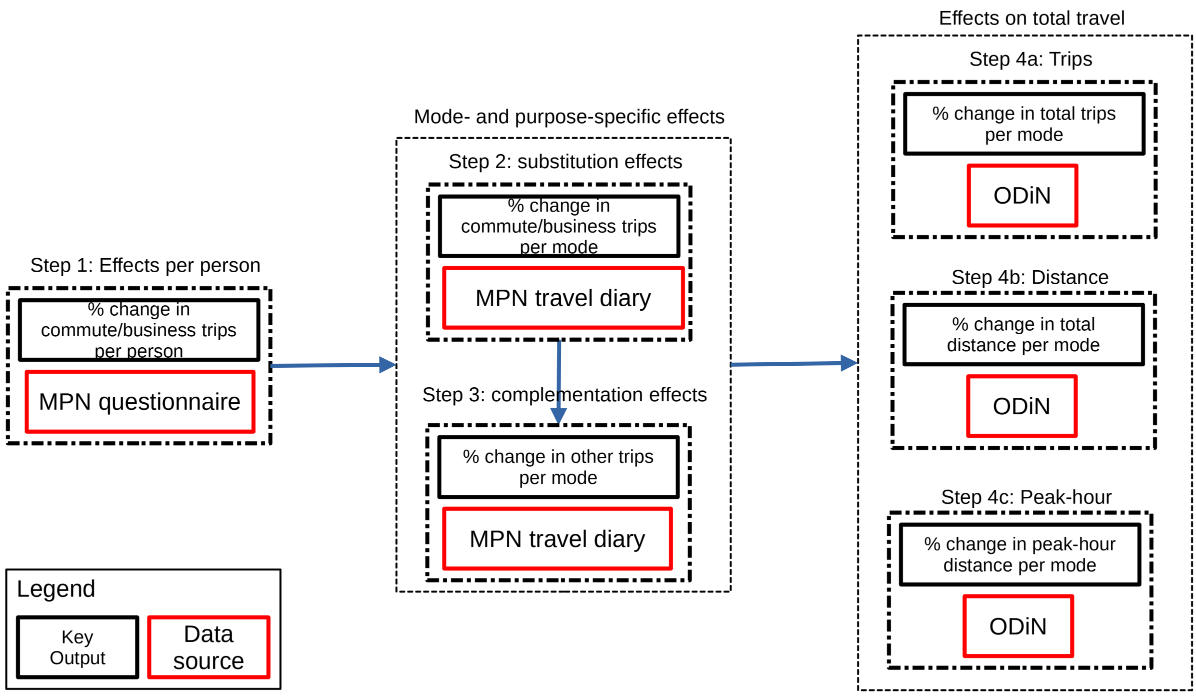


*Figure 4.3: Structure of the analysis resulting in estimated effects on mobility*

As discussed in section 3.1, we then need to take the complementation effect into account (step 3). This complementation effect compensates, at least to some extent, for the substitution effect. If we do not account for this effect at all, then we will overestimate the effect of working from home on travel behaviour. However, we do not think we can adequately assess the strength of the complementation effect using a questionnaire. Nor can we use data gathered during a pandemic to estimate its effects and extrapolate that to a world after the pandemic. Therefore, we must for now use assumptions instead. We assume that a reduction in commute trips because of working from home will be compensated by an increase in leisure trips of between 0 and 75% of the reduction in commute trips.

This numerical assumption is based on three pieces of evidence. First, a comparison of travel patterns of people who work from home and people who work on location based on pre-COVID data, which indicates that people who intensively work from home travel a bit less than people not working from home (Hamersma et al., 2021). Second, a longitudinal panel study that studies the effects of working from home on commute travel time and leisure travel time, which shows that the latter effect indeed exists and is positive but is less strong than the negative effect on commute travel time (Faber, Hamersma, Brimaire, et al., 2023). Third, our latest MPN-measurement also shows that a significant part of respondents indicate that they travel less on a day where they work fully from home, compared to a day where they make a trip to the work location (Figure 4.4). However, a substantial amount also indicates that they travel the same amount or not much less.

In summary, there is quite a bit of uncertainty about the size of the complementation effect. That uncertainty is reflected in the calculations by the relatively wide range of the size of the possible complementation effect, which compensates between 0 and 75% of the reduction in commute trips with an increase in trips made for other purposes. We do not foresee any such compensatory trips because of the reduction in business trips, because business trips normally take place during working hours and are not likely to be compensated outside working hours in the form of leisure

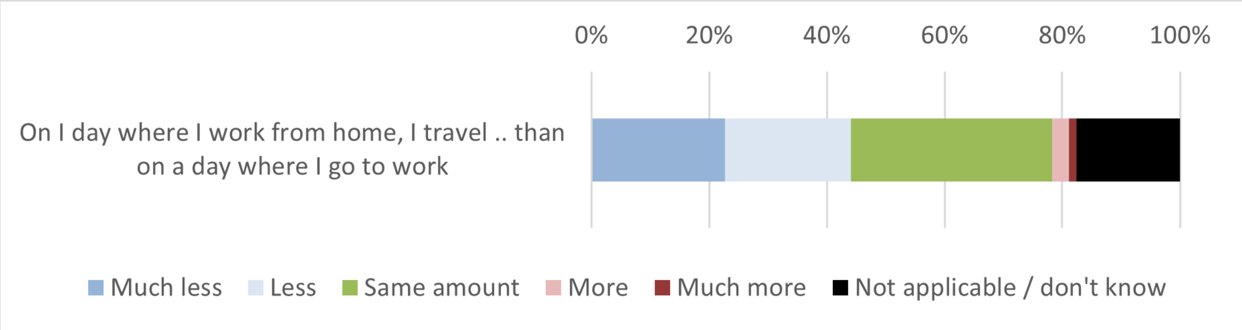


*Figure 4.4: Amount of travel on a day working from home, compared to a commuting day (Data: MPN, COVID-Measurement of May 2022, N = 955)*

travel.

Steps 2 and 3 result in mode-specific changes to commuting, business, and leisure trips. Using data from ODiN 2019, we calculate the net effect on mode use (step 4). Effectively, we use the share of purpose-specific trips, distances, and distances during peak-hours. We make these calculations for the number of trips (step 4a), the travelled distance (step 4b), and the distance travelled during peak-hours (step 4c).

### 4.4.3 Operationalisation and sampling

The main concepts used in the analyses steps of this paper relate to travel behaviour, working from home, and teleconferencing. This section will explain the operationalisation of these concepts into variables. We will also describe the sampling procedure for each of the analysis steps described in the section above.

#### Working from home and teleconferencing

Working from home is measured in both the annual waves and the COVID-waves, by asking the average number of hours people spent working from home in the last few weeks. Similarly, people were also asked to answer how many hours they expect to work from home in the future after the COVID-19 pandemic would be fully over and all restrictions would be lifted. The difference between the number of hours people worked from home in the last annual wave before the pandemic and the intended number of hours they would work from home after the pandemic is then used as an independent variable in the analysis. Effectively this variable captures the effect of a change in working from home during the pandemic on travel behaviour.

For teleconferencing, we do not have such a baseline of behaviour before the pandemic, as no questions relating to teleconferencing were included in the last annual pre-pandemic wave. Instead, respondents are asked whether they think they will hold more online meetings in the future after the pandemic is over than they did before the pandemic began:
*"Do you expect to hold digital meetings more or less often in the future on the longer-term, given that there are no COVID-related restrictions?'"*
Respondents could answer using seven answer categories, ranging from 'Much less often' to 'Much more often'. Given that almost no respondents indicated that they would do so much less

often or less often, we combined these categories with the category that indicated no change in our analysis.

#### Travel Behaviour

Travel behaviour is measured both using the questionnaire and the travel diary of the MPN, as well as the ODiN travel diary. The regression models estimate the individual-level effect of working from home and teleconferencing on the number of days that people expect to travel for a specific purpose in the future.

For commuting trips, this is the number of days per week, with possible answers ranging from zero to seven days per week. We asked respondents to indicate whether they would travel on a certain day of the week for commuting purposes: “Can you indicate on which days of the week you intend to commute in the future on the longer term, when all covid-related restrictions have been lifted?”. We then summed up the number of days they indicated to get the number of days with commuting trips per week. Respondents were also asked to retrospectively indicate on which days they commuted before the COVID-19 pandemic.

For business trips, which are typically undertaken much less frequently than commuting trips, we asked for the intended number of days per year with the following prompt: “How often will you travel for business-related purposes on the longer-term, when all covid-related restrictions are gone?” Respondents could answer in six categories, ranging from ‘(almost) never’ to ‘4 or more days per week’. Respondents were also asked to retrospectively answer the same question for the time before the COVID-19 pandemic, which we used as an independent variable.

We also record travel behaviour using trip diaries, which are used in steps 2, 3, and 4 of the analysis as visualized in Figure 3. For the MPN, the trip-diaries are used to weight the individual-level effects to mode- and purpose-specific effects. The ODiN travel diaries are used to calculate nationally representative shares of each purpose within each mode, which allows us to calculate the effects on total travel demand.

#### Description of final sample

The expected effects of working from home and teleconferencing on the behaviour of an individual is only calculated for people with gainful employment, as other groups of the population are not affected by working from home at all (and they also make no commuting / business trips). However, the effects we are interested in are the effects on total travel, of all people.

The MPN sample that is used to describe the developments in working from home and teleconferencing then consists only of individuals with gainful employment. A total of 955 complete respondents are used. The ODiN sample used to scale these findings to the national travel demand consists of all people within ODiN 2019, which were 53 380 respondents.

### 4.4.4 Regression model specification and estimation

As explained in section 4.2, we estimate two regression models to estimate the post-pandemic effects of working from home and teleconferencing on commute and business travel. The main idea behind the regression analyses is that we regress the future intended number of days with commute/business trips post-pandemic on five distinct categories of variables:

1. 1. The number of days with commute/business trips before the pandemic
2. 2. A set of socio-demographic variables pertaining to the individual
3. 3. A set of regional characteristics of the region where the respondent lives
4. 4. The intended change in working from home
5. 5. The intended change in teleconferencing

This approach is similar to the approaches of Melo and de Abreu e Silva (2017) and Caldarola and Sorrell (2022), with the exception that we have access to panel data. Our main interest is in the effects of variables 4 and 5 since these variables capture the effects of working from home and teleconferencing on travel behaviour change. We control this effect for socio-demographic (2) variables, including life-events, and regional (3) variables. Due to the availability of panel data, we can also control for the number of days with commuting or business trips before the pandemic (1). If people intend to have the same number of days with commuting or business trips after the pandemic as they did before the pandemic, then all variance of the dependent variable would be explained by these number of days of commuting or business trips before the pandemic. As a result, the other variables' estimates effectively pertain to the change in working from home and teleconferencing, respectively. We are also able to control for the effects of life-events, which are part of the socio-demographic variables (2).

The dependent variable in both analyses is the intended number of days with either commute or business travel, as introduced in Section 4.3.1. The commute-specific dependent variable is a count variable, with a maximum of seven (days per week). For this reason, we estimate a Poisson-regression model, as a regression model that uses OLS estimation will provide inefficient and biased estimates (Long & Freese, 2006). Strictly speaking, the business dependent variable is an ordinal variable. However, we treat it as a continuous variable by using numerical values corresponding to the middle of each category and do estimate a linear regression model using OLS. Furthermore, we assume in the interpretation of our results that these variables, which are measured in days, can be translated directly into changes in trips. Effectively, we assume that the reductions in terms of number of days with business or commute travel are directly proportional to the reductions in business or commute trips, respectively.

## 4.5 Results

This section contains the results from our analyses. The section is split into two parts. In the first, we use descriptive analyses to describe the developments in working from home and teleconferencing. In the second part, we describe the results from our calculations into the effects of working from home and teleconferencing on travel behaviour. More descriptive analyses using the same data can be found in de Haas et al. (2022).

### 4.5.1 Descriptive analyses

This section contains the descriptive analyses of the developments in working from home and teleconferencing during and after the COVID-19 pandemic.

Since the start of the COVID-19 pandemic, our respondents have drastically increased the numbers of hours they work from home per week. Before the start of the pandemic (October 2019) about 30% of our working respondents worked at home at least an hour per week. This increases to about 50% during the pandemic.

Figure 4.5 shows the average number of hours people spent working from home per week in May 2022. Aside from the total average, the number of hours is also given grouped by the main mode that people used to commute to work right before the COVID-19 pandemic started, which we determined using the questionnaire of the 2019 MPN wave. We observe that the average number of hours working from home per worker per week in May 2022 is more than two times higher than before the start of the COVID pandemic (before 3h per week; now 6.5h per week). People expect that this will decrease slightly in the next few months as we further transition to a new situation, to an average of 6h per week.

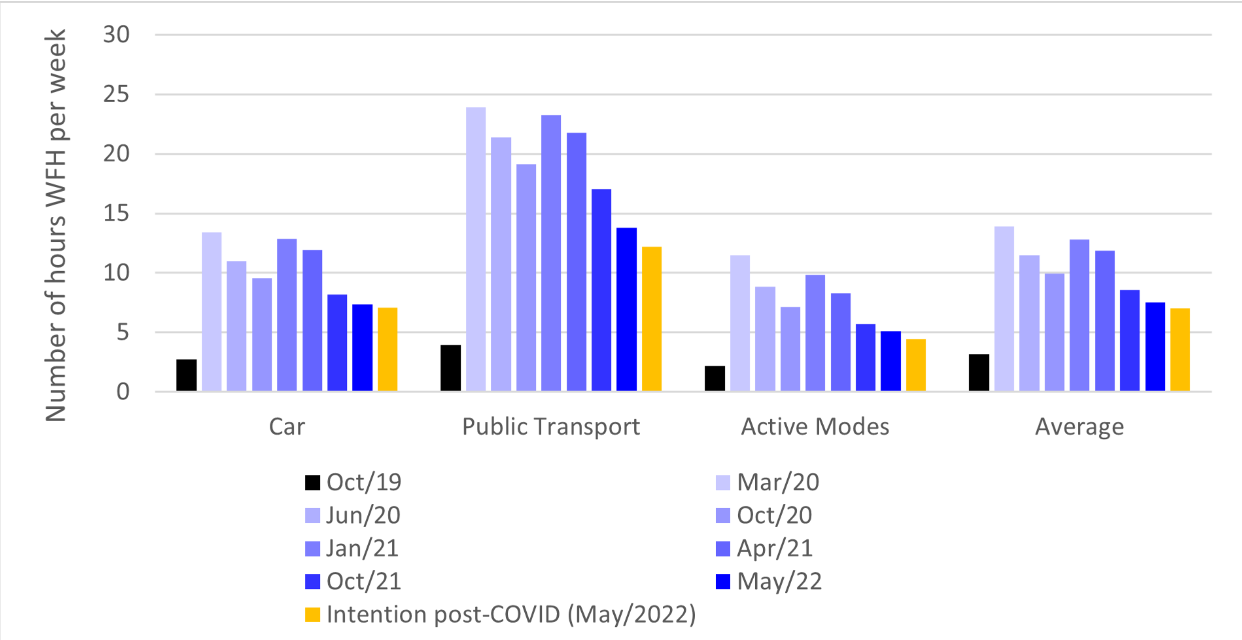


*Figure 4.5: Average number of hours worked from home per week, grouped by the main commute mode used before the pandemic (Data: MPN questionnaire, all measurements since October 2019, N = 955)*

The intended increase in working from home compared to before COVID is much larger among those who travel to work by public transport (from approximately 3.5h to 14.5h), compared to people who commute by car or cycling/walking (Figure 5). In addition, the intended increase is higher for people who attained (applied) university education (from approximately 5h to 11), for the people living in urban areas (from approximately 3h to 6.5h) and among those with an office job (from approximately 4h to 12h) or a management function (from 4h to 9h). We also observe stronger intended increases for people who work in larger organisations and for those with longer commuting times (for the latter, see also Hamersma et al. (2021)).

The use of digital technologies to meet with people for work purposes, which we refer to as teleconferencing, has increased since the beginning of the pandemic as well, as evidenced by Figure 4.6.

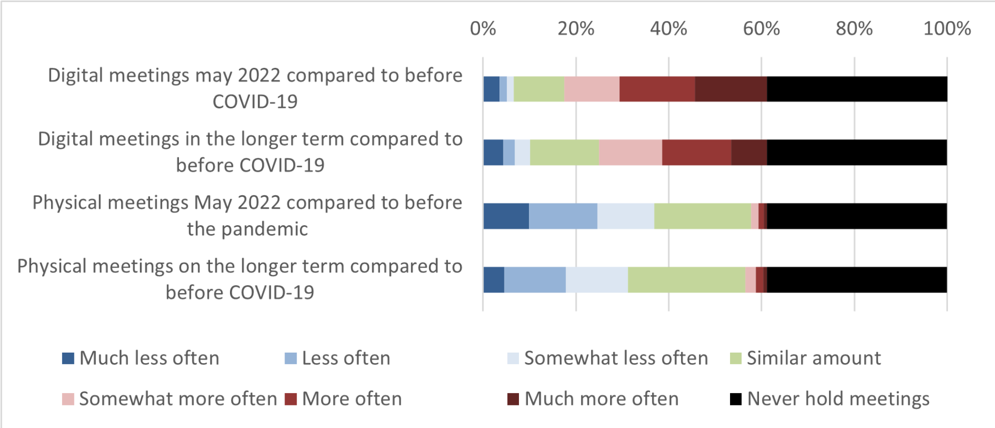


*Figure 4.6: Current and intended amount of physical and digital meetings compared to pre-COVID (Data: MPN COVID-measurement of May 2022, N = 955)*

Most of our respondents indicate that even in May 2022, they are still using teleconferencing much more often compared to before the pandemic. Furthermore, their intention is to continue doing so after the pandemic, although not quite as often as now. Physical meetings then seem to become less common, although a substantial number of our respondents indicate no change. Still, this is an indication that digital meetings are substituting physical meetings to some extent. Employees in care jobs and jobs in field service are less likely to reduce the number of physical meetings than the other distinguished job types. In larger companies, the share of employees who have reduced the number of physical meetings is larger than in smaller companies.

## 4.5.2 The effects on travel behaviour

This section contains the estimated effects of working from home and teleconferencing on travel behaviour. Following the steps identified in section 4.4.2, we first report the regression model estimates. This is followed by a range of expected mode- and purpose- specific effects, as calculated using the regression coefficients and travel diary data from the MPN. Then, these effects are used to calculate the effects on total travel demand, both in terms of trips, distances, and peak-hour distances using weights provided by ODiN. Finally, we discuss the possible effects of shifts in mode choice and spreading of travel per trip purpose.

### Regression model estimates

The model estimates for the effects of changes in working from home and teleconferencing on the expected changes in commute and business travel are provided in Table 4.2.

The estimated parameters for the intended increase of working from home have a strong effect on both the intended commute and intended business travel. Very few other parameters are statistically significant, indicating that it is indeed the change in working from home that is the

| | | Dependent variables | |
|---|---|---|---|
| **Variable** | **Levels** | **Intended number of weekly days with a commuting trip**[1] | **Intended number of yearly days with a business trip**[2] |
| **Intended increase in working from home (Hours per week)** | Does not work from home | Ref. | Ref. |
| | Works less than 8h per week | -0.528*** | -0.818 |
| | Less than 6h | -0.004 | 3.77 |
| | 6 – 13 | -0.230*** | -4.65* |
| | 14 – 20 | -0.438*** | -5.92*** |
| | 21 – 28 | -0.757*** | -7.355* |
| | More than 28h | -0.949*** | -18.779*** |
| **Change in teleconferencing** | No teleconferencing | Ref. | Ref. |
| | Less often or equal | 0.036 | -2.316 |
| | A bit more often | 0.056 | -3.204 |
| | Much more often | -0.071 | -12.1*** |
| | N | 955 | |
| **Model statistics** | Log-Likelihood | -1797.2 | -4366.3 |
| | Pseudo-$R^2$ | 0.312 | |
| | Adjusted $R^2$ | | **0.**799 |

1: estimates from a Poisson regression model; 2: estimates from an OLS regression model
$*p < 0.1$; $**p < 0.05$; $***p < 0.01$

*Table 4.2: Parameter estimates of working from home and teleconferencing on intended travel behaviour (Model based on data from MPN questionnaires)*

main driver behind the change in commute and business travel. Only people who have the intention to teleconference much more often also intend to travel less often for business purposes. Using these estimates, we can calculate the expected effects of increases in working from home and teleconferencing on commute and business travel after the pandemic.

For commute travel, we use the rate ratio (the exponent of the coefficient), which gives us the percentage change in the dependent variable, the intended number of days in a week where people will commute, that is associated with an increase in working from home for every individual. For example, this ratio for someone who expects to increase working from home by between 6 and 13 hours is equal to 0.795 (exponent of -0.230), which means that the intended percentage change in commute trips post-pandemic compared to pre-pandemic due to working from home for this individual is -20.5% (= (0.795 – 1) * 100). For business travel, we use the OLS-parameter coefficients directly to estimate the change in the number of business trips of working from home and teleconferencing for every individual. For example, someone who has the intention to increase their working from home by between 6 and 13 hours is expected to decrease their business trips as a result of the pandemic by 4.65 more trips than people who do not work from home. For both business travel and commute travel we calculate a lower- and upper bound for the effect by using the values of the parameters of a 95% confidence interval.

**Purpose specific effects**

The estimates from the regressions thus provide us with expected changes because of working from home and teleconferencing for commuting and business travel for every individual. Now, it is important to realize that the total expected change in travel is not the mean change per individual. First, we need to weight by the frequency of travel with each travel mode for every individual. For example, if people who started to work from home more than 28 hours during the pandemic only travelled by train, then only the use of this mode is affected by the change in commuting due to this change in working from home.

To provide mode-specific estimates then, we use the travel diaries of the MPN. More specifically, we use the travel diaries from 2018 and 2019, the last two measurements before COVID. All respondents of the additional COVID-measurements partook in these yearly waves as well. We then calculate the mode-specific average of the effects across the relevant trips in these diaries, using the individual-level values calculated using the regression coefficients.

The resulting estimates for the effects of working from home and teleconferencing on the number of mode- and trip-specific trips for commuting and business purposes is given in Table 4.3. This table contains a 95% confidence interval of the expected effect within each mode- and purpose. Since business trips were very rarely made either using bus, tram, metro (btm) or on foot, it is impossible to calculate reliable estimates for the effect on business travel for these modes.

To estimate a mode-specific complementation-effect, we then need to calculate the reductions in commute travel per individual and estimate corresponding increases in travel for other purposes. We therefore use the assumption that between 0 and 751) Only individuals who decrease their commute travel will increase their travel for other purposes. 2) People who decrease their commute travel more strongly will increase their travel for other purposes more strongly as well

We take this into account by estimating the upper-bound of the reductions in commute trips for each level of working from home used in the regression analysis. For example, for the people

| | **Car** | **Train** | **Bus, Tram, and Metro** | **Cycling** | **Walking** |
|---|---|---|---|---|---|
| **Trips (change in mode- and purpose-specific trips)** | | | | | |
| **Commute** | (-7%, -15%) | (-14, -26%) | (-10, -19%) | (-4%, -9%) | (-9%, -17%) |
| **Business** | (-2%, -12%) | (-4%, -22%) | -[2] | (-2%, -22%) | -[2] |
| **Other[3]** | Up to 4% | Up to 7% | Up to 7% | Up to 3% | Up to 3% |
| 1: based on a 95% confidence interval of the regression-model parameters | | | | | |
| 2: too few pre-pandemic btm and walking business trips to provide a reliable estimate | | | | | |
| 3: Minimum effect is 0%. Maximum effect is based on 75% of maximum decrease in commuting trips. | | | | | |

*Table 4.3: Expected range of changes in commuting and business trips due to working from home and teleconferencing per mode (Results based on MPN questionnaire and travel diary)*

who intend to increase the number of hours worked from home between 6 and 13 hours this upper bound is 31%. We then use the mode share for other purposes of each of these groups to translate these reductions in commute trips to increases in other travel per mode. These people make almost 3x as many other trips as commute trips, so this would correspond to an increase in other trips of roughly 10% within this group. We assume that up to 75% of the non-made commute trips are compensated by other trips, resulting in an increase of other trips for this specific group of 7.5%. The expected increase for groups who do not intend to increase their working from home of course are 0%, whereas the expected increases for groups who intend to work more hours is larger. We use a weighted mean of these expected increases within each group for each mode to calculate the expected mode-specific effect size. The resulting increases in trips for other purposes are given in Table 4.3.

#### Effects on net travel demand

Now that we have the three components of travel change due to working from home and teleconferencing, we can work out the estimated combined effect on total travel demand. We calculate the effects on three indicators: the number of trips made, the travel distance, and the travel distance during peak-hours (Figure 3). To do so, we use data from OdiN 2019. Effectively, we are using the national travel survey to weight the within-purpose change to the total change for each purpose. For example, since business travel is relatively less frequent, the within-business effects only result in relatively minor changes in total travel. To calculate the effects on distance travelled, we assume a directly proportional relationship between the effects on trips and the effects on distance. In other words, we assume that people who have the intention to reduce commute trips due to increases in working from home travel for the same distance as people who do not do so, conditional on the mode they travel with (since we use mode-specific effects). The effect on travel spread is then calculated using the shares of commuting and business travel in total travel in the morning and evening peak. We thus calculate only the effects of reductions in commute and business trips and increases in other trips. We do not yet take potential additional shifts away from peak-hours into account.

Table 4.4 presents the results of the impact of changes in commuting, business trips and trips for other purposes because of working from home and teleconferencing (A and B in Figure 4.1).

| | Car | Train | Bus, Tram, and Metro | Cycling | Walking |
|---|---|---|---|---|---|
| **Total trips** | | | | | |
| **Commute**[1] | (-3%, -1%) | (-10%, -6%) | (-5%, -3%) | (-2%, -1%) | (-1%, 0%) |
| **Business**[1] | (-0.3%, -0.1%) | (-0.7%, -0.1%) | N/A | (-0.1%, 0%) | N/A |
| **Other purposes**[2] | Up to 1% | Up to 1% | Up to 2% | Up to 1% | Up to 1% |
| **Net effect**[3] | (-3%, 0%) | (-11%, -4%) | (-5%, -1%) | (-2%, 0%) | (-1%, 1%) |
| **Total travel distance** | | | | | |
| **Commute**[1] | (-4%, -2%) | (-8%, -5%) | (-5%, -3%) | (-2%, -1%) | (0%, 0%) |
| **Business**[1] | (-0.8%, -0.1%) | (-0.9%, -0.2%) | N/A | (-0.1%, 0%) | N/A |
| **Other purposes**[2] | Up to 1% | Up to 2% | Up to 1% | Up to 1% | Up to 2% |
| **Net effect**[3] | (-5%, -1%) | (-9%, -3%) | (-5%, -1%) | (-2%, 0%) | (0%, 1%) |
| **Travel distance during morning peak-hours** | | | | | |
| **Commute**[1] | (-10%, -5%) | (-16%, -9%) | (-10%, -5%) | (-4%, 0%) | (-1%, -1%) |
| **Business**[1] | (-1.2%, -0.2%) | (-0.9%, -0.2%) | N/A | 0% | N/A |
| **Other purposes**[2] | Up to 1% | Up to 1% | Up to 1% | Up to 1% | Up to 5% |
| **Net effect**[3] | (-12%, -5%) | (-17%, -8%) | (-10%, -5%) | (-4%, 1%) | (-1%, 1%) |
| **Travel distance during evening peak-hours** | | | | | |
| **Commute**[1] | (-6%, -3%) | (-12%, -7%) | (-8%, -4%) | (-3%, -1%) | (-1%, 0%) |
| **Business**[1] | (-0.9%, -0.2%) | (-0.2%, -1.1%) | (0%, 0%) | (0%, -0.2%) | (0%, 0%) |
| **Other purposes**[2] | Up to 1% | Up to 2% | Up to 2% | Up to 1% | Up to 2% |
| **Net effect**[3] | (-7%, -2%) | (-13%, -5%) | (-8%, -3%) | (-4%, 1%) | (-1%, 1%) |

1: Range is based on 95% confidence interval of regression model

2: Lower limit is 0%. Upper limit is 75% of the maximum effect on commuting.

3: Range is based on combination of 95% confidence interval of regression model and uncertainty range of complementation effect

*Table 4.4: Expected range of changes in total travel due to working from home and teleconferencing per mode (Results based on MPN estimates, projected using ODiN data to get national-level statistics for total travel distance)*

These results again show an upper- and lower bound of the expected effect.

The calculations clearly show that train and btm-trips are more strongly affected when compared to the other travel modes. We saw before (Figure 4.5) that public transport travellers have increased their amount of working from home more than other travellers.

Whereas a net negative effect is expected for train, BTM, and to a lesser extent car and cycling, a positive effect is expected for walking. This is because the expected complementation effect

| | **No mode shift** | **Mode shift** |
|---|---|---|
| Not working from home | 388 (80%) | 98 (20%) |
| No increase | 82 (81%) | 19 (19%) |
| Increase | 220 (79%) | 59 (21%) |

*Table 4.5: Crosstabulation of intention to work from home and intention to change the main commute mode (Data: MPN questionnaire, measurement of May 2022. N = 955)*

seems to outperform the substitution effect (of lesser commuting and business trips) for walking. The main underlying reason is that few people walk for commuting or business travel, whereas many do so for other purposes.

We find that the effects on commuting are the main driver behind potential changes due to working from home and teleconferencing. This is because commuting is a much more frequent purpose when compared to business travel, which is relatively rare. As a result, even relatively substantial changes in business travel only have comparatively small effects on total travel.

The impacts on trips are comparable to the impacts on distances. Of course, this is a result of our assumption that the relative effect on distances is directly proportional to the effect on trips, conditional on the travel mode that is used. Effectively, the remaining differences then reflect the fact that the average distance travelled differs across the commuting, business, and other purposes. For the car, the effect for the commuting purpose in terms of distances is slightly larger than the effect in terms of trips. This reflects that for the car, the average distance travelled for commuting is larger than the average distance travelled for other purposes. The opposite is true for the train, resulting in comparatively smaller effects in terms of distances than in terms of trips.

The negative effects on travel behaviour are likely to be stronger in the morning peak (for example, for the car it is estimated to be -5 to -12%, compared to -1 to -5% on overall travel). This is because a relatively large share of travel in the morning peak consists of commuting travel. The effect in the evening peak is less strong than the effect in the morning peak because the evening peak consists of much more trips made for other purposes comparatively.

**Changes in mode choice and purpose-specific spread of travel**

As mentioned, in the above analyses we did not (yet) account for changes in mode choice for commuting-, business- or other trips (C, Figure 1), and potential shifts from on-peak to off-peak travel due to more working from home or teleconferencing (D, Figure 1). We analyse these possible effects using data from the special COVID-questionnaires of the MPN.

Regarding commute mode choice, we asked our respondents with which travel mode they would predominantly commute in the future after the COVID-19 pandemic would be fully over. We also asked them which was their main commute mode before the COVID-19 pandemic started. We do see some shifts here, mainly away from public transport towards the car and the active modes. However, the frequency of these mode shifts is not correlated with the intention to work more from home after the pandemic is over, as is shown in Table 4.5.

A Chi-square test (1.75, df = 3, p = 0.63) shows that there are no statistically significant differences between people who do not work from home, people who do not intent to increase the number of hours they work from home as a result of the pandemic, and people who do intent to do so when it comes to an expected mode shift for commuting. As a result, we do not expect that working from home will have an effect on commute mode choice. We have no very clear indication for the future intentions regarding mode choice of other travel. However, we did see large increases in the mode share of cycling and walking during the pandemic. For this reason, we expect a small mode shift towards the active modes for other travel.

Regarding peak-hour avoidance (D), we asked respondents whether they think they would travel less during peak-times when commuting after the pandemic than they did before the pandemic in our COVID-measurement of April 2021. (Figure 4.7).

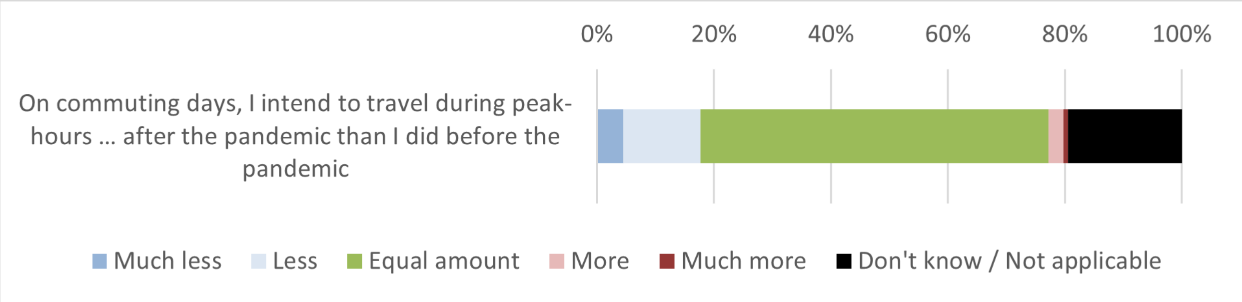


*Figure 4.7: Respondents' intended change in peak travel on days they need to go to work, compared to pre-COVID (Data: MPN COVID-Measurement April 2021, N = 955)*

Only a relatively small percentage of respondents ($< 20\%$) intended to travel less during the peak after the pandemic, with most respondents indicating that they either intended no change or couldn't answer the question. Respondents thus seem to indicate that they do not think that working from home or teleconferencing will lead to a noticeable shift towards off-peak travel, at least if no further measures are taken by either the government or employers.

We do expect small structural changes in the spread of commuting travel over the week. Although people on average intend to travel less for work on all days of the week due to more working from home and teleconferencing, Tuesdays and Thursdays are still the days with the most commutes. Wednesdays and Fridays are likely to become even less popular days to go to the office than they already were.

Table 4.6 summarizes the findings regarding the effects on trips (A+B), and the effects of mode choice (C) and spread of travel (D) for each main travel mode.

## 4.6 Conclusion and discussion

COVID-19 has accelerated the trend of an increase in working from home and teleconferencing in the Netherlands, as well as in many other countries. This study aimed to answer two questions. First, what are the expected structural, post-pandemic changes in working from home and teleconferencing and second, what effects will these changes have on travel behaviour. To do so, we used both panel data and a national-level cross-sectional travel survey.

Our findings show that there will be structural increases in working from home and teleconferencing due to the pandemic. We base this conclusion both on the drastic increase of working from home and teleconferencing during the pandemic, as well as on people's intentions for the

| | Car | Train | Bus, Tram, and Metro | Cycling | Walking |
|---|---|---|---|---|---|
| | | | **A+B Distance travelled** | | |
| **Total** | (-5%, -1%) | (-9%, -3%) | (-5%, -1%) | (-2%, 0%) | (0%, 1%) |
| **Morning peak** | (-12%, -5%) | (-17%, -8%) | (-10%, -5%) | (-4%, 1%) | (-1%, 1%) |
| **Off peak** | (-3%, 1%) | (-5%, 0%) | (-3%, 0%) | (-1%, 1%) | (0%, 1%) |
| **Evening peak** | (-7%, -2%) | (-13%, -5%) | (-8%, -3%) | (-4%, 1%) | (-1%, 1%) |
| | | | **C Mode choice** | | |
| **Commute and business** | | | No substantial effect expected | | |
| **Other travel** | Negative | Negative | Negative | Positive | Positive |
| | | | **D Peak avoidance** | | |
| **Day** | | | No substantial effect expected | | |
| **Week** | | | Less commute travel on Wednesday and Friday | | |

*Table 4.6: Summary of all expected travel effects due to more working from home and teleconferencing*

post-pandemic future. Findings show that the levels of working from home and teleconferencing as of May 2022 were still a bit higher than people's post-pandemic intentions. This means that as of May 2022, we were still in a transitionary phase after the Dutch government relaxed most of the COVID-related measures since March 2022. In addition, it is important to stress that working from home is impossible for roughly half of the workforce in the Netherlands. The half that can work from home more often consists of office- and managerial workers with a relatively high level of education.

Regarding the effects on travel behaviour, our findings suggest that the structural impacts on public transport and on morning peak travel are the strongest. This is because people commuting by public transport are more likely to work from home and that commutes are a relatively large part of (especially) morning peak travel, respectively. We estimate that structural, post-pandemic increases in working from home and teleconferencing will result in a negative effect on distances travelled by train (-3% to -9%) and by bus, tram, and metro (-1% to -5%). The estimated effect on the distance travelled by car (-1% to -5%), bicycle (-2% to 0%), and walking (0% to +1%) is smaller.

### Discussion

These findings indicate that structural changes in working from home and teleconferencing due to COVID-19 have important implications for the accessibility and sustainability of the transport system. The sizeable reductions in commute travel are likely to lead to a more spread-out travel demand, which could relieve congestion on roads and crowding in public transport. This finding is generally congruent with expectations and other results in the literature (Campisi et al., 2022; De Vos et al., 2020; van Wee & Witlox, 2021). However, there are some potential drawbacks to discuss. First, the size of the structural impacts on car travel seems to be limited and thus should not be overemphasized, especially against the backdrop of expected population growth and welfare increases. Second, the effects on public transport are stronger, which is a point of concern, at least on the shorter term (Tirachini & Cats, 2020). This result echoes general results and expectations in the literature, as found in Chapter 2. The lower number of passengers could result in less financial capacity to assure the quality of public transport. Lower-quality public transport would then drive people into other modes of transport, potentially creating a damaging spiral. When looking slightly further ahead, up to 2027, it is however important not to overestimate the total effect of working from home on public transport travel. Population growth and expected economic developments mean that demand (also for public transport) is still likely to exceed pre-pandemic public transport levels within these next five years, at least if service levels will not continue to be affected by lack of personnel (Kennisinstituut voor Mobiliteitsbeleid, 2022). The increase in working from home and teleconferencing thus mainly has a dampening effect on traffic growth. When considering the usefulness and necessity of infrastructure investments, it is important to be aware of this broader perspective.

**Policy Recommendations**

Based on our findings, working from home and teleconferencing have some desirable effects on the transportation system. The digital means of accessing the workplace allow a substantial share of people to forgo their physical commute. This reduction in commuting trips will likely lead to a travel pattern that is more spread out across the day, further reducing congestion even at similar total demand levels. There are however also some undesirable effects, especially regarding the public transportation system which sees a substantial drop in its use. This might also have repercussions for people who are not able to work from home, especially when the service levels of public transport would be adjusted to the lower demand. Such adjustments could result in more car dependency, which should be avoided as it would have negative effects on both the accessibility and the sustainability of the transport system.

From a transportation perspective, employers and governments should then probably try to strike a balance where some amount of working from home is facilitated, perhaps encouraged, but not enforced. To do so, employers could formalize the right to work from home in employment contract, provide facilities for hybrid meetings and pay for home office setups of employees. From a transportation perspective, they should also pay particular attention to spread travel and work location visits over the days of the week. Governments can introduce legal frameworks for flexible working, including working from home. They can simplify or expand fiscally attractive options for employers to pay for employees' home office setups and simplify hybrid work regulations. They too should try to encourage people to spread their office visits throughout the week and the working day. They could also look outside of the employment sphere, for example by introducing pricing schemes to discourage peak-hour travel on certain days or look at the educational system to facilitate working parents.

**Limitations**

There are some limitations of this paper that need to be discussed. First, it is important to mention that although we used data collected at a time when nearly all COVID-measures were lifted, the actual effects on travel still contain some uncertainty that is not already reflected in the results.

For example, we observe that the level of working from home and teleconferencing in May 2022 was still above the intended levels for the longer term (so long as measures are lifted). Regarding these intentions, it still needs to be seen whether they will be fully reflected in future behaviour. However, the intentions of respondents turn out to be rather stable over time and match recorded behaviour well. Second and related to the first point, we use stated intentions to estimate the structural effects. It would be interesting to use actual behaviour as the dependent variable in the future, when we have fully transitioned out of the pandemic. We could then also empirically test the critical assumption underlying our calculations regarding the complementary effect. Research into the relative strength of this effect, and more broadly into the validity of the constant travel time budget (Ahmed & Stopher, 2014) is necessary after the pandemic will be behind us. Third, we explicitly did not yet account for potential longer-term effects on people's residential and work location choices. It could be that people at least partly account for this in their intentions regarding working from home and commuting trips. We did ask people if they moved or thought about moving due to working from home possibilities, and results suggest these impacts still seem to be quite limited (see de Haas et al. [2022]). In addition, we did not calculate exact effects on accessibility and sustainability, although we expect those effects to be generally positive due to the decrease in peak travel and dampening effects on car travel. Fourth, this paper focused on the structural changes in working from home and teleconferencing due to the pandemic. There could be other potential structural effects of the COVID-19 pandemic on travel behaviour, such as changes in remote education, or a structural mode shift from public transport to car due to shifts in mode-related attitudes. When considering the overall effect of COVID-19 on travel behaviour, these effects also need to be considered. As time without COVID-measures goes on, it will become clearer to what extent these intentions of working people will become real behaviour. Of course, this could also be impacted by new policies by governments and employers, as well as other factors that affect travel behaviour.

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# Chapter 5

# The role of travel-related reasons for location choice in residential self-selection

This chapter is based on Faber, R., Merkies, R., Damen, W., Oirbans, L., Massa, D., Kroesen, M., & Molin, E. (2021). The role of travel-related reasons for location choice in residential self-selection. *Travel Behaviour and Society*, *25*, 120–132. https://doi.org/10.1016/j.tbs.2021.07.003

Abstract:

*Residential self-selection (RSS) is the theoretical mechanism that explains that the impact of the built environment on travel behaviour is weaker than bivariate correlations suggest, because mode attitudes influence both the built environment and travel behaviour and therefore at least partially account for the bivariate relationship. Recently, the concept of travel-related reasons for residential choice has been introduced, which reflects the actual extent to which the travel-related characteristics of the built environment were considered during the relocation decision. In this paper, we hypothesize that travel-related location reasons are stronger predictors of the built environment choice than generic mode attitudes. This hypothesis is examined by estimating both a cross-sectional and a longitudinal Structural Equation Model using data gathered in the Netherlands. The results suggest that the travel-related location reasons are indeed stronger predictors for built environment location than travel mode attitudes and that the directions of causality between attitudes, travel-related location reasons, the built environment, and travel behaviour often run in both directions. Substantively, our findings indicate that public transport use is most strongly affected by the built environment (after controlling for both stated reasons and attitudes), while car and bicycle use are hardly affected. From a practical point of view, this suggests that transforming the built environment to be more friendly to public transport may increase the use of public transport, but that, at least in the Netherlands, such a strategy would not work well if the aim were to reduce car use or increase bicycle use.*

## 5.1 Introduction

The car is the dominant travel mode in the European Union, accounting for more than half of all trips in 2015 (Fiorello et al., 2016). Even in the Netherlands, a densely populated country with a strong cycling tradition and an efficient public transport system, about 75% of all kilometres travelled are made by car (Kennisinstituut voor Mobiliteitsbeleid, 2019). Decreasing the reliance on the car and increasing the travel share of other modes is seen as desirable to increase sustainability (Wang & Lin, 2019), improve public health (de Nazelle et al., 2010; Grabow et al., 2011) and (possibly) reduce congestion (Hensher & Puckett, 2007). With this policy goal in mind, an important research objective has been to find factors that reduce the distance travelled by car.

One area of focus is the influence of the built environment, whose relation to travel behaviour has been widely established (Cervero & Duncan, 2002; Chen et al., 2008). Theories indicate that denser and better-connected areas promote the use of more active travel modes (public transport, walking and cycling), whereas environments characterised by loose suburban sprawl increase car dependence (De Vos et al., 2018; Humphreys & Ahern, 2019). Based on the assumption that the built environment influences travel behaviour, policies have been developed to increase the connectivity, density, and public transport accessibility of the built environment to facilitate the use of alternative travel modes to the private car (Cao et al., 2009; Ewing & Cervero, 2010).

However, the existence of a causal effect of the built environment on travel behaviour is contested. This is the result of the notion of residential self-selection (RSS), where demographics, travel preferences, and residential preferences underlie both the decision to live in a certain built environment and travel behaviour (Boarnet & Sarmiento, 1998; Cao, 2015; Chatman, 2009; van Wee, 2009). This notion of RSS then means that the direct effect between the residential built environment and travel behaviour can be explained, at least to some extent, by travel preferences. Policies aimed at changing the built environment will then have a weaker effect than expected when based on research that does not take RSS into account.

A recent development in this research area is the distinction between attitudes and more deliberate travel-related reasons to choose a specific residential location, which was made by Ettema and Nieuwenhuis (2017). This is an answer to one of the main questions regarding the RSS mechanism, namely to what extent attitudes determine a person's choice to reside at a specific location (Mokhtarian & Cao, 2008). These deliberate travel-related reasons are not simply residential preferences, as they do not reflect some favour or disfavour towards residential styles or layouts. They reflect the extent to which a travel preference actually affected the final decision to live in a certain neighbourhood.

Previous studies on travel-related location reasons have generally shown that they have a strong effect on the residential location decision and its built environment (e.g. Jarass and Scheiner (2018) and Wolday et al. (2018)). Based on the distinction between attitudes and reasons, Ettema and Nieuwenhuis (2017) made two interesting observations. The first of these is the finding that attitudes toward travel modes and residential location choice are only associated to a limited extent, which seemingly contradicts the main body of residential self-selection literature (Cao et al., 2009; Guan et al., 2020; van Wee & Cao, 2022). This finding can be explained by the notion that part of the seeming association between attitudes and residential location is explained instead by the travel-related location reasons. The second finding, that travel-related location reasons may be regarded as a more direct indicator of self-selection than travel attitudes, seems to provide more evidence for this notion.

This study builds on this conceptual distinction between travel attitudes and deliberate travel-related location reasons and further investigates the notion of residential self-selection when this distinction is made. The main hypothesis is that the concepts of travel attitudes and travel-related location reasons play a different role within the self-selection process. The travel-related location reasons are conceptually more direct indicators of the residential location choice, and we thus hypothesize them to have a stronger, more direct effect on the choice of built environment when compared to travel attitudes. On the other hand, travel attitudes capture more general travel preferences and are hypothesized to have a stronger effect on travel behaviour. If this is the case, future researchers of residential self-selection should try to include both attitudes and reasons in their work. This research thus does not directly intend to quantify the impact of RSS on the estimated effect of the built environment on travel behaviour. Rather, it seeks to increase the understanding of the mechanisms behind RSS.

To test these hypotheses data from the Netherlands Mobility Panel (MPN) are used, a panel that is broadly representative of the Dutch population. This is an improvement on the previous study of Ettema and Nieuwenhuis (2017), who used data gathered from connected, dense residential areas with high-quality public transport infrastructure. Another improvement in this study is the use of structural equation modelling, which enables the estimation of multiple equations simultaneously, where the dependent variable in one equation can be the independent variable of another equation (Bagley & Mokhtarian, 2002). SEM, especially when employing a longitudinal structure, is one of the preferred modelling techniques for studying RSS, because of the complex relationships between residential built environments, travel behaviour, attitudes, and reasons which have been outlined above and are discussed in more detail in section 2. Finally, the use of the MPN enables longitudinal testing of the relationships that are assumed to exist in the context of RSS. This is especially important given that the causal direction of the relationships between both the built environment and travel behaviour and travel attitudes and travel behaviour is unclear. This paper is the first to employ a longitudinal SEM to simultaneously test the effects of both travel attitudes and travel-related location reasons on travel behaviour and the choice of built environment.

The remainder of this paper is organized as follows. Section 5.2 dives deeper into the state of the literature and the available theories surrounding RSS and results in a conceptual model. Section 5.3 describes the research methods, operationalization, and model specification and estimation procedures. The results from the modelling procedure are described and interpreted in section 5.4. The conclusions are drawn in section 5.5, together with a short discussion of the paper and the policy implications that follow from the conclusions.

## 5.2 Theory and Conceptual Model

We developed a conceptual model, used to test the hypotheses. The following sections will elaborate on the concepts and relations in this model, providing the theoretical underpinning from the literature. Section 5.2.1 introduces the built environment and travel behaviour. Section 5.2.2 builds upon this foundation with the notion of residential self-selection and its related concepts. Section 5.2.3 describes the concepts of travel attitudes and travel-related location reasons and the relation between the two concepts. Section 5.2.4 discusses the research on causal relations within the context of residential self-selection. The resulting conceptual model is shown in section 5.2.5.

### 5.2.1 Influence of the built environment

The geographical layout and characteristics of the built environment have long been shown to influence travel behaviour. For example, Cao et al. (2006) used a quasi-longitudinal design to show that changes in the built environment affected travel behaviour. This geographical perspective has been used to claim that developments like urban sprawl are one of the causes of the increasing use of the private car. An extensive meta-analysis by Ewing and Cervero (2010) found that no individual part of the built environment is responsible for a substantial change in travel behaviour, but that many small changes in the built environment can have a combined effect that is large. Urban form characteristics such as density, settlement size, land-use mix, accessibility, and local street layout have been shown to have a cumulative effect on travel behaviour Headicar et al. (2009). The measurement of the built environment then plays a critical role on the estimated impact of the built environment on travel behaviour. Typically, studies focus on the 'five D's' of density, diversity, design, destination accessibility and distance to transit (Guan et al., 2020), which according to the authors of this review study might neglect social environment factors such as safety. Some studies also look into the perceptions of the built environment (Ma & Cao, 2017), although using objective measurements is still the standard in RSS research.

### 5.2.2 The role of residential self-selection

Initial studies focusing on the effects of the built environment on travel behaviour typically controlled for the possible confounding effect of socio-demographic variables (see e.g., Cervero and Kockelman (1997) and Crane and Crepeau (1998). Following the recognition that socio-demographics probably only partially capture self-selection mechanisms (Kitamura et al., 1997), later studies also included travel attitudes as control variables (see e.g., Handy et al. (2005, 2006). These travel attitudes have been linked to both travel behaviour and residential location choice (Cao et al., 2009; Wolday et al., 2018). Studies have indicated that people tend to move to neighbourhoods which facilitate the use of their preferred travel mode to some extent (e.g., De Vos et al. (2012), Handy et al. (2005), and Schwanen and Mokhtarian (2004). In this case, the underlying travel attitudes can explain at least some part of the relationship between the built environment and travel behaviour. For example, neighbourhoods close to train stations are more attractive to people who have a positive attitude towards using the train, which partly explains why people living in these areas are indeed more likely to use the train for their travel. As explained in the introduction, this mechanism is called residential self-selection (RSS).

Most studies into RSS find that controlling for travel attitudes does indeed decrease the estimated size of the effect of the built environment on travel behaviour, although a significant independent effect of the built environment is still found in nearly all cases (Cao et al., 2009). There is still much uncertainty about the size of the impact of RSS on the estimated effect on the Built Environment (Mokhtarian & van Herick, 2016; van Herick & Mokhtarian, 2020). These studies find that controlling for RSS results in estimated effects of the built environment of between 34 and 100 percent of the effect that was found without controlling for RSS, based on a review of other studies. A comparison of methodologies to estimate this proportion results in a best estimate that roughly 62% of the apparent effect of the built environment still exists after controlling for RSS (and thus that RSS accounts for the remaining 38%).

In addition to this uncertainty, most papers on RSS use empirical data from OECD countries (van Wee & Cao, 2022) and the estimate of its impact in non-OECD countries is even more unclear. The literature does show that differences between countries exist, even within OECD countries. It is therefore natural to assume that results from a specific country do not necessarily generalise to other countries, and that the differences between results grow larger the more the countries diverge in terms of travel behaviour, land use mix, transportation system, and other built environment characteristics.

### 5.2.3 Attitudes and Reasons

One key question revolves around the link between the travel attitudes and the residential location. The choice of residential location is of course affected by many other factors than just those related to travel (Cao & Chatman, 2016). This may lead to a dissonance between residential location choice and travel attitudes, as for example people who prefer to use the train are not always able or willing to reside close to railway stations. This possible dissonance led to the introduction of travel-related residential preferences by Næss (2009). People with strong travel-related residential preferences are more likely to move to residential areas that match their travel preference. A more direct measurement of the extent to which travel preferences influence the decision to live in a certain residential area are the deliberate travel-related location reasons introduced by Ettema and Nieuwenhuis (2017). These reasons reflect the actual extent to which the travel-related characteristics of the built environment were considered during the relocation decision. The two concepts of travel attitudes and travel-related location reasons are introduced in more detail in the following paragraphs.

Of these two concepts, travel attitudes are more often studied in the context of residential self-selection. In this paper the definition used by Bohte et al. (2009) is followed, which stems from Eagly and Chaiken, 1993, p. 1: “Attitude is a psychological tendency that is expressed by evaluating a particular entity with some degree of favour or disfavour”. Travel mode attitudes could therefore be considered to be the degree to which the traveller favourably or unfavourably evaluates the use of the travel mode in question. This evaluation could be based on the functional performance of the mode, for example in terms of travel time. It could also refer to symbolic-affective evaluations of the travel mode, for example the status associated with the use of the mode (Anable, 2005; Hunecke et al., 2007). This research uses both evaluations in the measurement of attitudinal indicators, which are combined into a single latent attitude for each travel mode. More information on the operationalisation of the travel attitudes can be found in section 3.2.

Travel-related residential preferences reflect the extent to which people prefer to live in a residential environment with certain travel-related characteristics, such as short distances to public transport access/egress points. Deliberate travel-related residential location reasons are more directly linked with residential location choice as they are meant to indicate to which extent these travel-related characteristics of the residential location have been considered in the relocation choice (Jarass & Scheiner, 2018). Conceptually, these travel-related location reasons are thus directly related to the decision to live in the current residential area. Broadly speaking then, travel attitudes are general evaluations of the various travel modes, whilst travel-related location reasons are more directly tied to the (re)location choice.

### 5.2.4 Causal relations in the context of RSS

Research into RSS uses several concepts: travel behaviour, the built environment, and travel attitudes. This research also brings up the concept of travel-related location reasons. As noted by both the recent reviews on RSS by van Wee and Cao (2022) and Guan et al. (2020), the causal order between these concepts is not always clear. Below these causal orders are discussed: first the classic specification is described, with the addition of location reasons. Then we highlight why this classic specification might be misleading, prompting the need for longitudinal models.

In their relatively early review of methodologies in the context of RSS, (Mokhtarian & Cao, 2008) describe multiple possible causal specifications between the three main concepts in the RSS context: attitudes as antecedents of both travel behaviour and the built environment, attitudes intervening in the relationship, and attitudes as a secondary or irrelevant concept. Heinen et al. (2018) extend these specifications with multiple others. The specification that is mainly used in the context of RSS-research is that where attitudes are antecedents of both built environment and travel behaviour, and where the built environment also directly affects travel behaviour. This classic specification is also used in the cross-sectional model specified in this research. The location reasons are specified similarly to the attitudes, as antecedents of both the built environment and travel behaviour. The only remaining relation then is that between attitudes and location reasons. This research postulates that travel attitudes have an effect on the travel-related location reasons. The rationale here is that, for example, people who feel more positively about public transport are more likely to make public transport access an important factor in their decision to relocate. In effect the attitudes thus precede the reasons in the causal order, where travel-related location reasons can be conceptualised as a concept in between attitudes and behaviour. Attitudes then are antecedent to all other concepts in this model.

A recent line of research, which has increasingly gained traction, has revealed that several of the relationships are bi-directional in nature. For example, Kroesen et al. (2017) revealed bi-directional relationships between travel behaviour and travel-related attitudes using panel data. In a similar fashion, De Vos et al. (2018) and Kroesen (2019) and van de Coevering et al. (2016) show that the residential location choice is not only influenced by travel-related attitudes and travel-related location reasons, but, in turn, also shapes the attitudes and/or reasons (at a later point in time). In a cross-sectional study, it is not possible to specify and assess these bi-directional relationships, instead only the traditionally assumed directions of causation are specified. To alleviate these concerns a longitudinal model is estimated, where the causal order between concepts is not imposed but estimated. The combination of both models are interpreted and discussed in the conclusion.

### 5.2.5 Conceptual model

The previous sub-sections have explained the concepts and links that are present in the conceptual model. The model builds on the basic notions of the influence of the built environment and socio-demographics on travel behaviour explained above. This basic model is extended by adding the notion of residential self-selection, where travel preferences underlie both the location choice (built environment) and travel behaviour. These travel preferences have been split into two distinct concepts, namely travel-related location reasons and travel mode attitudes, both of which are placed in an antecedent position relative to the built environment and travel behaviour. Furthermore, a causal relation between the more general travel attitudes and the more specific location reasons is

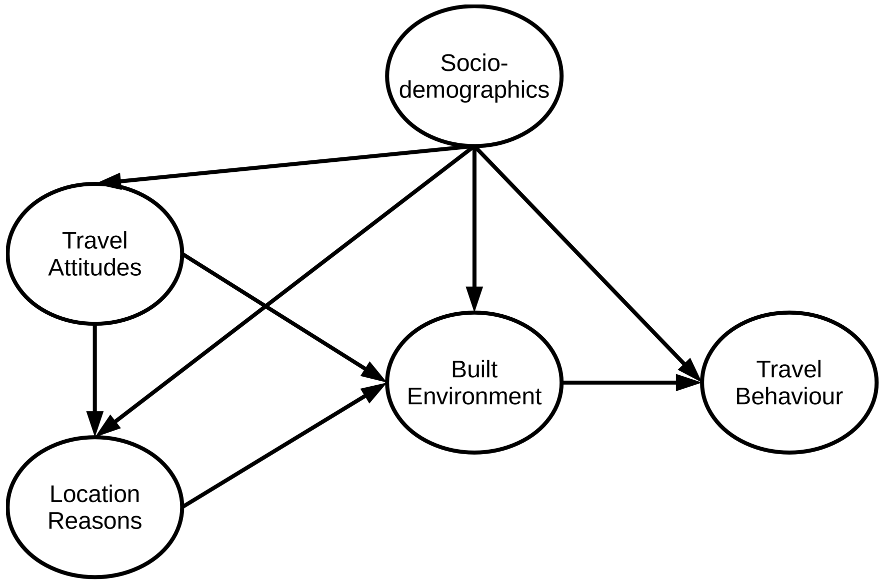


*Figure 5.1: Conceptual model of the concepts and relationships studied in this paper*

specified as well. Finally, socio-demographics are assumed to affect all concepts presented in the study. The conceptual model is given in Figure 5.1.

The model estimates the effect of the built environment on travel behaviour after controlling for both mode attitudes and travel-related location reasons. By doing so the effects of both the mode attitudes and location reasons on the (residential) built environment choice and travel behaviour are revealed. This enables us to check the hypothesis of this paper, which is that these two concepts have a different effect on both the choice of built environment and travel behaviour. Note that the causal order as given in the conceptual model is imposed on the cross-sectional model, but not on the longitudinal model, which tests these directions instead.

## 5.3 Research Methods and data

This section explains how the structural equation model is specified. Structural Equation Modelling (SEM) is a modelling approach with which one can simultaneously estimate a series of linked regression equations (Bollen, 1989). Such a series of linked regression equations is also called a path model, in which a relationship between two variables is called a path. A standardized coefficient estimated for a path has a similar interpretation as a standardized regression coefficient in ordinary regression analysis: it indicates the weight of the causal path and, therefore, how strong an independent variable influences the dependent variable, controlling for other variables in the model.

When using cross-sectional data, an empirical test of causality with SEM is not possible. The structure of the model is then informed by theoretical notions of causality (as discussed in section 2), leading to the assumed causal relationships visualized in the conceptual model in Figure 1. In addition, the use of SEM enables the inclusion of latent variables measured by multiple indicators whilst accounting for measurement errors in the measurement model. Since attitudes are psychological variables that are impossible to measure directly, measurement errors are expected and accounted for, which improves the accuracy of the modelling results.

The longitudinal analysis of this paper employs a two-wave Cross-Lagged Panel SEM (Finkel, 2011). This model makes no assumptions about the causal structure between variables in the model. Instead, it estimates relations between all variables measured in one wave and all variables measured in the other wave. Variables measured within the same wave are assumed to be correlated with one-another. This technique thus does not test a specific structure, but rather empirically measures possible causal relations between variables.

The dataset, sample selection and data preparation are described in section 5.3.1. Section 5.3.2 contains the operationalisation and a description of the variables used in the model and section 5.3.3 describes the model specification and estimation procedure.

### 5.3.1 Data description and preparation

The data used for the analysis is the second and fourth annual wave of the Netherlands Mobility Panel (MPN), collected in autumn 2014 and autumn 2016 respectively. The MPN is a web-based longitudinal activity-based household travel survey (Hoogendoorn-Lanser et al., 2015). The sample for the MPN is drawn from an existing access panel, managed by a fieldwork agency. Respondents in the panel are not able to register themselves, reducing selection biases. Furthermore, respondents can be drawn from the existing access panel based on socio-demographics, enabling the MPN to invite a broad range of respondents from the Netherlands to ensure the panel is roughly representative of the Dutch population. For more information on the sampling design the reader is referred to the paper by Hoogendoorn-Lanser et al. (2015) on the design of the MPN.

The MPN consists of both questionnaires and a travel diary. This research uses information gathered in the questionnaires, which are collected on both a personal and household level. The survey data is enriched with geospatial characteristics based on the residential location of the respondents. Further preparation of the data was conducted before being used in the structural equation model. For example, respondents younger than 18 years old were excluded based on the assumption that they have never actively decided on a residential location. Respondents with missing values on questions pertaining to the travel-related location reasons and/or the travel attitudes were removed as well, resulting in a final sample of 4 238 respondents for the cross-sectional analysis. Of these respondents, a total of 1 677 also had complete data for wave 4 and were thus included in the longitudinal analysis. The sample composition for both the cross-sectional and the longitudinal sample is given in Table 5.1.

### 5.3.2 Operationalisation

The process of operationalisation entails taking the concepts from the conceptual model and specifying how these concepts are measured by indicators. The following socio-demographic variables were considered relevant: age, gender, education, ethnicity, employment, personal income, and the number of children in the household. Age is measured in years and treated as a continuous variable in the model. The other socio-demographic variables are categorical variables, which have been dummy-coded. Travel behaviour is measured by the frequency of use of various travel modes. Respondents could provide answers on a 7-point scale, ranging from “Never” for 1 to “Four or more days per week” for 7.

| **Variables** | **Levels** | **Sample Distribution Cross-sectional (%)** | **Sample Distribution longitudinal (%)** |
|---|---|---|---|
| Age (years) | 18 - 39 | 38.5 | 39.4 |
| | 40 - 59 | 46.6 | 48.3 |
| | 60+ | 14.9 | 12.3 |
| Employment | Employed | 67.3 | 74.6 |
| | Not employed | 32.7 | 25.4 |
| Education | Low | 25.3 | 16.1 |
| | Middle | 40.3 | 39.1 |
| | High | 34.4 | 44.8 |
| Ethnicity | Western | 97.7 | 98.7 |
| | Non-Western | 2.3 | 1.3 |
| Gender | Male | 46.3 | 47.4 |
| | Female | 53.7 | 52.6 |
| | None | 8.8 | 5.7 |
| Personal Net Income | Low (1 - 1500) | 35.2 | 31.2 |
| (€/month) | Middle (1500-2500) | 31.7 | 36.1 |
| | High (> 2500) | 12.1 | 14.7 |
| | Unknown | 12.2 | 12.3 |
| | 0 | 78.2 | 77.5 |
| Nr. of children in | 1 | 12.2 | 11.9 |
| household | 2 | 7.6 | 8.2 |
| | 3+ | 2 | 2.4 |

*Table 5.1: Sample distribution of socio-demographic variables*

| | Car | Public Transport | | Bicycle |
|---|---|---|---|---|
| | | Train | BTM | |
| Travelling by (mode) is comfortable | 0.828 | 0.762 | 0.789 | 0.818 |
| Travelling by (mode) is relaxing | 0.767 | 0.739 | 0.777 | 0.847 |
| Travelling by (mode) saves me time | 0.725 | 0.659 | 0.703 | 0.616 |
| Travelling by (mode) is safe | 0.704 | 0.495 | 0.541 | 0.632 |
| Travelling by (mode) is flexible | 0.725 | 0.740 | 0.745 | 0.752 |
| Travelling by (mode) is satisfying | 0.836 | 0.787 | 0.802 | 0.863 |

*Table 5.2: Attitude indicators and their factor loadings on latent mode attitudes*

For the travel mode attitudes, six indicator questions are used for each travel mode. Each indicator is scored on a 5-point Likert scale. Questions relating to the train and bus, tram, and metro (BTM) are treated as indicators of a latent public transport attitude. The indicators and their factor loadings, resulting from principal axis factoring, are given for each mode in Table 5.2.

The travel-related location reasons are measured differently for each mode. Five questions are used in total, with one question being used for car-related reasons and two each for reasons related to public transport and the bicycle. The level of agreement with each statement is measured using a 5-point Likert scale. The statements read as follows: 1. The short distance to a highway was an important factor in my choice to reside at my current address. 2. The presence of a train station

| Computed distance between the home and ... | Centrality | Bus stop | Tram/metro stop |
|---|---|---|---|
| Nearest city centre | 0.826 | | |
| Nearest highway entry- or exit ramp | 0.674 | | |
| Nearest intercity train station | 0.861 | | |
| Nearest train station | 0.617 | | |
| Nearest bus stop that is serviced at least 4x / hour | 0.514 | 0.404 | |
| Nearest bus stop that is serviced at least 2x / hour | | 0.761 | |
| Nearest bus stop that is serviced at least 1x / hour | | 0.870 | |
| Nearest bus stop | | 0.737 | |
| Nearest metro or light rail stop | | | 0.976 |
| Nearest tram stop | | | 0.977 |

*Table 5.3: Built environment clusters and factor loadings*

within walking or cycling distance was an important factor in my choice to reside at my current address. 3. The presence of a bus, tram or metro station within walking distance was an important factor in my choice to reside at my current address. 4. The cycling distance to my workplace(s) was an important factor in my choice to reside at my current address. 5. A short walking and/or cycling distance to shops was an important factor in my choice to reside at my current address. The public transport reasons (nr. 2 and 3) are specified as a latent variable, which is measured with two indicators. The other questions are included as directly observed variables in the model.

The built environment of the residence is measured using two types of variables. The first is the urban density of the municipality where the household resides. This density is measured using a log-10 transformation of the inhabitants per square km in the municipality. The second category consists of computed straight-line distances from the home to relevant locations (Hoogendoorn-Lanser et al., 2015), such as a train station or the nearest urban centre. To avoid multi-collinearity problems, a principal component analysis was used to cluster these distances revealing three distinct components. The results of this analysis are given in Table 5.3, where factor loadings on the three components below 0.3 are not given.

Two of the components were straightforward to interpret, as the high-loading indicators related only to the distance to a tram/metro station for one dimension and the distance to bus stations for the other. The final dimension however consisted of more varied distances: the distance to the urban centre, distances to highway entry/exit ramps, and the distance to the nearest train stations and frequently serviced bus stops. This dimension is interpreted as the centrality of the residential location, as train stations and frequently serviced bus stops are typically located in or near city- or village centres. Factor scores are calculated for these three dimensions.

To reduce the complexity of the model one indicator is specified for all latent variables, calculated as a sum score of all indicators related to the respective construct. To account for the measurement errors in these composite indicators, the error variance of each composite indicator is fixed. This is calculated as the proportion error variance multiplied by the variance of the composite scale (Joreskog & Sorbom, 1993; Joreskog et al., 2001). The proportion error variance is equal to one minus the reliability, as measured by Cronbach's alpha. Unidimensionality is a critical assumption underlying this calculation, so principal axis factoring is used to determine the unidimensionality of all constructs. These analyses revealed that all constructs were found to be unidimensional, allowing us to compute a composite (sum) score for each latent construct.

| Concept | Variable(s) | Measured or Latent | Information on latent variables<br># Indicators | Variance | Cronbach's Alpha | Error variance |
|---|---|---|---|---|---|---|
| Travel Behaviour | Car Use | Measured | | | | |
| | BTM Use | Measured | | | | |
| | Train Use | Measured | | | | |
| | Bicycle Use | Measured | | | | |
| Passive Attitudes | Car Attitude | Latent | 6 | 15.4 | 0.863 | 2.11 |
| | PT Attitude | Latent | 12 | 67.0 | 0.913 | 5.83 |
| | Bicycle Attitude | Latent | 6 | 16.7 | 0.847 | 2.56 |
| Location Reasons | Car Reason | Measured | | | | |
| | PT Reasons | Latent | 2 | 6.07 | 0.731 | 1.63 |
| | Bicycle reason work | Measured | | | | |
| | Bicycle reason shops | Measured | | | | |
| Built Environment | Density | Measured | | | | |
| | Distances | Clustered<br>- Bus<br>- Metro/Tram<br>- Centrality | | | | |

*Table 5.4: Operationalisation of the concepts*

The operationalisation of the main concepts aside from socio-demographics in the conceptual model is given in Table 5.4 below. This table also contains the summary statistics for the latent variables, namely their reliability, variance, and error variance.

### 5.3.3 Model Specification

Two models are specified: a cross-sectional model and a longitudinal model. The cross-sectional model's specification is based on the structure of the conceptual model, as informed by the current literature on residential self-selection. The longitudinal model empirically tests these relations.

The cross-sectional model incorporates public transport (PT), car, and bicycle use as the (final) dependent variables. Structural relations as specified in the conceptual model are added to the model and exogenous variables can covariate with each other. Endogenous variables that are on the same level of the causal order are covaried as well. The model is estimated using maximum likelihood estimation as implemented in AMOS 26. After the initial estimation of the model, insignificant paths (p-value $< 0.1$) are removed from the model. Variables that do not have any causal relations with any other variable in the model are then also removed from the model to ensure the model is parsimonious.

Model fit of the cross-sectional model is assessed using four different goodness-of-fit statistics. The final estimated model has a chi-square value of 104.1 with 87 degrees of freedom and a p-value of 0.102. The CFI is 0.998, SRMR is 0.041 and RMSEA is 0.007. All goodness-of-fit statistics indicate good model fit (Hooper et al., 2008).

After the cross-sectional model was estimated, a smaller longitudinal model was specified as well. This model is based on public transport reasons and attitudes, as these variables are shown to have the biggest effect on the built environment and travel behaviour in the cross-sectional model. All variables except for the socio-demographic variables are entered within the model for both the 2014 and 2016 waves: since socio-demographics cannot be dependent variables, they were only entered for the 2014 wave. Then all variables within the same measurement wave are allowed to

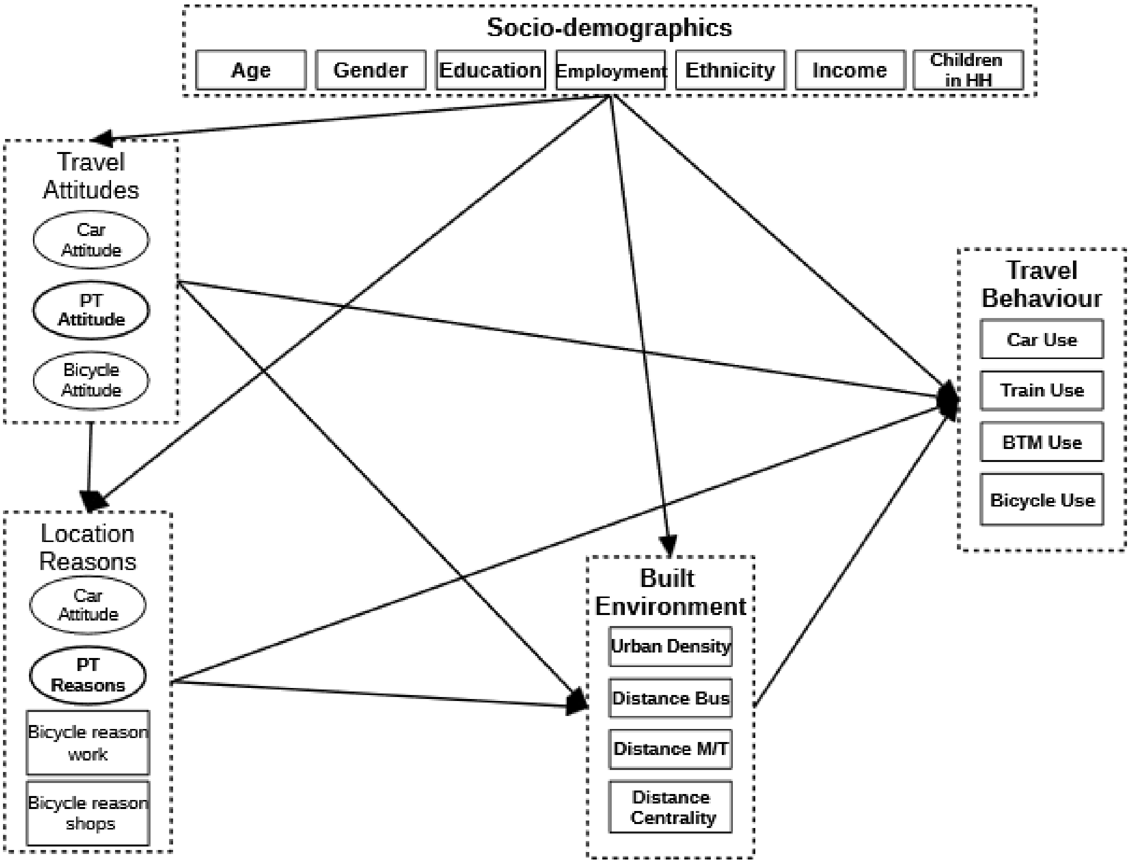


*Figure 5.2: Structure of the estimated cross-sectional structural equation model. Bold variables are included in the longitudinal model as well.*

covary with the other variables in this measurement wave. Finally causal connections are drawn between all variables in the 2014 wave and all variables in the 2016 wave. To make the model more parsimonious, all non-significant paths (p-value $> 0.1$) are then removed.

An overview of the structural model relations can be seen in Figure 5.2. This figure shows which structural relations are estimated between the various concepts. A structural line denotes that at least one variable within a concept is connected to at least one variable in another concept. Indicators and covariances are omitted to further improve visibility. All variables in bold are included in the longitudinal model as well.

## 5.4 Results

This section discusses the empirical results of this study. It does so in two parts: first the results from the cross-sectional model and then the results from the longitudinal model are presented and interpreted.

### 5.4.1 Cross-sectional results

Table 5.5 presents the estimated standardized direct paths from all independent variables towards the dependent variables. It also includes the standardized total effects of all variables on the main dependent variables of the model, those being Car use, Train use, BTM use, and Bicycle use. Since all non-significant paths (at a 10% threshold) were removed from the structural equation model during the model estimation procedure, all effects presented in Table 5.5 are statistically significant at this threshold.

First the effects of the residential built environment on travel behaviour are interpreted, followed by an interpretation of how the travel-related location reasons and travel mode attitudes affect both the choice of built environment and travel behaviour and how these effects are different between the two concepts.

Overall, the effects of the variables related to the residential built environment on the travel behaviour variables are rather small, although an effect does still exist after controlling for both travel attitudes and travel-related location reasons. This finding itself is in accordance with the literature, but some differences between the travel modes can still be highlighted. First, the only built environment variable with an effect on car use is the urban density of the residential environment. This effect size (-0.125) is the second largest of any individual effects of the built environment on travel behaviour. Meanwhile, we find only a small effect of the built environment on bicycle use (-0.044 for the distance of metro/tram stops). Use of the train is only affected by distance centrality (-0.075), a clustered variable that encompasses the distance to train stations. BTM use is affected by all built-environment variables, although to varying degrees. As expected, the distance to bus-stops has the largest effect (-0.130), followed by the centrality (-0.085), density (0.051) and distance to metro- and tram stops (-0.042).

When looking at the effects of attitudes and reasons on the residential built environment, the first thing that stands out is the minimal effect of attitudes. Four small effects are found: from car attitudes on density (-0.034) and bus stop distances (0.036), from PT attitudes to bus stop distances (0.029) and from bicycle attitude to density (0.030). The effects of the travel-related location reasons on the choice of built environment are both considerably stronger and more numerous. Particularly PT reasons have a strong effect on the density (0.341) and both the centrality (-0.203) and bus (-0.339) distances of the chosen residence. These findings support the hypothesis formulated in the introduction that the travel-related location reasons are a stronger, more direct indicator of the choice of built environment than travel attitudes.

More favourable mode attitudes have a direct positive effect on use of the same mode (0.205 for car; 0.255 for PT on train and 0.294 for PT on BTM; 0.511 for bicycle). The bicycle and the train seem to be complementary modes, as a more favourable attitude towards one of these modes leads to increased use of the other mode (0.056 for bike attitudes on train use; 0.028 for the reverse). Bicycle attitudes however have a negative effect on bus use (-0.033), indicating that these modes are less complementary. The private car is a clear competitor of the other modes, with more positive car attitudes leading to decreased train (-0.111), btm (-0.047) and bicycle (-0.131) use and more positive PT and bicycle attitudes leading to reduced car use (-0.033 and -0.111 respectively). The directions of the effects of the travel-related location reasons for choosing a residential location show a similar pattern, with two noticeable exceptions. The first being the change in direction between the train and the bicycle. As seen before, bicycle attitudes have a positive effect on train use, and PT attitudes have a positive effect on bicycle use. However, our

| | *Dependent Variables* | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Built Environment | | | | Attitudes | | | Reasons | | | | Car use | | Train Use | | BTM Use | | Bicycle Use | |
| *Independent variables* | Density | Distance Centrality | Distance M/T | Distance Bus | Car | PT | Bike | Car | PT | Bike Work | Bike Shop | Direct Effect | Total Effect | Direct Effect | Total Effect | Direct Effect | Total Effect | Direct Effect | Total Effect |
| **Socio-Demographics** | | | | | | | | | | | | | | | | | | | |
| Western ethnicity | -0.056 | 0.031 | | 0.040 | | -0.039 | | -0.060 | -0.072 | | -0.040 | | 0.020 | | -0.035 | | -0.047 | 0.030 | 0.037 |
| Gender (Male) | | | | 0.043 | 0.071 | | | | | | -0.069 | | 0.013 | | -0.001 | -0.025 | -0.028 | -0.042 | -0.057 |
| Age | -0.075 | 0.051 | 0.048 | -0.051 | -0.102 | 0.063 | 0.051 | | -0.084 | -0.047 | | 0.081 | 0.083 | -0.281 | -0.250 | -0.243 | -0.250 | -0.070 | -0.028 |
| High Education | 0.064 | -0.096 | | | -0.098 | 0.035 | 0.091 | 0.065 | 0.096 | | 0.060 | | -0.065 | 0.133 | 0.198 | 0.080 | 0.141 | 0.046 | 0.100 |
| Employment | | | | -0.050 | 0.051 | -0.123 | | | -0.142 | -0.065 | -0.057 | 0.106 | 0.184 | -0.088 | -0.192 | -0.101 | -0.205 | -0.054 | -0.061 |
| Children in hh | | 0.028 | | -0.047 | | -0.084 | | 0.047 | -0.120 | -0.036 | | 0.025 | 0.091 | -0.102 | -0.194 | -0.084 | -0.178 | | 0.003 |
| Income (None) | -0.045 | 0.053 | | | | | | 0.036 | | | | -0.045 | -0.031 | | -0.009 | | -0.012 | 0.032 | 0.030 |
| Income (Medium) | | | | -0.057 | 0.059 | | | 0.046 | | -0.023 | | 0.041 | 0.068 | 0.040 | 0.025 | 0.032 | 0.028 | -0.040 | -0.053 |
| Income (High) | | | | -0.077 | 0.081 | | | 0.076 | | | | 0.049 | 0.089 | 0.072 | 0.048 | 0.050 | 0.039 | | -0.015 |
| **Built Environment** | | | | | | | | | | | | | | | | | | | |
| Density | | | | | | | | | | | | -0.125 | -0.125 | | | 0.051 | 0.051 | | |
| Distance Centr. | | | | | | | | | | | | | | -0.075 | -0.075 | -0.085 | -0.085 | | |
| Distance M/T | | | | | | | | | | | | | | | | -0.042 | -0.042 | -0.044 | -0.044 |
| Distance Bus | | | | | | | | | | | | | | | | -0.130 | -0.130 | | |
| **Attitudes** | | | | | | | | | | | | | | | | | | | |
| Car Attitude | -0.034 | | | 0.036 | | | | 0.046 | -0.144 | -0.132 | -0.056 | 0.205 | 0.23 | -0.111 | -0.165 | -0.047 | -0.110 | -0.131 | -0.140 |
| PT Attitude | | | | 0.029 | | | | | 0.216 | 0.035 | 0.027 | -0.033 | -0.112 | 0.255 | 0.350 | 0.294 | 0.392 | 0.028 | 0.013 |
| Bike Attitude | 0.030 | | | | | | | | 0.036 | 0.150 | 0.111 | -0.111 | -0.124 | 0.056 | 0.042 | -0.033 | -0.047 | 0.511 | 0.534 |
| **Reasons** | | | | | | | | | | | | | | | | | | | |
| Car Reasons | -0.161 | | | 0.062 | | | | | | | | 0.213 | 0.233 | -0.152 | -0.152 | -0.140 | -0.062 | -0.045 | -0.045 |
| PT Reasons | 0.341 | -0.203 | | -0.339 | | | | | | | | -0.326 | -0.369 | 0.457 | 0.472 | 0.430 | 0.339 | -0.096 | -0.096 |
| Bike Work | -0.073 | | | 0.141 | | | | | | | | -0.049 | -0.040 | -0.095 | -0.095 | -0.088 | -0.110 | 0.133 | 0.133 |
| Bike Shop | 0.113 | | -0.093 | 0.074 | | | | | | | | 0.102 | 0.088 | -0.155 | -0.155 | -0.153 | -0.074 | 0.059 | 0.063 |

*Table 5.5: Standardized direct- and total effects of the cross-sectional model.*

results indicate that bicycle-related reasons have a negative effect on train use (-0.095 for bicycle to work; -0.155 for bicycle to shops) and that public transport reasons have a negative effect on bicycle use (-0.096). The second exception is the positive effect of bicycle to shop on car use (0.102). The effect of bicycle to work on car use meanwhile is in fact negative (-0.049), which is an interesting difference even if the effects are not large. This could possibly be explained by the fact that cycling to shops is relatively common in the Netherlands, when cycling to work is not. Having shops nearby thus is a more universal reason, whereas having a commute that one can cycle is only a strong reason for a location decision for more enthusiast cyclists who use the car less.

Differences between the effects of attitudes and reasons on travel behaviour can also be observed when looking at the effect sizes. The effect of the PT reasons on both train and BTM use is substantially larger than that of the PT attitudes (0.457 and 0.350 respectively for train; 0.430 and 0.294 respectively for BTM). Also noteworthy is the strong effect of PT reasons on car use (-0.326), which is again substantially larger than the effect of the PT attitudes (-0.033). For car reasons and attitudes the difference is much smaller, as the effect of car reasons and attitudes on both car use (0.213 and 0.205 respectively) and train use (-0.152 and -0.111 respectively) ais roughly similar. The effect of reasons is stronger on BTM use (-0.140 and -0.047 respectively), whilst the effect of attitudes is stronger on bicycle use (-0.045 and -0.131 respectively). Bicycle attitudes and reasons also follow an unclear pattern, caused in part by the sometimes different directions of the two bicycle reason variables. Bicycle attitudes seem to have a stronger effect on bicycle use (0.511) than bicycle reasons (0.133 for bicycle distance to work and 0.059 for bicycle distance to shops), whereas reasons have a stronger effect on train and BTM use.

These findings seem to shed a more nuanced light on the differences between travel attitudes and travel-related location reasons than the second formulated hypothesis, which stated that travel attitudes have a more general and stronger effect on travel behaviour than travel-related location reasons. The findings indicate a more exclusionary effect of travel-related location reasons, in particular with respect to the bicycle and public transport. The effects of public transport reasons on travel behaviour are stronger than the effects of public transport attitudes, contradicting the hypothesis. Bicycle attitudes meanwhile do have a stronger effect on travel behaviour than bicycle reasons, whilst car reasons and car attitudes have roughly equally strong effects on travel behaviour.

### 5.4.2 Longitudinal results

To complement the above cross-sectional model, a longitudinal analysis based on two waves is specified as well. Table 5.6 contains the standardized direct effects as estimated in the longitudinal model. All paths that were insignificant on a 10% threshold were removed.

First, the effects of a variable on itself are interpreted. These paths are indicated by an underscore in Table 5.6 and can be interpreted as the stability of the variable across the two measurements. The stability of the built environment variables is remarkably high, up to 0.968 for distance bus. This makes sense, given the relatively small gap between the two measurements (2 years). In this time, it stands to reason that not many people moved to a new environment and not many changes were made to the built environment. The main difference is the distance to a Metro or tram stop, which has a comparatively lower stability (0.803). Attitudes and reasons are less stable (0.725 and 0.718 respectively), but their stability is still higher than that of the travel behaviour

| | Dependent variables (2016) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *Independent variables (2014)* | Built Environment | | | | Attitudes & Reasons | | Travel Behaviour | | | |
| | Density | Distance Centrality | Distance Bus | Distance M/T | PT Attitudes | PT Reasons | Car Use | Train Use | BTM Use | Bike Use |
| **Socio-demographics** | | | | | | | | | | |
| Western ethnicity | | | | | | | | | | |
| Gender (Male) | | | | | | | | | | |
| Age | | | | | 0.059 | | | | 0.041 | 0.043 |
| High Education | | | | | | | | 0.091 | 0.040 | 0.032 |
| Employment | | | | | | | | | | |
| Children in hh | | | | | | 0.039 | | | | 0.046 |
| Income (None) | 0.019 | | | | | | | -0.035 | | |
| Income (Medium) | | | | | | | | | | |
| Income (High) | | | | | | | | | | |
| **Built Environment** | | | | | | | | | | |
| Density | 0.934 | | | | 0.059 | | | | 0.033 | |
| Distance Centr. | -0.022 | 0.957 | | 0.068 | 0.043 | -0.054 | | | | |
| Distance Bus | -0.013 | | 0.968 | | | | | | -0.062 | |
| Distance M/T | | | | 0.803 | | | | 0.027 | | |
| **Attitudes & Reasons** | | | | | | | | | | |
| PT Attitude | | | | | 0.725 | 0.053 | | 0.038 | | |
| PT Reasons | | | | | | 0.718 | -0.139 | 0.055 | 0.077 | |
| **Travel Behaviour** | | | | | | | | | | |
| Car Use | -0.017 | 0.015 | | | | | 0.504 | -0.069 | -0.058 | -0.098 |
| Train Use | -0.015 | | -0.014 | 0.031 | 0.055 | | | 0.634 | 0.088 | |
| BTM Use | | | | | | 0.059 | | 0.054 | 0.598 | |
| Bike Use | | | | | | | -0.052 | | | 0.654 |

*Table 5.6: Standardized direct effects of the longitudinal model*

variables (0.504 for car, 0.634 for train, 0.598 for btm, and 0.654 for bicycle). Especially car use seems to be a relatively unstable variable, which we did not necessarily expect. The results indicate that there is a small effect from PT attitudes on PT reasons (0.053), but no opposite effect. This is some evidence to support the notion that the more general attitudes would probably affect the reasons stated in section 2.4 which was reflected in the conceptual model of this study.

With respect to the built environment some effects on travel behaviour are found, even when controlled for attitudes and reasons. The effects are smaller and less numerous than in the cross-sectional model, but they do follow the pattern that PT use is most affected (despite only including PT-related attitudes and reasons). Especially the effect of the distance to bus stops on bus use (-0.062) is perhaps not entirely unsurprising, but it is strong evidence that the built environment has at least some independent effects on travel behaviour when controlling for RSS. Both attitudes and reasons have no effect on the built environment, which was surprising given the close conceptual relation between especially reasons and the built environment. Relations in the opposite direction were found however, indicating that people who in live more centrally located, denser neighbourhoods, are more likely to later state that the proximity of PT access points was an important factor in their decision to relocate to such areas. Distances to bus and metro/tram stops still have no effect on PT attitudes and reasons. Keep in mind that the time between the two measurements is relatively limited, which will probably impact these results as attitudes (and to a lesser extent reasons) are relatively stable over time, as is the built environment.

The effects between attitudes and reasons on one side and travel behaviour on the other are interesting for multiple reasons. First, we do find effects in both directions (both from attitudes/reasons to behaviour and the other way around). This means that the cross-sectional model always overestimates the effects of attitudes and reasons on travel behaviour, and thus possibly overstates the effects of RSS. Second, the effects are different for BTM and train use. For BTM use, we find effects on PT reasons (0.059), but not on PT attitudes. For train, we only find effects on PT attitudes (0.055) and not on PT reasons. In the reverse direction, PT reasons both affect train (0.055) and BTM (0.077) use, whereas PT attitudes only affect train use (0.038). Third, the effect of PT reasons on travel behaviour are stronger than the effect of PT attitudes, which contradicts our hypothesis stated in the introduction that attitudes would have a stronger effect on travel behaviour than reasons. Finally, the estimated effects of attitudes and reasons on travel behaviour are slightly stronger than the effects in the opposite direction.

## 5.5 Conclusion and discussion

This paper made use of a distinction between travel mode attitudes and deliberate travel-related reasons for residential location choice, first proposed by Ettema and Nieuwenhuis (2017), to investigate their separate effects in the mechanism of residential self-selection. The two main hypotheses were that travel-related location reasons have a stronger effect on the choice of built environment than travel attitudes, whereas travel attitudes would have a stronger effect on travel behaviour.

The results from the cross-sectional model seem to suggest that travel-related location reasons have a much stronger direct effect on the choice of built environment than travel attitudes for all three modes, and that public transport related location reasons have the largest effect on the choice of built environment. More specifically, the results suggest that people for whom public transport access was an important factor in their location decision are much more likely to live in denser areas with shorter distances to central facilities and bus stops. However, the longitudinal model was unable to find such a relation. Instead, a much smaller effect in the opposite causal direction was found. This would suggest that people who start to live in more centrally located neighbourhoods then retroactively say that public transport access was an important reason in their relocation decision. The same reverse causal effect was found between attitudes and the built environment. The first hypothesis of this paper, that deliberate travel-related reasons are more direct indicators of the built environment choice than travel attitudes, thus cannot be fully supported by the conducted analyses, despite the results from the cross-sectional model providing at least some indication that it may hold.

A further difference between the two concepts can also be observed in relations with travel behaviour. First, travel-related location reasons more often have a negative effect on the use of other modes than travel attitudes, a finding that holds across both models. This is seen most clearly in the bicycle and public transport attitudes and reasons of the cross-sectional analysis. More positive attitudes towards the bicycle and public transport cause an increase in the use of the other mode, whilst increasing values for transport related location reasons for one of these modes causes a decrease in the use of the other mode. Further evidence is found in the longitudinal analysis, where public transport reasons have a relatively strong negative effect on car use, whereas no effect of public transport attitudes on car use is found. This could be explained by the fact that people who have moved to a certain location due to their travel preferences are likely to ‘lock-in’ on that preference, meaning that they are less likely to use any other mode. Second, attitudes have a stronger effect on use of the same mode for car and bicycle than reasons. For public transport however, the travel-related location reasons seem to have a stronger effect based on the cross-sectional model. This result could partly be explained by the inability of the cross-sectional model to account for the possible bidirectional causal relations between the built environment and these reasons, as evidenced by the reverse causal effect found in the longitudinal analysis. Since the built environment affects behaviour more strongly for public transport compared to the other two modes, this could lead to an overestimation of the effect of the travel-related location reasons on public transport use.

Regarding the effects of the built environment on travel behaviour (when controlled for both underlying travel attitudes and travel-related location reasons), these are much larger for public transport than for either the car or the bicycle. In fact, both car and bicycle use are only affected by a single variable in the cross-sectional analysis and by no variables in the longitudinal analysis. Whilst in general terms these findings are not surprising given the findings in the literature (Cao et al., 2007, 2009; Mokhtarian & van Herick, 2016), the small effect of the built environment on car and bicycle use does stand out. Our findings show that distances to bus stops, metro/tram stops, and living in a centrally located neighbourhood have no impact on the use of the car. Interestingly, the findings also indicate that bicycle use is hardly affected by the built environment at all, which could be explained by the relatively high quality of the cycling infrastructure in the Netherlands combined with the proximity of most facilities. This means that most areas in the Netherlands are conducive to cycling at least to some degree. Hence, to accurately assess the role of the built environment on this mode of transportation, a multi-country perspective is necessary to obtain sufficient variation in the independent variables, i.e., the (general) proximity to locations and the quantity and quality of the cycling infrastructure.

To summarize, our findings provide some first, but inconclusive, evidence that the travel-related location reasons for choosing a residential location seem to reflect the effect of travel preferences on the residential location choice more accurately than travel attitudes. The attitudes reflect a more general effect of predispositions on travel behaviour. The travel-related location reasons have a stronger exclusionary effect on travel behaviour however. We also find evidence for the reverse causality hypothesis, both in the cases of the relations between attitudes/reasons with travel behaviour and with the built environment. This ties in with the current debate in the academic literature, identified both by Guan et al. (2020) and van Wee and Cao (2022) surrounding the direction of causality in the context of RSS. Our findings that the effect in the opposite causal direction is roughly as strong as the classic causal direction in the context of RSS are similar to findings of other recent research in a more general context (Kroesen & Chorus, 2017; Kroesen et al., 2017; van de Coevering et al., 2016).

In the context of RSS, the finding of bi-directional causal effects would imply that adding attitudes and reasons to models could run the risk of adding an endogenous variable, thereby underestimating the actual independent effect of the built environment on travel behaviour. On the other hand, not accounting for deliberate travel-related reasons for relocation could result in an overestimation of the independent effect on the built environment, given the relations we find between these reasons and both travel behaviour and the built environment. Which of these mechanism holds more, and thus whether research not encompassing travel-related reasons under- or overestimates the independent effect of the built environment, depends on the relative strengths of the bi-directional causal effects between these reasons and both the built environment and travel behaviour. This research provides some first evidence in this regard, namely that the relative effects are roughly of an equal size, but further research in this area is needed.

The findings of our research have several implications for policies that aim to reduce car use. Firstly, finding an independent effect of the built environment when accounting for residential self-selection implies that policies aimed at creating a built environment that is more friendly to public transport might increase the use of this mode. However, the independent effect on car use appears to be minimal due to underlying attitudes and reasons. This implies that policies aimed at reducing car use should also try to affect these variables. There is already a large body of work addressing the question of how travel-related attitudes can be influenced or better addressed by targeted policy efforts (see e.g., Anable (2005), Bamberg (2013), and Hunecke et al. (2010)).

There are four main limitations to this research, which could be improved upon by future research. First, there is a limited time between the two waves of the longitudinal analysis, which means that especially the built environment was very stable. Adding a third wave and/or focusing on those individuals who relocated during measurements could substantively change the findings of this research. The second limitation of this research is the measurement of the built environment, which arguably did not capture specific aspects related to bicycle use, such as the quantity and quality of the cycling infrastructure near the residence. Ideally, such variables should be included in future research efforts, especially since many cities across the world are trying to stimulate the use of this mode. The third limitation is the omission of the more indirect residential preferences. Knowing how travel attitudes, residential preferences, and travel-related residential reasons are connected to one-another and to travel behaviour and the choice of built environment would paint a more complete picture of RSS than the one in this study. Finally, this research only uses data collected in the Netherlands, a dense, well-connected OECD country. Using data from other areas of the world, especially non-OECD areas, could paint a more complete picture of the relations between the built environment, attitudes, travel-related residential reasons, and travel behaviour.

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# Chapter 6

# Investigating within-person effects between attitudes and travel behaviour

This chapter is based on Faber, R. M., de Haas, M. C., Molin, E. J., & Kroesen, M. (2024). Investigating changes in within-person effects between attitudes and travel behaviour during the COVID-19 pandemic. *Transportation Research Part A: Policy and Practice*, *185*, 104127. https://doi.org/10.1016/J.TRA.2024.104127

Abstract:

*Attitudes have been used as explanatory variables of travel behaviour for decades, typically under the assumption that there is a causal effect of attitudes on behaviour. However, recent research has shown that the relationship between attitudes and travel behaviour is bi-directional. In this study we use a longitudinal modelling technique on panel data to 1) separate within-person effects from between-person associations and 2) test whether the within-person effects changed during the COVID-19 pandemic. We find that the within-person effects were weaker during the pandemic than they were before the pandemic. In addition, the within-person effects were much smaller than would be expected based on methods that do not separate within-person effects from between-person associations. This means that researchers should be careful when basing policy recommendations on cross-sectional correlations between attitudes and behaviour for two reasons: first, the problem of endogeneity, and second, the highly relevant separation of within-person effects from between-person relations.*

## 6.1 Introduction

Many studies in the field of travel behaviour research use attitudes as explanatory variables of travel behaviour (Bohte et al., 2009; De Vos, 2022; Hoffmann et al., 2017; van Acker et al., 2010). Eagly and Chaiken, 1993, p. 1 define attitudes as “a psychological tendency that is expressed by evaluating a particular entity with some degree of favour or disfavour”. Following the theory of planned behaviour (Ajzen, 1985, 1991), researchers typically work under the assumption that attitudes affect behaviour when they cannot empirically validate the direction of the effects. However, research in the last decade has shown that this theoretical assumption does not hold up to empirical scrutiny (Chorus & Kroesen, 2014; Kroesen et al., 2017): using longitudinal data they show that the reverse effect, of behaviour on attitudes, is generally at least as strong as the assumed effect of attitudes on behaviour.

Even though this finding is very consistent, all evidence is based on data estimated before the COVID-19 pandemic. Research has however shown that the pandemic has resulted in unprecedented changes to travel behaviour (Beck & Hensher, 2020; De Vos et al., 2020) and travel attitudes (Beck et al., 2021; de Haas et al., 2020; de Palma et al., 2022; Eisenmann et al., 2021). More recent research has indicated that some of the behavioural changes are likely to have a structural component which will outlast the pandemic itself (Faber et al., 2023; Hensher et al., 2023). Importantly, these changes might also have affected the relationship between attitudes and behaviour. The relationship could have grown weaker, due to an increasing influence of other factors (for example, lockdown policies or fear of infection). These factors might have put constraints on the relationship between attitudes on behaviour as people were unable to exhibit their desired behaviour. However, one might also expect the relationship to have become stronger, as attitudes were pushed to unprecedented extremes and, assuming a non-linear relationship, these extremes could have a relatively larger effect on behaviour than more moderate attitudes. The nature of the relationship between attitudes and travel behaviour is important, as relatively large bi-directional effects would imply that the temporary deviations in the attitudes and behaviour seen during the pandemic would have a structural effect on the attitudes and behaviour post-pandemic. Therefore, it is important to consider whether the relationship between attitudes and travel behaviour changed during the COVID-19 pandemic.

This paper contributes to the existing literature on attitudes and travel behaviour by studying the changes in the relationship between the two concepts during the pandemic. To achieve this contribution, we use panel data collected from the Netherlands Mobility Panel (MPN), collected between 2014 and 2021. This dataset enables us to estimate the relationships between attitudes and travel behaviour both before the pandemic (2014 – 2018) and during the pandemic (2018 – 2021).

In addition, this paper makes another contribution to the literature on the relationships between travel attitudes and travel behaviour. Almost all previous studies with panel data that examine the longitudinal relationship between attitudes and behaviour in the field of travel behaviour research have used cross-lagged panel models (CLPM). This method is unable to separate between-person from within-person processes (Hamaker et al., 2015). Between-person processes refer to all mechanisms that result in differences in a variable, such as attitudes, across different individuals. As an example, we might consider two individuals, Alice and Bob. Alice has lived her whole life in a very rural area. As a result, she is likely to use the car more and have more favourable attitudes towards the car. Conversely, Bob has lived his whole life in a very densely developed city. As a result, he is likely to use public transportation more and have more favourable attitudes towards public transport. Within-person processes refer to changes in a variable that occur within the individual. For example, if Bob moves from his city towards a rural area, he is likely to start using the car more and as a result develop more favourable attitudes towards the car (Faber et al., 2021; Kroesen, 2019). Thus, there is a within-person effect of residential environment on travel attitude. Another useful example to illustrate the difference between within-person and between-person relations is given by Hamaker (2012): the between-person correlation between typing speed and typing errors is negative, as better typists both type faster and make fewer mistakes. However, if someone would be instructed to type faster, then they will make more typing errors. The within-person effect of typing speed on typing errors is thus positive. For more information on this topic, the reader is referred to the accessible paper by Hamaker (2012).

Since the previously used CLPM is unable to separate within-person processes from between-person processes, due to its assumption that there are no stable between-person differences. Since the causal mechanism between attitudes and behaviour, if such exists, takes place within the individual, disentangling between-person relations from within-person relations is highly relevant (Chorus & Kroesen, 2014; De Vos, 2022; Selig & Little, 2012). Furthermore, policy implications often revolve around policies that impact attitudes, with the end goal of indirectly changing travel behaviour through the within-person effect of attitudes on behaviour. The efficacy of such policies however depends on the existence of such within-person effects from attitudes on behaviour. As the CLPM can not distinguish within-person from between-person processes, this model is likely to overestimate the strength of this within-person relationship. For this reason, this paper uses an extension to the CLPM, the so-called random-intercept cross-lagged panel models (RI-CLPM), introduced by Hamaker et al. (2015). The chief benefit of the RI-CLPM is that it does allow us to separate between-person from within-person processes.

The rest of this paper is laid out as follows. Section 6.2 provides an overview of the literature on the relationship between travel attitudes and travel behaviour, as well as the literature on the effects of the COVID-19 pandemic on both attitudes and behaviour. The section culminates in two hypotheses that serve to guide our further analyses. Section 6.3 contains a description of the data and research methods used in this paper, and Section 6.4 presents the results from the analyses. The conclusions can be found in Section 6.5.

## 6.2 Literature overview

This section provides an overview of the literature on the relationships between attitudes and behaviour in the field of travel behaviour research. It starts by briefly summarizing the use of attitudes in travel behaviour research, which is followed by a discussion of the recent research stream that investigates the bi-directional causal relations between the two concepts. Afterwards, we discuss recent papers on the effects of the COVID-19 pandemic on both travel attitudes and behaviour. Finally, we state two guiding hypotheses that serve to focus the remainder of the paper.

### 6.2.1 Attitudes in travel behaviour research

Attitudes are broadly defined as the degree to which someone evaluates a certain object or behaviour as favourable or unfavourable (Ajzen, 1991; Eagly & Chaiken, 1993; van Acker et al., 2010). Such evaluations consist of affective, cognitive, and behavioural components (Ostrom, 1969; Parkany et al., 2004). The affective component refers to feelings towards the object in question, the cognitive component refers to beliefs and perceptions and the behavioural component considers overt actions and ways of behaving oneself (Ostrom, 1969; Rosenberg et al., 1960). In the social sciences, especially the field of social psychology, attitudes have been studied extensively (Bohner & Dickel, 2010). In line with the widely used theory of planned behaviour (Ajzen, 1985, 1991), attitudes are typically assumed to have a causal effect on behaviour. After the re-introduction of attitude research to the field of travel behaviour research, influenced by the work of Kitamura et al. (1997) and Gärling et al. (1998), this assumption has also taken hold in this field (van Acker et al., 2010). Under this assumption, the concept of attitudes has played a notable role in travel behaviour research, for example in research that applies the theory of planned behaviour to the field of travel behaviour (Bamberg, 2006; Eriksson & Forward, 2011; van Acker et al., 2010), in research studying the effects of the built environment on travel behaviour (Cao et al., 2009; van Wee & Cao, 2022), and in the research on- and applications of hybrid choice models (Ben-Akiva et al., 2002; Chorus & Kroesen, 2014).

### 6.2.2 Bi-directional relationships between attitudes and behaviour

The theoretical assumption that attitudes cause behaviour has been challenged in the field of travel behaviour studies by a recent line of research, which uses panel data to empirically estimate the bi-directional effects between attitudes and behaviour. Generally, this research line has found that the reverse effect - namely that of behaviour on attitudes – is at least as strong as the assumed effect of attitudes on behaviour (Faber et al., 2021; Kroesen et al., 2017; Olde Kalter et al., 2020). These results imply that using attitudes as pure independent variables of behaviour will result in an overestimation of the effect of attitudes on behaviour. As a result, the effects of any other variables in the analysis are likely to be underestimated.

There are several theoretical explanations for the effect of behaviour on attitudes. Most often, researchers refer to either cognitive dissonance or learning theories as explanations for the reverse causal effect (Van Wee et al., 2019). Notably, both these theories and the theories underpinning the original causal effect borrow heavily from social psychology and the causal effect of these theories is assumed to occur at the level of the individual. For this reason, research would ideally investigate the direction of the effects between travel behaviour and attitudes within the individual (De Vos, 2022; Hamaker, 2012). However, such research is very rare in the literature. Olde Kalter et al. (2021) studied within-person relationships between mode preferences and mode use of young adults, and they too found that the effect of mode use on mode preferences where stronger than the reverse effect. Kroesen and Chorus (2020) found no strong within-person relations between attitudes and behaviour. Kroesen et al. (2023) studied the within-person relations between train use and train attitudes during the COVID-19 pandemic. They found a reciprocal influence, where again the effect of mode use on attitudes was stronger than the reverse effect.

### 6.2.3 The effect of the COVID-19 pandemic on travel attitudes and behaviour

The COVID-19 pandemic has had a tremendous impact on our travel behaviour. Worldwide, people travelled less often and in different ways than before (Beck & Hensher, 2020; de Haas et al., 2020; Downey et al., 2022; Hensher et al., 2023; Kolarova et al., 2021; Rafiq et al., 2022). A part of this effect was temporary, due for example the lockdown policies restricting mobility or the fear of COVID-infections keeping people at home. However, some part of the effect seems to be structural in nature, outlasting the pandemic, as society has adapted to some changes in activity-travel, such as working from home (Bohman et al., 2021; Faber et al., 2023; Javadinasr et al., 2022; Manser et al., 2022).

Not all travel modes seem to be equally affected by the pandemic. Public transport use saw sharp declines (Tirachini & Cats, 2020) as people tended to avoid shared transport options (Bohman et al., 2021) and, in many countries, public transport commuters were more likely to be able to work from home (Hensher et al., 2023). Simultaneously some areas saw a shift towards the use of active modes (Campisi et al., 2022; Currie et al., 2022) as people made more short-distance trips.

The pandemic also affected travel-related attitudes (de Haas et al., 2020; van Wee & Witlox, 2021). Attitudes towards public transport have become more negative, which is probably caused by perceptions of comfort and safety which have shifted as a result of the pandemic and the (perceptions of) infection risk in shared modes of transport (Thomas et al., 2021; Tirachini & Cats, 2020). Attitudes related to private cars and the active modes generally became more positive during the pandemic (de Haas et al., 2020).

### 6.2.4 Research Hypotheses

The above information culminates in two hypotheses that are set to guide the further analyses in this paper, cohering to the two knowledge gaps introduced in the introduction. The literature convincingly shows that the COVID-19 pandemic has affected both travel-related attitudes and travel behaviour. In general, people became less mobile, shifted away from public to private forms of transport, and there was a small shift to active transport. Attitudes towards public forms of transport became less favourable. We hypothesize that the pandemic has also resulted in a change in the relationship between attitudes and behaviour. Such a change might affect the extent to which the (partly temporary) deviations above will continue to affect both travel attitudes and travel behaviour in the future. To investigate this hypothesis, we estimate a model with two sets of parameters: one set before the pandemic and one set during the pandemic. Both sets can then be compared to one another. The above information is summarized in hypothesis 1, below:

**H1** The relationships between travel mode attitudes and travel behaviour have changed during the COVID-19 pandemic

There is a growing body of literature that uses panel methods to show that there is a bi-directional relationship between travel attitudes and behaviour. However, there is limited research on the within-person effects between the two concepts. This is particularly relevant given that these within-person estimates provide a better approximation of the (assumed to be) causal process between attitudes and behaviour, as these psychological processes are assumed to take place within the individual (Chorus & Kroesen, 2014; De Vos, 2022). Hence, the separation of between-persons and within-persons relations provided by the RI-CLPM is theoretically highly relevant. We hypothesize that such a separation will result in different estimates for the effects between travel mode attitudes and travel behaviour. To investigate this hypothesis, we can compare the results from a method that does not separate between-person from within-person relationships to those from a method which does separate the two. This results in the second guiding hypothesis stated below:

**H2** Separating between-person correlations from within-persons effects results in different estimates for the effects between travel mode attitudes and travel behaviour

## 6.3 Research Methods

This section introduces the methods and data that are used to investigate the hypotheses mentioned above. First, the data are introduced in Section 6.3.1. Then the operationalisation of the variables is described in Section 6.3.2, followed by an introduction of the research methods in Section 6.3.3 and the estimation procedure in Section 6.3.4. Finally, we introduce some core concepts of graph theory in Section 6.3.5, which we use to facilitate the interpretation of our results.

### 6.3.1 Data and Sampling

This study uses data from the Netherlands Mobility Panel (MPN). The MPN is a longitudinal household panel that consists of a 3-day travel diary and a set of questionnaires (Hoogendoorn-Lanser et al., 2015). Travel behaviour was collected each year using the travel diaries, but data on travel mode attitudes were collected only in the waves of 2014, 2016, 2018, 2020 and 2021. This gives us five waves of data from the MPN to estimate the relations between travel behaviour and travel-related attitudes, of which three waves have been collected before the pandemic and two waves were collected during the pandemic. The time lag between the waves is two years for every wave pair, except for the last one between 2020 and 2021. As such, we would expect stronger relationships in this last wave-pair than in the previous ones. An overview of the measurements between 2019 and 2022 is given in Figure 6.1, together with the COVID-19 hospital admission rate and the Oxford Stringency Index in the Netherlands, which measures the stringency of the governments' COVID-19-related policies.

Since there are seven years between 2014 and 2021, panel mortality will both reduce and skew the pure-stayer sample severely. For this reason, we do not use a pure-stayer sample. Instead, respondents that fully participated in both the questionnaire and the travel diary in at least two consecutive waves are included in the analysis. In total, the sample consists of 6141 unique respondents, with between 2644 and 4130 respondents per consecutive pair of waves. The handling of the resulting missing data is described in the section on research methods below. The number of respondents and the distribution of some socio-demographic variables for each wave-pair is given in Table 6.1. The socio-demographics presented here are those that were recorded in the first of the two waves.

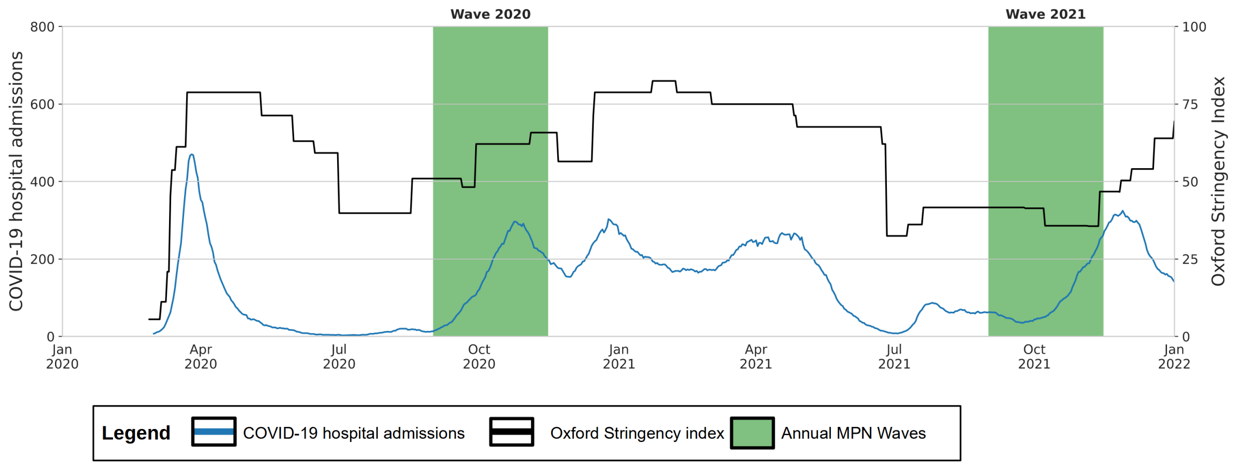


*Figure 6.1: Overview of the MPN measurements during the COVID-19 pandemic*

| | | **2014 - 2016** | **2016 – 2018** | **2018 – 2020** | **2020 – 2021** | **Population (2019)** |
|---|---|---|---|---|---|---|
| Sample size | | 2644 | 2833 | 4130 | 3917 | - |
| Gender (%) | Male | 46 | 46 | 47 | 47 | 49 |
| Age (years) | Mean | 45 | 45 | 48 | 49 | 49 |
| | Median | 46 | 45 | 50 | 52 | 49 |
| Education | High | 32 | 35 | 32 | 33 | 29 |
| | Middle | 48 | 41 | 38 | 37 | 42 |
| | Low | 20 | 24 | 30 | 30 | 29 |
| Owns driver's license (%) | Yes | 82 | 85 | 85 | 84 | 80 |
| Urban density (inh./km$^2$) | $>2500$ | 17 | 18 | 21 | 18 | 24 |
| | 1500 – 2500 | 28 | 35 | 33 | 34 | 30 |
| | 1000-1500 | 25 | 18 | 18 | 17 | 16 |
| | 500-1000 | 19 | 20 | 21 | 22 | 22 |
| | $<500$ | 10 | 8 | 8 | 9 | 8 |
| Household composition | Single | 21 | 22 | 23 | 25 | 22 |
| | Adults | 28 | 28 | 33 | 35 | 49 |
| | Adult(s) with children | 51 | 50 | 44 | 40 | 28 |

*Table 6.1: Sample distribution across the four wave-pairs*

| | Car | Public Transport | | Bicycle | Walking |
|---|---|---|---|---|---|
| | | Train | BTM[1] | | |
| Travelling by (mode) is comfortable | 0.845 | 0.758 | 0.812 | 0.848 | 0.868 |
| Travelling by (mode) is relaxing | 0.791 | 0.749 | 0.810 | 0.871 | 0.885 |
| Travelling by (mode) saves me time | 0.781 | 0.692 | 0.729 | 0.666 | 0.444 |
| Travelling by (mode) is safe | 0.778 | 0.467 | 0.553 | 0.695 | 0.714 |
| Travelling by (mode) is flexible | 0.796 | 0.742 | 0.767 | 0.789 | 0.772 |
| Travelling by (mode) is satisfying | 0.856 | 0.792 | 0.821 | 0.885 | 0.894 |
| 1: bus, tram, and metro | | | | | |

*Table 6.2: Latent travel mode attitude indicators and mean factor loadings across all included years*

### 6.3.2 Operationalisation

This paper investigates the bi-directional relationships between behaviours and attitudes that are specific to travel modes. Attitudes and behaviours of five distinct travel modes are studied: the car, the train, bus, tram, and metro (BTM), the bicycle, and walking. Travel behaviour is operationalized as the total distance travelled using each mode, as measured using the 3-day travel diaries of the MPN where respondents record the trips they made and estimate the distance they travelled for each trip. Attitudes are measured using six indicators for each mode, whereas public transport uses indicators related to both the train and BTM. Each indicator is scored on a 5-point Likert scale, varying between 'strongly agree' (1) to 'strongly disagree' (5). The unidimensionality of the indicators is checked using principal axis factoring. Since we use data from several years and we want to estimate the relationships between constructs over time, we need to ensure that the scale is constructed consistently over time (Selig & Little, 2012). To do so, the final factor scores were based on the average of the factor loadings as calculated on data for a specific year. These final factor loadings are given in Table 6.2.

The factor loadings are generally above the desired threshold value of 0.7. The internal reliability (Cronbach's Alpha) of each scale was then also tested and found to be more than acceptable in all cases ($> 0.8$). The final scale used in the models was calculated using a weighted mean of the indicators, which scales the final variables between 1 and 5, corresponding to the minimum and maximum value of the indicators.

Table 6.3 contains the mean values for the attitudes and the mode use variables as collected using the Netherlands Mobility Panel. We see that the public transport attitudes were least positive on average, whereas car attitudes were most favourable. During the pandemic, this difference only grew, as the attitudes towards the car became slightly more favourable whereas attitudes towards public transport grew less favourable. In terms of mode use, the car was also dominant throughout the study period. During the pandemic, public transport use fell rapidly and its recovery in 2021 was the slowest of all.

### 6.3.3 Method

To determine the longitudinal relationship between the variables, we use a random-intercept cross-lagged panel model (RI-CLPM). The RI-CLPM is an extension of a cross-lagged panel model

| | | 2014 | 2016 | 2018 | 2020 | 2021 |
|---|---|---|---|---|---|---|
| **Attitudes** | **Car** | 4.1 | 4.1 | 4.1 | 4.2 | 4.2 |
| Attitudes are measured using a scale ranging from 1 to 5 | **Public Transport** | 3.0 | 3.0 | 3.0 | 2.9 | 2.9 |
| | **Bicycle** | 3.8 | 3.8 | 3.8 | 3.8 | 3.8 |
| | **Walking** | | | 3.7 | 3.8 | 3.8 |
| **Mode Use** | **Car** | 71.1 | 76.0 | 76.3 | 46.9 | 57.4 |
| | **Train** | 14.0 | 15.95 | 12.75 | 3.08 | 6.57 |
| Km per person per three days | **BTM** | 2.96 | 3.64 | 2.66 | 0.788 | 1.20 |
| | **Bicycle** | 8.62 | 7.32 | 8.35 | 6.60 | 7.32 |
| | **Walking** | 1.53 | 1.43 | 2.48 | 2.95 | 2.90 |

*Table 6.3: Mean values of attitudes and mode use over time*

(CLPM; Finkel (2011). A CLPM is a structural equations model using longitudinal data, that specifies auto-regressive relationships. These are supposed to control for the stability of a variable over time. The cross-lagged relationships between the constructs are then supposed to represent the (causal) processes between the variables. As pointed out by (Hamaker et al., 2015), this approach assumes that the values for each variable for every person vary over time around the same mean. This assumption is problematic, as stable, time-invariant differences between individuals are observed in most variables.

Hamaker et al. (2015) therefore argue that researchers should not only control for temporal stability but also for time-invariant stability on the level of the individual. Effectively, doing so separates within-person differences over time from between-person differences over time. This is achieved by including random intercepts, which account for the trait-like, time-invariant stability of the variables. The random intercepts thus capture the between-person differences, allowing the (auto)-regressive structure to specifically capture within-person effects. These within-person effects are more likely to accurately represent the causal processes between attitudes and behaviour, which are assumed to occur on the level of the individual. Figure 6.2 presents a schematic view of the (RI-)CLPM, where the CLPM structure in full borders is complemented by the additional RI structure with dashed borders.

We use an extension on the RI-CLPM discussed by (Mulder & Hamaker, 2020), as we want to control for the allotment of specific days of the week to our respondents. Each respondent is allotted three days of the week, which stay the same over time. We regress the random intercepts on the allotted number of days at the weekend to control for this variation, which ensures that the correlations between the random intercepts are not affected by measurement bias.

### 6.3.4 Model estimation procedure

The structural equation models are estimated using Lavaan (Rosseel, 2012), a statistical software package for the programming language R (R Core Team, 2017). Three consecutively more complex models are estimated and compared, to ensure that the more complex models provide a better fit to the data:

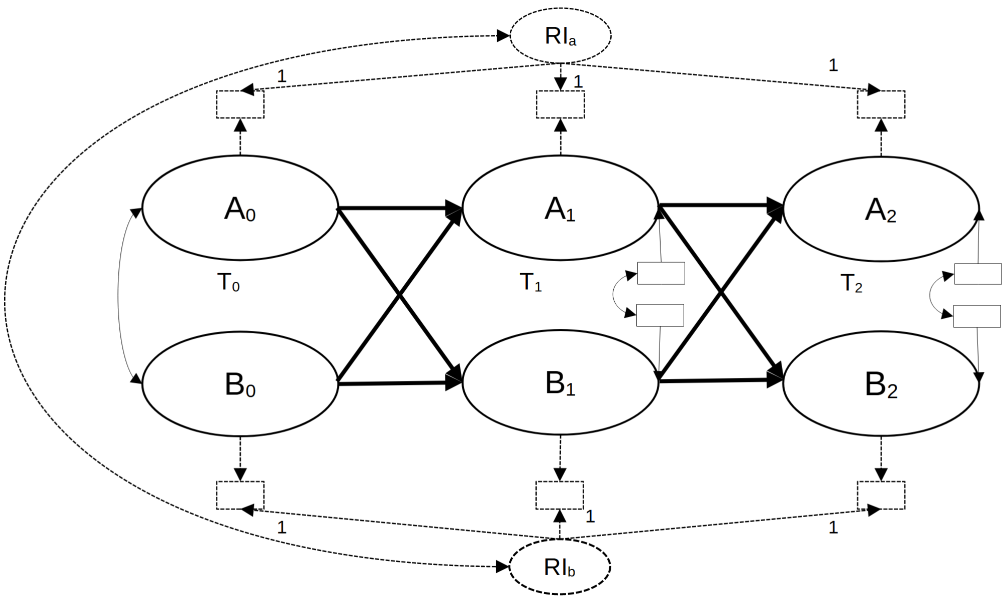


*Figure 6.2: Simplified schematic view of the (RI-)CLPM. The random intercept structure is dashed*

1. A CLPM
2. A RI-CLPM
3. A RI-CLPM where the random intercepts are regressed on allotted weekend days

As discussed previously in Section 6.3.1, the models are estimated using all respondents that participated in at least two consecutive waves where the attitudes are measured. As a result, the model must handle missing data and is therefore estimated using Full Information Maximum Likelihood (FIML).

All models described above can be seen as nested models, as the CLPM is a nested model of the RI-CLPM where the variance and covariance of all random intercepts are fixed to zero. Therefore, the estimated models' goodness-of-fit can be compared using the chi-square difference test. In addition, we look at more general goodness-of-fit indicators such as the CFI, RMSEA and SRMR as well as information criteria such as the BIC and AIC. The relevant goodness-of-fit statistics of the models are given in Table 6.4.

The RI-CLPM provides a very significant improvement on the CLPM, indicating that trait-like stability on the level of the individual exists within our variables. Adding the regression on the weekend days reduces the Chi-Square with 39.3 points at 9 additional parameters. This improvement is less drastic, but still statistically significant based on the Chi-square difference test.

### 6.3.5 Graph Theory

This paper will make use of some core concepts that are part of graph theory to explore and present the results. We do this to facilitate the interpretation of our results: the final model estimates roughly 70 parameters for the regressive structure of each wave pair and nearly 600 parameters in total. By envisioning the models as a graph, we can visualize and summarize these parameters. To

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| | CLPM | RI-CLPM | RI-CLPM; regress allotted weekend days |
| Est. parameters | 548 | 593 | 602 |
| Degrees of freedom | 484 | 439 | 430 |
| Df difference | | 45 | 9 |
| Chi-square | 5530 | 1168 | 1128 |
| Chi-square difference test | - | 4362 ($p < 0.001$) | 40 ($p < 0.001$) |
| CFI | 0.891 | 0.984 | 0.985 |
| RMSEA | 0.041 | 0.016 | 0.016 |
| SRMR | 0.053 | 0.029 | 0.029 |
| BIC | 133909 | 129940 | 129978 |
| AIC | 130225 | 125953 | 125931 |

*Table 6.4: Goodness-of-fit statistics for the structural equation models*

avoid any confusion, we do not use graph theory for the estimation of the model (such as discussed in Grace et al., 2012). We only use it to aid the interpretation of the outcomes. In this section, the main concepts from graph theory that we use are explained, both in general terms and in how they are used in this paper. Graph theory is the study of graphs, which contain nodes (vertices) and edges (links) that connect pairs of nodes. Graph theory has been applied to many fields. In travel behaviour research, usage typically involves the analysis of road or transit networks (e.g., Derrible and Kennedy (2011) and Salas-Olmedo and Nogués (2012)). In this paper, the nodes are the travel behaviour and travel attitude variables, and the edges are the standardized effects of the statistically significant paths between them. Doing so creates a weighted directed network of the significant effects between attitudes and behaviour. Using this network, we can calculate several useful statistics for the nodes in the network which summarize the available information. We use two main concepts:

1. Weighted Outdegree
   (a) This is the sum of the weights of the edges that depart from the node in question.
   (b) In our network, the outdegree represents the extent to which a variable determines variation in other variables.
2. Weighted Indegree
   (a) This is the sum of all edges that arrive at the node in question.
   (b) In our network, the indegree represents the amount of variation of the node that is explained by other variables.

Together, these concepts thus represent the extent to which a variable both affects and is affected by all other variables in the network.

## 6.4 Results

This section contains the results of the analysis. First, the relevance of separating within-persons from between-persons relations will be sketched and discussed in Section 6.4.1. Then, the changes in the relationship between attitudes and behaviour due to COVID-19 are interpreted in Section 6.4.2. Finally, Section 6.4.3 will contain the interpretation of the effects between attitudes and behaviour across the various travel modes.

### 6.4.1 Within-persons and between-persons relationships

As seen previously in 6.3.4, the RI-CLPM provides a better fit to the data than the CLPM. This indicates that stable, trait-like differences in attitudes and travel behaviours exist. The identification and estimation of these stable, trait-like differences also has implications for the parameters that are estimated within the bi-directional regressive structure. Since the CLPM does not control for these stable differences, they will end up within the regressive structure. As a result, the CLPM will as a rule estimate larger bi-directional effects than the RI-CLPM. We can compare the results from the CLPM with those from the RI-CLPM to see the extent of this difference.

First, we look at the visual difference between the graphs of the regressive structures of both the CLPM and the RI-CLPM. To do so, we have created two graphs to summarize the two models' estimates. The graph using the parameter estimates from the RI-CLPM is given in Figure 6.3, whereas the graph that uses the estimates from a CLPM is given in Figure 6.4. As a reminder from section 6.3.5, the nodes are the variables in the model, and the edges represent the standardized parameter estimates for the within-persons relations between these variables. As a result, the graphs might be read as follows: in Figure 3, we see a clear blue horizontal line for the car attitudes. This line extends throughout all years (2014 through 2021). This represents a positive within-person estimate for car attitudes on itself. In other words, if a persons' car attitude is above its expected value, then the next years' car attitude is also likely to be above its expected value. We see similar such horizontal lines for most variables, each indicating an autoregressive within-persons estimate. Aside from the horizontal lines, the figure contains several diagonal lines. An example is the positive effect from train use in 2014 to walking use in 2016. This effect indicates that if train use was higher than expected in 2014, then walking use is likely to be higher than expected in 2016. More generally, one might state that a busier looking figure, with more and thicker lines, indicates a more densely connected graph. This in turn means that there are more and stronger relationships between the variables contained within the model.

A visual inspection of both figures quickly shows that the RI-CLPM provides a much less densely connected network, indicating that this method produces fewer statistically significant relations between the variables in the model. Furthermore, the relations that are found to be statistically significant in both models are typically much weaker in the RI-CLPM than in the CLPM. Given the fact that the RI-CLPM both provides a better empirical fit to the data and provides theoretically more relevant estimates, the results from the RI-CLPM are to be preferred above those of a CLPM. Note then that these results confirm that the CLPM overestimates the strength of the (within-person) effects compared to the CLPM.

In the remainder of the results section, we will discuss and interpret the parameter estimates of the RI-CLPM to examine both whether the relationship between attitudes and behaviours changed

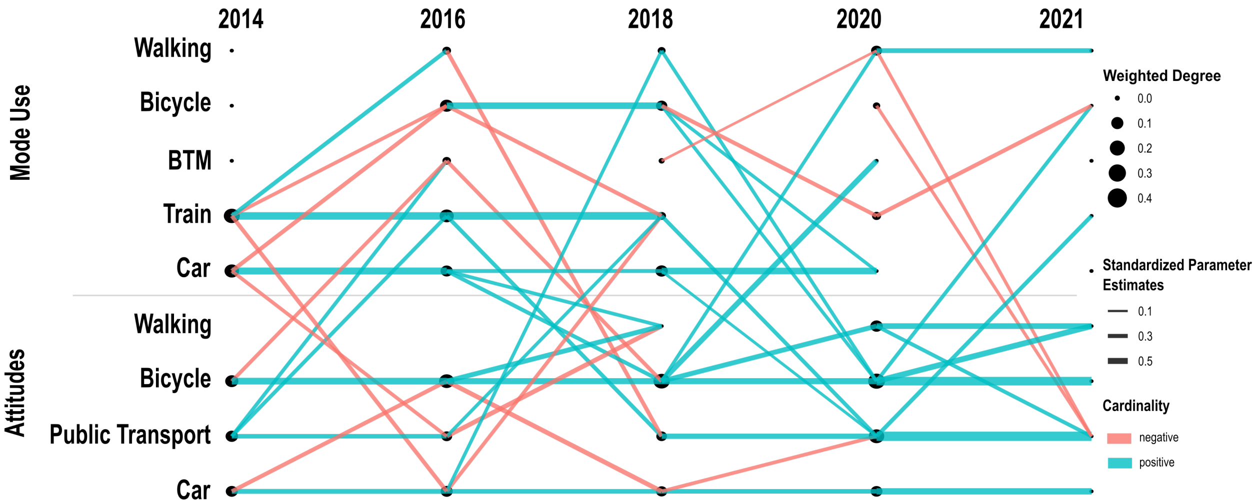


*Figure 6.3: Visualization of a graph of the within-person effects between attitudes and behaviour over time as estimated using a RI-CLPM*

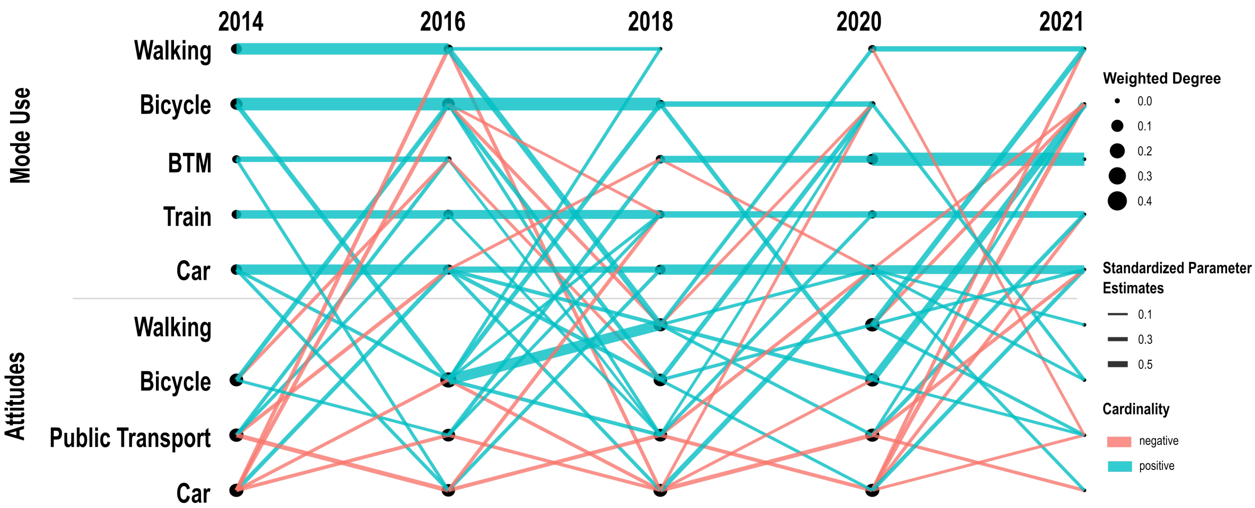


*Figure 6.4: Visualization of a graph of the effects between attitudes and behaviour over time as estimated using a CLPM*

during the COVID-19 pandemic (Section 6.4.2) and the extent to which there are relations between attitudes and behaviour across various travel modes (Section 6.4.3).

### 6.4.2 Changes during the COVID-19 pandemic

Before the node-specific attribute values are discussed, insights from a visual inspection of the graph of the RI-CLPM (Figure 3) can be discussed. First, one can see that there are fewer lines during the measurements spanning 2018 through 2021 than during the measurements between 2014 and 2018. This indicates that fewer relationships were significant during the COVID-19 pandemic than before. One might thus conclude that in general, the relationships between attitudes and behaviour were weaker during the pandemic. One explanation for this finding is that people's behaviour was affected more strongly by other factors, meaning that they were unable to show the desired behaviour. If this is the case, then we would expect the effects to revert to the pre-pandemic effects relatively quickly. Alternatively, the attitudes measured during COVID-19 could have reflected more temporary dispositions towards travel modes, which have weaker effects on mode use.

Second, some horizontal positive edges (= carry-over effects) can be found throughout the graph. These indicate that higher or lower scores on these variables, compared to the individuals' average, carry-over to the next measurement. We see some differences here: bike attitudes seem to be the most stable throughout the seven years analysed here, whereas walking and BTM mode use have no significant auto-regressive parameters before 2018. During the pandemic, the carry-over effect of train use also disappears.

A further discussion and interpretation of more specific results will use node attribute values. First, we will investigate the changes in the relationship between attitudes and travel behaviour due to COVID-19. To further investigate the changes in effects, we look at the weighted outdegree of the variables, where we only count those edges that run from an attitude to a behaviour or from a behaviour to an attitude. In other words, we only use effects running between attitudes and behaviour (for example, from car attitudes to car use) and not effects within attitudes (for example, from car attitudes to public transport attitudes). The weighted outdegrees are given in Table 6.5. As explained in Section 6.3.5, the weighted outdegree represents the amount of variance that a variable explains in other variables. Since we only count edges that run from attitudes to behaviour or vice versa, these degrees thus represent the total variance that one variable explains in variables of the other concept (for example, the variance that car attitudes explain in all mode use variables combined).

When interpreting Table 6.5, we can see a sizeable decrease in weighted out-degree during the last wave-pair, collected fully during the COVID-19 pandemic. This can be interpreted as another sign that the within-person effects between attitudes and behaviour weakened during the COVID-19 pandemic.

### 6.4.3 Relations between travel modes

By incorporating the effects between mode use and attitudes across travel modes into one model, we can provide a more complete picture of the relationships between behaviour and attitudes in the context of travel behaviour research. In this section, we will first discuss the combined effects

| | | 2014 → 2016 | 2016 → 2018 | 2018 → 2020 | 2020 → 2021 |
|---|---|---|---|---|---|
| Mode Attitude | Car | 0.000 | 0.089 | 0.000 | 0.000 |
| | Public Transport | 0.111 | 0.043 | 0.000 | 0.072 |
| | Bicycle | 0.054 | 0.000 | 0.169 | 0.054 |
| | Walking | | | 0.000 | 0.000 |
| | Sum | 0.165 | 0.132 | 0.169 | 0.126 |
| Mode Use | Car | 0.054 | 0.125 | 0.023 | 0.000 |
| | Train | 0.067 | 0.067 | 0.064 | 0.000 |
| | BTM | 0.000 | 0.059 | 0.000 | 0.000 |
| | Bicycle | 0.000 | 0.000 | 0.041 | 0.031 |
| | Walking | 0.000 | 0.063 | 0.044 | 0.033 |
| | Sum | 0.121 | 0.314 | 0.172 | 0.064 |

*Table 6.5: Weighted outdegree of the nodes, counting only edges that run between attitude and behaviour nodes*

between attitudes and behaviour. Then, we will discuss which modes' behaviour and attitudes have larger effects on the behaviour and attitudes of the other modes. Finally, we will interpret the between-person correlations between travel distances and travel attitudes across the various travel modes. From the graph presented in Figure 3, it is not immediately clear whether there are stronger effects from attitudes to behaviour or vice-versa. This means that from this visual summary, the default theoretical assumption that it is solely attitudes that affect behaviour, and not vice-versa, seems at odds with our findings This result is further backed up by interpreting the net-degrees of the various variables. These net-degrees are the net difference between the sum of all incoming edges (= variance within the variable that is explained by other variables) and the sum of all outgoing edges (= variance that the variable explains in other variables). As above, we only use edges (= within-person effects) that run between attitude- and behaviour variables. If attitudes thus would have a stronger within-person effect on behaviour than vice-versa, we would expect net positive degrees for the attitude variables and net negative degrees for the behaviour variables. These net-degrees are given in Table 6.6.

For both the 2016 and 2018 nodes, the sum of the net degree of the behavioural variables is greater than the sum of the net degree of attitudes, but this trend is reversed in 2020. Substantively, this means that behaviours had a larger effect on attitudes in the years before 2020, but that the reverse is true in the years since 2020. As discussed in Section 6.4.2, the network is unfortunately not very stable year-on-year. However, based on these results one can at least draw the general conclusion that the effect of attitudes on behaviour is not stronger than the reverse effect. This further confirms earlier findings of studies using panel data on the nature of the relationship between travel attitudes and travel behaviour (Kroesen, 2014; Kroesen et al., 2017). This relationship is empirically estimated to be two-sided, and separating within-person processes from between-person processes does not change this conclusion.

Comparing the effects of variables on the various travel modes, we can see that for the 2016 nodes, which for their net-degree calculation only use the wave-pairs $2014 - - > 2016$ and $2016 - - > 2018$, car use was the strongest explanatory variable in the network, as it has the largest net degree. As a result, this variable had the strongest explanatory power before the COVID-19

| | | **2016** | **2018** | **2020** |
|---|---|---|---|---|
| Mode Attitude | Car | 0.022 | 0 | 0 |
| | Public Transport | 0.009 | -0.131 | -0.015 |
| | Bicycle | 0 | 0.041 | -0.032 |
| | Walking | - | -0.056 | 0 |
| | Sum | 0.013 | -0.146 | -0.047 |
| Mode Use | Car | 0.125 | 0.023 | 0 |
| | Train | 0.008 | -0.031 | 0 |
| | BTM | -0.046 | 0 | -0.126 |
| | Bicycle | 0 | 0.041 | 0.031 |
| | Walking | 0.063 | 0.007 | -0.010 |
| | Sum | 0.15 | 0.04 | -0.105 |

*Table 6.6: Difference between weighted out-degree and weighted indegree, counting only edges between attitude- and behaviour-related variables.*

| | | Attitudes | | | | Mode Use | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Car | PT | Bike | Walk | Car | Train | BTM | Bike |
| Atti-tudes | Car | | | | | | | | |
| | PT | -0.215 | | | | | | | |
| | Bike | 0.023 | 0.278 | | | | | | |
| | Walk | 0.083 | 0.210 | 0.557 | | | | | |
| Mode Use | Car | 0.312 | -0.174 | 0.038 | 0.123 | | | | |
| | Train | -0.110 | 0.138 | 0.080 | 0.023 | -0.127 | | | |
| | BTM | -0.046 | 0.145 | -0.061 | -0.030 | -0.115 | 0.043 | | |
| | Bike | -0.165 | 0.209 | 0.414 | 0.075 | -0.178 | 0.181 | 0.051 | |
| | Walk | -0.155 | 0.061 | 0.139 | 0.354 | 0.000 | 0.023 | -0.030 | 0.017 |

*Table 6.7: Correlations between random intercepts*

pandemic. Public transport attitudes meanwhile had a strong net-negative degree only in 2018, which is probably the result of some structural change in the relationships between attitudes and behaviours due to COVID-19, as discussed in the previous section. A similar explanation can be used to explain the strong net-negative degree of BTM travelled distance for the 2020 nodes.

To complement the analyses of the within-person relations discussed above, we can look at the correlations between the various random intercepts, which capture the between-person relationships. These correlations are given in Table 6.7.

We see significant and strong correlations between the attitudes and behaviours of the various travel modes. In the quadrant to the bottom-left, the correlations between attitudes and travel distances are presented. As expected, attitudes and travel distances of the same mode are positively correlated. People who use a mode more also hold more favourable attitudes towards that mode. The correlations also show a clear divide between the car and the other modes. Car attitudes are negatively correlated with travel distances of all other modes, whereas PT attitudes are positively correlated with bike and walking travel distances, but negatively correlated with car distances. Attitudes to the active modes are only negatively correlated with local public transport use. As a result, we might conclude that people who generally favour the car and use it more are less likely to also favour the other modes and use those and vice-versa.

Similar conclusions can be drawn based on the right lower quadrant, where the correlations between the random intercepts of the travelled distances are shown. Car use is negatively correlated to the use of all other travel modes except for walking. The use of the train is relatively strongly positively correlated to cycling use. The correlation between train and bicycle use is much stronger than the correlation between train and BTM use. In The Netherlands, people often use bicycles as access- and egress modes of the public transport system. This would be one factor behind these positive between-person relations. However, given the shorter distance of trips made with busses, trams, and metros as compared to trains, these BTM modes are competitors of the bicycle as well. As a result, the positive relationship with train use is stronger than the relationship with BTM use.

In terms of attitudes (upper-left quadrant), we see a strong negative relationship between car- and public transport attitudes. Public transport and active modes' attitudes however are positively correlated. The correlation between bicycle and walking attitudes is very strong, indicating that people with favourable attitudes towards the one also have favourable attitudes towards the other.

## 6.5 Conclusion

This paper tried to answer two knowledge gaps in the literature on the relationship between travel attitudes and travel behaviour. The first knowledge gap considers whether this relationship changed during the COVID-19 pandemic. The second gap relates to the separation between within-person effects between travel attitudes and travel behaviour from the between-person correlations between these concepts. To address these knowledge gaps, we estimated a RI-CLPM on panel data from the Netherlands Mobility Panel spanning the years 2014 through 2021.

The results indicate that the relationship between attitudes and behaviour was weakened as a result of the COVID-19 pandemic, perhaps because other factors (such as constraints on mobility due to lockdown measures) played a larger role in determining behaviour and/or attitudes. As a result, we expect that the temporary deviations observed in both attitudes and behaviour during the pandemic will only have a diminished continued impact on the attitudes and behaviour post-pandemic. This could be considered good news, as it means that the more negative public transport and more positive car attitudes seen during the pandemic are unlikely to result in meaningful behavioural change post-pandemic. Regarding the second gap, we find that the separation of within-person from between-person effects is highly relevant. We find that stable, trait-like differences between persons exist, both for attitudes and travel behaviour. The between-person correlations are strong and significant, indicating that these stable, trait-like differences are correlated with each other. For example, people with more favourable bicycle attitudes tend to use the bike more often and tend to have more favourable public transport attitudes. Due to the existence of such between-person relationships, methods that do not account for them will overestimate the strength of the within-person effects of changes in attitudes on travel behaviour and vice versa.

These results imply that researchers who are not able to separate within-person effects from between-person correlations should be careful when interpreting results regarding the relationship between attitudes and travel behaviour. In particular, they should be careful when recommending policies intended to somehow intervene and change travel-related attitudes with the end goal of indirectly influencing travel behaviour. These policies depend on within-person causal effects from attitudes on behaviour (De Vos, 2022), and our results show that these within-person effects do exist, but that they are much weaker than one would expect based on cross-sectional data for two reasons. First, the already known problem of endogeneity, where part of the relationship runs in the opposite direction (Chorus & Kroesen, 2014), and now second, the discovery that part of this relationship depends on between-person differences rather than within-person effects.

There are several interesting avenues for future research to explore. First, now that most of the COVID-19 pandemic seems to be in the past we are getting access to data collected in a post-pandemic world. This would allow for estimations of the relations between attitudes and behaviour not just before and during, but also after the pandemic. It would be interesting to see whether these post-pandemic relationships are more similar to the relationships before or during the pandemic. This information could be used to confirm or reject our suspicion that these relations will return to pre-pandemic levels and to see whether there are any lingering effects of COVID-19-related changes in attitudes on post-pandemic travel behaviour. Second, it could be interesting to explore the within-person relationships between travel behaviour and different types of attitudes, such as attitudes related to climate change. Such research might for example find whether the increasing concerns relating to climate change will lead to changes in travel behaviour.

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# Chapter 7

# Latent growth curve trajectories for travel mode attitudes

Abstract:

*Improving our understanding of the changes in attitudes over time can help forecast future travel-related attitudes, and therefore also future travel behaviour. This study models the growth trajectories of car- and public transport attitudes as a function of both age and calendar year. We investigate the heterogeneity in the growth trajectories by using latent class growth models. These latent classes also allow us to study the differences in attitudes between generations. For both the car and public transport, we find three latent classes, whose growth trajectories as functions of the calendar year differ markedly. The growth of public transport attitudes follows a U-shaped pattern as a function of age, minimizing around age 40, while car attitude follows an inverted Ushape, maximising around age 40. We do not find substantial differences between generations, contradicting common statements that younger generations are less car-minded than earlier generations. We also find that the COVID-19 pandemic caused substantial changes in attitudes, with public transport attitudes becoming more negative and car attitudes becoming more positive. The magnitude of this change was related to the trajectory of attitude growth, with a larger drop for the group that was already less favourable towards public transport. In the years following 2020, most attitudes have trended back towards pre-pandemic values. However, the levels of the groups with more positive public transport attitudes have not fully recovered.*

## 7.1 Introduction

Since the reintroduction of travel-related attitudes to the field of travel behaviour research a quarter century ago (Gärling et al., 1998), the study of travel-related attitudes has quickly regained traction. Attitudes are here defined as 'a psychological tendency that is expressed by evaluating a particular entity with some degree of favour or disfavour', following Eagly and Chaiken (1993, p. 1). Within travel behaviour research we typically study attitudes towards travel modes (car, bicycle, public transport), as well as attitudes relating to activity or land use patterns. Most studies investigate the relationships between attitudes and travel behaviour, often using travel-related attitudes as explanatory variables for travel behaviour. Another research line focuses on travel-related attitudes themselves, rather than their relationship with travel behaviour. This type of study is comparatively less common in the field. Examples discuss the distinct types of travel-related attitudes and the measurement of such attitudes (Bohte et al., 2009), as well as differences in attitude values between various groups (Jensen et al., 2014; Zhou & Wang, 2019).

With this paper, we intend to further contribute to this research stream by explicitly accounting for the growth trajectory in travel-related attitudes over time. This contribution is a necessary step towards a further understanding of attitude dynamics, which can help the projections of attitudes into the future. Although many studies have focused on the relationship between attitudes and travel behaviour, no practiceoriented travel behaviour forecasting model includes travel attitudes as antecedents. Mokhtarian (2024) identifies the difficulty in forecasting travel attitudes themselves as one of the main objections against this inclusion. This study can be used as a first stepping stone toward the forecasting of these travel attitudes towards the future. These forecasts can be used to improve practiceoriented forecasting models, enabling policy makers to base infrastructure investment decisions on better knowledge.

To accomplish this contribution, we model attitudes as a function of two different dimensions of time: first, the effect of age, and second, the effect of the calendar year. To our knowledge, this is the first study to do so focusing on travelrelated attitudes. In other research fields, such growth studies of attitudes are relatively common. A nonexhaustive list of examples includes attitudes towards education (Arens & Niepel, 2019; George, 2000), parenting (Han & Lee, 2018; Hartman et al., 2003) and gender roles (Cunningham, 2008; Katz-Wise et al., 2010). By modelling two different dimensions of time, we can harness the power of the growth model in two ways. First, by investigating the effects of age on travel mode attitudes. By also accounting for generational effects, we are able to differentiate generational differences from ageeffects. Second, by studying the effects of the calendar year on travelmode attitudes we might see how attitudes develop over time and how they might change in the future. This information could potentially be used to inform travel behaviour forecasts. Since we know that considerable heterogeneity exists with respect to both behavioural and attitudinal changes during COVID19 (de Haas et al., 2020; Javadinasr et al., 2022), we explicitly account for this heterogeneity by estimating a latent class growth curve model.

In the remainder of this paper, we first provide an overview of the literature in Section 7.2:. We then discuss our methods and data in Section 7.3, followed by the results and discussion in 7.4. Finally, we end with the main conclusions and our intended future extensions of the present work in Section 7.5.

## 7.2 Literature Overview

This section contains a broad overview of the relevant literature on travel-related attitudes, growth modelling, and generational differences and effects in travel behaviour research.

### 7.2.1 Travel-related attitudes

In the study of travel-related attitudes, two streams can be distinguished: the first focusses on the relationships between travel-related attitudes and travel behaviour and the second focusses on travel-related attitudes themselves. Travel-related attitudes have long been recognised as fundamental determinants of travel behaviour and choices. Following popular psychological frameworks of behaviour, such as the theory of planned behaviour (Ajzen, 1985, 1991), these attitudes are often studied as antecedents of travel behaviour. Following their reintroduction to the field of travel behaviour research in the late 1990s (Gärling et al., 1998; Kitamura et al., 1997), attitudes have been studied in the context of residential self-selection (Cao et al., 2009; Næss, 2009), hybrid choice models (Ben-Akiva et al., 2002; Chorus & Kroesen, 2014; Vij & Walker, 2016), environmental concerns (Anable et al., 2006), and more (De Vos, 2022).

In the last decade, the relationship between travel-related attitudes and travel behaviour has been the subject of debate, in particular revolving around the causal order between the two concepts. Theories that place attitudes as pure antecedents of travel behaviour have been challenged using panel data and advanced statistical models. The overwhelming result of these studies is that there is a bidirectional relationship between the two concepts (Chorus & Kroesen, 2014; Kroesen et al., 2017), where the reverse effect of behaviour on attitudes can even be stronger than the effect of attitudes on behaviour.

Studies focussing on travel-related attitudes themselves are comparatively less common in the literature. This makes it even more difficult to use attitudes as determinants of travel behaviour in practical transport models that can be used for policy making. Such models depend on reliable information on the input variables for valid forecasts. For example, a consensus on which attitudes to include, the measurement of these attitudes, and the developmental trajectories of these attitudes in the past and into the future would help their inclusion in practice. Currently, much of this information is lacking. Some studies have focused on the identification and measurement of attitudes (Bohte et al., 2009; De Vos, 2022); however, no consensus has been reached in practice (Mokhtarian, 2024). At present, very few studies report the development of attitudes over time. Most of these studies have used data collected during the COVID-19 pandemic (de Haas et al., 2020; Mirtich et al., 2021) and are therefore not particularly useful for long-term forecasts of travel attitudes.

### 7.2.2 Growth Modelling

Growth modelling is used to capture changes and trends over time. The method is rooted in psychology (Meredith & Tisak, 1990) and is often used in the context of education and social sciences (Singer & Willet, 2003). At its core, the method is used to analyse growth (or change) in a dependent variable as a function of time. For a more methodological introduction, see Section 3.1. In this section, we will conceptually discuss the benefits of growth modelling and provide an overview of its applications in the field of travel behaviour research.

Modelling how travel attitudes evolve as a function of time provides valuable insights into the evolution of travel-related attitudes, enabling researchers to disentangle temporal effects associated with calendar years, age, or time elapsed since significant events. By examining changes over calendar years, we can understand the impacts of societal trends, technological advances, and policy interventions on travel attitudes. In this study, we use growth models to study the effects of the COVID-19 pandemic on travel-related attitudes: both the direct effects during the pandemic and the post-pandemic, more structural, effects. We compare this period, with relatively substantial changes in attitudes, with the years before the pandemic. Furthermore, age-related analysis sheds light on life stage influences, such as shifting travel preferences during transitions from adolescence to adulthood or retirement. In particular, this explicit modelling of the effects of age on travel-related attitudes allows us to disentangle, at least to some extent, age effects from generation effects, which we discuss in the next paragraph.

An extension of the growth model is that of the latent class growth model (Jung & Wickrama, 2007), which incorporates heterogeneity in the effects of time on the dependent variable. Latent classes are a familiar concept within travel behaviour research, mostly due to the popularity of the latent class choice model. The latent class growth model accounts for the heterogeneity in the effect of time on the dependent variable of a certain number of latent classes. Latent class membership can then be modelled as well, allowing for further insights into the heterogeneous effects of time.

### 7.2.3 Generational Differences in Travel Behaviour Research

Research on generational differences in daily travel behaviour and attitudes is quite sparse, and the existing research reveals mixed findings. Some studies suggest that such generational differences exist, especially between Generation X (born between 1965 and 1980) and Millennials (born roughly between 1980 and 1995). These articles find that Millennials have lower daily vehicle miles travelled compared to earlier generations (K. Wang & Wang, 2021; X. Wang, 2019; Zhang & Li, 2022), based on repeated cross-sectional data from the United States. A similar study on the differences between baby boomers (born between 1945 and 1964) and the silent generation (born between 1925 and 1945) shows some slight differences as well, with baby boomers having lower VMT than the silent generation at the same age (Li, 2023).

Others argue that the observed differences are often rather small and could be attributable to life stages (correlating with age), rather than cohort effects (Capasso da Silva et al., 2019; Etezady et al., 2021). Any causal interpretations can be questioned further by the Age-Period-Cohort problem (Bell, 2020), meaning that fully separating age, cohort (or generation), and period (or calendar year) is statistically impossible. We mention the age-period-cohort problem in a bit more methodological detail in Section 7.3.3,

### 7.2.4 Conceptual Model

The information provided above can be used to construct a conceptual model, which is used to further guide the analyses in this paper. This conceptual model is visualised below in Figure 7.1.

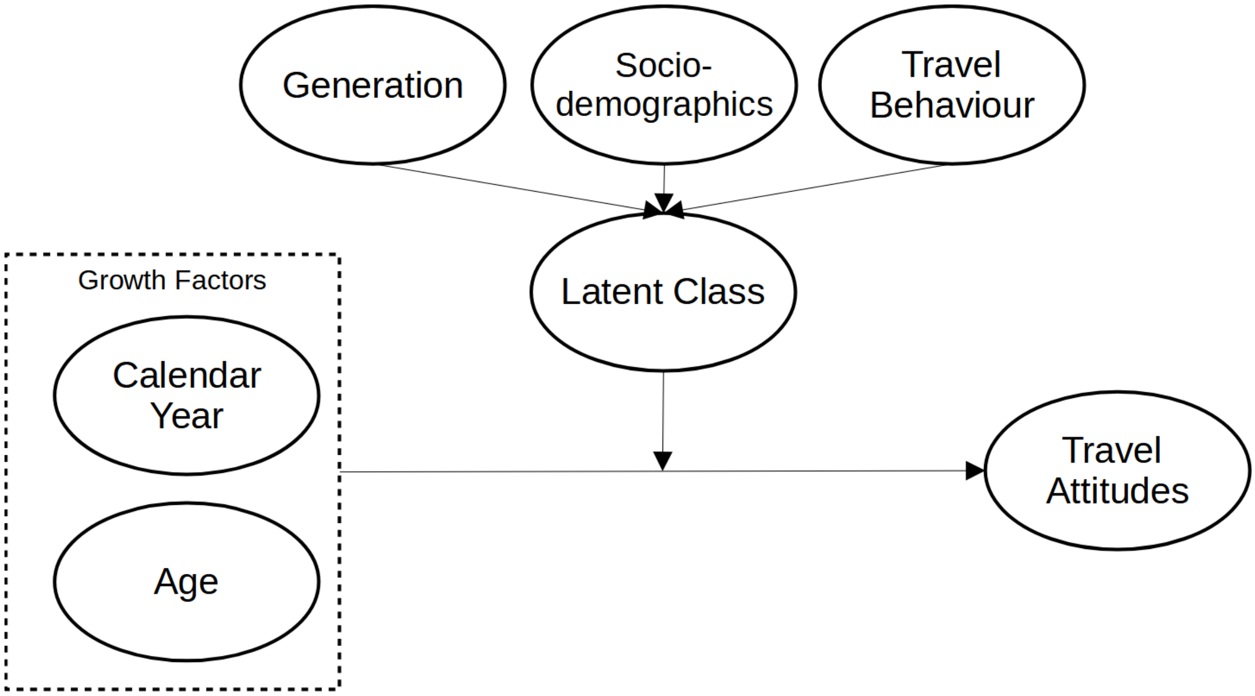


*Figure 7.1: Conceptual model used in this study*

We start with the building block of the growth model: the effects of time (both calendar year and age) on the dependent variable, which in this case are travel-related attitudes. The effects of calendar year are moderated by latent class membership. The latent class membership, in turn, is affected by the generation of the respondent, other sociodemographic variables, and travel behaviour. Note that this latter inclusion entails the assumption that behaviour causally affects attitudes, while the reverse effect is also present empirically. In our interpretation of the related results, we will ensure that we carefully interpret these effects.

# 7.3 Research Methods and Data

## 7.3.1 Research Methods

Latent growth curve modelling is a method originating in psychology and psychometrics, with the principal aim of understanding how psychological concepts and processes evolve. Growth modelling in general seeks to quantify temporal patterns in longitudinal data. Note that the growth need not be positive: Negative growth can also be modelled. In the simplest form, this method models the variable of interest as a function of an intercept (= the value at the start of the trajectory) and a slope (= the development over time), where the slope can be non-linear. At its root, this model assumes that the trajectories of all respondents vary around the same general trajectory estimated by the model. For an approachable introduction to growth modelling, the reader is referred to Curran et al. (2010). In its most basic form, the growth model estimates the average growth using a fixed intercept and slope. As a result, no heterogeneity is present between subjects within the model. This simple model can be formulated as in Equation 7.1, where the value of a dependent variable Y of respondent i at timepoint t is modelled using two parameters: an intercept $\beta_0$ and a linear slope $\beta_1$.

$$\gamma_{it} = \beta_0 + \beta_1 t + \varepsilon_{it} \tag{7.1}$$

As mentioned above, this model does not capture the heterogeneity between subjects. There are two principal methods to extend the model to capture this heterogeneity. The first is to add random effects, capturing individual-specific deviations from the estimated population-level parameters. The second method, which we use, is to allow multiple distinct latent classes k of individuals. Each class is assumed to follow a different developmental trajectory over time (Proust-Lima et al., 2012). It is possible to combine the two methods by estimating random effects within classes, but this method is prone to overspecification to the data (Proust-Lima et al., 2012, 2017). For this reason, we use only fixed effects within the latent classes. A simple latent class growth curve model then uses the following function given in Equation 7.2, where the parameters $\beta_0$ and $\beta_1$ are class-specific for each class k:

$$\gamma_{it|k} = \beta_{0,k} + \beta_{1,k} t + \varepsilon_{it|k} \tag{7.2}$$

This simplified model can be extended to a more general case, which combines both common fixed effects $\beta$ (which do not vary between the classes) and class-specific fixed effects $\alpha_g$, respectively associated with vectors of mutually exclusive covariates $X_1$ and $X_2$ as in equation 7.3. In a growth model, one set of these vectors will include one or more time-related variables, such as age or calendar year. By including quadratic or other non-linear components, a non-linear relationship between time and the dependent variable can be specified as well.

$$\gamma_{it|k} = \beta X_{1it} + \alpha_g X_{2it} + \varepsilon_{it|k} \tag{7.3}$$

This latent class growth curve model can be extended with a class-membership function, which is estimated in a similar fashion to the class-membership models from latent class discrete choice models. The class-membership probability $\pi_{n,k}$ is determined by class-specific constants $\delta_k$ and a function of estimable parameters $y_k$ and socio-demographic covariates $z_i$, as specified in Equation 7.4.

$$\pi_{i,k} = \frac{\exp(\delta_s + g(\gamma_k, z_i))}{\sum_s \exp(\delta_s + g(\gamma_k, z_i))} \tag{7.4}$$

### 7.3.2 Research Data

This study uses data from the Netherlands Mobility Panel (MPN), a longitudinal panel consisting of a 3-day travel diary and a set of questionnaires that started in 2013. The MPN recruits its respondents from a larger Internet Access Panel (IAP), the Kantar NIPObase. Respondents for this invite-only IAP are recruited using register data. The members are then invited to be part of the MPN, based on known sociodemographic characteristics such as sex, age, educational status, and household type. The response rate for the first invitation is roughly 35%. Once part of the panel, the response rates rise to 80-85% for each yearly wave. To combat this panel attrition, new respondents

| | | Sample (2018) | Population (2019) |
|---|---|---|---|
| Gender (%) | Men | 47 | 49 |
| | Women | 53 | 51 |
| Education (%) | Low | 30 | 34 |
| | Medium | 37 | 39 |
| | High | 33 | 26 |
| Age | Years (mean) | 48 | 46 |
| Generation (%) | Pre-WW2 (1900 – 1945) | 9 | 9 |
| | Babyboom (1945 – 1964) | 33 | 29 |
| | Generation X (1965 – 1980) | 26 | 25 |
| | Millennials (1981 – 1996) | 23 | 24 |
| | Gen Z (1997 – 2012) | 9 | 12 |
| Household Type (%) | Single | 22 | 20 |
| | Adults | 33 | 45 |
| | Adults and children | 45 | 34 |
| Urban Density Residential Municipality (addresses/m$^2$) | $< 500$ | 8 | 8 |
| | 500-1000 | 22 | 22 |
| | 1000-1500 | 17 | 16 |
| | 1500-2500 | 32 | 30 |
| | $> 2500$ | 21 | 24 |

*Table 7.1: Sociodemographic characteristics of the sample, compared to the population*

are regularly added to the panel. For more information on the MPN, see Hoogendoorn-Lanser et al. (2015).

We used six waves collected between 2014 and 2022. We only used waves collected during the even years (and 2021), since only during these waves attitudinal questions were included in the questionnaire. In total, we used a sample of 5,038 distinct respondents and 22,227 responses, which means that we collected an average of 4.5 waves of data per respondent. Below in Table 7.1 we show the distribution of the sample on some socio-demographic variables and compare these to the population.

As can be seen in the above table, the sample seems to be representative of the Dutch population in the included metrics. The one exception is the small over-representation of households with children, at the cost of households consisting only of adults.

The main variables of interest in this study are attitudes related to travel. As noted earlier, a distinction can be made between general and specific travel-related attitudes, where the former consists of attitudes toward subjects that are relatively far removed from the behaviour in question (such as attitudes towards climate action) and the latter consists of attitudes which are more closely aligned with the behaviour in question (such as travel mode attitudes). In this paper, we will study the more specific attitudes, as we expect there to be much stronger links with behavioural change. Since we study attitudes as dependent variables, the problem of endogeneity is not a primary concern. Attitudes toward three modes of travel (car, train, bus, tram, and metro [btm]) are measured using six indicator statements for each mode. Each indicator is scored on a 5-point Likert scale. The indicator statements related to the train and those related to bus, tram and metro (btm) are combined into a singular attitude towards public transport, because the twelve combined indicators formed a unidimensional scale, determined using principal-axis factoring. The resulting yearly factor loadings are then averaged across the waves to ensure that the constructed scale is a consistent measurement over time. The final factor loadings are given in Table 7.2.

Almost all factor loadings are above the desired threshold value of 0.7. The internal reliability of the scale was also found to be more than satisfactory ($\geq 0.8$).

In addition to attitudes, we use a few other variables within the model presented in this paper.

| | Car | Public Transport | |
|---|---|---|---|
| | | Train | BTM |
| Travelling by (mode) is comfortable. | 0.845 | 0.758 | 0.812 |
| Travelling by (mode) is relaxing. | 0.791 | 0.749 | 0.810 |
| Travelling by (mode) saves me time | 0.781 | 0.692 | 0.729 |
| Travelling by (mode) is safe. | 0.778 | 0.467 | 0.553 |
| Travelling by (mode) is flexible. | 0.796 | 0.742 | 0.767 |
| Travelling by (mode) is satisfying. | 0.856 | 0.792 | 0.821 |

*Table 7.2: Latent travel mode attitude indicators and factor loadings*

First, we use the age of the respondent and the calendar year of the wave to estimate the main growth trajectories. Assuming that there may be variation between subjects in growth trajectories that is explained by the gender and generation of the respondents, these variables are used to inform the part of the class membership of the model. Finally, we classify respondents as users of public transport or cars, based on the 3-day travel diary for 2018 and again use this information in the class membership function.

### 7.3.3 Studying Generational Differences

When trying to investigate the differences between generations in an outcome variable, some methodological difficulties must be overcome. The main obstacle is the age-period-cohort (APC)-problem. In summary, the core issue is that the effects of age, time periods, and birth cohorts are linearly dependent, as the current time period is a linear function of the birth cohort and the age of the respondent. This makes it difficult to statistically disentangle the effects of time period, age, and generations, even with longitudinal data.

One strategy to address this problem is to separate birth cohorts into wider ranges, alleviating the collinearity between age, period, and cohort to some extent. This is the strategy used in this paper. However, even so, causal interpretations should be avoided. We can, however, descriptively assess the differences between the generations, especially where the observed age-range overlaps the observed age-range of other generations. Since we have ten years' worth of data, there is considerable overlap between the generations.

### 7.3.4 Model Estimation

For both car and public transport attitudes, we estimated models ranging from 1 to 4 latent classes. The latent class growth curve or linear mixed models in this study are estimated using the statistical software package lcmm (Proust-Lima et al., 2017) for R (R Core Team, 2017). Some goodness-of-fit indicators for all models are given in Table 7.3 For both sets of attitudes, the four-class model performs statistically best as evaluated using both AIC and BIC. However, in both cases, the fourth additional class consists of a very small subset of respondents (less than 5%). For reasons of parsimony, we have therefore decided to use the 3-class model for both public transport and car attitudes.

| Number of classes | Log-Likelihood | Number of parameters | BIC | Size of the smallest class |
|---|---|---|---|---|
| Public Transport | | | | |
| 1 | -22,273 | 7 | 44,606 | - |
| 2 | -19,328 | 11 | 38,750 | 38% |
| 3 | -17,847 | 15 | 35,822 | 15% |
| 4 | -17,328 | 19 | 34,818 | 6% |
| Car | | | | |
| 1 | -21,104 | 7 | 42,266 | - |
| 2 | -18,032 | 11 | 36,158 | 41% |
| 3 | -16,734 | 15 | 33,596 | 9.8% |
| 4 | -16,414 | 19 | 32,991 | 3.8% |

*Table 7.3: Goodness-of-fit indicators for the estimated growth models*

## 7.4 Results and Discussion

### 7.4.1 Latent Classification and the Effects of Age

The estimated parameters and class sizes for both models are given in Table 7.4. The growth models are visualised in Figure 7.2, for public transport and the car, respectively. These figures show the estimated growth based on both the age of the respondent.

For public transport attitudes, there are three latent classes. The third class (‘public transport doubters’) is the largest in size, with approximately 63% of the respondents belonging to this class. The first class (’public transport sceptics’) and second (’public transport enthusiasts’) are substantially smaller, with approximately 16% and 22% of the respondents belonging to each class, respectively. Substantively, the intercept of the third class (2.97), which represents the average attitude of this class in 2014, is roughly in between that of the first class (2.18, lower) and the second class (3.65, higher). We named the classes accordingly. In the years before the pandemic, public transport attitudes became slightly, but statistically significantly, more favourable year-over-year (0.0201). There is a nonlinear growth of public transport attitudes as age increases, with the relationship seemingly following a drawn-out U-like pattern (see Figure 1). The minimum of the model-estimated growth curve is attained at the age of 43. Therefore, both younger and older people hold more favourable attitudes towards public transport than middle-aged people.

As for the attitudes towards the private car, we again find three latent classes with distinct growth trajectories. The second class is the largest, and its intercept lies between the two other classes, which is why we named it the ‘majority’. Slightly less than 40% of the respondents belong to the third class with the highest intercept value, correspondingly called the ’car enthusiasts’, and only 10% belong to the first class of ’car doubters’. From these class sizes and the intercept values given in Table 4 we can see that attitudes towards the car are generally more favourable and the class with a very high intercept value (4.51, car enthusiasts) is substantially larger than the public transport enthusiast class. Again, we find a nonlinear growth trajectory as age increases, however, for the car the pattern follows an inverted U-shape. The maximum of this shape is reached at the age of 39, which is strikingly similar to the age at which the minimum value towards public transport attitudes is reached.

| | Public Transport (PT) | | | Car | | |
|---|---|---|---|---|---|---|
| | **Class 1: PT-sceptics** | **Class 2: PT-doubters** | **Class 3: PT-enthusiasts** | **Class 1: Majority** | **Class 2: Car-doubters** | **Class 3: Car enthusiasts** |
| N (persons) | | 5 038 | | | 5 038 | |
| N (measurements) | | 22 227 | | | 22 227 | |
| Nr. Of Parameters | | 37 | | | 37 | |
| Log-likelihood | | -17 705 | | | -16 554 | |
| AIC | | 35 484 | | | 33 182 | |
| BIC | | 35 726 | | | 33 423 | |
| Class Sizes (%) | 15.6 | 62.1 | 22.3 | 52.0 | 9.7 | 38.2 |
| **Fixed effects in growth model** | | | | | | |
| Intercept (2014 + mean age) | $2.18^{***}$ | $2.97^{***}$ | $3.64^{***}$ | $3.87^{***}$ | $3.12^{***}$ | $4.51^{***}$ |
| Age (linear component) | | $0.0357^{***}$ | | | $-0.022^{***}$ | |
| Age (square root component) | | $-0.449^{***}$ | | | $0.258^{***}$ | |
| Years pre-pandemic | | $0.0202^{***}$ | | | $0.0222^{**}$ | |
| Pandemic-drop (2020) | $-0.430^{***}$ | $-0.213^{***}$ | $-0.130^{***}$ | $0.100^{***}$ | $0.084^{***}$ | $0.117^{***}$ |
| Years post-pandemic | $0.0597^{***}$ | 0.0139* | -0.00853 | $-0.0576^{***}$ | $-0.0873^{***}$ | $-0.0471^{***}$ |
| **Fixed effects in class-membership model** | | | | | | |
| Delta | $3.03^{***}$ | $3.44^{***}$ | | 0.254 | $-3.14^{***}$ | |
| **Generation** (Ref: Generation X (1965 – 1980)) | | | | | | |
| Pre-WW2 (1900 – 1945) | $-1.26^{***}$ | -0.263 | | $0.378^{*}$ | 0.130 | |
| Babyboom (1945 – 1964) | $-0.706^{***}$ | -0.0732 | | $0.186^{*}$ | 0.0415 | |
| Millennials (1981 – 1996) | 0.201 | 0.169 | | 0.130 | -0.257 | |
| Gen Z (1997 – 2012) | $-0.586^{*}$ | 0.0952 | | -0.211 | $-1.367^{***}$ | |
| Gender, men (ref.: women) | 0.176 | -0.0304 | Ref. class | $-0.454^{***}$ | $-0.564^{***}$ | Ref. class |
| PT user 2018 | $-1.52^{***}$ | $-0.640^{***}$ | | $0.558^{***}$ | $0.869^{***}$ | |
| Car user 2018 | $0.603^{***}$ | $0.624^{***}$ | | $-0.467^{***}$ | $-1.64^{***}$ | |
| **Education** (Ref: middle) | | | | | | |
| Low | -0.0987 | 0.15 | | 0.157 | $0.550^{***}$ | |
| High | -0.163 | -0.0213 | | 0.142 | $0.333^{**}$ | |
| Urban Density (inh./km$^2$) | $-0.464^{***}$ | $-0.389^{***}$ | | 0.0491 | $0.389^{***}$ | |

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, textsuperscript*** $p < 0.001$

*Table 7.4: Estimated parameters of latent class growth models for public transport and car attitudes*

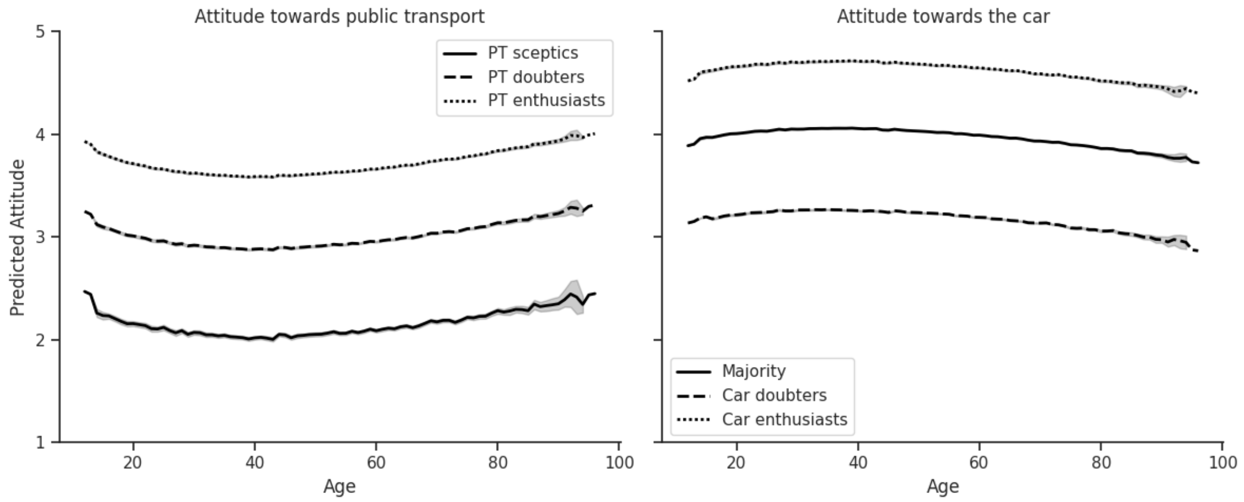


*Figure 7.2: Overview of attitude growth based on age of the respondent*

### 7.4.2 Class-membership function and generational differences

Turning our attention to the class-membership model, we find that gender, education, travel behaviour, urban density, and generation have strong effects on the class-membership probabilities. We will first discuss the sociodemographic effects, then the travel-behaviour relationship, and finally the generational differences.

#### Sociodemographic effects

In the class membership model, we find significant effects of gender in the model with car attitudes as the dependent variable: women are less likely to belong to the 'car enthusiast' class than men. Interestingly, the effects of gender on the public transport model are not statistically significant. Similarly, the effects of education are only statistically significant in the car model. The effect of education is multi-faceted: both people who have attained a lower final education and people who have attained a higher final education are less likely to belong to the group of car doubters than people who have attained a medium level of education. Finally, the urban density of the residence plays a fairly large role in the class membership of both the public transport and the car models. People who live in more dense neighbourhoods are more likely to belong to the PT-enthusiasts and the Car-doubters.

#### Relationship with travel behaviour

The use of public transport and cars in 2018 is highly related to class membership, and thus to the attitude growth trajectory. The causal direction of this effect is unclear. One could follow the normal interpretation of such class-membership covariates and argue that travel behaviour as recorded in 2018 affects which latent class people belong to, and thus explains part of the between-subject heterogeneity in attitude growth trajectory. If this is the case, then attitudes (and their trajectories) are affected by mode use, rather than the other way around. One could also argue for the opposite causal interpretation: people who belong to specific growth trajectories were more or less likely to have specific types of travel behaviour in 2018: people with less favourable attitudes

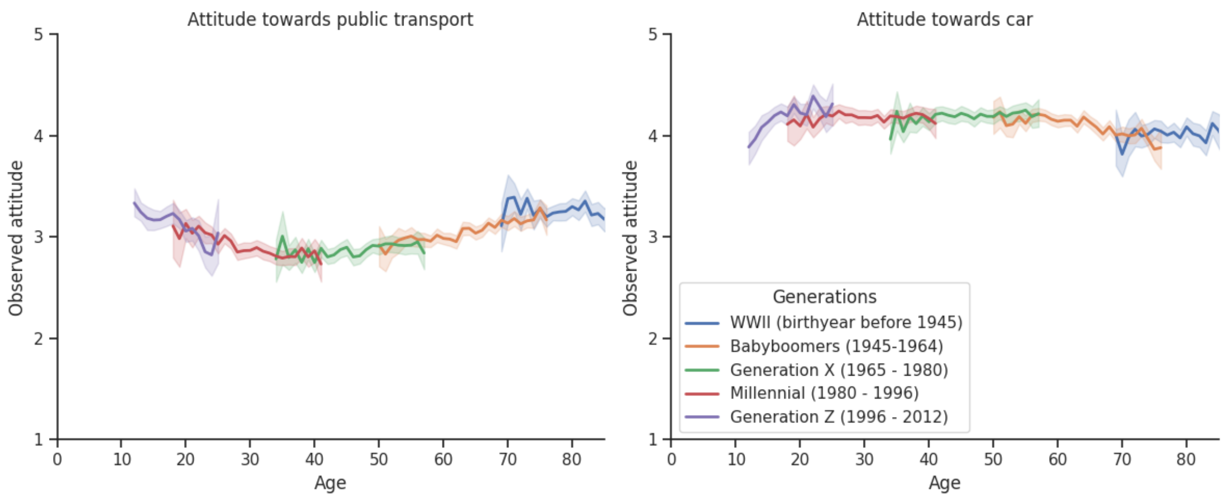


*Figure 7.3: Observed generational differences in public transport and car attitudes*

towards public transport then were more likely to not use public transport, and the model picks up on this correlation. In our view, based on the general evidence supporting a bidirectional causal effect between attitudes and behaviour (De Vos, 2022; Kroesen & Chorus, 2020), both arguments have merit. In either case, the model clearly establishes a strong link between attitude growth trajectory and travel behaviour.

#### Generational Differences

The final variable included in the class-membership function is the generation. As mentioned above in Section 7.2.3, generational differences in travel behaviour and travel-related attitudes are expected to exist. And indeed, some coefficients are statistically significant. However, the direction of these effects seems to contradict conventional wisdom. For example, we find that the youngest generation, Gen Z, more often belongs to the group of car enthusiasts than the other generations. Before we show the model-implied differences between the generations, based on the estimated class-membership parameters, we first want to take a deeper look at the data itself. By stacking ten years' worth of data, we can plot the average attitude towards both public transport and the car as a function of both age and generation. This plot is shown in Figure 7.3.

Because of the relatively long observational period of ten years, we see that there are relatively large areas where generations overlap each other, indicating that for the same age, we have observations from two distinct generations. These overlapping ages allow us to get an intuitive idea of the differences between generations. If, for example, generation Z had more positive attitudes than millennials, we would expect them to have more positive attitudes at the same age. However, we can see in the plot of the public transport attitude on the left that there are only slight differences between generations. During most overlap ages (ages 15-25 for Gen Z and millennials, ages 30-40 for millennials and generation X, ages 47 – 57 for Generation X and babyboomers, and ages 67 – 77 for babyboomers and the pre-WW2 generations), there are no visible differences between the generations. The only visual difference is that the pre-WW2 generations seem to be somewhat more positive than the babyboomers.

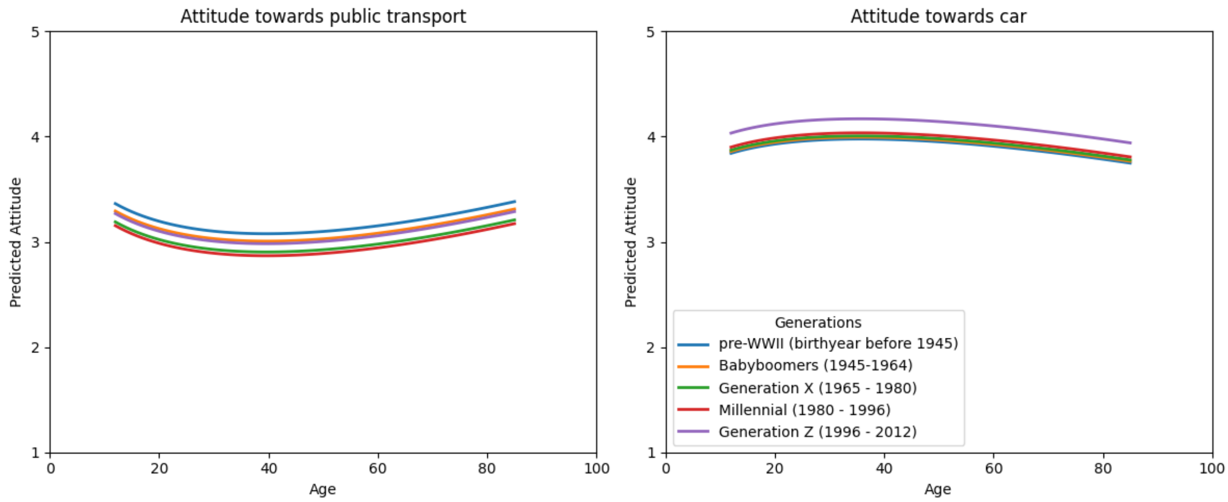


*Figure 7.4: Model-implied growth curves for different generations*

For attitudes towards the car, we can again see that attitudes are fairly similar between generations. The main exception to this general rule is notably the attitudes of the youngest generation, generation Z. They seem to have more favourable attitudes towards cars than the generation before them, the Millennials. When interpreting these results, we must note that this effect can also be attributed, at least to some extent, to the 'period' effect of the COVID-19 pandemic, which resulted in a temporary increase in attitudes towards cars (see next section).

Using our modelling framework, we can try to unravel the various effects and estimate the model-implied growth curves for each generation. To this end, we have set all other attributes to their mean values and then calculated model-implied growth curves between the ages of 18 and 85 for all generations. These curves are plotted in Figure 7.4.

As can be seen in the model-implied growth curves, most of the noise seen in Figure 2 has disappeared. For the attitudes towards public transport, we see a split between three more favourable and two less favourable generations. The more positive generations are both the older generations of the pre-WW2 generations and the babyboomers, as well as the youngest generation Z. For the car, there is only one generation with a different growth curve compared to the others, since generation Z has a more positive attitude towards the car than the other generations.

### 7.4.3 Development of attitudes as a function of the calendar year

In addition to the effects of age and generation discussed above, our model estimates growth curves as a function of the calendar year. Since we have data between 2014 and 2022, this allows us to estimate the 'normal' prepandemic growth curves, as well as the effects induced by the pandemic and the recovery period afterwards. The growth curves are plotted in Figure 7.5.

For public transport, we found a clear negative effect of the pandemic. This effect is seen in reverse for the car, where attitudes towards the car became more favourable in 2020 for all three latent classes. This effect was largest for the most positive group of car enthusiasts. In the years 2021 and 2022, as people became more accustomed to the changes brought by the pandemic, the trend reverted somewhat to the pre-pandemic situation. For the least positive class (car doubters),

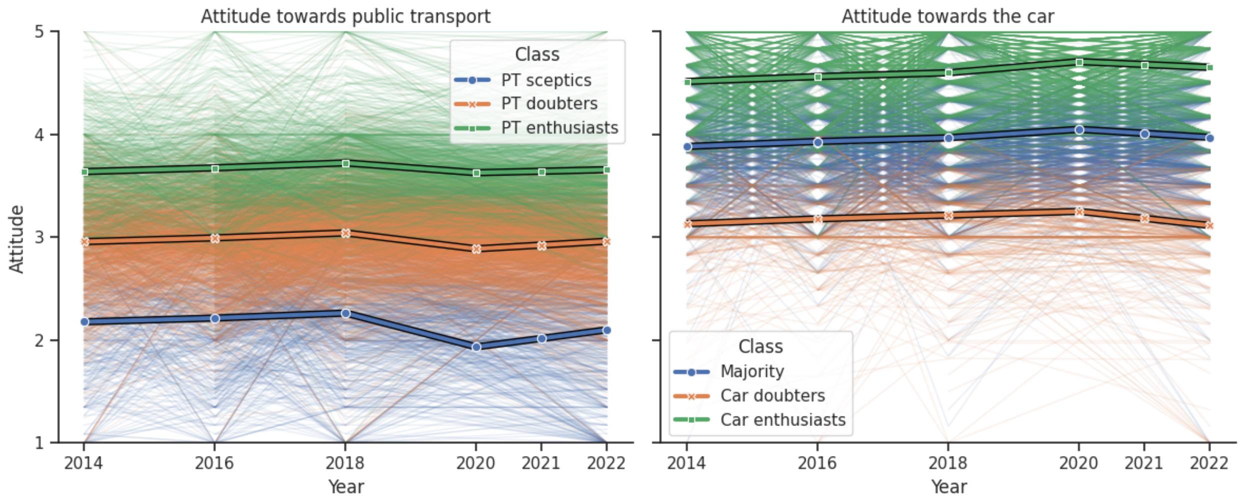


*Figure 7.5: Plotted growth curves as a function of the calendar year*

this negative effect was even stronger than the initial positive change. Thus, this class has a less favourable attitude towards the car in 2022 than it had in 2018.

The drop in public transport attitude due to the COVID-19 pandemic is negative in all three classes, indicating that the pandemic initially at least resulted in less favourable attitudes towards public transport. The magnitude of the drop varies between classes and is related to the attitude values seen before the pandemic: the lower the attitude was before the pandemic, the more it dropped during the pandemic. For the latent class with the lowest mean public transport attitude and the corresponding largest drop in 2020 (class 1, the public transport sceptics), we do, however, see a sharp recovery of the attitude in the years 2021 and 2022. This recovery is much smaller for the public transport doubters, with the median intercept value, and perhaps most worryingly even non-existent for public transport enthusiasts.

## 7.5 Conclusion

This study presented the results of two latent class growth models, studying the growth trajectory of attitudes towards public transport and the car. We set out to achieve two specific objectives: first, to determine how public transport and car attitudes grow over one's lifetime and separate the effects of generation from those of age, and second, to model how these attitudes changed during and after the COVID-19 pandemic.

In relation to the first objective, our studies show that there is a nonlinear growth trajectory of both public transport and car attitudes as a function of age. For public transport, this trajectory follows a U-like shape, with younger and older people being more positive and middle-aged people more negative towards public transport. The lowest value for public transport was found to be attained around the age of 43. For the car, the trajectory follows an inverted U-shape with a maximum value around age 39.

We find significant effects of generation on the membership probability of the latent classes, indicating that people in different generations follow (slightly) different growth trajectories. For public transport, we find that older generations are less likely to belong to the latent class with the lowest public transport attitude. For the car, our model shows the reverse: generation Z (birthyear between 1997 and 2012) is less likely to belong to the class with the lowest attitude. In general however, the differences between the generations are not substantial, especially compared to the effects of age. Where there are substantial differences, they seem to contradict common statements that younger generations are less car-minded and research findings that they use the car comparatively less (K. Wang & Wang, 2021).

Regarding the second objective, our results show that public transport attitudes became less positive during 2020 whereas car attitudes became more positive. The drop in attitudes towards public transport was much greater for people who already had less favourable attitudes towards public transport. In 2021 and 2022 there is some recovery of the public transport attitudes. This recovery, however, is insufficient to compensate for the initial drop in 2020, and moreover, it is smaller or even non-existent for the two latent classes with more positive attitudes towards public transport. Car attitudes reverted to values seen before 2020 during 2021 and 2022. For the least positive group, attitudes even became less favourable in 2022 than they were in 2018.

There are several next steps that we intend to make in the near future. We intend to test different specifications to ensure the model properly separates age-effects from generation effects. We also want to further improve the relationship with travel behaviour, ideally enabling us to test the direction of the effects within this growth modelling framework. Notwithstanding these future improvements, this study shows that growth modelling of travel-related attitudes provides new insights into the development of these attitudes and can aid the forecasting of future travel-related attitudes and thereby future travel behaviour.

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# Chapter 8

# Inferring modality styles by revealing mode choice heterogeneity in response to weather conditions

This chapter is based on Faber, R. M., Jonkeren, O., de Haas, M. C., Molin, E. J., & Kroesen, M. (2022). Inferring modality styles by revealing mode choice heterogeneity in response to weather conditions. *Transportation Research Part A: Policy and Practice*, *162*, 282–295. https://doi.org/10.1016/J.TRA.2022.06.003

Abstract:

*To inform policies aimed at more sustainable travel behaviour, previous research has investigated the concept of multimodality. The notion underlying this line of research is that increasing the degree of multimodality will lead to less car dependence and therefore more sustainable travel behaviour. This paper investigates multimodality by inferring modality styles and revealing their response to exogenous variation in the form of the weather. The main idea of this paper is that travellers with a more multimodal modality style are more sensitive to exogenous variation, and that they are therefore more likely to resort to the use of the car when 'car-favouring' conditions present themselves. The results show that the effects of weather conditions on mode choices do indeed differ between three modality styles. The identified modality styles can be summarised as (1) bike + car; (2) car mostly and (3) multimodal. For the third class, which has the highest degree of multimodality, the use of the sustainable modes is more strongly affected by weather conditions when compared to the first, less multimodal, class. The least multimodal second class meanwhile is least affected by a change in weather conditions. More multimodal travellers thus seem to be more susceptible to exogenous variation, which might prevent the formation of sustainable travel habits or patterns. Based on these results, the claim that a higher degree of multimodality will lead to more sustainable behaviour and that policy makers should aim to realise a shift towards more multimodal modality styles needs to be nuanced. Policy makers should instead focus directly on increasing the attractiveness of sustainable travel modes, which will inadvertently lead to more multimodal modality styles.*

## 8.1 Introduction

With climate change becoming an ever more pressing concern, policy makers are trying to find effective climate change mitigation and adaptation strategies. As part of these efforts, sustainability is becoming a key policy objective. Sustainable policies often seek to reduce greenhouse-gas emissions and/or decrease the dependency on non-renewable resources. Sustainability is also a key objective in the field of (personal) transportation, which has popularised policies aimed at increasing the use of non-motorised travel modes. To inform policies that seek to increase the uptake of these sustainable travel modes, recent research has focused on the concept of multimodality, which is typically defined as the degree to which a person uses multiple distinct modes within a certain time period (Nobis, 2007). Based on the (implicit) notion that multimodal travellers are more sustainable than the (strict) car user, recent research has focused on questions whether multimodal travellers emit less $CO_2$ (Heinen & Mattioli, 2019b; Keskisaari et al., 2017), use the car less (Heinen & Mattioli, 2019a), and are overall more sustainable (Nobis, 2007). In general, it is found that multimodal travel patterns are more sustainable than unimodal travel patterns.

Hence, there seems to be consensus in the literature that more multimodal travel patterns are more sustainable, and therefore increasing the number of multimodal travellers should be a policy objective. This paper argues that there is also a downside to the notion of multimodality. Assuming that multimodal travellers consider the use of various travel modes (at least more deliberately than habitual unimodal travellers), it can be hypothesized that these travellers will resort to the use of the car when "car-favouring" conditions present themselves. In short, the multimodal traveller runs a higher risk of falling back into an unsustainable car using pattern. Multimodal travellers for example might be more affected by seasonal effects, where sustainable travel behaviour is only realised in seasons with more pleasant weather conditions. On the other hand, unimodal sustainable travellers (e.g., those who exclusively use the bicycle or public transport) may be expected to keep travelling by their respective sustainable modes even in the face of such "car favouring" conditions.

In this paper, this notion is examined by determining how travellers with different modality styles react to variations in the weather. The weather is an exogenous factor that changes the utility of different travel modes on a daily and immediate basis. Travellers with different modality styles are thus subjected to similar exogenous variation, enabling valid comparisons of the effects of these shocks. The expectation is that unimodal travellers, i.e. those with a relative high baseline utility for a single mode, will be less affected by variations in the weather conditions (temperature, wind, etc.) than those with high baseline utility for multiple modes. The former group may be expected to keep travelling with their preferred mode (due to travel habits and/or structural constraints) while the latter group may be expected to deliberately take the weather into account in their decision to either travel by car in case of inclement weather or by bicycle or public transport in case of more favourable weather.

This research adds to the literature in two ways: first, by enriching our understanding of multimodality, more specifically modality styles, by showing how people within various modality styles react to the same exogenous variation. Second, by looking at the heterogeneity within the population with respect to the effect of weather on travel behaviour using revealed preference data. Both strands of the literature and these contributions are discussed in more depth in the next section of this paper.

To attain these objectives, a latent class discrete mode choice model is estimated using revealed preference data, in which alternative specific constants (ASC) of the considered modes and the parameters related to weather are freely estimated across the classes, while all other parameters (e.g., related to trip characteristics) are kept constant across the classes. Freely estimating the ASCs enables the effective capture of the existing multi- and unimodal preference profiles in the population. Freely estimating the weather parameters captures each latent group's sensitivity to the effects of the considered weather variables. To estimate the model, revealed preference data from the Netherlands Mobility Panel (MPN) are used. The MPN is a longitudinal panel dataset, where respondents participate across multiple years (Hoogendoorn-Lanser et al., 2015). The MPN consists of a three-day online travel diary and multiple questionnaires pertaining to, amongst other things, socio-demographic information and mode attitudes of the respondents. Both parts are combined for this research. This research uses the first five waves of data from the MPN, which are collected from 2013 through 2017.

The remainder of this paper is organised as follows. First, previous literature on multimodality, including modality styles, and the effect of weather on travel behaviour are described. This previous literature is used to establish a conceptual model. The research methods and data are described in the section thereafter, which is followed by the results section. Finally, the main conclusions, research contributions, and practical implications are discussed.

## 8.2 Previous studies and conceptual model

This research aims to synthesize two strands of the literature: one focusing on multimodality and modality styles and another on the influence of weather on travel behaviour. The information from both strands that is relevant for this research is summarized below, followed by a synthesis and the formulation of a conceptual model.

### 8.2.1 Multimodality and modality styles

Mode choice has long been one of the cornerstones of travel behaviour research as one of the four steps in the traditional four-step approach to transport modelling (McNally, 2000). A relatively recent research stream has focused on the intrapersonal variability of mode choices, also referred to as modal variability (Heinen & Chatterjee, 2015). This is defined as the number of different modes used during some observational period. The more distinct modes are used, the more multimodal a traveller is said to be (Nobis, 2007). Note that this definition does not refer to using multiple modes during a single journey, which is defined in this literature as intermodal behaviour (Crainic & Kim, 2007).

This intrapersonal modal variability can be analysed using segmentation techniques, where many different patterns are reduced to a smaller number of segments, clusters, or classes of individuals (Ton et al., 2019). These multimodal travel segments are also referred to as modality styles, under the assumption that the observed modal variability reflects behavioural predispositions to the use of travel modes (Vij et al., 2013). These behavioural predispositions are based on latent goals, where the use of a travel mode is a means to attaining these goals. Research into modality styles has been complemented by an analysis of the relation with socio-demographics

(Nobis, 2007; Olafsson et al., 2016), mobility attributes (Vovsha et al., 2013) and mode attitudes (Diana & Mokhtarian, 2009; Molin et al., 2016; Ton et al., 2019).

With respect to socio-demographics often-reported findings are that younger, higher-educated, and more urban-oriented travellers are more likely to adopt a multimodal behavioural pattern (Nobis, 2007). Research into attitudes has found that most people's behaviour is congruent with their attitudes, which means that they travel more with a mode that they have positive attitudes towards and vice versa (Molin et al., 2016; Ton et al., 2019).

To further understand the modality styles, a modelling approach can be taken, which is able to provide information about the effect of trip circumstances or mode attributes on mode choice for each modality style. The first application of this modelling approach is described in research by Vij et al. (2013). Their approach enables the distinction between two multimodal modality styles, where one is time-sensitive whereas the other is not. Two more recent studies, Prato et al. (2017) and Keskisaari et al. (2017) use a similar approach to identify relations between modality styles and mode choice probabilities. Prato et al. (2017) focus on short distance trips, as substitutions between motorised and non-motorised modes are more likely to be made for these shorter distance trips. They show that there is indeed taste heterogeneity between the different modality styles, which leads them to recognise that travellers within more multimodal modality styles are more easily swayed to move towards the use of active modes by policies. Keskisaari et al. (2017) show that the effect of travel distances on choice probabilities is heterogeneous across the modality styles they identify and go on to show that the greenhouse-gas emissions caused by the travel of the different modality styles varies considerably, partly because of the aforementioned heterogeneity.

### 8.2.2 Influence of weather on travel behaviour

The effects of weather on travel behaviour are discussed in the recent reviews of this literature by Böcker, Dijst, and Prillwitz (2013) and Liu et al. (2017) who show that weather (forecasts) systematically alter both travel demand and mode choices. This research area is growing rapidly, partly because of the increasing prominence of climate change, prompting the question what the effects of climate change on our travel behaviour might be (see e.g. Böcker, Prillwitz, and Dijst (2013), Markolf et al. (2018), and Mathisen et al. (2015)).

Use of the active modes is generally more sensitive to weather changes than use of motorised travel (Böcker et al., 2016; Sabir et al., 2010), with public transport falling somewhere in-between. Increasing levels of rain and wind especially have negative effects on the use of active modes (Gallop et al., 2018; Rérat, 2018; Zhao et al., 2018), with a smaller positive effect on the use of the private car (Hyland et al., 2018; Liu et al., 2015; van Stralen et al., 2015). Research suggests that there is an ideal temperature for active mode use (Khattak & De Palma, 1997; Miranda-Moreno & Nosal, 2011; Wadud, 2014), with both colder and hotter (Nkurunziza et al., 2012) temperatures leading to declined travel with active modes. The exact value of this ideal temperature could vary based on the local climate and the infrastructural and cultural adjustments that have been made to suit this climate. Importantly, evidence can thus be found that all modes are affected by weather circumstances although to varying degrees (Liu et al., 2017).

The circumstances of the trip are found to moderate the relationship of weather and travel behaviour. The effect of weather is stronger for leisure trips when compared to commute trips (Cools & Creemers, 2013; Helbich et al., 2014) and varies between inner-city and more peripheral regions (Helbich et al., 2014; Miao et al., 2019; Tao et al., 2018). One thus needs to control for trip circumstances when estimating the effect of the weather on the mode choice probabilities of the different modality styles.

Finally there has been limited research into inter-individual heterogeneity within the population with respect to the effect of weather on their travel behaviour. Heinen (2011) and Motoaki and Daziano (2015) both use stated preference data to show that less experienced cyclists are affected by bad weather to a greater extent than more experienced cyclists, whilst Nordbakke and Olsen (2019) show that travel habits and environmental attitudes are strongly related to weather tolerance, which they have defined as using non-motorized transport modes despite poor weather conditions.

### 8.2.3 Synthesis and Conceptual Model

The literature thus shows that most papers do find a sizeable effect of weather on travel behaviour. Inter-individual heterogeneity is hypothesized and investigated using stated preference (survey) data. The effect of the weather is incorporated into the conceptual model as an effect of weather variables on the utility of travel modes. To investigate the hypothesized heterogeneity this research estimates a latent class choice model. The latent classes within this model are assumed to be segments of the population with different behavioural predispositions towards travel modes. These segments can then be interpreted as modality styles (Vij et al., 2013). The modality styles then have a direct effect on a mode's utility, as a result from the behavioural predisposition towards travel modes. As a result, the latent classes both moderate the relationship between weather and utility (as hypothesized in the literature on weather and travel behaviour) and directly affect mode utility (as stated in the literature on multimodality and modality styles). Further information from the literature on multimodality and modality styles is used to identify the factors that influence the likelihood that one is a member of a certain latent class (i.e., the modality style). Both socio-demographics and mode attitudes are included as antecedents of the modality style, based on previous research findings in the literature on multimodality (amongst others Diana and Mokhtarian (2009), Molin et al. (2016), and Nobis (2007))

The main hypothesis of this paper is that modality styles moderate the relation between weather and mode utilities, meaning that the mode choices of people with different modality styles will respond differently to the same change in weather circumstances. Heterogeneity with respect to the influence of weather on travel behaviour is then captured and explained as a result from different behavioural predispositions towards travel modes. Figure 8.1 graphically presents the hypothesized relationships discussed above.

## 8.3 Research Methods

In this chapter the data and methods used for this paper will be introduced and discussed. The travel data are described first, followed by a description of the weather data and the combination of both data sources. The research methods used to analyse the data are discussed afterwards.

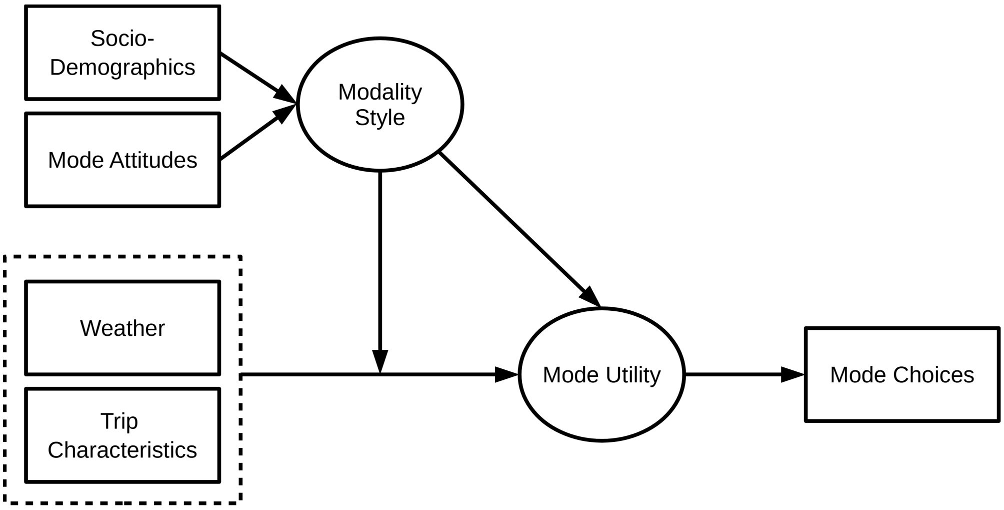


*Figure 8.1: Conceptual model*

### 8.3.1 Travel data

Travel behaviour data is obtained from the Netherlands Mobility Panel (MPN). The MPN is a longitudinal panel dataset, where respondents participate across multiple years (Hoogendoorn-Lanser et al., 2015). As the MPN is a household panel, each household member of 12 years and older is asked to participate. The first five waves of the MPN (2013-2017) are used for this analysis. Since attitudes were only recorded in waves 2 and 4 of the MPN, only people who participated in at least one of these waves are included in the analysis. In total, data from 6.715 unique respondents are used in these analyses. The MPN consists of both online questionnaires and a travel diary, where travel for three consecutive days is collected. The data for these diaries are collected yearly in the months of September through November. The trips recorded in the travel diaries are analysed using a latent class choice model. The modelling procedure is described in section 3.3.

The observation period of the travel diaries is relevant when estimating modality styles. The shorter this period, the less likely it is that multimodal behaviour, defined as using multiple modes for travel, is observed. The five available waves are combined to get information on as many days as possible for each respondent, with a minimum of one wave equalling three days of observation and a maximum of five waves equalling 15 days spread evenly throughout the five years.

Socio-demographic variables from the questionnaire are included in the modelling as well. Gender, employment status, education, and the urban density at the residential location of the respondent are all included. Three variables relating to the availability of travel modes are included. The first two concern personal ownership of a travel mode, namely the car and the electric bicycle. Ownership of an electric bicycle is included under the assumption that use of this mode is less sensitive to weather changes due to the electric assistance meaning both wind and rain cause less discomfort. The last variable is the ownership of a driver's license. The driver's license and car ownership are included under the assumption that people who have easy access to a car are more likely to switch to this mode during inclement weather conditions. The sample distribution of these variables as recorded in the latest year of participation for each respondent is given in Table 8.1.

| Variable | Levels | Distribution (%) |
|---|---|---|
| Gender | Female | 54 |
| | Male | 46 |
| Employment Status | Employed | 54 |
| | Unemployed | 46 |
| Age (years) | 12 - 39 | 47 |
| | 40 - 59 | 36 |
| | 60 + | 17 |
| Educational level | Low | 32 |
| | Med | 37 |
| | High | 31 |
| Urban density at residence (addresses / km$^2$) | $< 500$ | 9 |
| | 500-1000 | 20 |
| | 1000-1500 | 22 |
| | 1500-2500 | 32 |
| | $> 2500$ | 17 |
| Car owner | Yes | 68 |
| | No | 32 |
| Car driver's license holder | Yes | 81 |
| | No | 19 |
| Electric bicycle owner | Yes | 12 |
| | No | 88 |

*Table 8.1: Descriptive statistics for the socio-demographic variables*

To aid in identifying and profiling the latent classes mode attitudes are included in the class membership function (see Figure 8.1). These attitudes were collected as part of the questionnaire in both wave 2 and wave 4 of the MPN. For respondents who participated in both waves the attitudes from wave 4 were used. The attitudes towards travel modes are measured using six questions for each mode. Under the assumption that the response to these individual questions is caused by a latent attitude towards the travel mode in question, a factor analysis is used to determine the value of this underlying attitude for everyone. For each of the modes only one factor has an Eigenvalue larger than 1, resulting in the extraction of just this singular factor. The indicators and their factor loadings are given in Table 8.2.

| | Factor Loadings | | | |
|---|---|---|---|---|
| Questions | Car | Train | BTM | Bicycle |
| Travelling by (mode) is comfortable | 0.859 | 0.871 | 0.891 | 0.828 |
| Travelling by (mode) is relaxing | 0.771 | 0.853 | 0.876 | 0.864 |
| Travelling by (mode) saves time | 0.765 | 0.688 | 0.788 | 0.662 |
| Travelling by (mode) is safe | 0.742 | 0.576 | 0.553 | 0.688 |
| Travelling by (mode) is flexible | 0.789 | 0.735 | 0.820 | 0.783 |
| Travelling by (mode) is enjoyable | 0.852 | 0.882 | 0.897 | 0.877 |

*Table 8.2: Questions related to mode attitudes and their factor loadings.*

Almost all factor loadings are higher than 0.7, whilst all loadings are higher than 0.5. The factor scores for all attitudes are thus calculated using these six items. To calculate the latent factor a weighted regression is used, and the resulting values are standardized, resulting in factor scores with a mean of 0 and a standard deviation of 1.

Travel purpose is operationalized using dummy-coding with three levels: trips made for work, trips made for one's education, and leisure trips. The last level is used as the reference in the dummy coding scheme. Of all trips, 72% are made for a leisure purpose, 22% are made for work, and 7% are made for educational purposes. Finally, alternative specific travel times for each trip are derived using the Google Maps directions API. The origin- and destination addresses of each trip, as well as the time of travel are used for input of the API, which generates alternative specific travel times. In doing so, it accounts for the public transport network and any expected congestion on the road. The API was called roughly a month after the data was collected using a date that corresponds to the day of the week on which the actual trip took place. The distribution of the alternative specific travel times is given in Table 8.3.

| | Min. | Max. | Mean | Median | St. D. |
|---|---|---|---|---|---|
| Car Travel Time (min) | 1 | 203 | 11.3 | 7 | 13.8 |
| PT Travel Time (min) | 1 | 634 | 30.2 | 21 | 32.5 |
| Bicycle Travel Time (min) | 1 | 1344 | 28.6 | 9 | 63.2 |
| Walking Travel Time (min) | 1 | 7086 | 124 | 42.2 | 278 |

*Table 8.3: Descriptive statistics for alternative specific travel times.*

### 8.3.2 Weather data

For this paper objectively measured weather data provided by the Royal Netherlands Meteorological Institute (KNMI) are used. The dataset contains information on 45 different weather attributes, ranging from rainfall to solar radiation, as collected by 50 different weather stations placed throughout the Netherlands. Note that not all the weather stations collect all types of weather data. The data are collected every 10 minutes. Figure 8.2 shows the locations of the weather stations.

The weather variables included in our analysis are the observed levels of temperature, wind speed, precipitation, and solar radiation. These variables are selected because of a series of (count) regression analyses, which showed that no other variables had a significant impact on the use of any of the modes included in this analysis. It is worth pointing out that data is collected during autumn in the relatively mild climate of the Netherlands, and that as such no days with snow were part of the sample.

The weather data needs to be matched to the travel behaviour data based on spatial and temporal dimensions. In doing so, we aimed at assigning weather to trips based on the weather that impacted the mode choice decision of that trip. For this data preparation process the programming language Python is used, mainly relying on the package pandas (McKinney, 2010). Code is written and tested in the JupyterLab IDE (Kluyver et al., 2016). The exact procedure is described in the following section.

The location of the trip origin is used to locate the weather station from which the weather data are read. This location is known up to the postal code area from which the trip departed. The size

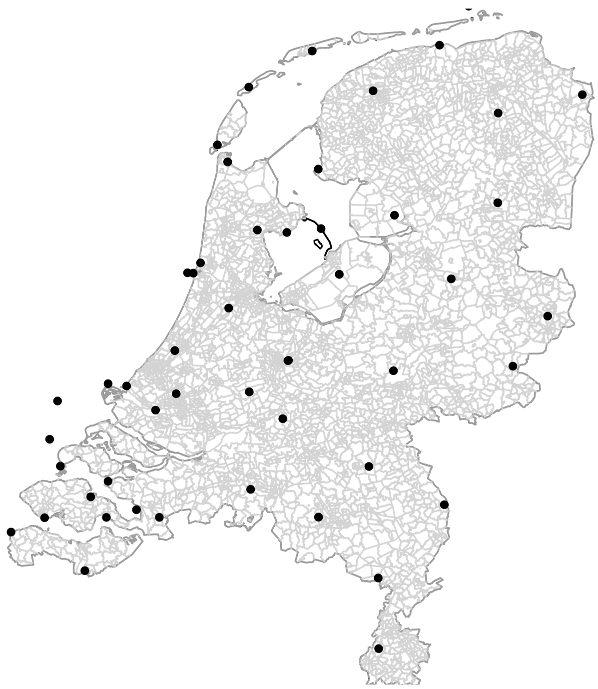

*Figure 8.2: The locations of weather stations and the size of postal code areas in the Netherlands*

and spread of these postcode areas are visualized in Figure 8.2. Weather data is collected from the closest weather station to the postal code area where the trip originated. If the data were not available for the weather station, the next-closest weather station is used instead. The maximum distance allowed between the trips' origin and the weather station is 30 km: if no weather station is available within this distance the trip is removed from the analysis. The average distance between trips and weather station when a connection is made varies slightly for each type of weather variable and is lowest for wind-related variables at 12.8 km and highest for cloud-related variables at 14.1 km. Daily average values are collected from each weather station, weighted by the overall number of trips made in each hour. This means that weather during the night, which has relatively little impact on travel behaviour, is not influential whilst weather during travel peak-hours is weighted more strongly. To give an indication for the weather in the Netherlands during the sampling period descriptive statistics for the weather variables as connected to the trips in the MPN are given in Table 8.4. The weather variables are standardized before inclusion in the model.

| | Min. | Max. | Mean | Median | St. D |
|---|---|---|---|---|---|
| Temperature (°C) | 0.976 | 20.9 | 11.4 | 11.7 | 3.79 |
| Wind Speed (m/s) | 0.284 | 18.5 | 4.01 | 3.61 | 0.284 |
| Rain Intensity (mm/h) | 0 | 1.96 | 0.0921 | 0.00383 | 0.185 |
| Sunshine (W/m$^2$) | 8.40 | 301 | 107 | 90.4 | 68.9 |

*Table 8.4: Descriptive statistics of weather variables*

### 8.3.3 Modelling Procedure

To analyse the effects of weather on mode choices and the differences of this effect between travellers with varying behavioural profiles a Latent Class Choice Model (LCCM) is estimated (Greene & Hensher, 2003). We only allow the alternative specific constants (ASCs) and weather parameters to vary between classes. The variation of ASC's allows for the capture of different modality styles, while the variation of the weather parameters allows for the identification of different effects that the weather has on the mode choices for each class. Since one of the objectives of this paper is to find heterogeneity specifically with regards to the effects of the weather on travel behaviour, we do not let other parameters vary across classes. This allows the latent classes to capture taste heterogeneity with respect to weather, and not for example heterogeneity with respect to travel times.

The LCCM then enables capturing taste heterogeneity within the population, essentially by estimating separate effects of one explanatory variable on the choice probability for each latent class. These effects can be used to provide more insight into the sensitivity of different modality styles to trip circumstances, highlighting the behavioural predispositions of the different classes. Further information on the latent classes is retrieved by the estimation of class-membership probabilities for each individual respondent based on a certain set of socio-demographic characteristics.

The utility function of all LCCM classes is based on random utility maximization and uses a linear-additive MNL structure. The model varies the parameters of each latent class and the covariates of the class membership function to maximise the likelihood of the data given the model. A difficulty for latent class models in general is that the log-likelihood function is not concave, which means that the maximum likelihood estimation procedure is prone to get stuck in a local optimum. To alleviate this issue multiple sets of starting values for the parameters and covariates are used before estimating the model, which increases the odds of finding the global optimum (Bierlaire et al., 2010).

The number of classes is exogenous to the utility maximization and thus needs to be determined by the modeller. To find the optimal number of classes two criteria are used: statistical performance and behavioural interpretability. Multiple models are estimated with an increasing number of classes. After estimating the four-class model we found that it was statistically better performing than the three-class model (based on AIC, BIC, and the Likelihood Ratio Test), but that the four classes were difficult to interpret. For this reason, the three-class model has been selected.

In revealed preference data the chosen alternative is observed directly, but the other considered alternatives are not. This is a well-known problem when using revealed preference data to estimate choice models, which revolves around the fact that choice sets by their nature are mental processes, and are thus latent: it is impossible to determine the actual considered choice set using this type of survey data (Ben-Akiva & Lerman, 1985). This problem necessitates the approximation of the true considered choice set (Ton et al., 2020). This choice set is approximated using deterministic constraints, which are based on availability and consideration of a travel mode (Calastri et al., 2017). Mode availability depends on whether a traveller has access to some travel mode, irrespective of the context of a specific trip. People that do not have access to a bicycle will not have the bicycle as an available alternative for any trip. Consideration of a travel mode in contrast is trip-specific, and consideration set formation stipulates that some alternatives might not be considered for a specific trip. Despite having access to a bicycle, a traveller will not actually consider using a bicycle for a 100km round trip for example.

| | MNL (no weather) | MNL (incl. weather) | LC (no weather) | LC (incl. weather) |
|---|---|---|---|---|
| Within-sample fit statistics | | | | |
| N | 6 434 individuals; 37 896 trips | | | |
| $LL_0$ | -43421 | | | |
| $LL_\beta$ | -28 278 | -28 102 | -23 822 | -23 662 |
| $LL_\beta$ per obs. | -0.746 | -0.742 | -0.629 | -0.624 |
| Nr. of parameters | 15 | 27 | 47 | 83 |
| Rho-square | 0.348 | 0.353 | 0.451 | 0.455 |
| AIC | 56 586 | 56 258 | 47 745 | 47 491 |
| BIC | 56 714 | 56 488 | 48 172 | 48 200 |
| Out-of-sample fit statistics | | | | |
| N | 2 548 individuals; 8 363 trips | | | |
| Hit rate | 0.667 | 0.679 | 0.707 | 0.708 |
| Mean(chosen) | 0.571 | 0.574 | 0.591 | 0.594 |
| $LL_\beta$ | -6 109 | -6 089 | -5 713 | -5 694 |
| $LL_\beta$ per obs. | -0.730 | -0.728 | -0.683 | -0.680 |

*Table 8.5: Goodness-of-fit statistics for four models, increasing in order of complexity*

One type of availability constraint is imposed on the bicycle and the car, which are only part of the choice set if at least one bicycle or car respectively is owned within the household of the respondent. There are two main consideration constraints. The first sets a maximum distance for the bicycle and for walking. These modes are not part of the choice set for trips longer than this imposed maximum distance. The maximum distance is based on the 97.5th percentile of the travelled distance using these modes rounded upwards, resulting in maximum distances of 10km and 20km for walking and the bicycle, respectively. The second rule looks at whether public transport is a reasonable alternative compared to the car and bicycle. Public transport is excluded for trips where it was not available (which for example is often the case for trips made during the night). It is also excluded for people who own a car if it takes either 90 minutes longer than the car or takes more than three times as long as the car, with a minimum of a 30-minute difference.

Finally, this research only uses trips that originate at the residence of the traveller. In almost all cases this is the location where the mode choice is made: if one travels to work by car then the decision to travel back by car is also often already made. This decision is supported by the data, which show that in a large majority of cases the mode used to depart the home is also used for all subsequent trips until one arrives back at the residence. In total, 46.259 unique trips (all departing from the residential location of the traveller) are used to estimate the choice model.

The choice model is estimated using the Apollo package (Hess & Palma, 2019a, 2019b) for the programming language R (R Core Team, 2017). We estimated MNL models with and without weather variables and 3-class LC models, both with and without weather variables. The models are specified in increasing order of complexity, where we test both in-sample and out-of-sample performance of the models. All four models are first estimated on data from waves 1 through 4 of the MPN and then tested out-of-sample on wave 5. The performance of these models is presented in Table 8.5.

| | Car | PT | Bike[a] | Walk[a] |
|---|---|---|---|---|
| Constant across classes | | | | |
| Square Root Travel Time | 1.108*** | 1.371*** | -0.865*** | |
| Travel Time | -0.1788*** | -0.118*** | 0.0140*** | |
| Purpose (work) | | 1.218*** | 1.508*** | -0.008 |
| Purpose (education) | | 3.318*** | 3.249*** | 1.361*** |
| Alternative Specific Constants | | | | |
| Class 1 | | -5.62*** | 4.72*** | 4.52*** |
| Class 2 | | -7.80*** | 1.39*** | 3.12*** |
| Class 3 | | -3.69*** | 3.09*** | 6.04*** |
| Significance of Robust T-ratio: * = 0.05, ** = 0.01, *** = 0.001 | | | | |
| a. One parameter per travel time component is estimated for bike and walk simultaneously | | | | |

*Table 8.6: Estimated non-weather parameters.*

We see a small, but significant improvement within-sample for the models using weather variables, both for the MNL and LC models (based on likelihood-ratio tests, p-values 0.000 for both). We also see an improvement in model performance out-of-sample for the LC models compared to the MNL models, which is important as LC models can be prone to overfitting. Finally, the LC model including weather variables performs slightly better out-of-sample than the model not including weather variables. We conclude here that the LC model including weather provides the best fit both within- and out-of sample. Since this model also allows for further behavioural insight, we think this is the preferable model. We report on the findings with this model fitted to data from all 5 MPN waves in the results section below.

## 8.4 Results

The results from the latent class choice model estimation with three latent classes are described in this section. First, the classes will be interpreted, followed by an interpretation of the effects of the weather variables on the mode choices for each latent class. The modality styles can be interpreted straightforwardly by using the estimated choice probabilities for each mode in average weather conditions. These choice probabilities are based on alternative specific constants, which are varied across classes, and travel time parameters, which are fixed across classes. There are also variables for the purposes of work and education which offset the alternative specific constants for these specific purposes. The alternative specific constants for each class, as well travel time and trip purpose parameters are given in Table 8.6.

The estimated parameters regarding travel time, given in Table 8.6, seem plausible, especially when taking into account that they are estimated on revealed-preference data where travel times across modes are highly correlated. The combination of the square-root and linear component create non-linear utility functions with respect to travel time. For the car and public transport the initial slope of this function is positive, which changes to a negative slope after 10 minutes and 34 minutes respectively. This can be explained given an otherwise unobserved preference to use these modes to travel greater distances. Use of both modes for example is associated with time spent getting the vehicle ready and parking it (in the case of the car) or with getting to the transit stop and potential lay-overs (in the case of public transport). Since the model does not otherwise capture this phenomenon, it is ingrained in the function with respect to travel time (by including both the linear and square-root component).

To obtain a more intuitive picture as to how the different classes are affected by travel time and trip purpose, we calculated the choice probabilities for certain trips. Table 8.7 presents the choice probabilities for leisure, work, and educational trips at both the mean and median travel distances and travel times (see Table 8.3 for these values). The weather conditions here are assumed to be average, meaning that the standardised values are set to 0 and the weather parameters thus have no effect on the estimated probabilities. These choice probabilities under average weather conditions are used for a first interpretation of the modality style of each class.

| | Class 1 | | | | Class 2 | | | | Class 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Car | PT | Bike | Walk | Car | PT | Bike | Walk | Car | PT | Bike | Walk |
| Class | Median values (travel distance = 3 km) | | | | | | | | | | | |
| Leisure | 0.35 | 0.01 | 0.62 | 0.02 | 0.91 | 0 | 0.06 | 0.03 | 0.48 | 0.1 | 0.17 | 0.25 |
| Work | 0.11 | 0.01 | 0.87 | 0.01 | 0.75 | 0.01 | 0.22 | 0.02 | 0.26 | 0.19 | 0.41 | 0.13 |
| Education | 0.02 | 0.02 | 0.96 | 0.01 | 0.35 | 0.03 | 0.58 | 0.04 | 0.06 | 0.33 | 0.5 | 0.11 |
| | Mean values (travel distance = 9.1 km) | | | | | | | | | | | |
| Leisure | 0.75 | 0.03 | 0.22 | 0 | 0.98 | 0 | 0.01 | 0 | 0.75 | 0.18 | 0.04 | 0.02 |
| Work | 0.41 | 0.05 | 0.55 | 0 | 0.94 | 0.01 | 0.05 | 0 | 0.47 | 0.39 | 0.12 | 0.01 |
| Education | 0.1 | 0.1 | 0.8 | 0 | 0.72 | 0.08 | 0.2 | 0 | 0.11 | 0.72 | 0.16 | 0.01 |

*Table 8.7: Estimated choice probabilities of travel modes in average weather conditions.*

The estimated probabilities show three distinct patterns. The estimated probabilities for class 1 point to the use of either car or bicycle for almost all trips during average weather circumstances. Depending on the travel distance (and associated travel times) and travel purpose, either the car or the bicycle is most likely to be used. Class 2 is the most unimodal, with remarkably high estimated probabilities for the use of car under all circumstances. Only educational trips are relatively multimodal for this group, although the estimated probability for car is still very high compared to the other two classes. The choice probability estimated for Class 3 are much more mixed and vary more across the travel distances and travel purposes. This class is the most multimodal. When travel times are smaller, this class shows sizeable shares of walking, whereas both other classes' walking share is close to zero for nearly all trips. PT share is also higher than for the other two classes, especially for non-leisure trips.

These findings are complemented by an interpretation of the class-membership model, which shows how mode attitudes and socio-demographics impact the likelihood of being a part of a class. The class-membership parameter estimates are given in Table 8.8.

These class-membership parameter estimates show us a couple of interesting things. First, one can see that there are more people in classes 1 and 2 compared to class 3 based on the delta values. In total, 45% of people are assigned to class 1, whereas 39% and 16% are assigned to classes 2 and 3, respectively.

Second, mode ownership and mode attitudes have a significant effect on the class-membership probabilities. This result is to be expected, if the latent classes are to be identified as modality styles. People who own a car or a driver's license are much more likely to be part of class 2, whereas people who own an e-bike are more likely to be part of class 1. More positive bicycle and

| | Class 2 | Class 3 |
|---|---|---|
| Delta | -1.18*** | -3.30*** |
| Male | -0.09 | -0.06 |
| Age | 0.13*** | 0.17*** |
| Employed | 0.62*** | 0.03 |
| Education | -0.02 | 0.11** |
| Urban Density | -0.08* | 0.25*** |
| Owns E-bike | -0.41** | -0.40 |
| Owns Car | 0.96*** | 0.19 |
| Owns Driver's License | 1.76*** | 0.12 |
| Car Attitude | 0.51*** | 0.10 |
| Train Attitude | -0.28*** | -0.10 |
| BTM Attitude | 0.17** | 0.41*** |
| Bike Attitude | -1.07*** | -0.73*** |
| Class 1 is the reference alternative. The parameters for this class are fixed to zero. | | |
| Significance of Robust T-ratio: * = 0.05, ** = 0.01, *** = 0.001 | | |

*Table 8.8: Class-membership parameter estimates*

car attitudes increase the likelihood of the respondent being part of classes 1 and 2, respectively. Attitudes towards public transport are a bit more ambivalent, with local transport (Bus, Tram and Metro) attitudes leading to increased probability of being part of class 3 while train attitudes mostly result in an increased probability of being part of class 1. In summary, the mode attitudes and ownership variables are congruent with the observed mode choice behaviours as given in Table 8.7.

The above analyses lead to the conclusion that the latent classes identified by the model can be described as modality styles, conform the expectations set out in the conceptual model. The classes are all a different modality style. The interpretations given to the classes in the remainder of this paper are as follows: class 1 is 'bike + car', class 2 is 'car mostly', and class 3 is multimodal.

The objective set out in the introduction of this paper is to find whether these modality styles moderate the effect of the weather on travel behaviour. To meet this objective, the weather parameters need to be analysed. These weather parameters are given in Table 8.9.

Two different methods are used to illustrate the effects of the parameter estimates. First, the model-level elasticities of travel time and weather are given. This serves to illustrate the relative effect of weather variables compared to travel time according to the model. Afterwards, we show the estimated choice probabilities for each class under various weather conditions to interpret the different effects of weather for each class. The model-level elasticities for travel time for each of the four modes and for the four weather variables are given in Table 10. These elasticities are calculated by separately increasing the respective values of each variable by 10% and then letting the model estimate new predictions. The natural log of the summed difference between the predicted likelihoods of choosing an alternative before and after changing these values by 10% are then divided by the natural log of 1.10 to get the elasticities presented in Table 8.10.

A few conclusions can be drawn based on the elasticities. First, the elasticities of travel time look relatively good and are generally compatible with values often found in the literature. There is one exception, namely the travel time elasticity of car. The effects of car travel time on mode

| Class | | PT | Bike | Walk |
|---|---|---|---|---|
| 1: Multimodal | Temperature | 0.068 | 0.101** | 0.049 |
| | Wind | 0.010 | -0.044 | 0.062 |
| | Rain | 0.157** | -0.134*** | -0.089* |
| | Solar Radiation | 0.152* | 0.110** | 0.091 |
| 2: Bike + Car | Temperature | 0.101 | 0.123*** | -0.111 |
| | Wind | 0.106 | -0.089 | -0.084 |
| | Rain | -0.048 | -0.073 | 0.018 |
| | Solar Radiation | -0.119 | 0.053 | 0.138 |
| 3: Car mostly | Temperature | -0.132 | 0.389** | 0.162 |
| | Wind | 0.109 | -0.394*** | -0.276*** |
| | Rain | -0.153* | -0.142* | -0.109 |
| | Solar Radiation | 0.057 | 0.033 | -0.174* |
| The car is the reference alternative. The parameters for this mode are fixed to zero. | | | | |
| Significance of Robust T-ratio: * = 0.05, ** = 0.01, *** = 0.001. | | | | |

*Table 8.9: Parameter estimates for the effect of weather on travel mode utility.*

| | Car | PT | Bike | Walk |
|---|---|---|---|---|
| Travel Time | | | | |
| Car | -0.049 | 0.72 | -0.0033 | -0.073 |
| PT | 0.048 | -0.50 | 0.000 | -0.011 |
| Bike | 0.18 | 0.28 | -0.40 | 0.16 |
| Walk | 0.093 | 0.10 | 0.016 | -0.90 |
| Weather | | | | |
| Temperature | -0.06 | -0.17 | 0.15 | -0.041 |
| Wind | 0.038 | 0.17 | -0.069 | -0.023 |
| Rain | 0.010 | 0.017 | -0.018 | 0.0020 |
| Solar Radiation | -0.027 | 0.053 | 0.037 | -0.017 |

*Table 8.10: Model-level elasticities of mode shares with respect to travel times and weather variables*

| | Weather | | | | Class 1: Bike + Car | | | | Class 2: Car Mostly | | | | Class 3: Multimodal | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Temp (°C) | Wind (m/s) | Rain (mm/h) | Sun ($W/m^2$) | CR[1] | PT[1] | BC[1] | WK[1] | CR[1] | PT[1] | BC[1] | WK[1] | CR[1] | PT[1] | BC[1] | WK[1] |
| Mean | 11.4 | 4.01 | 0.092 | 107 | 0.11 | 0.01 | 0.87 | 0.01 | 0.75 | 0.01 | 0.22 | 0.02 | 0.26 | 0.19 | 0.41 | 0.13 |
| Rainstorm | 10 | 15 | 1.5 | 25 | 0.35 | 0.01 | 0.63 | 0.01 | 0.89 | 0.01 | 0.08 | 0.02 | 0.66 | 0.26 | 0.04 | 0.04 |
| Overcast | 10 | 3 | 0 | 10 | 0.12 | 0.01 | 0.86 | 0.01 | 0.76 | 0.01 | 0.21 | 0.02 | 0.24 | 0.17 | 0.41 | 0.18 |
| Wind, Rain | 10 | 7 | 1 | 100 | 0.22 | 0.01 | 0.76 | 0.01 | 0.83 | 0.01 | 0.14 | 0.02 | 0.5 | 0.21 | 0.19 | 0.1 |
| Near freezing | 2 | 4 | 0 | 100 | 0.13 | 0.01 | 0.85 | 0.01 | 0.79 | 0.01 | 0.17 | 0.03 | 0.33 | 0.35 | 0.21 | 0.12 |
| Mild, clear | 15 | 2 | 0 | 150 | 0.09 | 0.01 | 0.9 | 0.01 | 0.71 | 0.01 | 0.27 | 0.02 | 0.17 | 0.11 | 0.6 | 0.12 |
| Warm, sunny | 20 | 2 | 0 | 250 | 0.06 | 0.01 | 0.92 | 0.01 | 0.66 | 0.01 | 0.31 | 0.02 | 0.12 | 0.07 | 0.74 | 0.08 |

1: CR = Car, PT = Public Transport, BC = Bicycle, WK = walk

*Table 8.11: Estimated choice probabilities for a median distance commute trip under various weather conditions.*

choice for the active modes is in the wrong direction, and the elasticity of car-use on car travel time is relatively low. The model is unable to effectively disentangle the effects of these travel times because of the high correlations between car and active mode travel time in the revealed preference data we used. Second, most weather elasticities seem to be about one order of magnitude smaller than the travel time elasticities. There are some exceptions, namely the elasticity of bicycle w.r.t. temperature (0.15) and the elasticity of public transport use w.r.t. wind (0.17). These values indicate that the effects of the weather are small compared to the effects of travel time.

Now the varying effects of the weather on mode use for the three different modality styles can be analysed, which is done by showing the estimated choice probabilities for each class under various weather conditions. This allows for an easy interpretation of the effect of the weather on the mode choice behaviour of each latent class. Reference weather scenarios are used to calculate these choice probabilities. The weather scenarios are realistic (if for some scenarios extreme) weather patterns for the weeks in which the data were collected, namely late Summer – Autumn in the Netherlands. The reference weather scenarios and the choice probabilities in these scenarios are given for a commute trip with median travel times in Table 8.11. When interpreting this table, one should keep in mind that this is a relatively short trip and thus that bicycle and walking mode shares are relatively high.

Interpreting Table 8.11, one can first see that the weather can have a sizeable effect on predicted travel demand, especially for the active modes. However, the effects of travel time and travel purpose variations on predicted choice probabilities, as seen in Table 8.7, were larger and more varied. This is in-line with the elasticities reported earlier in Table 10. Second, on a general level the results show that temperature and solar radiation have a positive effect on the use of active modes, whilst wind and rain negatively affect the shares of these modes, again mostly congruent with the elasticities.

Finally, we can see that the effect sizes of the weather variables vary markedly across the classes. The effect on public transport use is greatest by far for the multimodal class, which makes sense given the fact that this class uses public transport (much) more frequently than the other classes. In general, the relative stability of predicted choice probabilities for both the 'bike + car' and 'car mostly' classes contrast sharply to the variation that can be seen for the multimodal class. The effect is clearest for the two most extreme days given here. For the rainstorm day, the predicted use of the bicycle is reduced from 0.41 to 0.04 for the multimodal class, which is accompanied by an increase of the car share from 0.26 to 0.66. The bike + car segment also sees a decrease of the bike share, but it is relatively much smaller (from 0.87 to 0.63). On the other end of the weather spectrum, warm and sunny weather induces multimodal travellers to use the bicycle more often (0.41 to 0.74), an effect that is decidedly smaller for both the 'bike + car' (0.87 to 0.92) and the 'car mostly' (0.22 to 0.31) modality styles. The latent classes, earlier identified as modality styles, thus clearly moderate the effect of the weather on travel behaviour. The more multimodal third class is most sensitive to weather effects, whereas the least multimodal second class is least sensitive to weather effects.

## 8.5 Conclusion & Discussion

This paper set out to investigate whether travellers with a more multimodal modality style are more sensitive to changes in the weather circumstances of their travels. This idea is investigated using a latent class choice model, which estimates separate effects of the weather for different parts of the population, segmented by modality style. The results show that the effects of weather conditions on mode choices do indeed differ between three identified modality styles, that is, (1) bike + car; (2) car mostly and (3) multimodal. For the more multimodal third class, the use of the sustainable modes is more strongly affected by weather conditions when compared to the first, less multimodal class. Inclement weather (wind, rain) has a much greater impact on the use of the bicycle for the third class. Simultaneously, the least sustainable second modality style, which mostly consists of car use, is also affected to a lesser extent by weather conditions. More pleasant weather conditions are for the most part unable to entice people within this segment to use more sustainable modes.

These findings have several research implications, both for the literature on weather and travel behaviour and for the literature on multimodality. This paper has uncovered heterogeneity with respect to the effect of weather on travel behaviour on the level of the individual traveller using revealed preference data. This is to the best of our knowledge the first paper to do so, complementing similar findings on stated preference data by Heinen (2011) and Motoaki and Daziano (2015). Simultaneously we are able to effectively capture modality styles using latent class choice models, which has only rarely been done before (for example by Vij et al. (2013)). This approach enables us to provide more behavioural insight into the modality styles compared to the more often used clustering approaches, as behavioural parameters can be estimated for each group. This allows us to not only use the mode choices as indicators of modality styles, but also to see (and ideally, understand) how these mode choices came to be. In other words, the ability to capture modality styles in choice models allows us to show and explain intra-personal heterogeneity in mode choice behaviour and link that heterogeneity to the modality style.

The findings reported in this paper shed a new light on the concept of multimodality, as they suggest that multimodality should not be the primary goal of transport policies. More multimodal travellers are less likely to keep using sustainable modes after exogenous variation has decreased the utility of these modes, in contrast to less multimodal travellers. On the other hand, more multimodal travellers are more likely to use sustainable modes if exogenous variation increases the utility of these modes. To make matters more concrete, from the perspective of sustainability, the less multimodal 'bike + car' group can be preferable compared to the multimodal segment, especially for people who travel relatively shorter distances. In our view, policy makers should thus not focus as much on the concept of multimodality. Rather, they should make more sustainable travel modes more attractive and focus on decreasing unimodal car use. The concept of multimodality thus can still be useful, but it should be applied with more reference to the actual sustainability of the modes in question and the behavioural change that leads to the more multimodal travel pattern. There are two other, slightly more speculative practical implications of this paper. First, we find that more experienced cyclists are less susceptible to adverse weather conditions, as are people who own an e-bicycle. These results would suggest that policy makers could increase bicycle use in adverse conditions both by getting people to ride bicycles in more welcoming weather conditions first and by increasing electronic bicycle adoption. An important disclaimer here is that the direction of causality could realistically (partly) run in the opposite direction: more weather-resistant people are more likely to cycle more often and to buy an electronic bicycle. Second, our finding that the weathers effects are heterogeneous in the population could lead to more detailed forecasts of how climate change will alter travel demand. The effects of the weather are very much specific to the geographical region at hand and the specific effects of climate change are also to some extent region dependent. Our findings do however confirm once again that climate change will not only affect travel infrastructure, but also travel demand and that policy makers are advised to take this into account in planning infrastructure investments.

There are several limitations of this paper, which could be inspiration for future research. First, all choices were observed for trips during late Summer and Autumn in the Netherlands. This means that no seasonal variation was observed and that the weather range is relatively limited. Future research into inter-individual heterogeneity of the effect of weather on travel behaviour might use data from regions with more extreme climates or data from an entire year to fill this remaining research gap. Second, research could try to enumerate the effects of the weather in terms of travel costs. This would enable policy makers to understand the effects of climate change on travel demand in monetary terms, which could be useful for example in travel infrastructure appraisal. Third, this paper uses the weather as one example of exogenous variation. To further substantiate our conclusions, that certain modality styles are more sensitive to exogenous variation, other examples of exogenous variation might be used instead. Future research could use the ability to identify modality styles using latent class choice models to give more behavioural insight into the modality styles. A useful approach would be to investigate the sensitivity of different modality styles to other (not weather-related) exogenous variation in travel circumstances. Finally, future research might cross-validate findings from different methods to identify modality styles (latent class cluster analysis, latent class choice models, other clustering techniques) on a similar data set. This would provide additional robustness to findings pertaining to modality styles with any of the cross-validated methods.

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# Chapter 9

# Estimating the effects of life-events and mobility tool ownership on mode choice behaviour

Abstract:

*Mode choice is an essential subject within travel behaviour research. Typically, mode choice has been studied using cross-sectional (discrete choice) models, which assume that all choices are made simultaneously. In this study, we relax this assumption by explicitly incorporating the time when a choice is made within the modeling framework, using a latent transition choice model. This model allows for the identification of the effects of life-events and (changes in) mobility tool ownership on mode choice probabilities over time. To estimate the model, data from the Netherlands Mobility Panel gathered between 2016 and 2022 are used. The model identifies two latent classes, 1) a car-dependent modality style and 2) a multi-modal modality style. The transition probabilities between these classes in-between two consecutive waves are estimated, as well as the effects of life-events and mobility tool ownership on these transition probabilities. We find substantial and statistically significant effects from changes in vehicle ownership on the transition probabilities, indicating that electric bicycle ownership leads to a substitution of the car towards the bicycle on shorter-distance trips even after controlling for lead- and self-selection effects.*

## 9.1 Introduction

Mode choice analysis is a fundamental subject within travel behaviour research (McNally, 2000). The dominant approach to modelling mode choice behaviour has been based on utility-maximization discrete choice theory since the 1970s (McFadden, 1974; Train, 2009). Traditionally, discrete choice models are employed in a static fashion, meaning that they do not consider changes in preferences over time (Ben-Akiva et al., 1997). Given the habitual nature of travel behaviour (Aarts & Dijksterhuis, 2000; Gärling & Axhausen, 2003) this assumption seems reasonable. Habits can often be difficult to break, frustrating policymakers' efforts to change travel behaviour. But behavioural changes do occasionally occur (Schwanen et al., 2012; Strömberg et al., 2016). Moreover, from a policy perspective, understanding when individuals change their travel behaviour and travel preferences is vital information for crafting policies to achieve desired behavioural changes. Such periods of change can be seen as 'windows of opportunity', where policies can have a larger impact on behavioural change.

One research stream focusing on behavioural change is the mobility biographies framework, where the study of behavioural change has focused on life-events, such as residential relocations, starting families, or changing jobs (Müggenburg et al., 2015; Rau & Manton, 2016). In this literature, these life-events are then seen as windows of opportunity for behavioural change (Scheiner, 2017). Previous work has indeed shown that people's habits are indeed prone to change during these events (de Haas et al., 2018; Müggenburg et al., 2015). Aside from life-events, which are more general changes as one goes through life, research has also investigated the effects of mobility tool ownership, such as vehicle or public transport card ownership, on travel behaviour (Loder & Axhausen, 2018; Nurul Habib et al., 2018; Scott & Axhausen, 2006). However, these studies have only looked at the effect of life-events on mode use (Gao et al., 2023), rather than on mode choice. Mode use here is defined as the result of both the trip generation process (which trips will a certain person make) and the mode choice process (given a certain trip, which mode will a certain person choose). Since mode use combines both trip generation and mode choice, studies that focus on mode use, for example in terms of total kilometres or number of trips travelled with certain travel modes, cannot disentangle possible changes in trip-generation from changes in mode choice preferences. Furthermore, these studies typically use clustering approaches (de Haas et al., 2018; Olde Kalter et al., 2021) as opposed to discrete choice modelling techniques. Consequently, they have not been able to study how attribute tastes and preferences change as a result of life-events.

In a separate research stream emerging in the last decade, some transport researchers have developed longitudinal choice models to study mode choice behaviour (Xiong et al., 2015; Zarwi et al., 2017). These longitudinal choice models enable the study of evolving preferences over time. However, this previous work however did not focus on the effects of multiple changes within the individual, such as life-events. Zarwi et al. (2017) studied the effects of changes to the transportation system, whereas Xiong et al. (2015) looked at one set of general 'life-stages'.

This paper intends to further combine the fields of mobility biographies, including mobility tool-ownership, and the longitudinal study of mode choice behaviour. The main aim is to study how individual characteristics, including life-events and changes in mobility tool ownership, shape mode choice preferences over time. To achieve this objective, we will employ the relatively rare latent transition choice model. This model is an extension of a normal latent class choice model, where time dynamics are explicitly considered in the class-membership function and individual respondents' transitions between classes over time are modelled explicitly. As a result, it is a relatively parsimonious way to effectively model the change of mode choice preferences over time. The model utilizes panel data from the Netherlands Mobility Panel (MPN), which is enriched with the life-events and changes in mobility tool ownership.

## 9.2 Literature Overview and Conceptual Model

In this section, we will introduce the relevant literature and use it to build a conceptual model that will guide the analyses in this paper. The literature overview consists of three building blocks: first, we will provide an overview of studies into behavioural change. Second, we will look at mode choice analysis and the idea of modality styles and third, we provide an overview of the literature on longitudinal choice models in travel behaviour research. Finally, we synthesize the findings from these building blocks in a conceptual model.

### 9.2.1 Behavioural change in transportation

One subject area within travel behaviour research is that of the inertia that is present when people make decisions. This area works under the assumption that decision makers' choices are driven to some extent by habits, contrasting the usual assumption of full rationality for each new choice situation that underlies typical choice models (Aarts & Dijksterhuis, 2000; Gärling & Axhausen, 2003; Neal et al., 2012). The formation and breakdown of these habits are key topics of interest. Moments when habits are broken down are seen as the key windows of opportunity for changing people's travel behaviour. Two such potential 'habit-breaking' moments are life-events and changes in mobility tool ownership (Clark et al., 2014; Gao et al., 2023; Janke & Handy, 2019).

Life-events are key events in one's life course that entail a disruption to day-to-day life (de Haas et al., 2018; Müggenburg et al., 2015), therefore breaking habitual travel behav-iour. Such events can be related to family life (childbirth, marriage, leaving the home, residential relocations) and employment (gaining or losing employment, gaining or losing working from home abilities; Gao et al. (2023)). These life-events can prompt a person to re-evaluate their habitual behaviour and thus provide a critical window of opportunity to enact behavioural change (Janke & Handy, 2019; Kløckner, 2013). Up to this point, the longitudinal studies on life-events in travel behaviour research has focused on cluster analyses (de Haas et al., 2018; Kroesen, 2014). These analyses reveal shifts in travel patterns, but they are unable to show changes in attribute preferences and elasticities as a result of the life-event.

Another area of travel behaviour research focuses on so-called mobility tools: vehicles, drivers' licenses, and (discount) passes for public transport(Scott & Axhausen, 2006). The acquisition of these tools is based on longer-run expectations of mobility needs. Simultaneously, these tools allow their owners to more easily, cheaply, and/or effectively use certain transport modes. As a result, they create lock-in effects (Scott & Axhausen, 2006): owning a car makes the car a more attractive option even for trips that might be more suitable to the bicycle or public transport. Consequently, mobility tool ownership is closely linked to the existence of travel habits and could be a crucial explanation for the modality styles introduced above.

### 9.2.2 Mode choice analysis and modality styles

Discrete choice modelling has been a cornerstone of travel behaviour research since the introduction of random utility-maximisation theory within discrete choice analysis (McFadden, 1974). Two impactful applications of these models are the estimation of the value of travel time, typically using stated preference data based on route choices (Small, 2012; Wardman et al., 2016), and the modelling of mode choice in large-scale travel demand models (Ben-Akiva & Lerman, 1985; Train, 2009). One key improvement on the discrete choice theory workhorse, the multinomial logit model, is that of the nested logit model (Carrasco & Ortúzar, 2002; Daly & Zachary, 1979; Williams, 1977). The nested logit model groups subsets of alternatives that are similar in some unobserved characteristics, enabling it to remove the irrelevance of independent alternatives (IIA) property of the multinomial logit model. This improvement is highly relevant in the case of mode choice analysis, as some modes compete more with other similar modes than they do others (Train, 2009).

Owing to the exponential increase in computing resources, the investigation of preference-heterogeneity within the population rose to the forefront of modeling efforts since the 1990s. For example, much interest has been paid to the distribution of the value of travel time across the population (Cirillo & Axhausen, 2006; Fosgerau, 2006; Hensher & Greene, 2003; van Cranenburgh & Kouwenhoven, 2021). Simultaneously, for mode choice analysis, research has shown how preferences for various modes vary across the population (Bhat, 2000; Cherchi et al., 2017). One concept that helps to communicate heterogeneity in mode choice preferences is that of modality styles. Modality styles are discrete segmentations, based on variations between people in underlying preferences to use certain modes (Diana & Mokhtarian, 2009; Molin et al., 2016; Vij et al., 2013). Typically, these modality styles are uncovered using clustering methods, where people are grouped based on the number of times they make use of certain travel modes (Faber et al., 2022). Another method to identify these modality styles is the latent class choice model (Faber et al., 2022; Keskisaari et al., 2017; Prato et al., 2017; Vij et al., 2013). Using this method has the advantage that it ties the concept of modality styles into discrete choice theory.

### 9.2.3 Longitudinal Choice Modeling and Latent Transition Choice Model

Traditionally, choice models have been employed in a static, time-indifferent, fashion (Train, 2009). These models are agnostic to the process or order of the choices made and therefore operates under the implicit assumption that (from the modellers' perspective) all choices are made more or less simultaneously. As a result, the time when a choice is made is not considered in the modelling process. We want to note that for many, perhaps even the vast majority of choice modelling, this assumption is completely valid (Ben-Akiva et al., 1997). However, this static paradigm does entail that the analyst is unable to determine the effects of changes in characteristics, either on the level of the trip or the decision-maker, on the choice probabilities over time (Hamaker, 2012). Instead, differences between respondents can be used to estimate the effects of certain characteristics. These ef-fects are then often assumed to be similar to longitudinal changes within respondents over time, for example when the choice model is used to forecast future travel demand after some changes have been made. The problem with this method is that it is uncertain whether the between-respondent effects are similar to the effects within respondents. Take for example the potential effect of electric bicycle ownership. Within a static approach, a model might estimate the effect of e-bike ownership on bicycle choice probability by comparing the difference in choice probabilities across respondents that either do or do not own such a vehicle. However, it is not unlikely that respondents who own an electric bicycle are more avid cyclists in the first place, which prompted them to buy an e-bike. There is thus likely to be a rather strong self-selection effect, making it difficult to ascertain the effect that electric bicycle ownership would have on the choice behaviour of people who do not yet own such a vehicle.

Two potential approaches to solve this problem are commonly found in the literature: first, and most prevalent, is the use of stated preference data. These analyses explicitly ask respondents to make choices considering hypothetical scenarios, where the researcher is free to design the experiment, and they can vary the attributes or scenarios associated with certain choices. In our example, respondents could be prompted to make choices between the bicycle and the car, first without considering electric bicycle ownership and then in the hypothetical scenario where they did own such a vehicle. However, as stated preference choices are made 'on paper' they suffer from a potential lack of external validity (Louviere et al., 2000; Murphy et al., 2005). For example, respondents might not be familiar enough with an electronic bicycle to give reliable estimates of how owning such a vehicle would change their mode choice behaviour.

The second solution is to use multiple measurements per individual, ideally taken across a wide enough range of time, and to then explicitly model the time when the choices are made within the modelling context (Ben-Akiva et al., 1997). One example of such a choice model is the latent transition choice model, also known as the Markov choice model (Ben-Akiva et al., 1997; Liao et al., 2018; Xiong et al., 2015; Zarwi et al., 2017). The latter name derives from the Markov process, where the probability of each event only depends on the state of the previous event and not on any previous states. The former name, which we prefer to use in this article as it aligns more closely with common nomenclature in the field of travel behaviour research, originates from latent transition cluster modeling, which has been a popular approach to study longitudinal data in the field of travel behaviour research for some time (see for example Kroesen (2014)). The model works by allowing the class membership probabilities, estimated on the level of the individual, to change over time (Anderson, 1954; Böckenholt & Langeheine, 1996; Wiggins, 1955). These changes, or transitions, can then be affected by external factors or other changes within the individual, such as life-events or changes in mobility tool ownership. As a result, these models allow for the modeller to estimate the effects of changing circumstances or explanators of choice behaviour on the level of the individual. It therefore allows us to estimate the effect of certain characteristics on choice behaviour within individuals.

### 9.2.4 Conceptual Model

The relationships in the literature mentioned above are graphically summarized below in Figure 9.1. This conceptual model is then used to further guide the analyses in the paper.

To build the conceptual model, we start with the discrete choice building block, which assumes that observed mode choices can be explained using both the observed and unobserved attributes of each travel mode alternative for the trip. In this study, we will use alternative specific travel times and travel distances as these attributes. We then assume that distinct modality styles exist, and we let the effect of the attributes on mode choice vary across these modality styles. Then we allow socio-demographic factors, life-events, and mobility tool ownership to affect the class

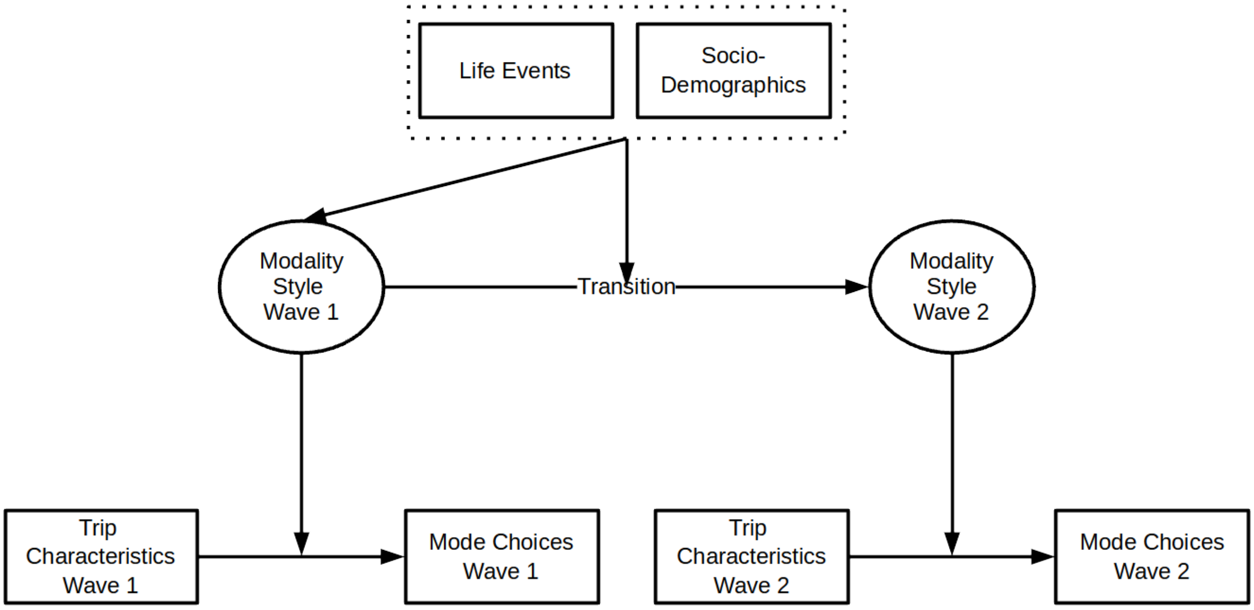


*Figure 9.1: Conceptual model of the latent transition choice model*

membership probability of these modality styles. Following the reasoning that the modality styles are largely inert, class membership in the first wave affects class membership in the second wave. Finally, we include a moderating effect of life-events, (changes in) mobility tool ownership, and socio-demographic factors on the probability that someone switches between modality styles.

## 9.3 Research Methods

### 9.3.1 Mathematical Model

The latent transition choice model builds on the standard latent class choice model, with the addition of latent transition parameters, which are used to estimate the class transition probabilities between the longitudinal waves. For an overview of the mathematical definition of the latent class choice model, the reader is referred to (Ben-Akiva et al., 1997) and (Hess & Daly, 2014).

For the latent transition choice model, the log-likelihood function for observing $a$ series of choices $k$ made by decision maker $n$ belonging to class $s$ at timepoint $t$, with alternatives $i$, can be written as a function of taste parameters $\beta_s$. The taste parameters are thus conditional on decision maker $n$ belonging to class $s$ at wave $t$ in equation 9.1:

$$LL(\beta) = \sum_{n=1}^{N} \ln \prod_{t=1}^{T} \sum_{s=1}^{S} \pi_{n,t,s} \left( \prod_{k=1}^{K} P_{n,t}(i_{k,t}|\beta_s) \right) \tag{9.1}$$

The key addition here is that the class-membership probability $\pi$ is dependent on the wave $t$ at which the choice was made. The class-membership function of the latent classes for wave 1 follows conventional standards and is estimated as a multinomial logit function based on a class-specific constant $\delta_s$, as well as function $g$ of a vector of parameters $y_s$ and a vector of socio-demographic characteristics, life-events, and mobility tool ownership $z_{n,t}$, as given in equation 9.2.

$$\pi_{n,s,t=1} = \frac{\exp(\delta_s + g(\gamma_s, z_{n,t}))}{\sum_s \exp(\delta_s + g(\gamma_s, z_{n,t}))} \tag{9.2}$$

The class-membership function of the latent classes for the second wave, however, is specified to be conditional on the class-membership probability of the first wave. The transitions between the classes are then modelled as in equation 9.3, where the probability that a decision maker n who belonged to class $r$ in wave 1 will belong to class $s$ at wave 2 is equal to the transition probability $tr_{n,s,r}$ of class $r$ to class $s$, multiplied by the class-membership probability of belonging to class $r$ in wave 1:

$$\pi_{n,s,t=1} = \sum_{s=1}^{S} \sum_{r=1}^{R} (tr_{n,s,r})(\pi_{n,t=1,r}) \tag{9.3}$$

These transition probabilities themselves are modelled as multinomial logit functions as well, such that the transition probability depends on a transition parameter $\varphi_{s,r}$ associated with the transition from class r at the previous wave to class s at the current wave and a function g of both parameters $y_{s,r}$ and a vector of sociodemographic characteristics, life-events and (changes in) mobility tool ownership $z_{n,t}$, as given below in equation 9.4:

$$tr_{n,s,r} = \frac{exp(\phi_{s,r} + g(\gamma_{s,r}, z_{n,t}))}{\sum_s exp(\phi_{s,r} + g(\gamma_{s,r}, z_{n,t}))} \tag{9.4}$$

### 9.3.2 Research data

We use trip data from the travel diary of the Netherlands Mobility Panel ([MPN], for more information see Hoogendoorn-Lanser et al., 2015), a household panel in the Netherlands that comprises an extensive questionnaire and a 3-day travel survey. Respondents for the MPN are recruited from the Kantar NIPObase, an invite-only internet access panel (IAP). Invitations for the Kantar NIPObase are sent out based on register data. Members of the larger NIPObase IAP are then invited for the MPN separately, based on their socio-demographic characteristics. Between 30 and 50% of respondents from the larger IAP decide to join the MPN upon receiving an invitation. When respondents have entered the MPN, their yearly response rates for each wave vary around 85%.

We use data from the yearly waves between 2016 and 2022. For each unique respondent, we select one set of two consecutive waves. If there were sets of consecutive waves where life-events or changes in mobility tool ownership happened between the two waves, then we always selected one of these sets. This procedure ensures that the final dataset contains as many life-events and changes in mobility tool ownership as possible. If no life-events or changes in mobility tool ownership happened, then one set of consecutive waves is drawn at random for each person. The sample descriptives for the final sample, as collected during the first wave used in the dataset, is given in Table 9.1.

The sample descriptives are very similar to the population values for nearly all variables. The only exception is household type, as our sample consists of comparatively more households with children. This is most likely the result of the biased sampling procedure introduced above, where

| | | Sample (%) | Population (12+ inhabitants of the Netherlands, 2019; %) |
|---|---|---|---|
| Gender | Male | 48 | 50 |
| | Female | 52 | 50 |
| Age (Years) | 12-24 | 14 | 18 |
| | 25 – 44 | 30 | 28 |
| | 45 – 64 | 35 | 33 |
| | 65 + | 21 | 21 |
| Education | Low | 30 | 34 |
| | Medium | 36 | 40 |
| | High | 34 | 26 |
| Urban Density residential municipality (addresses/m$^2$) | $< 500$ | 8 | 8 |
| | 500-1000 | 22 | 22 |
| | 1000-1500 | 17 | 16 |
| | 1500-2500 | 32 | 30 |
| | $> 2500$ | 22 | 25 |
| Household Type | Single | 22 | 20 |
| | Only adults | 31 | 46 |
| | Adults and children | 46 | 34 |

*Table 9.1: Sample descriptives compared to population distribution*

we purposefully oversampled sets of waves that include life-events. As life-events are more common within households with children, these types of households will be oversampled as well. This enables us to identify the effects of life-events on the transition probabilities more reliably.

The primary unit of analysis of the mode choice model is the trip. Principally, we analyse trips as recorded by respondents in each waves' travel diary. However, not all trips in the travel diary are useful for our analysis. Therefore, some selection criteria are used. First, only trips that departed from the residential location were selected, as the residence is typically the location where the mode choice decision is made. Second, all trips made with modes other than the car, public transport, the bicycle, or on foot were discarded. The shares of the other modes are marginal, and estimating valid attribute-parameters for them is therefore not feasible. Third, trips for which a very large distance ($> 200km$) was reported are excluded, as the decision-making process for such trips differs from that of the more typical, daily trips. These selection criteria leave us with a total number of 28,117 trips made by 4,789 unique respondents.

### 9.3.3 Operationalisation

We use alternative-specific travel times and travel distances as the trip-specific explanatory variables in the model. These travel times and -distances are calculated using the Google Directions API based on the origin, destination, and departure time of the trip. In the utility function, we use both a linear and a square root transformation of travel time for each mode to capture possible non-linear effects of travel time on the utility of each mode. Travel distance is used in the utility

| | | Min. | Mode | Mean. | Max. |
|---|---|---|---|---|---|
| Travel Time (min.) | Car | 1 | 7 | 12.5 | 141 |
| | Public Transport | 1 | 22 | 34.5 | 2234 |
| | Bicycle | 1 | 10 | 31.9 | 671 |
| | Walking | 1 | 33 | 114 | 2373 |
| Travel Distance (km) | Bicycle | 0.1 | 2.9 | 10 | 212 |
| | Walking | 0.1 | 2.6 | 9.2 | 195 |

*Table 9.2: Descriptive statistics for the alternative-specific travel times and travel distances of all trips in the dataset*

function of the active modes. Finally, aside from alternative specific constants for all trips we also use a dummy-variable for trips that are made with other people. This dummy variable is used to correct for the fact that such shared trips are more often made with the car compared to the other modes, allowing for better estimates of the travel time and travel distance parameters. This dummy variable is kept fixed across the latent classes. The final utility functions then are given in equation 9.5 below. Note that the parameter pertaining to travel distance is only estimated for the active modes.

$$Utility = asc + dummy_{sharedtrip} + \beta_{traveltime} + \beta_{\sqrt{traveltime}} + \beta_{traveldistance} \tag{9.5}$$

The utility functions are kept relatively simple, to balance with the complexity of estimating the transitions between latent classes. Estimating both a very complex utility function and the transition parameters would quickly lead to an over-specified model. For the travel times and travel distances, which are the key explanatory variables in the utility functions, descriptive statistics are given in Table 9.2.

In the class-membership and transition functions, we use socio-demographic characteris-tics, life-events, and (changes in) mobility tool ownership. For the life-events and (changes in) mobility tool ownership, we have used the variables given in Table 9.3, which are presented together with their absolute and relative occurrence in the sample. The correlations between these variables are not very high, with the exception of the variables pertaining to car ownership and access to cars. The highest correlation here however is 0.68, and therefore there are no strong concerns regarding multicollinearity.

## 9.4 Results

This section presents and discusses the main results. First, we show the goodness-of-fit of increasingly complex models, starting with a multinomial logit model and ending with a latent transition choice model which includes covariates. We show that the latter model provides the best fit to the data. Then, the class-specific parameters of this model are introduced, and we show that the latent classes can be interpreted as modality styles, as they reflect underlying predispositions to use certain travel modes. We will then discuss the class-membership results, which is followed by a discussion of the transitions between the two classes.

| | Occurrence (N; %) |
|---|---|
| **Life-events** | |
| Residential relocation | 290 (6.1%) |
| Change of job | 558 (12%) |
| Birth of a child | 147 (3.1%) |
| Shift to working from home | 204 (4.5%) |
| **Mobility Tool Ownership** | |
| Car ownership | 3,405 (71%) |
| Always has access to car | 2,910 (61%) |
| Never has access to car | 915 (19%) |
| E-bike ownership | 955 (20%) |
| Owns Personal Public Transport Card | 3,282 (69%) |
| **Changes in Mobility Tool Ownership** | |
| Gained personal car | 260 (5.5%) |
| Lost personal car | 223 (4.6%) |
| Gained access to car | 303 (6.3%) |
| Lost access to car | 220 (4.6%) |
| Gained electric bicycle | 515 (11%) |
| Gained public transport card | 181 (3.8%) |
| Lost public transport card | 175 (3.7%) |

*Table 9.3: List of life-events and mobility tool ownership variables and their occurrence in the data*

### 9.4.1 Model Selection

The choice models are primarily estimated in Apollo (Hess & Palma, 2019a, 2019b). As the model is non-trivial to implement in Apollo, we validated the results by using a separate implementation in Matlab. To test whether the latent transition choice model offers an empirical benefit over more parsimonious models, we estimated six models, each increasing in complexity. Table 9.4 contains the goodness-of-fit statistics of these six models:

1. A MNL model
2. A nested logit model
3. A conventional latent class choice model
4. A latent class choice model that allows for the sizes of the classes to vary per wave
5. A latent transition choice model
6. A latent transition choice model with covariates

From the second model onwards, a nesting structure is used, with one nesting level. The root level contains the car and one nest, which contains the alternatives public transport, the bicycle, and walking. This nesting structure is based on the idea that public transport, the bicycle, and walking substitute each other more directly than they do the car. A comparison of the second model with

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| | MNL-model | Nested Logit model | 2 class latent class model | 2 class latent class model. change size across waves | 2 class latent transition choice model. No covariates | 2 class latent transition choice model. With covariates |
| Est. parameters | 10 | 11 | 20 | 21 | 22 | 80 |
| | | | **Goodness-of-fit statistics** | | | |
| N (individuals) | | | 4 789 | | | |
| N (choices) | | | 28 117 | | | |
| $LL_0$ | | | -37 923 | | | |
| $LL_\beta$ | -20 421 | -19 941 | -17 350 | -17 350 | -17 279 | -16 682 |
| Mean $LL_\beta$ per person | -0.724 | -0.706 | -0.617 | -0.617 | -0.616 | -0.586 |
| $\rho^2$ eq. shares | 0.462 | 0.474 | 0.543 | 0.543 | 0.544 | 0.560 |
| $\rho^2$ obs. shares | 0.314 | 0.331 | 0.418 | 0.418 | 0.420 | 0.440 |
| AIC | 40 863 | 39 904 | 34 740 | 34 742 | 33 937 | 33 525 |
| BIC | 40 946 | 39 994 | 34 905 | 34 915 | 34 784 | 34 185 |
| | | | **Cross-validation** | | | |
| $LL_\beta$ per obs. In sample | -0.731 | -0.715 | -0.622 | -0.622 | -0.619 | -0.598 |
| $LL_\beta$ per obs. Out of sample | -0.706 | -0.689 | -0.600 | -0.600 | -0.597 | -0.578 |
| % Diff. | -3.57% | -3.61% | -3.52% | -3.52% | -3.53% | -3.37% |

*Table 9.4: Goodness-of-fit statistics for the choice models*

the first model reveals whether this nesting structure improves model fit. Based on the literature and the conceptual model, we expect this to be the case for mode choice analysis on our revealed preference dataset. A more complicated nesting structure was tested where the active modes were separated into a further subnest, but this structure offered no improvement.

The third model explores whether people's preferences for mode alternatives are heterogeneous by estimating two separate latent classes. For the sake of parsimony in what is otherwise already a relatively complex model, we decided to fix the number of classes to two for all latent class models. Adding additional latent classes would result in an exponential growth of possible transitions and, therefore, transition parameters. Given the relatively modest probability of transitions between classes, we think that the dataset is not large enough to support more than two latent classes.

The fourth model can capture behavioural changes across the population, which would result in different class sizes for the two waves. However, this model is not able to estimate which individuals' behaviour has changed. The fifth model, the latent transition choice model, is an improvement in that respect, as it can now assess which individuals transition between the estimated latent classes. Then, finally, we report a model (model 6) with covariates of both the initial class-membership and transition probabilities. This model enables an estimation of factors that influence the transition probabilities. These allow for much richer behavioural interpretations of the results.

As can be seen in Table 4, the nested logit model (model 2) provides a much better fit to the data than the MNL model 1, indicating that there are nesting structures in the mode choice data. Furthermore, the nesting parameter lambda, is found to be significantly different from 1 (not reported in Table 4), which also indicates the presence of nesting structures. The latent class models, starting with model 3, outperform the standard models, indicating the presence of mode choice heterogeneity. Model 4 does not provide a better fit to the data than model 3, meaning there are no substantial changes in mode choice behaviour across the population between the two waves. The transition model, model 5, however, provides a statistically significant better fit than both previous latent class models (LRT =142, df = 1, $p < 0.001$). It also performs better in the 5-fold cross-validation tests, where the dataset is split into five parts and the model is subsequently estimated

| | Class 1 | | | | Class 2 | | | |
|---|---|---|---|---|---|---|---|---|
| | **Car** | **PT** | **Bicycle** | **Walking** | **Car** | **PT** | **Bicycle** | **Walking** |
| **ASC** | - | -1.77 (-9.15) | 0.76 (5.16) | 3.83 (18.7) | - | 1.22 (9.65) | 3.67 (22.7) | 5.23 (13.1) |
| **Shared Trip dummy** | - | -0.98 (-10.4) | -0.89 (-13.0) | -0.322 (-4.39) | Same as class 1 | | | |
| **Travel time** | 0.0176 (9.04) | | | | 0.026 (7.27) | | | |
| **Square root travel time** | -0.910 (-10.6) | | | | -0.86 (-10.05) | | | |
| **Square root travel distance** | - | - | -0.389 (-10.8) | -0.996 (-11.1) | - | - | -0.220 (-13.1) | -0.712 (-6.50) |
| **Nesting parameter** | 0.725 ($-7.45^{a}$) | | | | 0.493 ($-12.0^{a}$) | | | |

In this and following tables, robust t-ratios given between parentheses
a: Robust T-ratio with respect to 1

*Table 9.5: Estimated class-specific model parameters*

using four parts and tested on the remaining hold-out part. The model that uses covariates to determine the class-membership and transition probabilities (model 6) then statistically outperforms the latent class transition model without covariates (model 5) as well (LRT = 1193, df = 58, p $< 0.001$). This model will be used for further examination in the remainder of this paper.

## 9.4.2 Interpreting the latent classes as modality styles

Table 9.5 reports the class-specific parameter estimates. Note that these parameter estimates, which are conditional on class-membership, are stable over time and thus the same for both waves.

We find that the alternative-specific constants (ASCs) are very different for the two classes, which supports the notion that both classes represent modality styles that reflect underlying predispositions towards the use of certain travel modes. The ASCs of public transport, bicycle, and walking are all smaller for the first than the second class. This provides a first indication that the first class is in general more inclined towards the use of the car than the second class. Both travel time parameters are positive, but both square root travel time parameters are negative. The net effect of these parameters is that all modes' elasticities with respect to travel time are negative for both classes, as is to be expected. Similarly, travel distance has a negative effect on active mode use.

To provide a more intuitive picture of the mode choice differences between the two classes, we have calculated the conditional probabilities for each of the two classes for trips falling within several 'distance' bands. To do so, we used the average travel time per mode for all trips within the dataset that corresponded to a given distance. Note that this procedure introduces some noise, particularly for the longer distances, which average out travel times and travel distances over fewer trips. As a result, there are some fluctuations in the graph for distances lager than 10km. The estimated conditional probabilities for both classes and distances between 0 and 20 km are given in Figure 9.2.

Figure 2 shows that there is a large difference in conditional choice probabilities between the two classes. For the first class, the probability of using the car increases rapidly as distances increase. The car becomes the dominant mode around 2.5km and then the choice probability

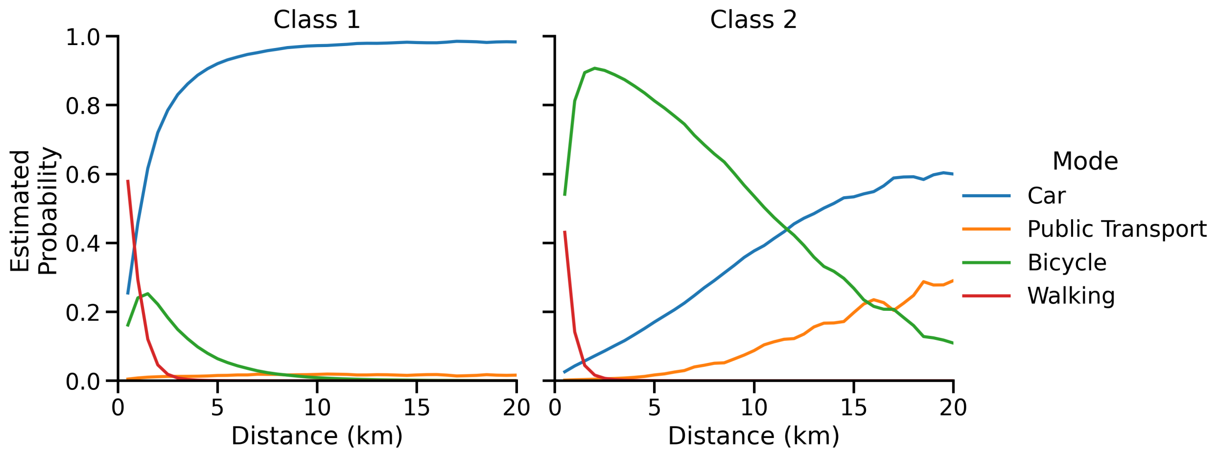


*Figure 9.2: Estimated conditional mode choice probabilities on average trips between 0 and 20 km*

asymptotically increases towards a choice probability nearing 1 for trips longer than roughly 10 km. For the second class however, the bicycle is the dominant mode up until trips of roughly 10 km in length. At that point the car becomes the most probable mode, followed by public transport. Based on these conditional mode choice probabilities for each class, we can identify the first class as 'Car-oriented' and the second class as 'Multimodal'. In the estimated choice model, roughly 60% of people belong to the 'car-oriented' class and 40% to the 'multimodal' class in the first wave.

### 9.4.3 Class-membership function

Now that the latent classes have been identified as two distinct modality styles ('car-oriented' and 'multimodal'), we interpret the class-membership function. The parameters estimated in the class-membership function show the relation between class-membership and socio-demographics, life-events, and (changes in) mobility tool ownership. These parameters are given in Table 9.6. Importantly, the class-membership function is specific to membership in the first wave, before any transitions might have happened. The life-events and changes in mobility tool ownership have thus not happened yet. The direction of the causal effect therefore is not clear: either people with certain behaviours are more likely to undergo life-events/changes in mobility tool ownership or people might already be aware of upcoming life-events and have already changed behaviour accordingly. Thus, there might be both selection effects (first option) or lead-effects (second option).

The socio-demographic and mobility tool ownership parameters show that the class-membership estimates are congruent with the earlier identification of the classes as modality styles. People who own a car, a driver's license, and always have access to a car are more likely to belong to the car-oriented modality style. Conversely, people who own electronic bicycles or public transportation cards are more likely to belong to the multi-modal modality style. Similarly, as expected, young people and people with lower incomes are more likely to belong to the multi-modal modality style as well.

| | Class 2: 'Multi-modal' (ref: class 1, 'Car-oriented') |
|---|---|
| delta | -1.06 (-2.36) |
| **Socio-demographics** | |
| Age <= 24 (ref: age 65+) | 1.11 (5.13) |
| Age 25 – 44 (ref. age 65+) | -0.0293 (-0.163) |
| Age 45 – 64 | -0.129 (-0.841) |
| Employed | 0.0828 (0.0653) |
| Works from home | -0.05 (-0.439) |
| Low income (ref: med income) | 0.269 (2.64) |
| High income (ref: med income) | 0.172 (1.15) |
| Children in household | 0.0790 (0.65) |
| Urban Density | -0.0547 (-0.84) |
| **Life-events (between wave 1 and wave 2)** | |
| New Job | -0.124 (-0.86) |
| Started working from home | 0.0793 (0.363) |
| Child Born | -0.564 (-2.20) |
| Residential Relocation | 0.063 (0.33) |
| **Mobility Tool Ownership**, wave 1 | |
| Personal Car | -1.12 (-6.02) |
| Access to Car, always | -1.91 (-13.9) |
| Access to Car, never | 0.443 (1.40) |
| Drivers' License | -2.01 (-5.50) |
| Electronic Bicycle | 0.938 (7.84) |
| PT-card | 0.396 (3.69) |
| **Changes in Mobility Tool ownership** (between wave 1 and wave 2) | |
| Lost personal car | 0.363 (1.84) |
| Gained personal car | -0.676 (-2.80) |
| Lost access to car[a] | 1.33 (6.95) |
| Gained access to car[a] | -0.892 (-4.06) |
| Gained electric bicycle | 0.840 (5.88) |
| Gained PT-card | 0.395 (1.85) |
| Lost PT-card | -0.42 (-1.51) |

*Table 9.6: Parameter estimates of the class-membership function for the first wave*

| | Transition 'Car-oriented' to 'Multi-modal' | Transition 'Multi-modal' to 'Car-oriented' |
|---|---:|---:|
| Transition parameter ($\phi$) | -7.84 (-3.71) | -5.50 (-4.53) |
| **Socio-demographics** | | |
| Age $\leq$ 24 (ref: age 25+) | 1.50 (2.80) | n.s. |
| **Life-events** | | |
| New Job | 0.785[a] (1.86) | n.s. |
| Started Working from Home | 0.66 (2.05) | n.s. |
| Higher Income | -1.91 (2.06) | n.s. |
| Residential Relocation | n.s. | 0.84[a] (1.77) |
| **Mobility Tool Ownership in first wave** | | |
| Access to Car, always | -1.08 (-2.38) | n.s. |
| Access to Car, never | n.s. | -1.32 (-1.97) |
| Electronic Bicycle | 1.26 (3.44) | n.s. |
| PT-card | 1.71 (2.84) | n.s. |
| **Changes in Mobility Tool Ownership** | | |
| Gained personal car | n.s. | 2.51 (2.05) |
| Gained access to car | n.s. | 2.84 (2.63) |
| Gained electric bicycle | 1.76 (4.35) | n.s. |

a: only statistically significant if we accept a 10% threshold for significance testing

*Table 9.7: Parameter estimates of the transitions (non-significant parameters not shown)*

Furthermore, the class-membership estimates reveal some interesting effects of life-events and changes in mobility tool ownership on modality style membership. Prospective parents were more likely to belong to the 'car-oriented' modality style before the child was born, even after controlling for the effects of age. Similar lead- or selection effects can be found for most changes in mobility tool ownership. People who bought a personal car between waves 1 and 2 were already more likely to belong to the 'car-oriented' modality style than would otherwise be expected, as were people who gained the ability to always access a car. A similar but opposite effect is found for the addition of an electric bicycle: people who gained an electric bicycle in between the two waves were already more likely to belong to the multi-modal modality style.

### 9.4.4 Transitions between modality styles

The main advantage of the latent transition choice model is that we can combine the above within-class mode choice probabilities with calculations regarding the transition probabilities between the latent classes. Furthermore, the model calculates to which extent the transition probabilities between the classes are affected by life-events and changes in mobility tool ownerships.

Below, we first present the statistically significant transition parameters, as well as the socio-demographic, life-events, and mobility tool ownership parameters in Table 9.7. For the sake of parsimony, variables without any significant effect are not shown in the table. Following a short discussion of the existence and direction of some effects below the table, we will illustrate the effects of a selection of life events and changes in mobility tool ownership on transition probabilities.

Both transition parameters are negative and statistically significant, indicating that transi-tions between classes are relatively rare events. There is a very limited effect of static socio-demographic variables on the transition probabilities. This is to be expected, given that the effects of static socio-demographic covariates on class membership are already estimated in the class-membership model of the first wave. There are some effects of life-events, although they are not very strong. Interestingly, both working from home and starting a new job are associated with shifts away from the car-oriented modality style, although both effects are not very strong. This however does indicate that people start making different mode choices after they start working from home, which is a relevant finding given the large increase in working from home during and after the COVID-19 pandemic.

There are relatively strong effects of both mobility tool ownership in wave 1 and changes in mobility tool ownership between the two waves on the transition probabilities. When interpreting these coefficients however, we must be careful regarding the assumed direction of causality. For example, we might interpret the negative coefficient (-1.08) of 'always having access to car' in wave 1 on the transition from car-oriented to multi-modal modality styles in two distinct ways: first, that always having access to a car prevents people from making this transition. This assumes that mobility tool ownership is a cause of our travel behaviour and our changes therein. Second, that people who are otherwise disinclined to make such a transition, and thus probably are relatively car-dependent, are more likely to ensure they always have access to a car. This assumes that our travel behaviour, and especially our habitual patterns, causally affect our mobility tool ownership. In practice, both directions are likely to exist (Nurul Habib et al., 2018; Scott & Axhausen, 2006). Below, we will try to keep both options in mind, but for reasons of legibility will not discuss both options for each coefficient.

The first thing to notice is that all effects are in the expected direction, given the interpretation of the latent classes as modality styles: people who always have access to a car are less likely to transition from the car-oriented to the multi-modal modality style, whereas people who own electric bicycles or public transport cards are more likely to do so. Similarly, the effects of changes in mobility tool ownership also follow the expected direction. These effects are relatively strong as well: both gaining ownership of a personal car (2.51) and the closely related gaining the ability to always access a car (2.84) make it much more likely that someone transitions from the multi-modal to the car-oriented modality style. Gaining ownership of an electric bicycle makes people more likely to switch from car-oriented to multi-modal modality styles (1.76).

These transition parameters can be used to calculate transition probabilities. Using these transition probabilities, we can create transition matrices, which are shown in Table 9.8.

As can be seen in the upper-left quadrant of table 8, the class membership of people who do not undergo any life-events or changes in mobility tool ownership is very stable, as roughly 94% and 92% of car-oriented and multi-modal people remain in their respective modality styles. This picture shifts dramatically for those who gain or lose a car and for those who gain an electric bicycle. Two things stand out: first, that gaining a car leads to a relatively higher chance to transition towards a car-oriented modality style (26%) than losing one leads to a transition towards a multi-modal modality style (15%). Car-oriented behaviour therefore seems to be more stable than multi-modal travel behaviour, and there is some asymmetry in the effect of vehicle ownership. Second, that gaining an electric bicycle is fairly effective at getting people to transition towards a multi-modal modality style.

| | | People *without* life-events or changes in mobility tool ownership | | | People who gained a car | |
|---|---|---|---|---|---|---|
| | | Wave 2 | | | Wave 2 | |
| | | Class 1 | Class 2 | | Class 1 | Class 2 |
| Wave 1 | Class 1: Car-oriented | 0.939 | 0.0609 | Class 1: Car-oriented | 0.967 | 0.0337 |
| | Class 2: Multi-modal | 0.0723 | 0.928 | Class 2: Multi-modal | 0.264 | 0.736 |
| | | People who lost a car | | | People who gained an electric bicycle | |
| | | Wave 2 | | | Wave 2 | |
| | | Class 1 | Class 2 | | Class 1 | Class 2 |
| Wave 1 | Class 1: Car-oriented | 0.847 | 0.153 | Class 1: Car-oriented | 0.833 | 0.167 |
| | Class 2: Multi-modal | 0.0337 | 0.967 | Class 2: Multi-modal | 0.00929 | 0.991 |

*Table 9.8: Transition matrices for respondents without life-events and for those with changes in mobility tool ownership*

A final result with respect to the transition probabilities is that we find relatively weak effects of life-events on transition probabilities. Perhaps these life-events don't lead to changes in mode choice, but only to changes in mode use. This can be the result of changes in the activity-pattern generation, for example by affecting either trip generation or trip distribution rather than mode choice. Residential relocations to urbanized areas for example might lead individuals to make more shorter-distance trips, which are more likely to be made using the bicycle and walking. However, there need not be a change in sensitivity to travel distance and thus no large change in behavioural parameters. Given the same trip, the respondent would still make roughly the same choices. However, the types of trips made might have changed. Another explanation might be that life-events coincide with changes in vehicle-ownership. As we explicitly model the effects of vehicle-ownership, this indirect effect will not show up in the model. However, the corelations between life-events and changes in vehicle ownership were relatively small ($< 0.2$). Therefore this explanation is unlikely to fully explain the weak effects of life-events.

### 9.4.5 Enumeration of transition effects on choice probabilities

To get a more intuitive understanding of the meaning of the transitions between the modality styles, we used the estimated LC transition model to calculate mode choice probabilities for individuals with varying states of vehicle ownership. As a result, we can see the effect that changes in vehicle ownership have on the mode choice probabilities. We illustrate this result using two different approaches. First, to show the effect of changes in car access, we show the estimated choice probabilities for trips made by people grouped by car ownership. As people's car ownership changes, so does their estimated probability of belonging to a certain modality style. Due to these transitions between the modality styles, their estimated choice probabilities change as well as is shown in Figure 9.3.

A couple of observations can be made based on Figure 9.3. First, car ownership is a large determinant of travel behaviour: people who own a car are much more likely to choose the car. Second, the effect of buying a car is much larger than the effect of selling a car. The increase in car probability is much larger for people who bought a car than the decrease for people who sold a car. Third, there are substantial lead effects: people who buy a car between the two waves already use the car much more often than people who do not do so.

For the second illustration, we again use the reference trips within each kilometre band, which we used earlier to illustrate the difference between the modality styles. Now, we plot the uncondi-

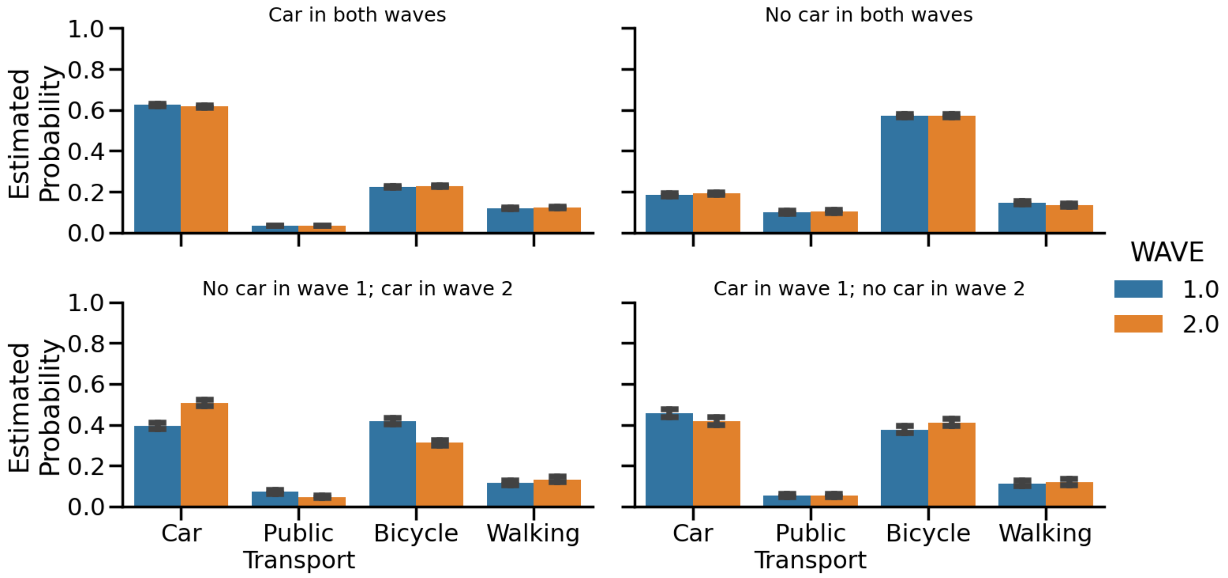


*Figure 9.3: Estimated mean mode choice probabilities conditional on (changes in) car ownership.*

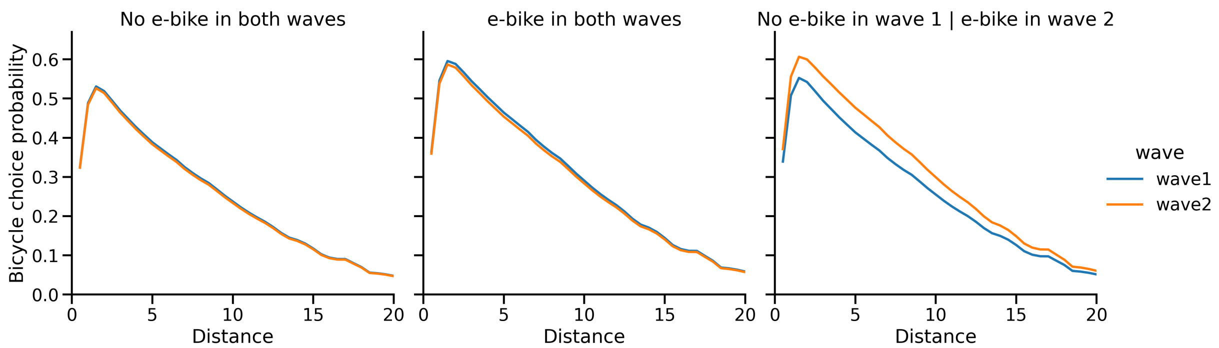


*Figure 9.4: Estimated mean mode choice probabilities conditional on (changes in) car ownership.*

tional bicycle choice probability of people grouped by e-bike ownership in Figure 9.4. This allows us to show how the probability of choosing the bicycle across various distance ranges changes as a result of differences in e-bike ownership.

We want to highlight two results here. First, that buying an electric bicycle increases the probability of choosing the bicycle. For the two groups whose electric bicycle ownership did not change, we observe no change in mode choice probability for the bicycle. For the group that did buy an e-bike, we observed a sizeable increase in the predicted market share of the bicycle from the first to the second wave. Model estimates of the treatment effect of the untreated, that is, people who did not already buy an electric bike, of buying an electric bicycle are roughly in the range of 8 percentage points, with the mode share of the bicycle increasing from 33% to 41%. This increase corresponds with a decrease in the estimated mode share of the car. As such, our results indicate that the electric bicycle substitutes car use, especially for shorter-distance trips up to roughly 15km in length.

## 9.5 Conclusion

In this paper, we used a latent transition choice model to estimate the longitudinal transitions between modality styles. Two latent classes are found, which can be identified as two distinct modality styles, namely 'Car-oriented' and 'Multimodal'. The 'car-oriented' modality style is found to be more sensitive to travel time increases than the multimodal modality style. The modality styles are relatively stable over time, especially in the absence of any life-events or changes in modality styles. The car-oriented modality style is found to be more stable than the multi-modal modality style. Life-events only have relatively minor effects on the transition probabilities between the modality styles: people who started a new job or increased the hours they worked from home moved from the car-oriented to the multimodal class slightly more often. These findings seem to contradict earlier studies showing relatively larger effects of life-events on travel behaviour (Clark et al., 2014; Gao et al., 2023; Olde Kalter et al., 2021; Rau & Manton, 2016). These previous studies typically used clustering approaches, which cannot disentangle trip generation changes from mode choice changes. Our results therefore suggest that life events mostly affect trip generation rather than the mode choice process itself.

Ownership of mobility tools and changes therein have much larger effects on the transition probabilities. Whilst the existence and direction of these effects are not wholly surprising (car ownership increases the probability one belongs to the car-oriented modality style, and electric bicycle ownership increases the probability one belongs to the multi-modal modality style), some findings are still very noteworthy.

First, we find clear evidence for an asymmetry in the effect of car ownership, where gaining a car has a much larger effect on the transition probabilities than losing a car. As a result, attaining ownership of a car seems to have an irreversible effect on one's travel behaviour, even if the car has to be sold. From a policy perspective – assuming that reducing overall car use is the policy objective – it is therefore important to facilitate lifestyles that do not depend on car ownership and provide carless people with similar levels of accessibility as car owners. Second, we find evidence of either lead- or self-selection effects, where people who buy a car or bicycle in-between the two waves already respectively used the car or the bicycle more often in the first wave than those who did not buy such a vehicle. These findings point to the importance of establishing good counterfactuals when studying the effects of vehicle ownership on travel behaviour, for example by using longitudinal data. Third, we find that, even after controlling for these selection effects, buying an electric bicycle results in a noticeable shift towards the more multi-modal modality style. The transition towards the less time- and distance sensitive multi-modal modality style also suggests that buying an electric bicycle makes bicyclists less sensitive to increases in travel time and travel distance. As a result, the bicycle choice probability increases substantially, especially for shorter-distance trips up to roughly 15km in length. These findings complement earlier studies using longitudinal clustering and structural equation modeling methods (de Haas et al., 2022; Kroesen et al., 2017).

The latent transition choice model thus enables us to improve further our understanding of the effects of changes in mobility tool ownership on mode choice behaviour. However, even though the model captures dynamic effects and thus uses the possibilities of panel data, the causal direction is still difficult to establish. This is due to the yearly occurrence of the data, which means that changes in mobility tool ownership and changes in choice behaviour seem to coincide together. This ambiguity makes it more difficult to draw clear behavioural conclusions. A second drawback of the current approach relates to the relatively low occurrence of life-events and changes in mobility tool ownership. As a result, the power of the model to reliably assess the effects of these changes on mode choice behaviour is limited. The estimation of the model is also made more difficult, as it is dependent on relatively limited observations where changes in choice behaviour occur. A final limitation we would like to highlight is that the current model is only estimable with two latent classes. As the number of latent classes increases, the number of transitions between classes increases exponentially. To illustrate, even a three-class solution would require the estimation of six transition parameters. Combined with the difficulties mentioned above, this was not feasible. The downside of a two-class solution is that they might oversimplify the existing heterogeneity with respect to mode choice behaviour.

There are several areas for future research that seem worthwhile. First, we could estimate a model using more longitudinal waves. This could prove especially fruitful given the relatively low occurrence of life-events. The ability to use more data could enable us to provide more reliable estimates of the effects of changes in life-events on travel behaviour. Second, we could add more detailed life-events and perhaps model changes of the transport system as well. Examples of the first type could include whether a residential relocation moved towards a more car-oriented or a more multi-modal oriented residential environment and a related example of the second type is to study whether autonomous changes in the built environment have an impact on the transition probabilities. More generally, longitudinal choice models can be used to estimate the stability of preferences regarding attributes such as time and cost, which could be interesting to empirically estimate longitudinal effects of, for example, changes in income on the value of travel time. Finally, use of more intensive longitudinal data could allow for a better understanding of the directions of causality involved. The yearly waves in the MPN are unable to capture when exactly behavioural shifts occurred, and if they preceded or followed life-events or changes in mobility tool ownership. Daily longitudinal data, for example using GPS tracking devices, combined with more complex travel surveys could help to further our understanding of the causality involved.

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# Chapter 10

# Conclusion

*Wat is mijn kathedraal?*
*Ik werk aan een kathedraal die ik niet ken en als hij voltooid is,*
*zal ik er niet meer zijn en niemand zal weten dat ik eraan heb gewerkt.*

*What is my cathedral?*
*I am working on a cathedral I do not know and when it is finished,*
*I will no longer be there and no one will know that I worked on it.*

Alfred Issendorf in 'Nooit meer slapen' by W. F. Hermans

This dissertation contains eight studies aimed at contributing to three well-established research lines in travel behaviour research. In the introduction of this dissertation, we discussed a common dilemma for policy makers: they want to increase the sustainability of the transport system, without reducing the (perceptions of) accessibility. All eight studies contained within the dissertation can be linked to this dilemma. Below, we will state the overarching conclusions and the policy implications that follow from these conclusions for each of the substantive sections. This will be followed by some reflections and directions for future research.

## 10.1 Overarching conclusions and policy implications

### 10.1.1 The effects of working from home on the transport system

Working from home and teleconferencing are forms of digital accessibility (Van Wee et al., 2013): people are able to perform work-related activities by digitally connecting with others. Digital accessibility is a potential substitute for physical accessibility: in the case of working from home, people substitute their physical commute for a digital one. Taking only the narrow view of the interests of travel behaviour policy, such substitutions would allow policy makers to escape their dilemma: working from home would reduce travel demand and the associated forms of pollution, without reducing people's accessibility. Furthermore, since working from home would mainly replace commutes during peak-hours (Beck & Hensher, 2021), the peak-demand of the transportation system would be reduced, with the associated benefits to both congestion and crowding of public transport.

At first sight, working from home thus offers many benefits and, again, taking only transportation-related effects into account, one would think that policy makers should strive to increase the number of people who work from home. However, there are three important drawbacks to consider, which follow from the conclusions of the chapters in the dissertation. We will work out these conclusions and their effects on the policy implications in the following.

**Conclusion 1: The effect of working from home on travel demand is strongest for public transportation**

In all three chapters of this section, the differences in the effect of working from home on travel behaviour between various travel modes have been analysed. All analyses point to the same conclusion: working from home is much more popular with people who commute to work by public transport than people who commute using other modes. There are various reasons for this finding, but the two main ones are that people who commute by public transport (and especially the train) are more likely to work in jobs which are well-suited for working from home, and commutes by public transport are often relatively long, further incentivising people to work from home and save a lengthy commute.

As a result, public transport is much more affected by increases in working from home than other modes. This is exacerbated by the fact that commute travel accounts for a relatively larger share of total travel demand for public transport than for the other modes. From the point of view of policy makers, this finding may be problematic. To be sure, there are some benefits to reduced commute demand by public transport: on a daily level, peak-hour demand is flattened, reducing crowding in public transport and allowing for a more even PT schedule. However, there are also negatives: reductions in public transport commutes have fairly limited effects on the sustainability of the transportation system, if indeed there are any. Furthermore, these reductions in demand threaten to undercut one of the main funding streams behind public transport, namely employer-paid and government-subsidised commute travel. A large reduction in commute travel in public transport, especially if it were to be structural, would threaten the ability of public transport operators to provide a product that can compete with other travel modes for commuters and non-commuters alike. The effect we estimated in the third chapter is already substantial (between 5% and 13% for the train and 3% and 8% for BTM), but probably not large enough to lead to this disastrous scenario. However, it is an effect that policy makers need to keep in mind when evaluating the benefits and drawbacks of potential policies aimed at increasing working from home.

**Conclusion 2: Working from home not only results in a reduction in commute travel (substitution effect), but also an increase in leisure travel (complementary effect).**

As already outlined in the considerable literature on this topic, the substitution of commute travel is not the only effect of working from home on travel behaviour (Andreev et al., 2010; Elldér, 2020). There is also a complementary effect, where working from home complements certain trips and forms of travel demands rather than substitutes it. Indeed, the relative sizes of these two effects are still not entirely clear, although the results from the third chapter of this thesis show that the substitution effect, at least expressed in terms of hours spent on travel, is larger than the complementary effect. However, policy makers should be careful not to overestimate the net (negative) effect of working from home on total travel demand, focussing on the substitution effect at the expense of the complementary effect. This is particularly relevant because the complementary effect is likely to take place on a longer timescale than the substitution effect. Following increases in working from home, one would thus expect the substitution effect to appear particularly strong at the beginning whilst the complementary effect takes more time to materialise.

Aside from the substitution and complementary effects mentioned above, both of which are primary effects at the level of the individual, meaning that he or she who works from home both reduces their commute travel (substitution) and increases their leisure travel (complementary), there are also second-order changes to the transportation system that should be considered. These second-order changes are the result of actions of people whose working from home behaviour has not changed, who respond to the primary effects as people start to work from home. These effects can be categorised as rebound effects (Rietveld, 2011). A possible example is that reductions in congestion due to working from home might entice other people to travel on the road more, thereby increasing travel demand and thus congestion again. Whilst public transport operators are likely to re-calibrate the supply of public transport vehicles to the new levels of demand rather quickly, this is not possible for road transport. As a result, the rebound effects are likely to be greater for road travel than for public transport. Perhaps some road infrastructure investments could be re-adjusted based on the lower expectations of travel demand due to working from home, but this takes place on a very different timescale (multiple decades).

In the above, we have not exhausted the list of complexities involved in the relationship between working from home and the demand for travel. Other possible effects typically run through the decision-making processes regarding the location of the residence or work, especially in relation to one-another. It has often been said, but not studied in a very exhaustive way, that people will accept longer daily commutes if they work from home for more days in the week.

In any case, it is clear that the relationship between working from home and travel behaviour is more complicated than it would seem at first sight, and therefore that the decision whether or not working from home should be stimulated by the government should take these complexities into account.

### 10.1.2 Travel-related attitudes, and their relations with travel behaviour

The study of travel-related attitudes can have policy implications in three different ways. First, inform policy makers on the possible effects of policies that target attitudes with the ultimate aim of changing behaviour. Second, to ensure that policies that target other variables (such as the built environment) are based on accurate information, obtained after controlling for the influence of travel attitudes if these are a common antecedent of both the variable in question and travel behaviour. Third, determine whether attitudes in the population are changing irrespective of specific interventions and whether these changes are likely to have an effect on travel behaviour in the long term.

In the following, we state three conclusions from our research that can be directly linked to these policy implications. The first and second of these conclusions both affect the first two types of policy implications, and therefore they are grouped together.

**Conclusion 3: The causal relationship between travel-related attitudes and travel behaviour is bi-directional**

**Conclusion 4: The between-person correlations between attitudes and behaviour are stronger than the within-person effects**

The combined implication of these conclusions is that mode-related attitudes should not be a primary target of policy makers if their ultimate goal is to change travel behaviour. The rationale behind such policies is that an individual whose attitudes are made to be more favourable towards a mode, will then start to use that mode more often. The efficacy of these policies therefore depends on a within-person effect from travel mode attitudes towards travel behaviour. Our studies show that this within-person effect is rather weak, much weaker than simple bivariate correlations would suggest. A further difficulty for policy makers is that actually changing people's attitudes towards certain travel modes seems to be a difficult endeavour in the first place. Our studies thus suggest that policy makers should not rely on policies aimed at changing people's attitudes to induce some desirable behaviour change.

Finally, our studies show that controlling for attitudes can be important when trying to assess the independent effects of other variables on travel behaviour. However, researchers should be careful when designing the causal structure of their study. Attitudes cannot be placed as sole antecedents of other factors, as both of our longitudinal studies show strong bi-directional effects. Studies or models that do use attitudes as pure antecedents are thus likely to underestimate the independent effects of third variables included in the analysis. For example, in the literature on residential self-selection, conceptual models that place travel-related attitudes as a common antecedent of both travel behaviour and the built environment risk underestimating the causal effect that an intervention in the built environment will have on travel behaviour.

**Conclusion 5: After controlling for the effects of age, the differences in attitudes between generations are negligible**

Another point to mention is that policy makers and the general public sometimes seem to think that younger generations have less favourable attitudes towards the car, and that this is one of the reasons for the 'peak car' phenomenon (Focas & Christidis, 2017; Goodwin & van Dender, 2013; Van Acker, 2018). This hypothesis is then extrapolated to indicate that younger generations – including those who have not yet been born - will likely hold less and less favourable attitudes towards the car over time.

This dissertation does indeed find that younger people have less favourable attitudes towards the car. However, this difference cannot be simply attributed to generational differences. The results show that as younger generations get older, their attitudes towards the car become more favourable and their attitudes towards public transport become less favourable. Where we observe direct overlap between generations, we do not find that younger generations have less favourable attitudes towards the car than older generations do. This can be explained, at least in part, by the findings from the previous chapters that attitudes are affected by behaviour. As people grow older, their mobility becomes more car-oriented, and therefore their attitudes follow suit. As a result of this finding, policy makers should not depend on some innate force ensuring younger generations hold less and less favourable attitudes towards the car and, therefore, will use the car less often over time.

Summarising the policy implications of this chapter, we can state that targeting attitudes in the hope of changing travel behaviour does not seem to be a fruitful policy instrument. Rather, they should focus on the primary attributes that affect people's choices for certain travel modes: travel costs, travel time, travel comfort, and the perception of these variables. Indeed, if people's behaviours change due to changes in these attributes, then their attitudes will follow their behaviour.

### 10.1.3 The effects of exogenous shocks and life events on travel behaviour

The final section of the dissertation is different from the previous two parts, as it does not refer to a specific substantive research topic. Rather, the two chapters in the final section present research into the effects of more or less exogenous influences on travel behaviour. In the first of those chapters, the exogenous influence is that of the weather. In the second, they are life events and the – admittedly less exogenous – ownership of mobility tools.

**Conclusion 6: More multi-modal travellers are more sensitive to exogenous variation**

First, we show that multimodal travel behaviour is more sensitive to exogenous variation than monomodal travel behaviour. As a result, we can extrapolate that monomodal travellers are less likely to change their behaviour due to a policy or intervention. If monomodal travellers used a travel mode that is seen as desirable, this could be considered good news. However, monomodal travellers typically rely on the private car for most or all of their travels. Since private car use is less sustainable than bicycle or public transport use, policy makers might want to try to stimulate the specific group of monomodal car travellers to adopt a more multimodal behavioural pattern. Following on from the conclusions of the second section of the dissertation, fruitful instruments are those that are known to have the strongest effect on mode choice, such as travel times and travel costs.

A similar notion can be based on the results of the second chapter in that section, showing that people who gain a car switch to a more monomodal car-oriented modality style, whereas the effect of reducing the number of cars is much less substantial. Preventing the formation of monomodal car-oriented travel patterns is therefore one of the more promising avenues for policy makers who intend to reduce car usage in the long term. The key is to prevent or delay the switch towards monomodal car use that people seem to make as they age and undergo key life events such as gaining employment or starting a family. Note that while our results showed that these life events had relatively little effect on mode choice (given that we make a certain trip, what mode are we choosing?), we know from earlier studies that they are linked to changes in mode use (the total use of travel modes, affected by both trip generation and mode choice). This would indicate that life events affect the trip generation process, so the decisions how many and which trips to make, more than the mode choice process.

To prevent or delay the transition towards a monomodal car-oriented modality style, policy makers can choose to either make the car less attractive (the stick) or to make other modes more attractive (the carrot). The former option is less appealing for policy makers, as people generally strongly dislike policies that make car use less attractive. As a result, political support for policies that increase the price of car use – or even policies that merely seem to increase this price – is very difficult to achieve. A more palatable approach, therefore, is to try to increase the attractiveness of other modes. In general, such carrot measures are less effective than stick measures (Börjesson & Eliasson, 2026). Our studies provide direct evidence for the effectiveness of one carrot: people who acquire an electric bicycle transition towards a more multi-modal modality style. They use the bicycle more, and their sensitivity towards travel time and travel distance by bike seems to decrease.

## 10.2 Reflections and directions for future research

To finalise the dissertation, below we will reflect on the substantive and methodological aspects of the dissertation and we will list some areas that seem particularly fruitful ground for future research.

### 10.2.1 Substantive reflections and directions for future research

*The effects of working from home on the transport system*

This dissertation thoroughly analysed the effects of working from home on the transport system using a combination of longitudinal and cross-sectional data analyses. We improved our understanding of the relationship between working from home and travel behaviour and provided useful estimates of the structural effects of the increase in working from home as seen during the COVID-19 pandemic, on travel behaviour. However, there are multiple avenues for future research to build on our work.

First, our studies do not fully disentangle the various forms of heterogeneity within the population concerning the effects of working from home on travel behaviour. The main form of heterogeneity that we have tackled concerns the question of who is more likely to work from home: we find that people with higher incomes, who attained a higher educational degree, work office jobs, and commute by public transport are more likely to work from home compared to the general population. However, there are other forms of heterogeneity that must be studied. For example, it would be interesting to see if there is heterogeneity in the effect of working from home on travel behaviour in the population. Of particular note are differences between the genders, different age-groups, and between people who recently started to work from home and those who have done so for a long time.

Second, our studies rely on self-reported intentions and expectations for travel behaviour and working from home after the pandemic to estimate structural effects. Now that the COVID-19 pandemic has been behind us for several years and society seems to have settled at a new behavioural baseline, it would be very interesting to explore whether these stated intentions align with actual behaviour and what we can learn from those individuals where these two do not match.

Finally, only a few studies address longer-term changes in activity travel due to working from home. People often expect these changes to exist, following the reasoning that, as people work from home, they are more likely to move further away from their work or to accept work further away from their residence. At the time of writing, this research area is somewhat underexplored. Again, as we settle into a new baseline for behaviour, now would be a fruitful time to study whether people who started working from home during the pandemic have accepted longer commutes than people who have not done so.

*Travel-related attitudes and their relations with travel behaviour*

This dissertation contains three studies on travel-related attitudes and their relationship with travel behaviour. Aside from the chapter-specific limitations mentioned in the separate chapters, the following overarching limitations and directions for future research can be identified.

First, these chapters all use the same set of attitudes: specific attitudes towards various travel modes. In the study on residential self-selection, we contrasted these specific attitudes with travel-related reasons for choosing a specific residential location. However, using more attitude- or attitude-adjacent variables could provide further insights in each chapter. For example, in the chapter on the relationship between travel-related attitudes and travel behaviour, it might be interesting to also include more general attitudes which can be related to travel behaviour, such as attitudes towards climate change (mitigation) or sustainability. The inclusion of such attitudes would also help to provide more information on the question of whether differences in travel-related attitudes can be attributed to age- or generational effects.

A further general limitation is the rather sparse collection of attitudinal information. By default, the seven indicators used to measure travel-related attitudes are collected only once every two years. Although this is probably often enough to detect population-level shifts in attitudes under normal circumstances, it would be very interesting to purposefully collect such information more often when we suspect that travel-related attitudes might shift. We have done so at the population level by also measuring attitudes in 2021, as we suspected that the COVID pandemic could have resulted in a large shift in overall attitudes. However, it would be interesting to target specific individuals, for example, those who have recently changed their travel behaviour or who have gone through certain life events, such as residential relocations. This would collect richer information at the individual level, which could be used to more finely investigate the relationship between attitudes and travel behaviour.

*The effects of exogenous shocks and life events*

As mentioned in the introduction, the chapters in this section have comparatively less in common than the chapters within the other sections. As a result, most of the limitations and research recommendations can be found in the individual chapters. However, we can provide some overarching directions for future research.

In this section, we only tested two sources of potential exogenous shocks or exogenous variation: the weather and life events. We posit that people whose behaviour is more variable – specifically, more multi-modal - are more sensitive to exogenous shocks. Multi-modal travellers are more likely to switch to weather-exposed travel modes when the weather is favourable, but also more likely to switch away from these modes when the weather is unfavourable. Similarly, in the second study on life events, we see that people are more likely to switch towards the more monomodal car-oriented modality style when they buy a car than they are to switch back when they lose the car. The monomodal modality style seems to have created a stronger habit. This overarching conclusion is interesting and should be further investigated by studying the effects of various other forms of exogenous variation on people's travel behaviour.

### 10.2.2 Methodological reflections and directions for future research

*Longitudinal data collection*

This dissertation makes use of longitudinal data for almost all its studies. Longitudinal data has some key benefits over cross-sectional data, as already explained in the introduction of the dissertation. However, the only source of longitudinal data used in these studies is the Netherlands Mobility Panel. As a result, most studies use a very similar longitudinal structure: multiple sets of yearly waves. This yearly longitudinal structure is definitely an improvement over cross-sectional data collections, but further improvements can be made.

First, the time-gap between measurements should ideally be tailored to the specific subject of the study. More precisely, it should depend on the time in which the studied variables are assumed to have an effect on one-another. We might, for example, theorise that weekly changes in working from home behaviour will have immediate effects on average weekly travel behaviour. Capturing these changes with annual measurements is clearly not the most effective strategy. On the other hand, we suspect that the effects between attitudes and travel behaviour occur within a much longer time frame and that yearly observations are perhaps too frequent. A further consideration here is that of the total window of observation. Ideally, this window of observation again matches the subject of the study. The fixed structure of the MPN makes this difficult to achieve. For example, we might expect short- and long-term effects of working from home on our travel behaviour. The long-term effects, which arise from changes in residential or employment locations, can only be fully observed after a long time.

Note that the studies on the direct effect of the COVID-19 pandemic on our travel behaviour are a shining example of utilising the flexibility in the MPN to address these two shortcomings of the normal MPN-rhythm. Soon after the pandemic broke out, we decided that annual measurements would not be frequent enough to observe the key behavioural changes and their causes that we wanted to study. As a result, we added more frequent measurements. Then, as the pandemic ran its course, we ensured that we maintained frequent measurements until it was fully over and the yearly rhythm would suffice again. For key changes induced by the pandemic, we continue to ask relevant questions in our yearly questionnaires to ensure that long-term effects can be estimated.

Ideally, we would have used a similar approach for all our studies as well: adapting the measurements perfectly to the subject of the study should lead to more reliable and valid results. However, longitudinal data collection is already very expensive, both in terms of monetary costs and the required time investment. Setting up a specific longitudinal panel for each research question would be even more cost prohibitive.

*Variables considered and sampling method*

Another potential drawback of the MPN is related to the specific variables available for analysis. In any survey-based data collection, there is a trade-off between the depth of information collected pertaining to a certain subject and the number of subjects collected. This is a result of the fact that the burden placed on the respondents must stay within certain limits, otherwise either the quality of the answers or the response rate will drop (Kunz & Gummer, 2025; Rolstad et al., 2011). As the MPN is set up to collect a lot of information related to travel behaviour and multiple potential causes and effects related to travel behaviour, the depth of the information collected must be carefully determined. As a result, some more detailed information is not available: for the studies on working from home for example it would have been useful to know if people worked a full day at home or only part of the day, and for the studies on attitudes more indicators could have been useful.

A further complicating factor is that the longitudinal nature of the data collection process means that there is a lot of inertia in the exact measurement method. We are obliged to keep the specific wording, answer options, and order of the questions the same across multiple waves to ensure that the measurement remains consistent over time. Any change in any of the aforementioned characteristics would result in a structural break, making longitudinal analyses more difficult. As an example, the same set of indicators has been used to measure attitudes in the MPN since the first measurement back in 2014.

Finally, the MPN is set up to be generally representative of the Dutch-speaking population of the Netherlands, aged 12 and older. This is a sampling design that is generally useful and can be applied to many research topics. However, a notable downside is that it is difficult to oversample specific groups with rare but desirable behavioural characteristics. For example, in the context of studying life events, it would be useful to purposefully oversample individuals who underwent such life events.

*Research Methods*

Within the dissertation, a variety of quantitative research methods are used: structural equation modelling and discrete choice modelling are the two main branches, but we have also utilised growth models, relatively simple regression modelling techniques, and descriptive statistical analyses. This use of multiple, very different research methods has two potential benefits: first, that larger overall questions can be subdivided into distinct studies, each of which uses the specific method that is most suited to their aims. Second, a similar research question can be studied from different perspectives using various methods. The results from these various research methods can then be used to gain a deeper understanding of the problem than one would attain by using only one method.

Within the dissertation, we have utilised the first benefit most clearly in the section on working from home. There, we started with simple descriptive analyses of the immediate effects of the

COVID-19 pandemic on travel behaviour. Based on these results, we postulated that there could be a structural effect of increased working from home behaviour after the pandemic subsides. To properly study this effect, we used structural equation models to better understand the relationships between working from home and travel behaviour. This information was then used to substantiate some assumptions we made to estimate the size of the expected structural effect, for which we used a relatively simple regression modelling approach.

However, the dissertation does not realise the second potential benefit mentioned above, as each research question is only studied with one specific method. Some research questions, perhaps re-framed from slightly different perspectives, would lend themselves to being studied using different methods. Replicating certain findings or results in this dissertation using different modelling techniques would therefore be an interesting direction for future research.

The final methodological limitation of the dissertation that we want to mention here is that all studies are primarily based on quantitative research methods. In various instances, our research could have benefited from qualitative research methods to delve deeper into the causal phenomena we studied. Examples of potentially interesting research methods include the use of focus groups to help qualitatively disentangle age from generational effects and interviewing people who work from home to determine what potential effects on their mobility and travel behaviour they deem likely to exist (Clifton & Handy, 2003). In general, an interplay between qualitative and quantitative studies is necessary to improve our understanding of human behavioural processes and the causal relationships therein.

*Causal inference*

As outlined earlier in the introduction, policy makers are often interested in answers to causal questions: if we do X, will that result in improvements in y? Because providing causal answers to these questions is notoriously difficult, there is a discrepancy between the questions that policy makers seek answers to and the answers that science can provide.

As a result, policies that should be based on scientific research are not properly grounded in scientific facts. The scientific field of travel behaviour research, alongside many other similar fields, should therefore try to bridge the gap between the causal world of policy making and the traditionally associative world of behavioural science. There is no obvious solution to this problem; otherwise, it would not exist in the first place. However, but there are some steps that can be taken to bridge the gap. Here, we identify two distinct steps.

The first step is to increase awareness of the causal relationships that lie at the heart of the specific subject of the research we are studying. Essentially, this means that the research community should confront the problem of causality head-on. Perhaps this sounds rather easy or obvious, but it does constitute a break with the past, where causal inference was often explicitly scoped out of the scientific process. The typical reasoning that was applied is that causal inference is difficult and/or impossible with the available data; therefore, we cannot make causal conclusions and should avoid causal interpretations of our results. The problem with this approach is that the practical implications of most studies ultimately do revolve around causal interpretations.

As a result, causal interpretations will be made even if the authors themselves carefully avoid causal language. Without changing anything about the statistical methods used, more careful reasoning about the causal relationships at play within the research subject could improve the practical usefulness of scientific research.

The second step is to use research methods and research designs that provide stronger support for causal interpretations. It will be no surprise to the reader of this dissertation, which includes many longitudinal studies, that longitudinal methods are one avenue that should be explored more often. This is particularly true if we are unsure of the causal direction between two key concepts, such as the relationship between travel-related attitudes and travel behaviour. Empirical evidence has shown that this relationship is bi-directional (Kroesen et al., 2017). Assumptions that state there is a singular direction are thus very likely to either overestimate or underestimate the causal effects they are studying. Another advantage of longitudinal studies, or any repeated measurements study, is the ability to control for all time-constant differences between the measurement units (often individuals). This again enables a stronger causal interpretation, as many possible confounders can be controlled. This also allows for a separation of observed correlational structures into within-person effects, taking place within the individual, and between-person correlations, which are observed between individuals (Hamaker et al., 2015).

Note that longitudinal methods are only one avenue for further exploring causal relationships, and we do not want to either explicitly or implicitly suggest that cross-sectional methods are unable to support causal conclusions. Whichever method is used, the most important step towards improving causal inference is to conceptually map the causal relationships at play within the research subject and determine what interventions or treatments could affect the outcome(s) of interest (Pearl, 2009). Such conceptual work is key for valid causal inference.

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## Summary

Travel behaviour is in a state of transition, towards a sustainable transport system. This dissertation examines how people make travel-related decisions, using longitudinal data and statistical models. The substantive focus is on working from home, travel-related attitudes, and external influences such as the weather and life-events. The results improve our understanding of decision-making within travel behaviour, enabling policy makers to make better-informed decisions in the face of the transition.

## About the Author

Roel Faber completed his PhD at TU Delft alongside his research at KiM Netherlands Institute of Transport Policy Analysis, combining academic studies with policy-relevant research. His work explores various facets of travel behaviour, using a range of quantitative modeling methods.

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