The Impact of Public Transport Disruptors on Travel Behaviour

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Nejc Geržinič

Delft University of Technology

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The Impact of Public Transport Disruptors on Travel Behaviour

Dissertation

for the purpose of obtaining the degree of doctor

at Delft University of Technology,

by the authority of Rector Magnificus Prof.dr.ir. T.H.J.J. van der Hagen,

chair of the Board of Doctorates,

to be defended publicly on

Monday 18 December 2023 at 15:00 o'clock

by

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Dedicated to my mother

Nobena juha se ne poje tako vroča, kot se skuha.

Slovenian proverb, expressing that in time something turns out not to be as difficult, threatening or dangerous as it first seems

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The past four years (and nine months) spent on my PhD research have been an important and life changing adventure, from a professional but also a personal point of view. Through my work, I have gotten to know and had the privilege to work with some truly amazing and inspirational people. And on a personal level, the time during my PhD has been one of personal discovery and reflection, which was in large part enabled by the people who surrounded me. That is why I want to take the opportunity to acknowledge the many people who have had a profound impact on my life in these years. I was truly lucky to get to know so many, that I will not be able to mention them all, which in no way reduces their importance in my life.

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Nejc
November, 2023

Content

Acknowledgements ... i
Summary ... 9
Samenvatting ... 15
Povzetek ... 21

Chapter 1: Introduction ... 29
1.1 Disruptors of public transport ... 30
1.2 Objective of dissertation research ... 31
1.3 Discrete choice theory and methods ... 31
1.3.1 Revealed and stated preference data collection ... 32
1.3.2 Accounting for traveller heterogeneity ... 33
1.3.3 Socio-demographic and attitudinal information ... 33
1.4 Contributions and relevance of the research ... 34
1.4.1 Theoretical and practical contributions to science ... 34
1.4.2 Societal relevance of behavioural research ... 35
1.5 Disruptors in different types of trips ... 36

Chapter 2: Mode choice in the presence of On-demand mobility services in urban areas ... 41
2.1 Introduction ... 42
2.2 Literature review ... 43
2.3 Methodology ... 45
2.3.1 Survey design ... 45
2.3.2 Model estimation ... 48
2.3.3 Data collection ... 50
2.4 Results ... 51
2.4.1 Results of discrete choice model ... 52
2.4.2 Service familiarity and Exploratory Factor Analysis ... 54
2.4.3 Results of the latent class model ... 56
2.5 Discussion ... 61
2.6 Conclusion ... 63

Chapter 3: Waiting time variability of on-demand mobility services in urban areas....................67
3.1 Introduction....................68
3.2 Methodology....................71
3.2.1 Survey design....................71
3.2.2 Model estimation....................73
3.2.3 Data collection....................79
3.3 Results....................81
3.4 Conclusion....................83
3.4.1 Discussion of model outcomes....................83
3.4.2 Discussion of model formulation....................85
3.4.3 Implications....................86

Chapter 4: Mode and station choice in the presence of on-demand mobility services....................89
4.1 Introduction....................90
4.2 Methodology....................92
4.2.1 Survey design....................92
4.2.2 Model estimation....................96
4.2.3 Data collection....................97
4.3 Results....................98
4.3.1 Descriptive statistics....................99
4.3.2 Attitudinal statements and service familiarity....................99
4.3.3 Market segmentation....................101
4.4 Model application: Scenario analysis of market potential....................108
4.4.1 Introducing an on-demand service....................108
4.4.2 Level-of-service variation....................110
4.5 Conclusion....................112
4.5.1 Discussion and key findings....................112
4.5.2 Policy implications....................113
4.5.3 Limitations and future research....................114

Chapter 5: Mode choice in the time of COVID-19 for long-distance international trips 117
5.1 Introduction 118
5.1.1 Risk perception 118
5.1.2 COVID-19 pandemic 119
5.2 Methodology 120
5.2.1 Hierarchical information integration 120
5.2.2 Survey design 121
5.2.3 Model estimation 127
5.2.4 Data collection 129
5.2.5 COVID-19 situation and survey context 130
5.3 Results 131
5.3.1 Segment 1: Time-sensitive travellers 132
5.3.2 Segment 2: Prudent travellers 134
5.3.3 Segment 3: Frequent train-loving travellers 134
5.3.4 Segment 4: Cautious car travellers 136
5.4 Implications 138
5.5 Conclusion & Discussion 140

Chapter 6: Conclusion 145
6.1 Main findings and conclusions 146
6.2 Implications for practice 149
6.3 Future research directions 151

Appendices 155
Appendix A 157
Appendix B 160
Appendix C 161
Appendix D 162
Appendix E 163
Appendix F 164
Appendix G 166
Appendix H 167

Bibliography 169
About the author 183
List of publications 185
TRAIL Thesis Series 187

Summary

Public transport systems have been and continue to be shaped by disruptive forces. Internal disruptors (i.e. electrification, digitalisation etc.) allow public transport to improve and enable it to provide a higher level-of-service. External disruptors, on the other hand, compel public transport to adapt its services in order to recover and adapt to this new environment. External disruptors may take a form of a new competing alternative (i.e. mode of transport), chipping away at the market share of public transport. A recent and highly disruptive example of this is shared mobility, an umbrella term including a wide variety of alternatives, such as ride-hailing, bike-sharing, car-sharing, etc. Alternatively, external disruptors may fundamentally change the demand for public transport or travel altogether. Two notable examples of this are climate change, and especially the recent COVID-19 pandemic. At any event, a crucial determinant of the disruptor's impact on public transport lies in the users themselves and their corresponding attitudes and preferences towards travel. Analysing travellers' reaction to a disruptor is therefore essential for understanding the impact it will have on public transport and provides valuable advice for measures that need to be taken on the strategic, tactical and operational levels.

The aim of this thesis is therefore to provide a better understanding of the behavioural impact that external disruptors (may) have on public transport. We apply a variety of choice modelling approaches and propose extensions to existing models that improve how we capture travel behaviour. To study the impact of different types of disruptors on different trip types, this dissertation is divided into three parts, namely studying the impacts on short-, medium- and long-distance trips. Although disruptors can broadly be grouped as mentioned above, each individual disruptor ultimately has its own unique impact on public transport. In this research, we focus on the impact of ride-hailing (on-demand mobility) and COVID-19.

The first step of this research (*Chapter 2*) investigates the **impact of introducing on-demand mobility (including ride-hailing) on everyday trips in urban areas**. Although ride-hailing services (such as Uber, Lyft, DiDi, etc.) are the most well known examples, many similar services also exist, namely flexible public transport, microtransit, taxis etc. We analyse these services jointly, by referring to them as "on-demand mobility services" or FLEX, which a term often used for microtransit services in the Netherlands (where our data collection was based). Using stated preference data from the Dutch Mobility Panel (MPN), we apply a Latent Class Choice Modelling approach with a static class membership function. The resulting market segmentation shows four distinct user groups with respect to commute and leisure travel in urban areas. Two of the four segments (with a combined market share of ~36%) show potential for using on-demand services. Especially the segment labelled Flex-ready individuals (~9%) show a high willingness to use on-demand service, also being open to pooling. For them, cost is the defining factor of their decision-making, having a fairly low willingness-to-pay. Tech-ready individuals (~27%) on the other hand show less potential for using on-demand services and are more inclined that others to opt for a private trip, having a high willingness-to-pay and a somewhat stronger aversion to sharing. The two remaining groups, the Sharing-ready cyclists (~55%) and Flex-sceptic individuals (~9%), show (almost) no interest in on-demand services for short urban trips, preferring to use their bike and car respectively.

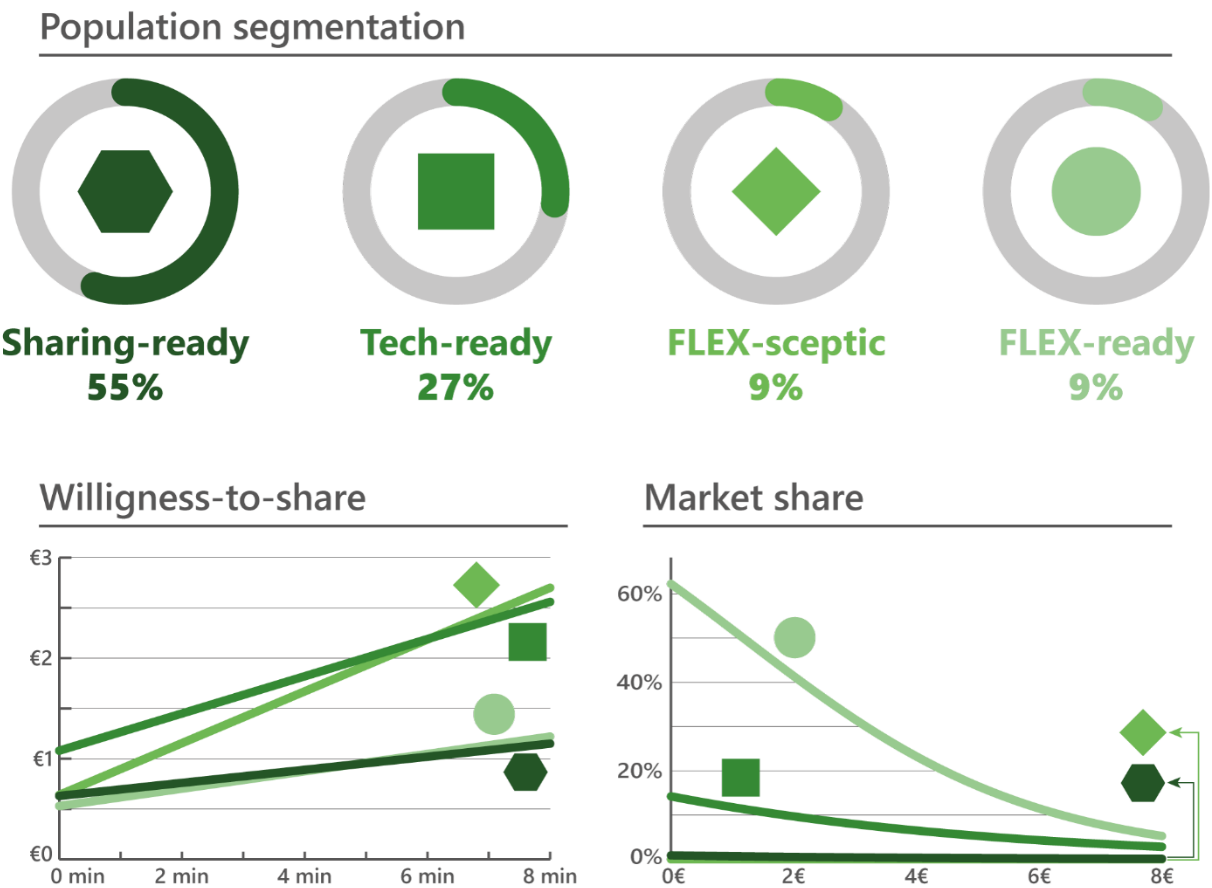


Figure 1.1 Graphical summary of Chapter 2: Population segmentation, Willingness-to-share and Market share of on-demand services in urban areas

Secondly, we expand on the knowledge of on-demand mobility for short trips, by analysing the **perception of waiting time variability for on-demand services** (*Chapter 3*). Given the specific nature of on-demand services (a tailored, personal service), the perception of waiting time may differ substantially from public transport waiting time variability. To simulate reliability in a stated preference (survey) setting, respondents are given a predicted level of service (waiting time) for two competing companies. Once they have chosen one or the other, the actual waiting time is presented. This task is repeat 32-times in total, with the predicted (pre-trip) information remaining constant through the iterations, whereas the actual waiting times are randomly drawn from a pre-specified log-normal distribution. The two competing companies are associated with different log-normal distributions, capturing different levels of reliability, which the respondents internalise through trial-and-error. This data is then analysed using the instance-based learning approach with a mixed logit model formulation. The former analyses how important past experiences are on future decision-making (how much they contribute to the decision), whereas the latter analyses the importance of the parameters and their distribution within the population. The results show that experiences quickly become less relevant, with the most recent experience having the most impact by far on the next choice (accounting for 75% when the respondent has only two experience and still 55% with ten experiences). This means that operators will not pay the consequences of a badly executed service for long, they only need to do their very best the very next time. With respect to waiting time, respondents are willing to pay approximately €0.30 to €0.44 for every minute of saved unplanned waiting time. If the trip gets cancelled (by the driver, lack of vehicles available or some other reason), the penalty the traveller associates with this is equivalent to roughly €4.45. In other words, this is the discount the traveller is expecting in the next instance, for them to still consider travelling with this company. Finally, users may also experience a perceived barrier to entry before trying a new service, which seems to be valued at some €1.98.

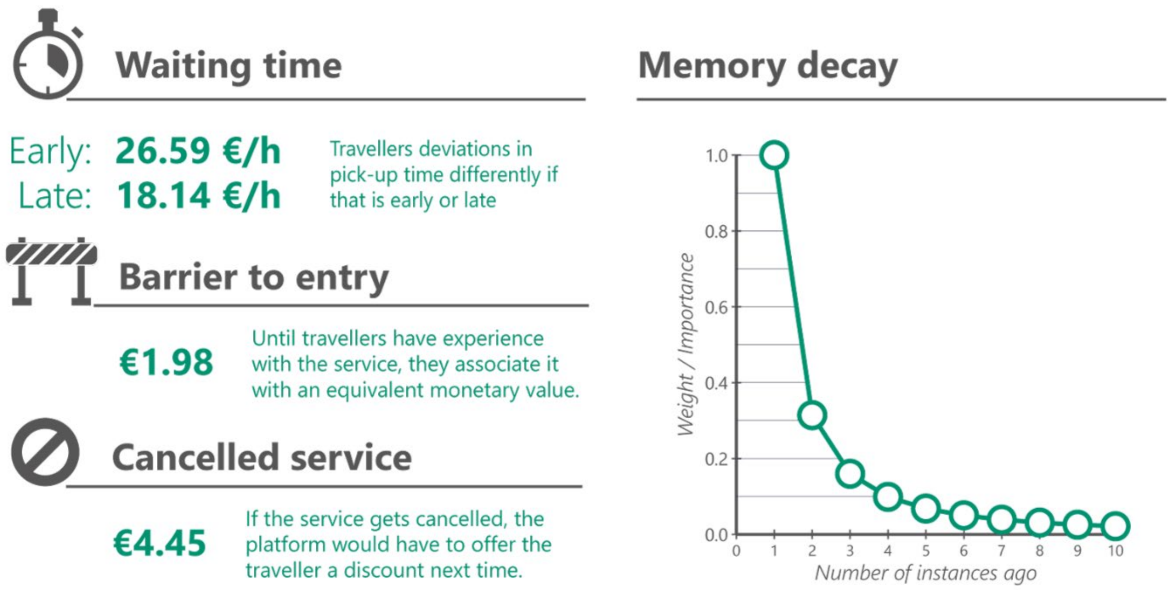


Figure 1.2. Graphical summary of Chapter 3: Valuation of waiting time, barrier to entry and cancelled service, and the importance of past experiences in a memory decay function

Thirdly, as on-demand services do not only compete, but may also complement public transport, we study the **potential of on-demand services as an access mode for a medium-distance intercity trip** (*Chapter 4*). Here, we investigate a 2-stage trip where the main leg is performed by train and accessing the train station can be done by bicycle, car, local public transport (bus, tram, metro) or on-demand mobility. To study how characteristics of these two trip legs are traded-off, respondents have to make a mode-choice and a station-choice decision. The obtained data is analysed with a Latent Class Choice Model, where the classes have different nesting specifications. Nesting is used to analyse if there are similarities between alternatives. Since the respondents perform two choices, we specify two different nesting structures, where in one case, the first choice (upper nest) is the access mode, while in the other, the station is the first choice. To illustrate, a mode-first nest implies that travellers first decide to use their bike to access the station, then they decide which station to go to. A station-first nest inversely implies that the traveller first chooses their preferred station, then how they will get there. By modelling this through a latent class model, individuals are probabilistically assigned to the class that best correspondents with their stated choices. Our results show that the split between mode-first and station-first choices is almost half-half, with 52% falling under the former and 48% under the latter. This approach also provides us with insights into substitution patterns in cases of introducing new modes (on-demand mobility) and/or new stations. We see that on-demand mobility has a small market share and performs better for accessing stations where public transport supply is limited and the distance may be too long to cycle. We also note that on-demand services cannot act as a replacement of public transport, as most of its users would shift to car and bicycle. If on-demand mobility is introduced alongside public transport, an above-average share of users would switch from the car.

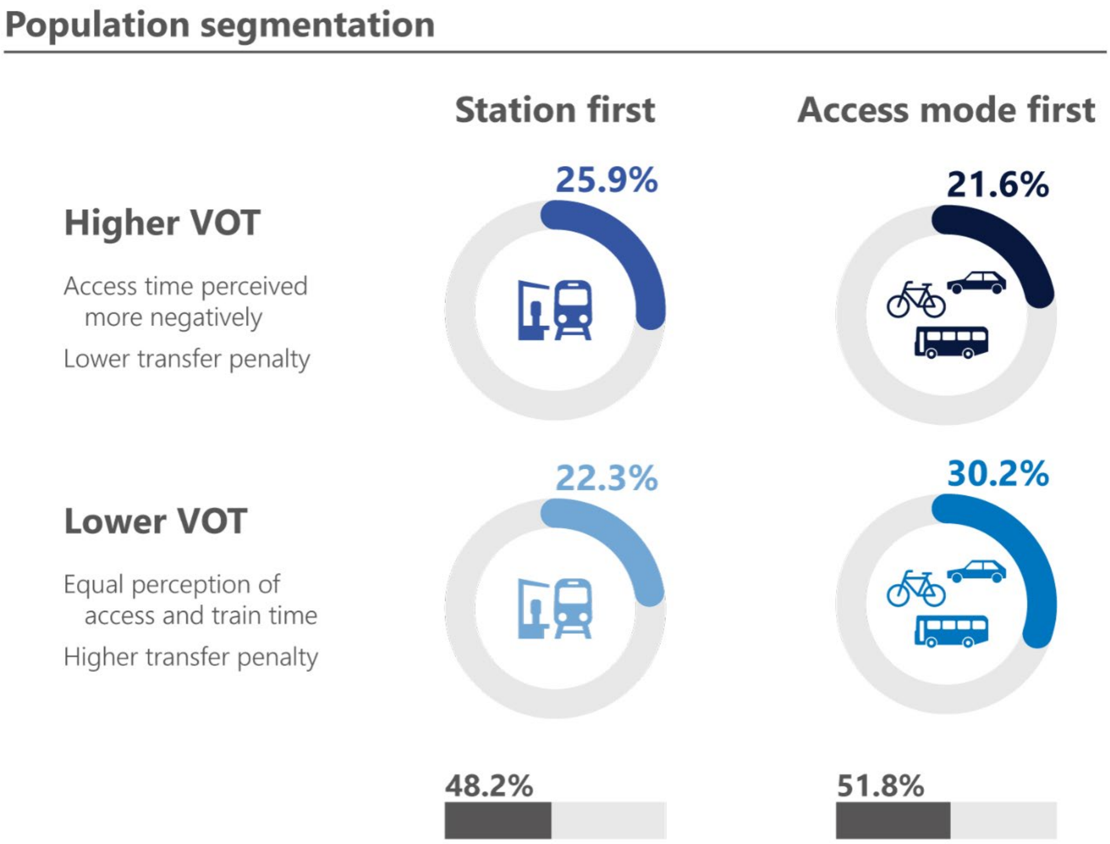


Figure 1.3. Graphical summary of Chapter 4: Population segmentation between those choosing the access mode first and those choosing the station first – also divided between two different VOT groups

Finally, considering long-distance and particularly international trips, we study the **impact of travellers perception of COVID-19 infection risk in long-distance mode choice** (*Chapter 5*). As COVID-19 travel restrictions were slowly being lifted, many still avoided long-distance travel due to a potentially higher perceived risk of infection. To evaluate travellers' risk perception, we carried out a stated preference survey, utilising the Hierarchical Information Integration approach. This allows us to quantify people's perceived level of risk on a Likert-scale, based on various risk-related indicators (mask mandates, vaccination rate, travel advice, etc.). Risk perception is then included in a stated choice experiment as an attribute to be traded-off along with price, time and comfort, to gain a better understanding of how risk is traded-off. A novel modelling approach is developed to capture this two-stage approach from a market segmentation perspective. Firstly, the discrete choice data is modelled by means of a Latent Class Choice Model. Secondly, making use of the probabilistic class allocation, each respondent is associated with probabilities of belonging to each class, which are then used to estimate separate weighted least squares regression models to determine how different risk-related indicators influence the perception of risk for different user groups. We uncover four distinct user groups with respect to long-distance travel under the premise of COVID-19 risk perception. Two traveller groups have a higher willingness-to-pay (72€/h and 50€/h) and tend to be more mode agnostic (preferring either car or train for shorter and flying over longer distances). The other two segments have a lower willingness-to-pay (38€/h and 15€/h) and tend to be more bound to a single mode for trips of all lengths (train and car respectively). The perception of risk also differs between the groups, with two perceiving it as time-dependent (disutility is higher if the trip is longer), whereas the other two see it as time-independent, merely associating it with a specific mode (disutility of risk is equal for trips of any length with the same mode). With respect to risk-related indicators, the most consistent are infection and vaccination rate at the destination, increasing and decreasing perceived risk respectively. A significant, albeit more mixed impact can be observed for government travel advice, mask mandates and proof of a negative test, vaccination, and/or recovery.

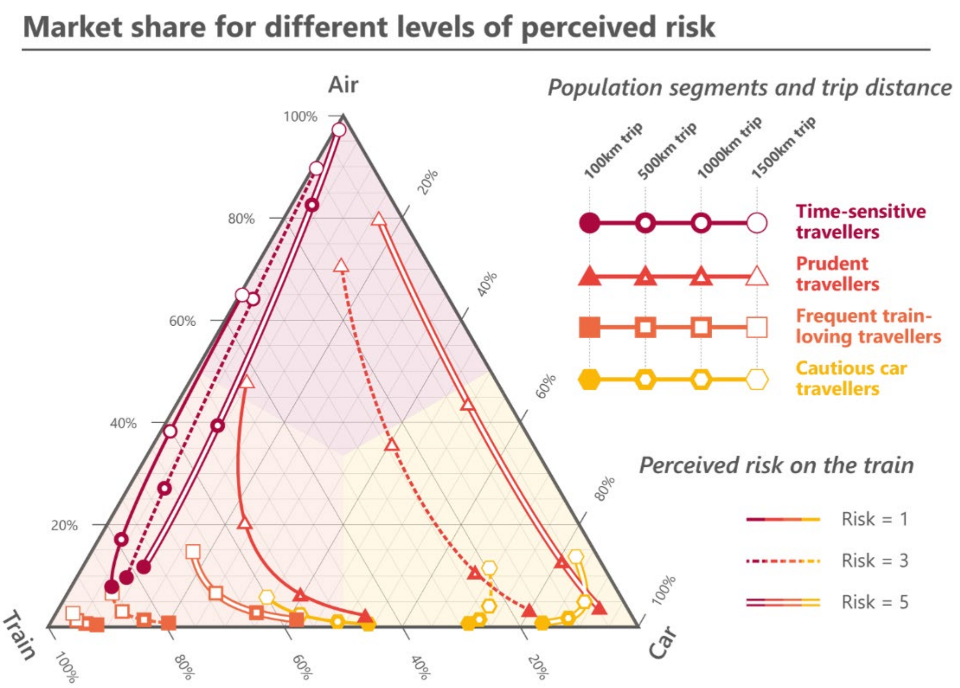


Figure 1.4. Graphical summary of Chapter 5: The impact of perceived risk on market share of different long-distance travel modes

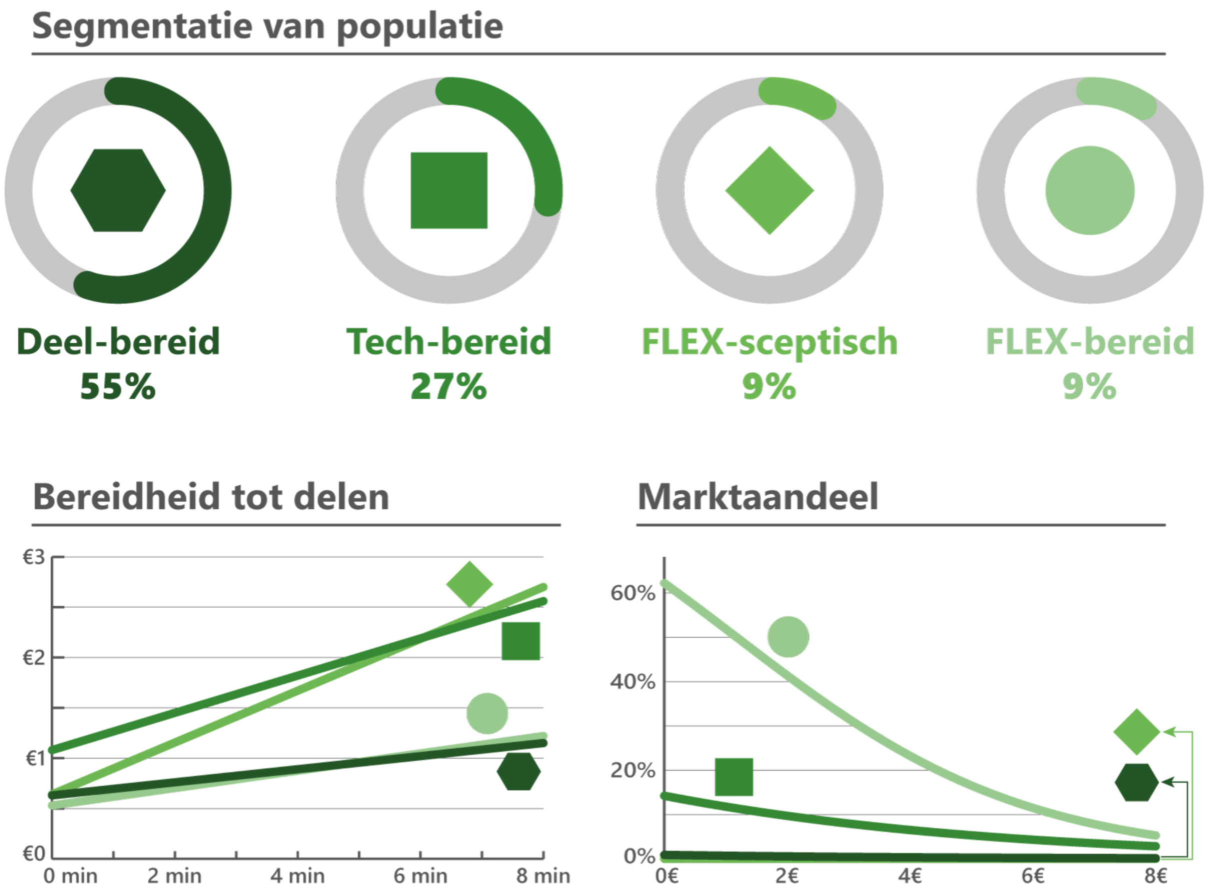
To sum up, this dissertation provides insights into how external disruptors affect public transport and its patronage. Through the use of various established and newly developed discrete choice modelling approaches, we investigate how shared mobility (specifically on-demand mobility services) and COVID-19 infection risk are perceived by travellers and how they impact the use and attractiveness of public transport for short-, medium- and long-distance trips. Based on these insights, we outline several recommendations for practice (public transport operators, on-demand mobility service providers and policymakers) on what kind of measures should be taken, depending on what the aim of their actions / policies is. The main finding for shared mobility is that, if sustainability is a key goal, the introduction of shared modes needs to be coordinated with public transport services. This involves decisions on the type of service to be introduced, the area of operation, information and fare integration etc. Although these services have the potential to completement public transport well, left unchecked they may also eat into each other's market share if not done right. With respect to COVID-19, train travel seems be associated with the highest level of perceived risk, meaning that to maintain its market share and encourage sustainable travel, appropriate safety measures need to be taken to assure the travellers of their safety, with potentially additional pricing measures needed to encourage train travel and discourage other modes of long-distance travel.

Samenvatting

Openbaarvervoersystemen zijn en worden gevormd door disruptieve krachten. Interne disruptieve factoren (zoals elektrificatie, digitalisering e.d.) zorgen voor verbetering van het openbaar vervoer, waardoor het een hoger serviceniveau kan bieden. Externe disruptieve factoren dwingen het openbaar vervoer daarentegen tot aanpassingen van de diensten om zich te herstellen en zich aan te passen aan de nieuwe omgeving. Dergelijke disruptieve factoren kunnen zich voordoen in de vorm van een concurrerend alternatief (bijvoorbeeld een nieuwe vervoerswijze) waaraan het openbaar vervoer marktaandeel verliest. Een recent en zeer disruptief voorbeeld hiervan is deelmobiliteit. Dit is een overkoepelende term voor een grote verscheidenheid aan alternatieven, zoals ritdiensten, deelfietsen en deelauto's. Daarnaast kan een externe disruptieve factor zorgen voor een fundamentele wijziging van de vraag naar openbaar vervoer of naar reizen in het algemeen. Twee belangrijke voorbeelden hiervan zijn klimaatverandering en, met name, de recente coronapandemie. Bij dit soort gebeurtenissen zijn de gebruikers zelf en hun houding en voorkeuren wat betreft reizen belangrijke determinanten voor de gevolgen die de disruptieve factor heeft op het openbaar vervoer. Analyse van de reactie van reizigers op een disruptieve factor is dan ook van belang om inzicht te krijgen in de gevolgen die deze zal hebben op het openbaar vervoer. Ook biedt een dergelijke analyse waardevolle input voor noodzakelijke strategische, tactische en operationele ingrepen.

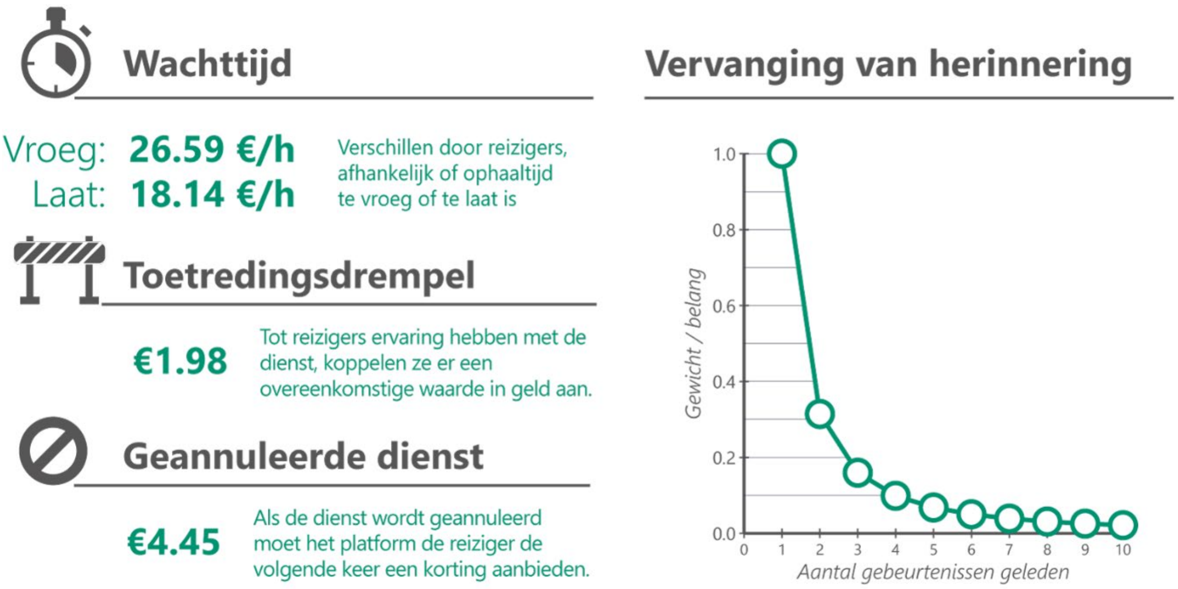
Het doel van deze thesis is dan ook om meer inzicht te bieden in de gedragseffecten die externe disruptieve factoren (kunnen) hebben op het openbaar vervoer. We passen verschillende benaderingen voor keuzemodellen toe en doen voorstellen voor extensies waardoor bestaande modellen voor reisgedrag verbeteren. Voor het onderzoek naar de verschillende soorten disruptieve factoren voor verschillende soorten ritten is dit promotieonderzoek opgedeeld in drie delen, namelijk voor de effecten op ritten over een korte, middellange en lange afstand. Hoewel disruptieve factoren grofweg op deze manier kunnen worden ingedeeld, heeft elke individuele disruptieve factor uiteindelijk eigen, unieke gevolgen voor het openbaar vervoer. Voor dit onderzoek richten we ons op ritdiensten (vraaggestuurde mobiliteit) en COVID-19.

In het eerste deel van dit onderzoek (*Hoofdstuk 2*) bespreken we de **gevolgen van de opkomst van vraaggestuurde mobiliteit (inclusief ritdiensten) op dagelijkse ritten in stedelijke gebieden.** Naast de bekendste ritdienstaanbieders (Uber, Lyft, DiDi enz.) bestaan nog talloze soortgelijke diensten, zoals onder meer flexibel openbaar vervoer, micromobiliteit en taxi's. In onze analyse behandelen we al deze diensten onder de noemer 'vraaggestuurde mobiliteit', of FLEX, de term die vaak wordt gebruikt voor micromobiliteitsdiensten in Nederland (waar we onze data hebben verzameld). We maken gebruik van aangegeven voorkeurdata van het Mobiliteitspanel Nederland en passen daarop een Latent Class Choice-model toe met een statische klasselidmaatschapfunctie. Dit levert een verdeling van de markt op in vier verschillende gebruikersgroepen wat betreft woon- werkverkeer en recreatief reisgedrag in stedelijke gebieden. Twee van deze vier segmenten (met een gezamenlijk marktaandeel van ~36%) zijn potentiële gebruikers van vervoersdiensten op afroep. Met name in het segment genaamd Flex-geneigde personen (~9%) bestaat een grote bereidheid tot het gebruik van vervoersdiensten op afroep en ook tot het delen van ritten. Voor deze mensen zijn kosten de bepalende factor in hun besluitvorming; hun bereidheid te betalen is aan de lage kant. In het segment Tech-geneigde personen (~27%) is het potentieel voor het gebruik van vervoersdiensten op afroep echter kleiner. Deze personen kiezen eerder dan anderen voor een niet gedeelde rit, hun bereidheid te betalen is groot en ze hebben een iets sterkere aversie tegen deelmobiliteit. De twee overige groepen, de Deel-geneigde fietsers (~55%) en de Flex-sceptische personen (~9%) hebben (nauwelijks) belangstelling voor vervoersdiensten op afroep voor korte ritten in de stad. Zijn geven de voorkeur aan respectievelijk hun fiets en hun auto.



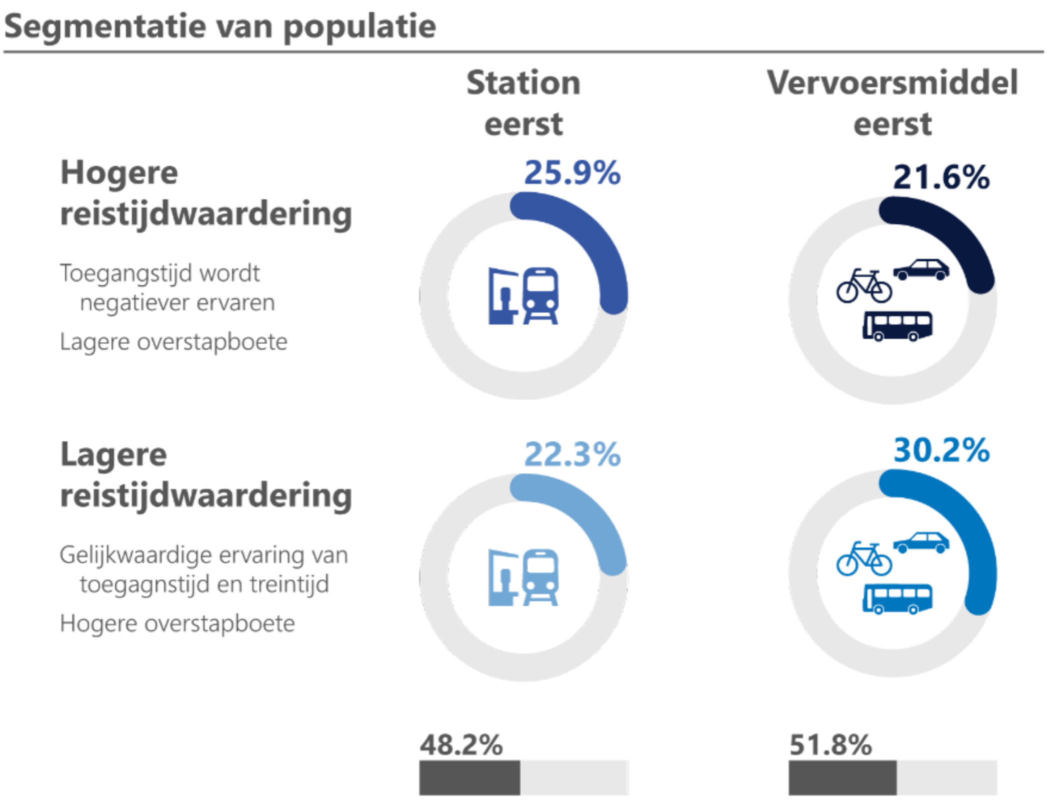
Afbeelding 1.5 Grafische samenvatting van hoofdstuk 2: Segmentatie van de populatie, bereidheid tot deelmobiliteit en marktaandeel van vervoersdiensten op afroep in stedelijke gebieden

Ten tweede bouwen we voort op de kennis over mobiliteit op afroep voor ritten over korte afstanden, door een analyse van de **perceptie van de variabiliteit van wachttijden voor vervoersdiensten op afroep** (*Hoofdstuk 3*). Gezien de specifieke aard van vervoersdiensten op afroep (een persoonlijke service op maat) zou de perceptie van de wachttijd aanzienlijk kunnen afwijken van de wachttijdvariabiliteit van het openbaar vervoer. Om betrouwbaarheid in een stated-preference (onderzoeks)setting te simuleren, horen respondenten een raming van het serviceniveau (wachttijd) van twee concurrerende ondernemingen. Wanneer ze een keuze hebben gemaakt, horen ze wat de daadwerkelijke wachttijd is. Deze taak wordt in totaal 32 keer herhaald, waarbij de geraamde informatie (voor de rit) constant blijft tijdens de verschillende herhalingen, terwijl de daadwerkelijke wachttijden willekeurig worden getrokken uit een vooraf gespecificeerde lognormale verdeling. De twee concurrerende bedrijven zijn gekoppeld aan verschillende lognormale verdelingen, die staan voor verschillende niveaus van betrouwbaarheid. De respondenten internaliseren deze via trial-and-error. Deze data wordt vervolgens geanalyseerd op basis van de instance-gebaseerd-leren methode met een mixed-logitmodelformulering. Met de eerste methode wordt geanalyseerd hoe belangrijk eerdere ervaringen zijn voor toekomstige besluitvorming (in hoeverre deze bijdragen aan de beslissing), terwijl met de laatstgenoemde het belang van de parameters wordt geanalyseerd en de verdeling daarvan binnen de populatie. Uit de resultaten blijkt dat ervaringen snel minder relevant worden; de meest recente ervaring heeft veruit de meeste invloed op de volgende beslissing (voor 75% wanneer de respondent slechts twee ervaringen heeft opgedaan en nog steeds voor 55% bij tien ervaringen). Dat betekent dat vervoerders niet lang nadeel ondervinden van een slechte serviceprestatie, ze moeten met name devolgende keer hun uiterste best doen. Respondenten blijken bereid circa € 0,30 tot € 0,44 te betalen voor een minuut minder ongeplande wachttijd. Wanneer de reis wordt geannuleerd (door de chauffeur, vanwege een gebrek aan beschikbare voertuigen of om een andere reden), koppelt de reiziger hier een boete aan die gelijkstaat aan grofweg € 4,45. Met andere woorden: willen reizigers overwegen de volgende keer met hetzelfde bedrijf te reizen, dan is dit de korting die ze verwachten. Tot slot kunnen gebruikers ook een toetredingsdrempel voor het uitproberen van een nieuwe service ervaren, die rond € 1,98 blijkt te liggen.



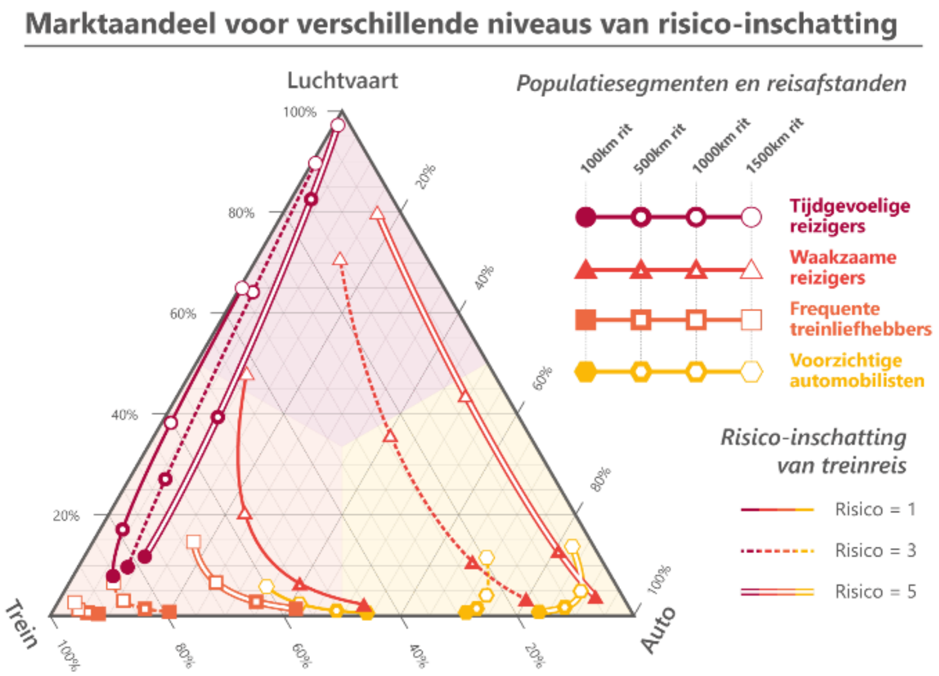
Afbeelding 1.6 Grafische samenvatting van hoofdstuk 3: Waardering van wachttijd, toetredingsdrempel en geannuleerde dienst, en het belang van eerdere ervaringen in een memory-decay-functie.

Vervoersdiensten op afroep concurreren niet alleen metopenbaar vervoer, maar kunnen ook een aanvulling daarop zijn. Daarom onderzoeken we ten derde het **potentieel van vervoersdiensten op afroep om een OV-halte te bereiken voor een middellange reis tussen steden** (*Hoofdstuk 4*). Hierbij onderzoeken we een tweeledige reis, waarvan het belangrijkste deel per trein wordt afgelegd en het treinstation wordt bereikt via fiets, auto, lokaal openbaar vervoer (bus, tram, metro) of mobiliteitsdienst op afroep. Respondenten moeten daarvoor een keuze maken voor een vervoersmethode en een station, waarna we onderzoeken hoe de kenmerken van deze twee delen van de reis tegen elkaar worden afgewogen. De aldus verkregen data wordt geanalyseerd met een Latent Class Choice Model, waarin de klassen verschillende nestingspecificaties kennen. Nesting wordt toegepast om te bepalen of er overeenkomsten bestaan tussen alternatieven. Aangezien de respondenten twee keuzen maken, onderscheiden we twee verschillende nestingstructuren. In het eerste geval is de toegangsmethode de primaire keuze (bovennest), in het andere geval is het station de primaire keuze. Ter illustratie: een nest waarin de toegangsmethode voorop staat impliceert dat reizigers eerst besluiten om op hun fiets naar het station te gaan en vervolgens besluiten naar welk station ze gaan. Een nest waarin het station voorop staat betekent dat de reiziger eerst een station kiest en vervolgens een vervoersmiddel om daar te komen. Door dit proces in een Latent Class model weer te geven, worden personen probabilistisch toegewezen aan de klasse die het meest overeenkomt met de keuzes die zij opgeven. Uit onze resultaten blijkt dat de verdeling tussen eerst de vervoersmethode of eerst het station bijna half om half is: respectievelijk 52% en 48%. Deze benadering biedt ons ook inzicht in substitutiepatronen in het geval van introductie van nieuwe vervoersmethodes (mobiliteit op afroep) en/of nieuwe stations. We zien dat mobiliteit op afroep slechts een klein marktaandeel heeft en dat dit beter scoort om bij stations te komen waar het aanbod van openbaar vervoer beperkt is en de afstand wellicht te groot is om te fietsen. Daarnaast merken we op dat vervoersdiensten op afroep geen vervanging voor openbaar vervoer kunnen zijn, omdat de meeste gebruikers dan zouden overstappen op de auto en de fiets. Wanneer mobiliteit op afroep naast het openbaar vervoer wordt geïntroduceerd, stapt een bovengemiddeld groot deel van de automobilisten hiernaar over.



Afbeelding 1.7 Grafische samenvatting van hoofdstuk 4: Verdeling van populatie tussen mensen die de vervoerswijzee voorop stellen en mensen die stationskeuze voorop stellen - ook verdeeld tussen twee verschillende VOT-groepen

Op het gebied van langeafstandsreizen, en dan met name internationale reizen, onderzoeken we de **invloed van de perceptie van reizigers van het risico op een COVID-19-besmetting bij hun keuze voor een reismethode voor een lange afstand** (*Hoofdstuk 5*). Toen de reisbeperkingen in het kader van COVID-19 langzaamaan werden versoepeld, vermeden veel mensen langeafstandsreizen nog steeds, mogelijkomdat ze dachten dat er een verhoogd besmettingsrisico was. We hebben een stated-preference-onderzoek gedaan om de risico-inschatting van reizigers vast te stellen, waarbij we de Hierarchical Information Integration-methode hebben toegepast. Hiermee kunnen we het door mensen ingeschatte risiconiveau op een likertschaal kwantificeren op basis van diverse risicogerelateerde indicatoren (verplichte mondkapjes, vaccinatiegraad, reisadviezen enz.) De risico-inschatting wordt vervolgens meegenomen in een stated-choice-experiment, als een kenmerk dat wordt afgewogen tegen prijs, reistijd en comfort, om meer inzicht te krijgen in de risicoafweging. Er wordt een nieuwe modelmethode ontwikkeld om deze tweeledige methode vanuit het perspectief van marktsegmentatie weer te geven. Ten eerste wordt de discrete-choice-data in een Latent Class Choice Model weergegeven. Ten tweede wordt met behulp van de probabilistische klasse-allocatie voor alle respondenten bepaald hoe waarschijnlijk het is dat ze behoren tot de verschillende klassen. Aan de hand van deze waarschijnlijkheid worden verschillende gewogen kleinste-kwadraten-regressiemodellen opgesteld om te bepalen hoe verschillende risicogerelateerde indicatoren de risico-inschatting voor verschillende gebruikersgroepen beïnvloedt. We ontdekten vier verschillende gebruikersgroepen wat betreft langeafstandsreizen onder de premisse van de risico-inschatting van COVID-19. Twee groepen reizigers hebben een grotere betaalbereidheid (€72/u en €50/u) en zijn vaak onverschilliger wat betreft vervoersmethode (ze geven de voorkeur aan ofwel de auto of de trein voor kortere afstanden en aan vliegen voor langere afstanden). Twee andere segmenten hebben een mindere betaalbereidheid (€38/u en €15/u) en zijn vaak meer gehecht aan één vervoersmethode, ongeacht de reisafstand (respectievelijk de trein en de auto). De risico-inschatting verschilt ook tussen de groepen: twee groepen schatten dit in als tijdsafhankelijk (onnut groter als de reis langer is), terwijl de overige twee dit zien als tijdsonafhankelijk en vooral een verband zien met een specifieke methode (disutility van risico met dezelfde reismethode is gelijk ongeacht de reisafstand). Wat betreft risicogerelateerde indicatoren zijn de infectie- en vaccinatiegraad op de bestemming het meest consistent, waardoor het waargenomen risico respectievelijk toeneemt en afneemt. Een belangrijker, maar wel gemengder effect blijkt uit te gaan van reisadviezen van de overheid, een mondkapjesverplichting en verplichte bewijzen van een negatieve test, vaccinatie en/of herstel.



Afbeelding 1.8 Grafische samenvatting van hoofdstuk 5: Het effect van risico-inschatting op marktaandeel op diverse reismethoden voor lange afstanden

Samengevat biedt dit proefschrift inzicht in de invloed van externe disruptieve factoren op het openbaar vervoer en het gebruik daarvan. Door middel van diverse bestaande en nieuw ontwikkelde discrete-choice-modellen hebben we onderzocht hoe reizigers kijken naar deelmobiliteit (met name vraaggestuurde mobiliteit) en het risico op een COVID-19-besmetting en wat de invloed daarvan is op het gebruik en de aantrekkingskracht van het openbaar vervoer voor reizen over korte, middellange en lange afstanden. Op basis van deze inzichten doen we verschillende aanbevelingen voor de praktijk (aanbieders van openbaar vervoer, aanbieders van vervoersdiensten op afroep en beleidsmakers) over te nemen maatregelen, afhankelijk van het beoogde doel van hun ingrepen/beleid. Wat betreft deelmobiliteit is de belangrijkste uitkomst dat als duurzaamheid een kerndoel is de introductie van dergelijke vervoersmethodes moet worden afgestemd op openbaarvervoerdiensten. Daarbij kan onder meer worden gedacht aan het soort dienst dat wordt geïntroduceerd, het gebied waarin de dienst wordt aangeboden en integratie van informatie en vervoerstarieven. Hoewel deze diensten potentieel een goede aanvulling zijn op het openbaar vervoer, kunnen ze elkaar zonder goed toezicht ook beconcurreren. Wat betreft COVID-19 lijkt de risicobeoordeling voor treinreizen het hoogst. Dit betekent dat voor het behoud van het marktaandeel van het treinverkeer en het stimuleren van milieuvriendelijk reizen de benodigde veiligheidsmaatregelen moeten worden genomen. Mogelijk zijn er ook extra prijsmaatregelen nodig om het reizen per trein te stimuleren en andere methodes voor langeafstandsreizen te ontmoedigen.

Povzetek

Sisteme javnega prevoza so oblikovale in še vedno oblikujejo moteče sile. Notranje motnje (npr. elektrifikacija, digitalizacija itd.) omogočajo izboljšanje javnega prevoza in tako zagotavljajo višje ravni storitev. Po drugi strani pa zunanje motnje silijo javni promet, da prilagodi svoje storitve, si opomore in prilagodi novemu okolju. Zunanje motnje so lahko nova konkurenčna alternativa (tj. način prevoza), ki zmanjšuje tržni delež javnega prevoza. Nedavni in zelo dober primer zunanje motnje je skupna mobilnost, krovni izraz, ki vključuje veliko različnih alternativ, kot so prevozi na klic, souporaba koles, avtomobilov itd. Zunanje motnje lahko tudi temeljito spremenijo povpraševanje po javnem prevozu ali potovanjih nasploh. Dva pomembna primera sta podnebne spremembe in zlasti nedavna pandemija COVID-19. Ključni dejavnik vpliva motnje na javni promet so uporabniki ter njihov pogled na in percepcija potovanj. Analize odziva potnikov na motnje so zato bistvenega pomena za razumevanje njihovega vpliva na uporabo javni promet, saj olajšajo sprejm in izvajanje ukrepov na strateški, taktični in operativni ravni.

Cilj te doktorske naloge je zagotoviti boljše razumevanje vpliva vedenja, ki ga imajo (lahko) zunanje motnje na javni promet. V nalogi uporabimo različne modele diskretne izbire in predlagamo razširitve obstoječih modelov, ki izboljšujejo način zajemanja potovalnih navad. Da bi preučili vpliv različnih motenj na različne tipe potovanj, je raziskava razdeljena na tri dele, in sicer na preučevanje vpliva na potovanja na kratke, srednje in dolge razdalje. Čeprav je mogoče motnje na splošno razvrstiti v skupine, kot je navedeno v zgornjem odstavku, ima vsaka posamezna motnja na koncu svoj edinstven vpliv na javni promet. V tej raziskavi se tako osredotočamo na vpliv storitev prevoza na klic (mobilnost na zahtevo) in COVID-19.

V prvem delu te dizertacije (2. poglavje) je raziskan **vpliv uvedbe mobilnosti na zahtevo na vsakodnevna potovanja v mestih**. Čeprav so najbolj znani primeri storitev prevoza na zahtevo ponudniki prek mobilnih aplikacij (kot so Uber, Lyft, DiDi itd.), obstajajo tudi številne podobne storitve, in sicer fleksibilen javni prevoz, mikro javni prevoz, taksiji itd. Te storitve analiziramo celovito in jih imenujemo "*storitve mobilnosti na zahtevo*" ali FLEX, kar je izraz, ki se pogosto uporablja za storitve fleksibilnega javnega prevoza na Nizozemskem (kjer je potekala raziskava). Podatke o izraženih preferencah, pridobljenih iz *Nizozemskega panela za mobilnost* (MPN) analiziramo z modelom diskretne izbire z latentnimi razredi, pri katerem uprorabimo statično funkcijo za pripadnosti posameznemu razredu. Tako dobljena segmentacija trga kaže štiri različne skupine uporabnikov glede na potovanja na delo ali v prostem času. Dva od štirih segmentov (s skupnim tržnim deležem ~36 %) imata potencial za uporabo mobilnosti na zahtevo. Zlasti segment, označen kot *FLEX-pripravljeni posamezniki* (~9 %), kaže veliko pripravljenost za uporabo storitev na zahtevo in je odprt tudi za deljenje prevoza. Zanje so stroški prevoza odločilni dejavnik pri sprejemanju odločitev, saj precej nizko vrednotijo čas (izboljšave v potovalnem času). *Tehnično-pripravljeni posamezniki* (~27 %) po drugi strani kažejo manj pripravljenosti za uporabo storitev na zahtevo in so bolj nagnjeni k temu, da se odločijo za zasebno potovanje, visoko vrednotijo svoj potovalni čas in imajo nekoliko večji odpor do souporabe. Preostali dve skupini, *souporabni kolesarji* (~55 %), in *FLEX-skeptični posamezniki* (~9 %), ne kažejo (skoraj) nobenega zanimanja za mobilnost na zahtevo za kratka mestna potovanja in raje uporabljajo kolo oziroma avtomobil.

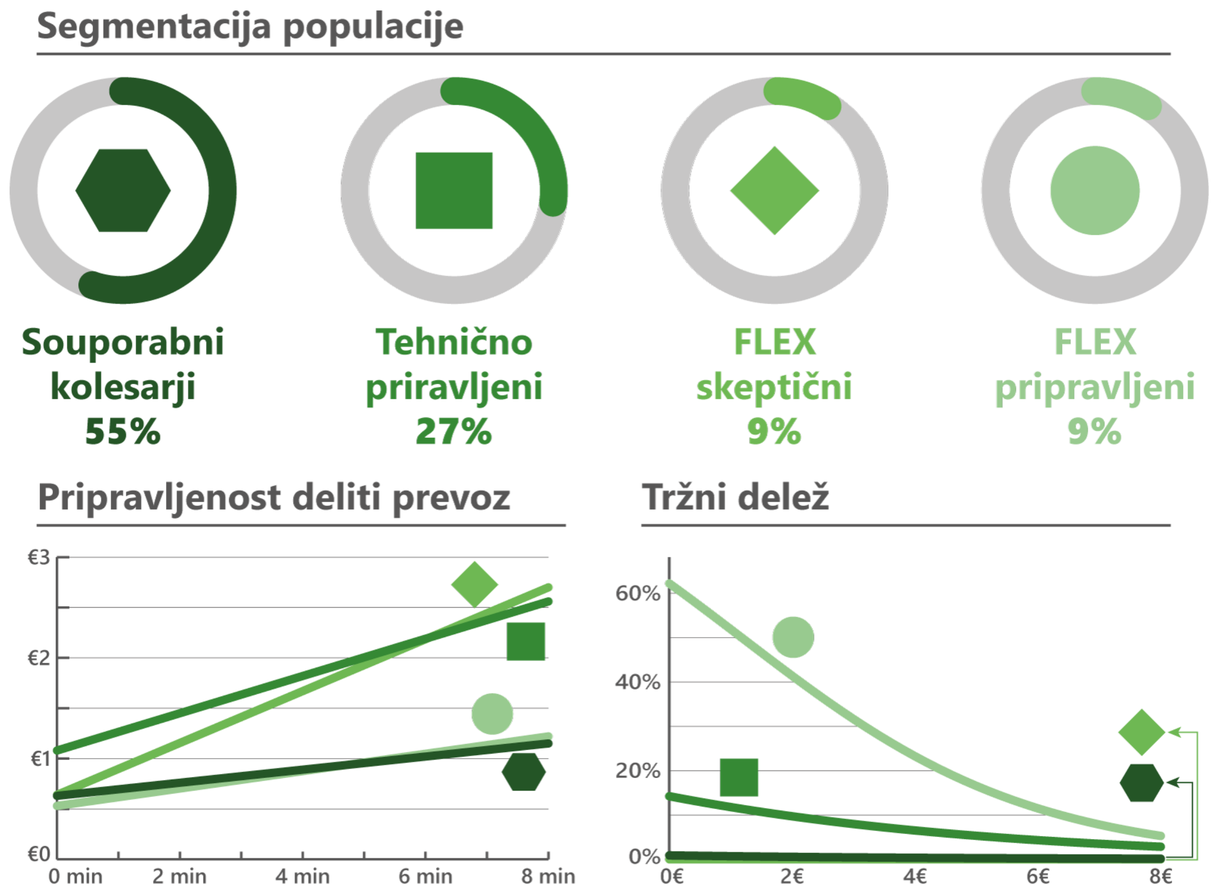


Figure 1.9 Grafiči povzetek 2. poglavja: Segmentacija populacije, Pripravljenost deliti prevoz in Tržni delež za prevoze na klic na urbaniziranih območjih

V drugem delu znanje o mobilnosti na zahtevo za kratka potovanja nadgradimo z analizo **kako potniki dojemajo nepredvidljivost časa čakanja pri storitvah na zahtevo** (3. poglavje). Glede na posebno naravo storitev na zahtevo (osebna storitev, brez urnikov, po potrebi) se lahko dojemanje časa čakanja bistveno razlikuje od dojemanja čakanja na javni prevoz. Da bi simulirali zanesljivost v okviru izražene preference (anketa), anketirancem prikažemo predvideno raven storitve (čakalni čas) za dve konkurenčni podjetji. Ko izberejo eno ali drugo, jim prikažemo dejanski čas čakanja. Ta postopek ponovimo 32-krat, pri čemer predviden nivo stortive (pred potovanjem) ostane nespremenjene, medtem ko se dejanski čakalni časi izberejo naključno iz vnaprej določene logaritemsko-normalne porazdelitve. Vsako od podjetij je povezano z lastno logaritemsko-normalnimi porazdelitvijo. Na ta način zajemamo različne ravni zanesljivosti, ki jih anketiranci ponotranjijo skozi vseh 32 iteracij. Podatke analiziramo z modelom izkustvenega učenja, ki bazira na mixed logit modelu diskretne izbire. Prvi analizira kako pomembne so izkušnje za sprejemanje odločitev (v kakšnem obsegu prispevajo k odločitvi), drugi pa analizira pomembnost parametrov in njihovo variacijo v populaciji. Rezultati kažejo, da imajo novejše izkušnje največji vpliv na naslednjo izbiro (zadnja izkušjna predstavljajo 75% delež vseh izkušenj, če ima anketiranec le dve izkušnji, in še vedno 55% delež, če ima deset izkušenj). To pomeni, da operaterji ne bodo dolgo plačevali posledic slabo izvedene storitve, le v prvi naslednji situaciji se morajo potruditi po svojih najboljših močeh. Kar zadeva čas čakanja, so anketiranci pripravljeni plačati približno od €0,30 do €0,44 za vsako prihranjeno minuto nenačrtovanega časa čakanja. Če je potovanje odpovedano (s strani voznika, zaradi pomanjkanja razpoložljivih vozil ali kakšnega drugega razloga), je kazen, ki jo potnik povezuje s tem, enaka približno €4,45. Z drugimi besedami, to je popust, ki ga potnik pričakuje v naslednjem primeru, da bi še vedno razmišljal o potovanju s tem podjetjem. Nazadnje, uporabniki občutijo tudi oviro za vstop (pred prvo uporabo nove storitve), ki je v povprečju ovrednostna €1,98.

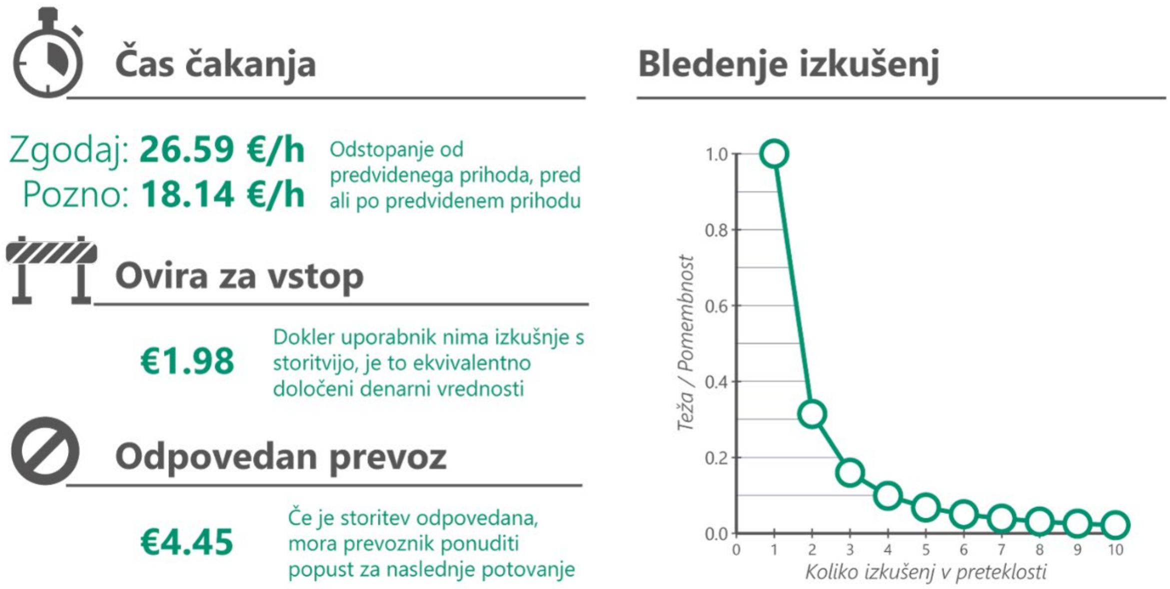


Figure 1.10. Grafiči povzetek 3. poglavja: Vredotenje časa, Ovira za vstop, Odpoved prevoza in pomembnost in bledenje preteklih izkušenj za odločanje v prihodnosti

Ker storitve na zahtevo niso le konkurenčne javnemu prevozu, temveč ga lahko tudi dopolnjujejo, smo preučili tudi **potencial prevoza na zahtevo kot načina dostopa do medmestnega javnega prevoza** (srednje razdalje) (4. poglavje). V tej raziskavi preučujemo dvodelno potovanje, pri katerem se glavni del opravi z vlakom, pot do železniške postaje pa je mogoče opraviti s kolesom, avtomobilom, lokalnim javnim prevozom (avtobus, tramvaj, podzemna železnica) ali prevozom na zahtevo. Da bi preučili, kako se vrednotijo značilnosti obeh delov potovanja med seboj, smo anketirance vprašali o izbiri načina prevoza in izbiri postaje. Pridobljene podatke smo analizirani z modelom diskrentne izbire z latentnimi razredi, kjer imajo razredi različne specifikacije gnezdenja. Modeli gnezdenje se uporabljajo, ko obstajajo podobnosti med alternativami. Ker anketiranci opravijo dve izbiri (izbira prevoznega sredstva in izbira postaje), določimo dve različni strukturi gnezdenja: v enem primeru prva izbira (zgornje gnezdo) prevozno sredstvo dostopa, v drugem pa je prva izbira postaja. Za ponazoritev: pri gnezdu "najprej prevozno sredstvo" se potnik najprej odloči, da bo za dostop do postaje uporabil npr. kolo, nato pa se odloči, do katere postaje se bo odpravil. Gnezdo "najprej postaja" pomeni obratno, da potnik najprej izbere želeno postajo, nato pa sredstvo, kako bo prišel do nje. Z modeliranjem tega z modelom latentnih razredov se posameznike verjetnostno razvrsti v razred, ki najbolj ustreza njihovim navedenim izbiram. Rezultati kažejo, da je delitev med izbiro načina prevoza in izbiro postaje skoraj pol na pol: 52 % potnikov spada v skupino "najprej prevozno sredstvo", 48 % pa v skupino "najprej postaja". Ta pristop nam omogoča tudi vpogled v vzorce zamenjave v primerih uvajanja novih načinov prevoza (mobilnost na zahtevo) in/ali novih postaj. Vidimo, da ima prevoz na zahtevo majhen tržni delež in se bolje obnese pri dostopu do postaj, kjer je ponudba javnega prevoza omejena, razdalja pa je lahko predolga za kolesarjenje. Ugotavimo tudi, da prevoz na zahtevo ne more nadomestiti javnega prevoza, saj bi se večina njihovih uporabnikov preusmerila na uporabo avtomobilov in kolesa. Če se prevoz na zahtevo uvede poleg javnega prevoza, bi se nadpovprečno velik delež uporabnikov preusmeril z avtomobila.

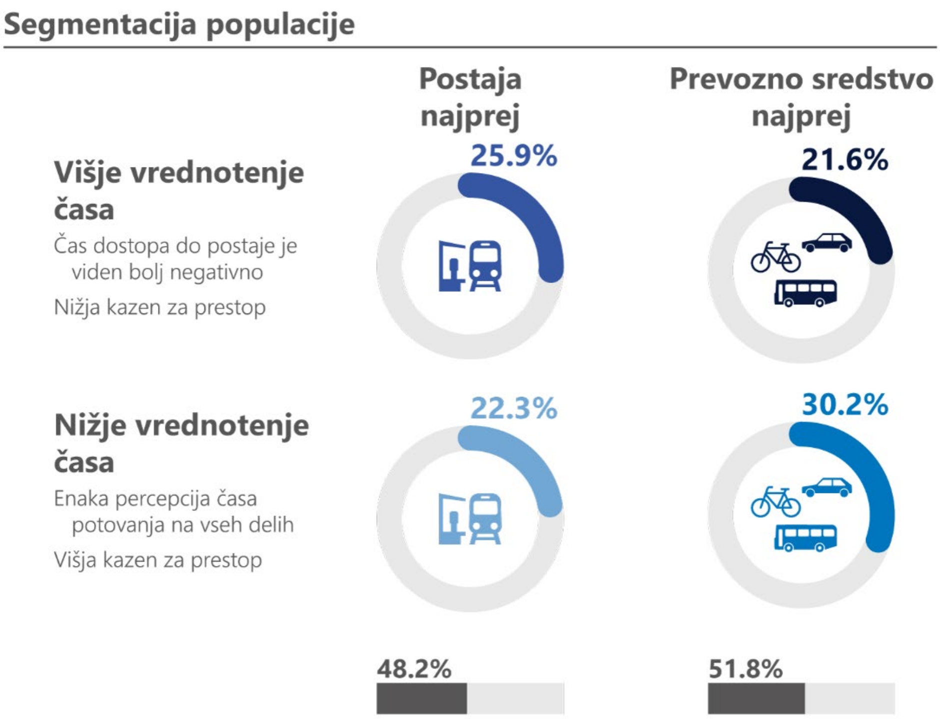


Figure 1.11 Grafiči povzetek 4. poglavja: Segmentacija populacije glede na gnezdenje odločitev (prevozno sredstvo ali postaja najprej) ter glede na vrednotenje časa

Nazadnje, ob upoštevanju potovanj na dolge razdalje in zlasti mednarodnih potovanj, smo preučili **vpliv tveganja okužbe s COVID-19 pri izbiri načina potovanja na dolge razdalje** (5. poglavje). V času odprave omejitvenih ukrepov so se mnogi še vedno izogibali mednarodnim potovanjem (potovanje na dolge razdalje) zaradi potencialno večjega tveganja okužbe. Da bi ocenili zaznavanje tveganja potnikov, smo izvedli anketo o izraženih preferencah z metodo hierarhične integracije informacij. Ta nam omogoča, da na podlagi različnih kazalnikov, povezanih s tveganjem (obvezne maske, delež precepljenosti, uradni nasveti za potovanje itd.), določimo subjektivno zaznano stopnjo tveganja na Likertovi lestvici. Dojemanje tveganja je nato vključeno v poskus dikretne izbire kot lastnost, ki jo je treba upoštevati, skupaj s ceno, potovalnim časom ter nivojem udobja (prvi ali drugi razred). Razvili smo nov pristop modeliranja, ki zajema ta dvostopenjski pristop z vidika segmentacije trga. Najprej analiziramo podatki z modelom diskretne izbire z latentnimi razredi. Nato z uporabo verjetnostne razporeditve razredov vsakemu anketirancu pripišemo verjetnost pripadnosti posameznemu razredu. Le-to uporabimo v ločenih regresijskih modelih z napako v spremenljivkah, ki prikažejo kako različni s tveganjem povezani kazalniki vplivajo na zaznavanje tveganja za različne skupine uporabnikov. Na podlagi tveganja okužbe s COVID-19 smo odkrili štiri različne skupine uporabnikov v konteksu potovanj na dolge razdalje. Dve skupini potnikov sta pripravljeni plačati več za skrajšanje svojega potovalnega časa (72€/h in 50€/h) in sta bolj neopredeljeni glede prevoznega sredstva (na krajših imajo sicer raje avtomobil ali vlak, na daljših pa letenje). Druga dva segmenta sta pripravljena plačati manj (38 €/h in 15€/h) in sta bolj vezana na eno samo prevozno sredstvo, za vsa potovanja, neodvisno od razdalje (vlak oziroma avtomobil). Tudi percepcija tveganja se med skupinama razlikuje, saj ga dve skupini zaznavata kot časovno odvisno (tveganje okužbe čutijo v odvisnosti od časa izpostavljenosti, torej če je čas potovanja daljši), drugi dve pa ga zaznavata kot časovno neodvisno in ga povezujeta le z določenim načinom prevoza (tveganje je enako za potovanja z istim prevoznim sredstvom, ne glede na trajanje). Glede kazalnikov, povezanih s tveganjem, sta najbolj pomembna stopnja okuženosti in precepljenost na destinaciji, ki povečujeta oziroma zmanjšujeta zaznano tveganje. Pomemben, čeprav bolj mešan vpliv, je mogoče opaziti pri vladnih nasvetih za potovanje, obvezi za uporabo mask in dokazilu o negativnem testu, cepljenju in/ali prebolelosti (PCT).

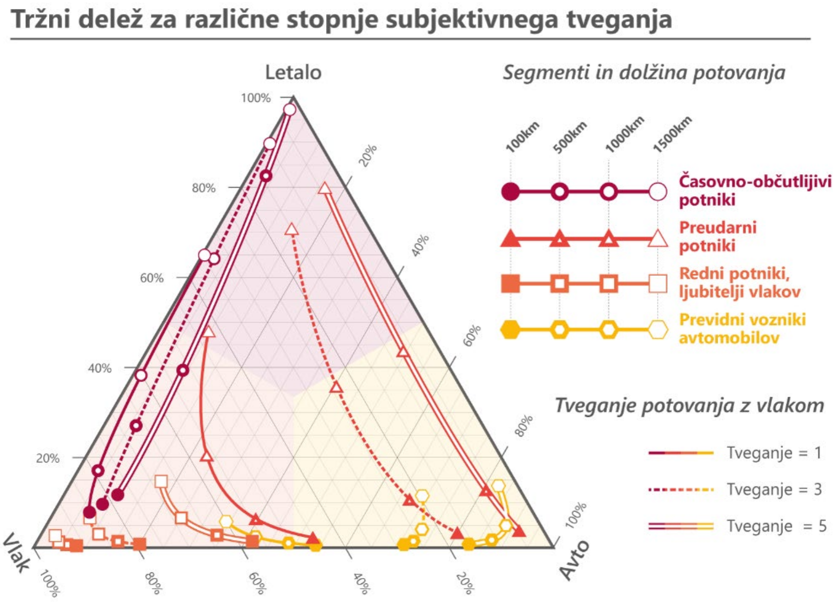


Figure 1.12 Grafiči povzetek 5. poglavja: Vpliv subjektivnega tveganja na tržni delež pri mednarodnih potovanjih ter potovanjih na daljše razdalje

Če povzamemo, ta disertacija ponuja vpogled v to, kako zunanje motnje vplivajo na javni prevoz in njegovo uporabo. Z uporabo različnih uveljavljenih in novo razvitih pristopov modelov diskretne izbire raziskujemo, kako potniki zaznavajo skupinsko mobilnost (zlasti storitve prevoza na zahtevo) in tveganje okužbe COVID-19 ter kako vplivata na uporabo in privlačnost javnega prevoza za potovanja na kratke, srednje in dolge razdalje. Na podlagi teh spoznanj navajamo več priporočil za prakso (izvajalce javnega prevoza, ponudnike storitev prevoza na zahtevo in oblikovalce politik) o tem, kakšne ukrepe je treba sprejeti glede na zastavljene cilje. Glavna ugotovitev za deljeno mobilnost je, da je za čim bolj trajnostno naravnano mobilnost potrebno uskladiti prevoz na klic in javni prevoz. To vključuje odločitve o vrsti storitve, ki jo je treba uvesti, območju delovanja, integraciji informacij in cen itd. Čeprav lahko te storitve dobro dopolnjujejo javni prevoz, lahko, če se ne izvajajo pravilno, tudi medsebojno tekmujejo. V zvezi s COVID-19 se zdi, da je potovanje z vlakom povezano z najvišjo stopnjo zaznanega tveganja, kar pomeni, da je treba za ohranitev njegovega tržnega deleža in spodbujanje trajnostnega potovanja sprejeti ustrezne varnostne ukrepe, da se potnikom zagotovi občutek varnosti, pri čemer so morda potrebni dodatni cenovni ukrepi za spodbujanje potovanja z vlakom in odvračanje od drugih načinov potovanja na dolge razdalje.

Chapter 1:

Introduction

1.1 Disruptors of public transport

Public transport, sometimes also referred to as (public) transit, is one of the oldest forms of mobility. It is not a single mode of transport, but rather a term used for any collective mode of transport, accessible to the general public, operating based on a pre-defined schedule and running on fixed routes (Vuchic, 2007). Throughout history, public transport has continuously been evolving and adapting, with this evolution often being pushed by disruptors. A disruptor can be seen as anything or anyone that disrupts the status quo and compels the person or system affected to take action and adjust ("Cambridge Dictionary," 2022). To better understand differences between disruptors, we can classify them as internal vs. external or short-term vs. long-term. An internal disruptor is for example a technological innovation (steam engine, electricity, internal combustion engine, etc.), whereas new services, brought on by the sharing economy (ride-hailing, car-sharing, bike-sharing, etc.) could be classified as external disruptors. From the perspective of time, short-term disruptors have a temporary impact on the market (natural disaster, war or pandemic (COVID-19)), while long-term disruptors persist and fundamentally change the industry and market (self-driving cars, certain sharing economy services,…).

In recent years, many external innovation-related disruptors affecting public transport are a result of the rapid popularisation of the sharing economy (Cagle, 2019), brought on by digitalisation and the mass adoption of the internet and smartphones. Countless new transport services (ride-hailing, car-sharing, bike-sharing, shared e-scooters, etc.) have entered the mobility ecosystem, with varying levels of success and impact. On-demand mobility services (ride-hailing, demand responsive transit, microtransit etc.) in particular have shown to be a major contender in the realm of personal mobility (Gehrke et al., 2019; Henao & Marshall, 2018; Rodier, 2018; Young et al., 2020). The concept of Mobility-as-a-Service (MaaS) is another product of digitalisation and the wish to bundle-up all the new and upcoming alternatives. Digitalisation can also be seen as an internal disruptor, helping public transport reinvent itself, both from an opportunity perspective, and to mitigate the effects of all these new services entering the market. While many of these disruptors promise to revolutionise travel by offering a superior service to public transport, several also showcase how they can work together with public transport (Gehrke et al., 2019; King et al., 2020; Tirachini & del Río, 2019), modernising and improving the level-of-service that is so often performing below many users' expectations.

Another disruptor affecting public transport and the level-of-service, perhaps the most impactful external disruptor of public transport in recent years has been the COVID-19 pandemic. With public life effectively shutting down and demand for travel plummeting, public transport has seen a ridership drop unlike any time in history (Currie et al., 2021; de Haas et al., 2020; Shamshiripour et al., 2020). And while society now seems to be leaving the pandemic and its restrictions behind, many consequences of it persist and are likely to remain a part of everyday life for some time to come. Working from home, avoiding crowded spaces, reduced public transport patronage, increased use of private modes and less or shorter distance international travel are just some of the changes that might be sustained.

While dealing with the aforementioned (and many other) disruptors, public transport is also seeing a fundamental change in light of the impending climate emergency and the need to take action to curb climate change and mitigate its consequences. Disruptors have the potential to aid in the transition to a more sustainable (public) transport system, by helping improve the attractiveness of public transport and providing additional alternatives to less sustainable transport modes. How this is operationalised however is crucial.

Changes in a transport system are often guided by transport policies, with the aim of achieving a desired outcome, be it sustainability, social inclusion, profitability etc. Transport policies rely on series of complex transport models and simulations which provide some insight into how different policies may play out and what are the benefits and drawbacks of each. While no model is able to completely accurately predict all outcomes, they can provide a good idea of what is to be expected.

A critical component of transport models is the behavioural foundation: how individual travellers are likely to behave. Given the relative novelty of many disruptors, many behavioural aspects of their implications remain unknown and thus it is less certain what the best course of action is. Additionally, many behavioural studies do not consider that travellers can be vastly different in their preferences, attitudes and socio-demographic standing. Ways of capturing this traveller heterogeneity exist but can vary greatly in how appropriate they are for capturing a certain aspect of behaviour (Greene & Hensher, 2003).

1.2 Objective of dissertation research

The overarching objective of this thesis is thus to **quantify the behavioural impact of external disruptors on public transport and its (potential) users**. This research is set in the context of disruptors which have substantially shaken up the public transport industry in recent years, investigating trips of varying length and purposes. The focus is primarily on the context of the Dutch travelling public but can be extrapolated onto other contexts with similar characteristics.

To expand upon this objective, four topics are identified and corresponding research questions formulated, which are addressed in the subsequent chapters of this research:

1. **How would the introduction of on-demand mobility services impact everyday trips in urban areas?**
2. **Given that the performance of any kind of transport service is inherently variable, how does this variability impact the perception of said service?**
3. **In what way and order do users make choices when making a multi-leg public transport trip involving on-demand mobility?**
4. **What was the impact of the COVID-19 pandemic and the restrictions across countries on travel behaviour for long-distances cross-border travel?**

1.3 Discrete choice theory and methods

A common approach to analyse choice behaviour of individuals is by means of a Discrete Choice Modelling (DCM), which are used to analyse data gathered through Discrete Choice Experiments (DCE) (Train, 2009). Discrete choice modelling analyses how individuals make trade-offs, choosing a "discrete choice" among a finite set of alternatives. Alternatives are characterised by a set of attributes (characteristics), which can take on a variety of different levels (values). The observed choice behaviour can then be modelled by a large variety of models. The simplest and most widely used, the multinomial logit (MNL) model, only considers the alternatives and their related attributes (Train, 2009). Typically, it is also assumed that the decisions are based on individuals maximising their expected utility (Random Utility Maximisation (RUM)) (McFadden, 1974). More advanced models are able to include nesting effects (similarities between a subset of alternatives) (Train, 2009), heterogeneity among respondents (different trade-off behaviour), socio-demographic and attitudinal characteristics of individuals (Greene & Hensher, 2003; Hess, 2014) or different decision rules (Random Regret Minimisation (RRM)) underlying the trade-off behaviour (Chorus et al., 2008). Below, the approaches chosen in our research are discussed in more detail.

1.3.1 Revealed and stated preference data collection

Investigating travellers' attitudes and preferences requires data on their behaviour and opinions with respect to travel. Two of the most common approaches for analysing travel behaviour is through (1) Revealed preference (RP) data or Stated preference (SP) data. The main difference between the two approaches is evident from their names. RP involves data where the travellers' behaviour is examined in real life, observing what they choose, how they respond to changes etc. SP on the other hand, relies on survey-based data, where (potential) travellers are invited to fill-in in a questionnaire in which they are presented with hypothetical scenarios and need to indicate their preferred choice. Both approaches naturally have benefits and drawbacks, with the shortfalls of one usually representing the advantages of the other.

SP has the downside of hypothetical bias, meaning that respondents may act differently in real life then what they indicated in the survey. This typically manifests itself with respondents tending to exhibit behaviour which is more societally acceptable, sustainable, are willing to spend more money etc (Loomis, 2011; Murphy et al., 2005). In RP, this is not an issue, as choices are what the travellers have shown to choose, meaning it is as real as it can get.

On the other hand, RP has three major downsides, which are both mitigated in SP. Firstly, as RP is observing existing behaviour, it makes it very difficult to evaluate the market potential and preferences with respect to services, that are either not present at all, are still in their pioneering phases, or only being used by a small minority of individuals. It is also unclear which attributes (e.g. travel time, cost, comfort,…) the traveller considered when making the decision. Secondly, RP data often lacks any kind of additional information on the traveller. Simply observing users' behaviour, it is very difficult to know their socio-demographic and attitudinal characteristics, limiting the analysis to choice behaviour only. Thirdly, to properly evaluate choice behaviour, a set of alternatives (referred to as a "*choice set*") is required. In RP, it is often not certain which alternatives the traveller considered. Researchers can imply possible choice sets among which the alternative was selected, but this can never be fully certain. An incorrectly specified choice set can have negative ramifications for the analysis. For example, if an alternative is assumed to be known to a traveller, but they do not actually know or consider it, the model assumes this alternative is not relevant or interesting to the respondent, resulting in a mis-specified model and an underrepresented market share.

All three shortfalls are addressed in SP. As it involves hypothetical scenarios, the researcher may include any type of service they wish, as long as the respondents find it believable and realistic. Secondly, the researcher may include additional socio-demographic and attitudinal questions in the survey, which can help in understanding the choices travellers make. Thirdly, the researcher is also the one deciding which alternatives are shown in the choice set, meaning they have full control over what the respondents see, evaluate, and base their decision on. The selection of alternatives and attributes is fully within their control.

In this research, our data collection is based primarily on the SP approach. As digitalisation-related disruptors represented a niche market share and are still fairly new, there is limited data available to rely on the RP approach. With many sharing economy-related disruptors, data is predominantly in the hands of private operators. By applying SP instead, we are able to evaluate the full potential of on-demand mobility. Additionally, by capturing attitudinal and socio-demographic information, it allows us to better understand how individuals use of public transport will be affected in the light of different disruptors (on-demand Mobility, COVID-19).

1.3.2 Accounting for traveller heterogeneity

As stated in the objectives, capturing the different preferences and trade-off behaviour within the population is important for better understanding how different groups behave in the analysed situations. The composition of these groups may change over time, shifting the average population behaviour. Within DCM, there are two predominant modelling approaches used for analysing the heterogeneity in choice behaviour – the (1) Mixed Logit (ML) model and the (2) Latent Class Choice Model (LCCM) – capturing heterogeneity in a fundamentally different way (Greene & Hensher, 2003; Hess, 2014; Train, 2009). ML assumes that sensitivity to an attribute in the sample/population is (normally) distributed and is able to determine the mean and standard deviation of this distribution. Other types of distributions can also be estimated, such as a log-normal, uniform, triangular etc. LCCM divides the population into a discrete number of classes or segments, estimating a separate model for each segment. Each segment has a unique set of parameters and individuals are then probabilistically assigned to each segment, based on their observed choice behaviour and potentially also their socio-demographic and/or attitudinal data (Greene & Hensher, 2003; Hess, 2014).

The benefit of ML is that it is much more parsimonious, meaning it achieves a higher model fit with a comparatively low number of parameters. It is also not prone to getting stuck in local optima when estimating the model. LCCM on the other hand is more straightforward when interpreting the results, as each segment has its own set of taste parameters, indicating their sensitivity to price and willingness to pay for service and quality improvements. The addition of socio-demographic and attitudinal information in the class allocation is also highly informative of the class characteristics (Greene & Hensher, 2003).

Both approaches require specification from the researcher. In ML, different distributions should be tested to determine the optimal. In LCCM, the number of classes needs to be specified. In both cases, model fit and various statistical tests aid in this decision, as well as a-priori expectations, past findings, and interpretability of the results. In this research, both approaches are utilised, depending on main goal of the research question in each individual section.

1.3.3 Socio-demographic and attitudinal information

An important aspect of choice behaviour, aiding in the explanation and understanding of behaviour, are the perceptions of individuals and their socio-demographic information. These constitute their beliefs, opinions which manifest themselves through and inform their choices, while the latter can be anything from their age, gender, education level, income, household size, car ownership etc. which directly or indirectly impact their choices.

Given the relevance of this data, a variety of ways of including it in DCMs exist. The simplest form is by including them as interaction effects on specific attributes. A typical example would be adding an interaction effect of income onto the cost parameter, as one would logically assume that individuals with a higher income are less sensitive to price. Multiple socio-demographics and attitudes can be combined into factors through a prior analysis and included into choice models in what are known as Hybrid Choice Models. In LCCMs, as mentioned in the previous subsection, this data can directly enter the class allocation function, providing information on the characteristics of the different population segments, enabling a direct relation between to their choice behaviour. For more complex attitudinal analyses, attitudes towards a certain topic can be analysed in a Hierarchical Information Integration approach (Louviere, 1984; Molin & Timmermans, 2009). Respondents first answer a set of attitudinal and perception-related questions on a specific topic that is being investigated (like comfort, safety, risk,...). This is then integrated as a subjective factor in the DCE alongside other attributes and can be linked back to the initial experiment and evaluated.

As this information is highly relevant in understanding behaviour, it is also a key element of our research. We explore different ways of incorporating this into the choice models, selecting the most appropriate approach for addressing the aim of each individual analysis.

1.4 Contributions and relevance of the research

Given the objectives of the dissertation, outlined in Section 1.2, this research presents multiple contributions that are relevant both for the scientific community and for society at large.

1.4.1 Theoretical and practical contributions to science

This dissertation contributes to science by providing novel choice modelling formulations, to better capture observed behaviour. Additionally, we also add to the knowledge and understanding on on-demand mobility services. Key contributions from each chapter are outlined below.

- ***Chapter 2: Analysing the structure of the (Dutch) population with respect to their travel behaviour preferences using on-demand mobility services in an urban setting.***
  For the first time in the field, we apply the LCCM approach to investigate a travellers mode choice in relation to on-demand mobility services. We also add to the field by comparing both commute and leisure trip purposes and how preferences for both types of trips differ.

- ***Chapter 3: Extending the Instance-Based Learning (IBL) approach and investigating travellers' sensitivity to unplanned waiting time for on-demand mobility trips.***
  IBL has primarily been applied to car route choice and the unexpected delays due to traffic. Additionally, we believe there has not yet been a study which evaluates the way in which the human memory stores experiences/instances. With that, we provide two advances in the field. Firstly, we test three novel ways of memory storage and measure how well they are able to capture the actual behaviour. Secondly, we apply this approach to examine how sensitive travellers are to unplanned waiting time, both for

longer and shorter than expected waiting times. Additionally, we also test and quantify the value of choice inertia, present in habitual behaviour of users.

- ***Chapter 4: Classifying individuals based on the order of their decision-making in multi-leg trips by means of an LCCM with varying nesting structures***
  Almost all public transport trips are made up of multiple trip legs, often with a main leg, an access and egress leg. Each is associated with its own choices, all of which are interrelated. To fill the gap in literature on how the population is divided with respect to the order of their decision-making, we estimate a Nested logit LCCM, where the structure of nests differs between classes. This provides, for the first time, insights into what share of the population prefers to decide on the main leg first and what share the access leg first.

- ***Chapter 5: Applying segmentation on an HII approach and quantifying the perception of risk when travelling over long distances***
  We extend the HII approach, often utilised for analysing complex attitudinal topics, by combining it with an LCCM model, allowing us to, for the first time, segment respondents on their attitudinal statements, not only on their observed discrete choices. Additionally, we use this newly developed approach to investigate and segment travellers in the context of making long-distance international trips, under the prevailing context of the COVID-19 pandemic. We quantify the impact of risk factors and mitigation policies on the individuals' perceived risk.

1.4.2 Societal relevance of behavioural research

In addition to scientific contributions, this thesis provides novel information that is of interest to a variety of stakeholders. Three of the main ones are public transport operators themselves (having to react to the impact of disruptors), providers of on-demand mobility services (as the disruptor themselves) and policymakers (who have to steer policy with respect to the changes brought on by disruptors). In this section, the relevance of this thesis for all three groups is discussed in more detail.

❖ Relevance for Public transport operators

This thesis deals with the impact of different disruptors on existing modes and focusing on public transport, making the relevance for operators of public transport clear. In the research, we investigate the reaction of different user groups with respect to on-demand mobility services and the COVID-19 pandemic. We analyse their perception of public transport and it's many travel-related characteristics (travel time, price, comfort etc.) in relation to other modes. We also apply the results on multiple case study examples, to highlight and make clear how these disruptors would potentially affect usage of public transport. This gives the operators information on how to potentially adapt their service to be better prepared for these disruptors. With many operators also incorporating on-demand services into their portfolio, the results concerning travellers' perception of the on-demand mobility services may also be of interest to them. Comparing the perception of public transport and on-demand, operators can decide where it makes more sense to keep operating fixed-line public transport services and where a change to demand-based services may indeed be preferential.

❖ **Relevance for On-Demand Mobility Service providers**

As three chapters of this thesis are directly related to on-demand mobility, the findings of this thesis are also highly relevant for the providers of such services. User preferences regarding different travel time components (in-vehicle, walking and waiting time) and how the are willing to trade these off with price and comfort are crucial for service providers for helping them tailor such services. In particular when designing pooled on-demand services, trade-offs between detour ratios, waiting time and comfort (sharing) need to be designed carefully to capture as many travellers as possible, while limiting the total distance driven. Through market segmentation, service providers can also design different types of services, to better capture different user groups. And by understanding how impactful past experiences are on future choices and preferences, providers can tweak their offers for returning customers in order to keep them on their platform and using their service. Cooperation with traditional fixed-line public transport may also be of interest to on-demand mobility service providers and thus the results regarding the interplay between these two modes is of interest also to them.

❖ **Relevance for Policymakers**

Finally, as public transport is often provided as a public service, transport policy is usually the most important instrument used for guiding regulation and development. Policymakers therefore need information on the perception and behaviour of the travelling public with respect to disruptors, in order to implement policies which will have the desired effect (i.e. improving accessibility, equity, safety, security, profitability,…). Policies often rely on complex transport models, for which detailed and accurate behavioural information on individuals' is crucial. Additionally, as individuals are different, market segmentation approaches applied in this research are very relevant, as they showcase to policymakers not only what the average behaviour in the population is, but the different user groups and their individual needs, preferences and desires with respect to mobility. This way, a more complete image of the travelling public can be obtained and thus better, more tailored solutions and policies can be put forward, which are able to more accurately address the needs of these individual groups.

1.5 Disruptors in different types of trips

To understand and outline in greater detail, how disruptors affect trips of different lengths and purposes, the four chapters of the dissertation are divided into three distance classes, based on the distance of the analysed trip. The shortest are trips within a single urban (in the Dutch context), followed by medium distance trips between urban areas, which are still performed on a daily or weekly basis (for commute purposes), with the last distance class capturing long-distance trips, such as business trips, leisure / holiday trips etc. To highlight the outline of this dissertation is presented in Figure 1.1.

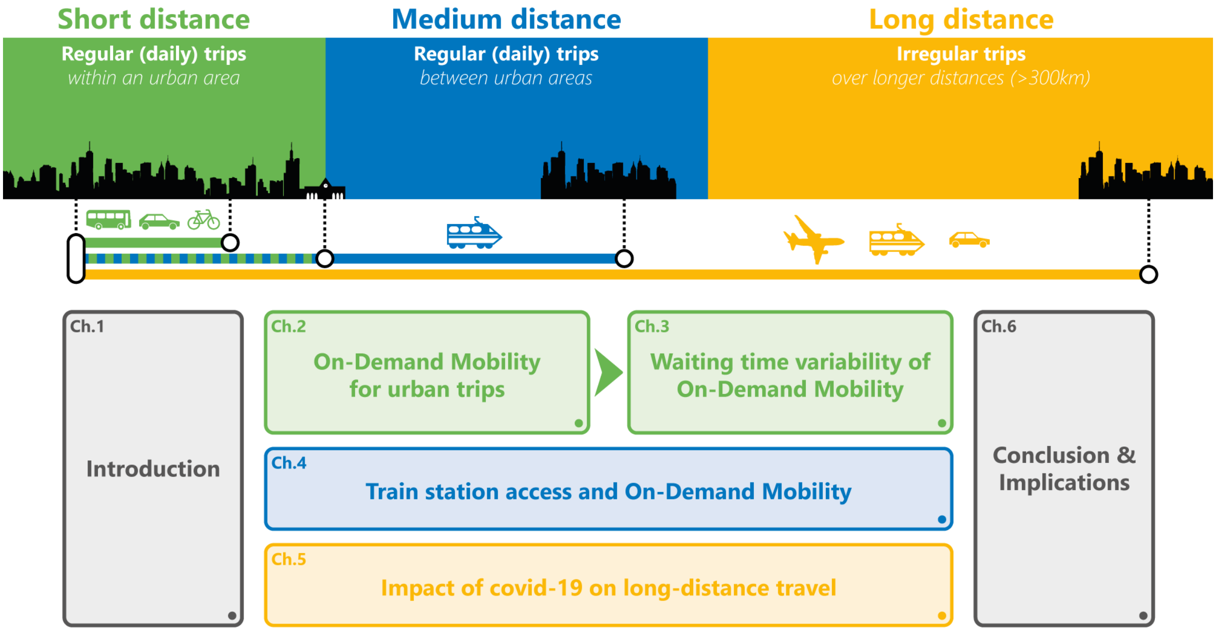


Figure 1.1 Thesis outline – the relation between disruptors of public transport and different types of trips

Firstly, in *Chapter 2*, trips in an urban setting are analysed. Specifically, to analyse the impact and market potential of ride-hailing and other on-demand ride services, they are compared with the bicycle, private car and public transport, for short daily trips of approximately 5km. Trips for both a commute (work, education) as well as for leisure purpose are investigated. Individuals are then split into different segments, based on their travel behaviour preferences.

Secondly, *Chapter 3* continues the analysis of on-demand mobility in urban areas, by exploring the sensitivity of travellers to the variability of waiting time. As on-demand mobility services operate on-demand, they are inherently more variable in their level of service. We investigate how the mismatch between promised waiting time and the actual waiting time of travellers impacts their future choices. We present them with two on-demand mobility companies, each with its own operating strategy and thus different levels of variability. By repeating the binary choice between these two companies multiple times, we are able to extract how much value travellers place on the unexpected waiting time, as well as understanding how quickly memories of past experiences fade.

In *Chapter 4*, the short urban trip becomes part of a longer trip between two urban areas. The chapter investigates the potential of on-demand mobility as a mode for accessing train stations and how it can impact both the station access mode choice as well as station choice, by expanding the catchment area of stations. As the access trip is similar to the short trip in an urban setting (distance, context, alternatives), it is indicated with a dashed green line in Figure 1.1. Individuals are again segmented based on their travel behaviour preferences, with the addition of a nesting structure. Given the two-level choice of both access mode and train station, two nesting structures are utilised to analyse what share of the population will first choose their preferred access mode (and then which station to travel to) and what share will first select their preferred train station (and then how to get there).

Chapter 5 investigates even longer interurban trips. Where trips in *Chapter 4* are still of the distance of regular commute trips (in the Dutch context) (~50-100km), *Chapter 5* investigates infrequent, international trips, of at least 300km and ranging to over 1,000km. Here, the impact of the COVID-19 pandemic and the severe limitations it imposed on international travel are investigated. An HII approach is operationalised to delve deeper into the risk perception of travellers. In this chapter, respondents are segmented based on their international-travel preferences, after which the segmentation structure is also applied onto their risk perception attitudes.

Finally, *Chapter 6* summarises the main findings on how different disruptors, investigated in this thesis, impact public transport. The results are discussed and the conclusions are generalised beyond the context of the Dutch travelling public. The implications of these impacts are discussed, followed by recommendations for policymakers, practitioners and researchers.

Chapter 2:

Mode choice in the presence of On-demand mobility services in urban areas

On-demand mobility services are one of the most prominent external disruptors of public transport. They are promising to revolutionise urban travel, offer people more flexibility in their everyday travel, while at the same time lowering their dependence on the private car and public transport. However, preliminary studies are showing that these services may actually increase the total vehicle kilometres travelled, resulting in worsening road congestion in cities. This chapter aims to assess the potential demand for on-demand mobility services in urban areas, in order to better understand the impact introducing on-demand services would have on existing travel behaviour.

Section 2.1 outlines the research gaps in the field and defines the terms used to refer to the various types of on-demand services emerging as disruptors of public transport. In Section 2.2, the literature covering these various types of on-Demand services, their role in the current mobility environment and analyses related to their adoption and use are presented. Section 2.3 outlines the methodology used to address the identified gaps, starting with the survey design, followed by the modelling framework and concluded with the description of the data collection process. Section 2.4 highlights the results and the identified user groups, with Section 2.5 showcasing their respective potential for using on-demand services. Chapter 2 is concluded with a discussion of implications and policy recommendations in Section 2.6.

This chapter is based on the following article:

Geržinič, N., van Oort, N., Hoogendoorn-Lanser, S., Cats, O., & Hoogendoorn, S. (2023). Potential of on-demand services for urban travel. Transportation, 50(4), 1289-1321.

2.1 Introduction

A recent societal trend that made its way into the transportation domain is the sharing economy (Cagle, 2019). One of its exemplars, present around the world, is the ridesourcing company Uber (also known as a Transportation Network Company or TNC), which began operations in 2009. Since then, a myriad of TNCs have appeared around the world (Lyft, DiDi, Grab etc.)

Recent findings suggest that ridesourcing companies may be a contributing factor to worsening traffic conditions in cities, particularly in downtown areas (Balding et al., 2019; Erhardt et al., 2019; Rodier, 2018). One reason for this is a relatively large proportion (30-60%) of empty vehicle miles travelled (VMT) while roaming and waiting for travellers (Henao & Marshall, 2018). The other reason lies in ridesourcing substituting other existing modes. While the majority seem to replace car and taxi trips (40-70%), up to 30% of TNC users would have used public transport otherwise while 8-22% would not have travelled at all (Rodier, 2018). (Henao & Marshall, 2018) looked at the impact of mode substitution and found that almost 37% of ridesourcing VMT is generated by users who would have otherwise gone by public transport, active modes (walking and cycling) or not have travelled at all. They conclude that, were it not for TNCs, these travellers would have generated almost 50-times fewer VMT.

While the increasing adoption of ridesourcing services seems to exacerbate congestion in cities, the technology and service they introduce provide opportunities for improving accessibility and equity in urban mobility. One of the possibilities are pooled on-demand trips – as opposed to private trips - where passengers with a similar trajectory and departure time are combined and travel with the same vehicle, increasing vehicle occupancy and reducing VMT (Henao & Marshall, 2018). Developing the necessary sharing algorithms and showcasing the benefits is a central topic of many papers in the field (Alonso-Mora et al., 2017; Bischoff et al., 2018; Inturri et al., 2019; Kucharski & Cats, 2020; Lokhandwala & Cai, 2018; OECD, 2015; Ota et al., 2015; Sayarshad & Oliver Gao, 2018).

For ridesourcing services to offer an attractive pooling alternative it is essential to get a better understanding of travellers' preferences. Firstly, we need to have good insight into the attitudes towards on-demand mobility on one hand and alternative modes in the urban environment on the other hand. This will allow assessing how the use of certain modes will be affected with the introduction of on-demand mobility services. Secondly, to get as many people as possible to use pooled ridesourcing, we also need to identify travellers' willingness to share rides and how this relates to other travel preferences.

In this paper we use the terms 'ride-hailing' and 'ridesourcing' when referring to services and companies such as Uber, Lyft, DiDi etc. These however are not the only types of on-demand transport services. Some incumbent public transport companies offer demand responsive transit (DRT) or microtransit in low demand areas, offering a flexible alternative to the fixed bus lines, such as Mokumflex (Coutinho et al., 2020) and Breng flex (Alonso-González et al., 2018). From a traveller's perspective, microtransit and (pooled) ride-hailing are largely similar, as in both cases travellers order a ride using a smartphone app, website or by calling, for a trip from A to B without transferring, that the vehicle would not have made otherwise. A notable difference between the two services is that microtransit may not be able to offer a door-to-door service and thus a certain access time is necessary. As we account for access walking time in the study, these transport services are from here on referred to as **on-demand services** or **Flex** services. They can be ordered either as **private** (the rider requests a direct trip, without other passengers) or **pooled** (the vehicle may take small detours to pick up and drop off other passengers along the route) and are referred to as such.

2.2 Literature review

The impact of on-demand services on the use of public transportation has already been the topic of several studies. Ride-hailing services can complement public transport by offering first/last mile access/egress service, making PT more attractive (Mohamed et al., 2019). Additionally, on-demand services can be used for making trips that are not served well by public transport, like tangential trips carried out by Kutsuplus in Helsinki (Haglund et al., 2019). The Bridj service in Sydney offers both feeder service to train stations during peak times and stop-to-stop services during off-peak times (Perera et al., 2019). Another way on-demand services can complement public transport is to provide services in late evenings and early mornings. Many ride-hailing trips are already made at these times (Fridays and weekends in the late evening), mostly for leisure purposes (King et al., 2020; Mohamed et al., 2019; Tirachini & del Río, 2019). Given that these trips happen at times when public transport services are mostly limited or non-existent, some studies suggest that car and taxi trips are the most likely to be affected. On the other hand Young et al. (2020) found that a large part of ride-hailing trips substitute public transport. They analysed ride-hailing trips in Toronto and found that a third of all trips were only up to 15 minutes faster than public transport and only around 25% were more than half an hour quicker.

Most studies on the matter are inconclusive and assert that ride-hailing is being used as both a substitution for PT and a complementary service to PT (Gehrke et al., 2019; King et al., 2020; Tirachini & del Río, 2019). With respect to the impact of ride-hailing on active modes, the results are less clear and also less transferrable to the Dutch context, as most studies on this topic were carried out in areas where active modes are less prominent. Notably, Gehrke et al. (2019) report that in Boston, active modes are mainly being replaced by on-demand services in bad weather, whereas in good weather conditions, ride-hailing was found to mainly replace car and public transport trips, indicating that active modes are not severely impacted. This finding is also corroborated by Henao & Marshall (2018) for data from Denver, reporting that about 12% of ride-hailing trips are substituting active modes. Neither study however reports the modal share of active modes in their respective cities, so the scale of impact on active modes is unclear.

To better understand the behavioural trade-off travellers make when faced with an option to choose for on-demand services, several studies employed stated preference (SP) experiments. Most of these studies applied either a multinomial logit (MNL) a mixed logit (ML) model formulation (Table 2.1). They mostly introduce pooled on-demand next to the car and/or public transportation. Liu et al. (2018) carried out a study in New York, comparing pooled and private ride-hailing with car and public transport and found the highest preference for car, followed by PT, with on-demand services at the bottom (private being preferred over pooled). The same preference order amongst modes was also found in studies in Chicago (Frei et al., 2017), Ann Arbor, Michigan (Yan et al., 2019) and in North England (Ryley et al., 2014), while Choudhury et al. (2018), who carried out the survey in Lisbon, found a higher preference for public transport compared to car, while on-demand services were still less preferred. They hypothesize that the former can be attributed to the high quality public transport and congested roads in the city centre. They compared a much larger number of alternatives and trip contexts by employing novel four-step multi-dimensional pivot SP experiment. Alongside the previously mentioned modes, they also considered car rental, bus, express bus, train/metro, bus + train/metro and a park-and-ride alternative. Their findings show a higher willingness-to-pay for car-based modes (including on-demand mobility) and lower for public transport modes. A similar Willingness to Pay (WtP) pattern was observed by Frei et al. (2017), who also modelled the impact of weather on the attractiveness of ride-hailing and found that colder and rainy weather makes it more attractive for respondents, compared to using the car or public transport.

To the best of our knowledge, Yan et al. (2019) are the only ones to carry out an SP survey of an on-demand service, where cycling was also offered as an alternative. They jointly modelled the revealed preference (RP) behaviour and SP survey responses of the university faculty members and found a relatively high preference for on-demand service in the SP only analysis (above car and cycling) and a somewhat low preference, using combined RP-SP data, where on-demand is behind the car and transit, while still preferred over cycling. A major limitation of their study is that on-demand services were offered for free and the only cost parameter in the survey was car parking cost, hampering a monetary evaluation in the form of willingness to pay.

Another avenue of exploring the attractiveness and adoption potential of on-demand services is through different latent class clustering methods. Applying a latent class adoption model (Alemi et al., 2019) on the California Millennials dataset (Circella et al., 2016), to analyse the potential of the respondents to adopt ride-hailing revealed that among the three uncovered classes, the most likely to adopt ride-hailing are those who are highly educated and independent Millennials, living in urban areas and are without children, whereas the least likely to adopt it are those living in rural areas.

Pooling on-demand trips is also associated with both physically sharing the vehicle with other people and can lead to an uncertain increase in both waiting and travel time. The Dutch population seems to be fairly evenly split between those more open to sharing (usually to reduce their trip cost) and those who are not, either for privacy reasons or time-related reasons (Alonso-González et al., 2020). With respect to the valuation of travel time variability, Alonso-González et al. (2020a) report that a large majority of the population has a balanced time-cost sensitivity next to two smaller groups that are either more time-sensitive or more cost-sensitive. The perception of reliability was found fairly similar across the classes, with the variable travel and waiting times being valued between 0.5 and 1-times the value of actual travel and waiting time.

This study adds to the existing literature by analysing respondents’ mode choice in a setting where both private and pooled on-demand services exist alongside cycling, cars and public transport (Table 2.1). In contrast to most literature undertaking such research, heterogeneity among decision-makers is accounted for by employing a latent class choice model (LCCM), instead of a mixed logit model specification. Using an LCCM enables the identification of market segments and through performing a posterior analysis, we obtain detailed insights into the different classes’ socio-demographic characteristics, their attitudes and current travel behaviour.

Table 2.1. Overview of studies using stated preference data collection for analysing on-demand mobility

	Data collection	Choice model estimated	Geographical location	Pooled on-demand	Private on-demand	Cycling	Public transport	Car
Frei et al.(2017)	SP	MNL & ML	Chicago	X			X	X
Liu et al. (2018)	SP	ML	New York	X	X		X	X
Yan et al. (2019)	RP & SP	MNL & ML	Ann Arbor (Michigan)	X *(SP)*		X	X *(RP)*	X
Ryley et al.(2014)	SP	ML	North England	X			X*	X*
Choudhury et al.(2018)	SP	ML (& nested logit)	Lisbon	X	X		X	X
Alonso-González et al.(2020)	SP	LCCM	The Netherlands	X	X			
This study	**SP**	**LCCM**	**The Netherlands**	**X**	**X**	**X**	**X**	**X**

* *In their SP survey,* (Ryley et al., 2014) *showed respondents one existing mode (public transport or car) alongside DRT*

2.3 Methodology

To analyse the role of on-demand mobility services and the perceptions and preferences related to them, we employ a stated preference approach. On-demand services are not yet widespread in the Netherlands, and while many people have heard of such services, many have not used such services yet, as highlighted by Bronsvoort, Alonso-González, Oort, Molin, & Hoogendoorn (2021). Given this circumstance, we opt for a SP choice experiment.

2.3.1 Survey design

To elicit respondents' decision-making behaviour with respect to on-demand mobility, a stated preference survey is constructed and conducted. In the survey, on-demand mobility is labelled as "*Flex*" to ease communication (Alonso-González, van Oort, et al., 2020b), as such services typically have the "Flex" suffix (*Brengflex* (Arnhem-Nijmegen), *TwentsFlex* (Rijssen-Holten), *Mokumflex* (Amsterdam) etc.). Flex is positioned next to the most commonly used modes for urban trips in the Netherlands, namely the bike, car and public transport. Walking was excluded due to the longer trip distance and also to reduce the number of alternatives shown. Modes are compared based on in-vehicle time, walking time, waiting time, trip cost and whether or not the ride is shared. In the Netherlands more than half of all the trips are up to five kilometres long and another 20% are between 5 and 15 kilometres (de Graaf, 2015). To determine the attribute levels, a trip that is approximately five kilometres long is selected and a range of values for a trip of such distance is obtained from (Google, n.d.). All but one attribute ("*Type of ride*") are described with three levels, to allow the analysis of non-linear attribute evaluation. The four modes along with their respective attributes and levels can be seen in Table 2.2. This design is used to assess preferences for two different trip purposes: a commute trip (travelling to work or education) and a leisure trip (travelling for recreation, visiting friends / family). Each choice set contains five alternatives, with two "*Flex*" alternatives alongside the three existing modes. This, together with the "*Type of ride*" attribute allows a direct comparison between two

"*Flex*" alternatives, be it two shared options, two private options or one shared and one private (as seen in Figure 2.1).

Table 2.2. Modes, attributes and attribute levels used in the Urban survey

Attributes	Bike	Public transport	Car	Flex
Walking time [min]	-	1, 5, 9	0, 5, 10	0, 3, 6
Waiting time [min]	-	1, 5, 9	-	1, 5, 9
In-vehicle time [min]	12, 16, 20	8, 12, 16	8, 12, 16	8, 12, 16
Type of ride	-	-	-	shared, private
Cost [€]	-	0.5, 2, 3.5	1, 5, 9	2, 5, 8

To avoid making a-priori assumptions on parameter values and willingness-to-pay (WtP), an orthogonal design is selected for this survey (Walker et al., 2018). Findings from studies on the perceptions of on-demand mobility are not fully in agreement, and if the actual preferences among the respondents do not align with those of the priors, a D-efficient design might become highly inefficient (Walker et al., 2018). An orthogonal design is generated in the software tool Ngene (ChoiceMetrics, 2018). The design is made up of 72 choice sets, which are blocked over 12 blocks of six choice sets. Each respondents is randomly allocated to two different blocks, one for a commute and one for a leisure trip purpose. The 12 blocks are randomly allocated to respondents to guarantee an approximately equal number of observations per block and trip purpose. One example choice set (originally in Dutch) can be seen in Figure 2.1. Respondents who do not have access to a car in their household are presented with choice sets without the car alternative. It should be noted that the "*Waiting time*" attribute for public transport and "*Flex*" are not presented to respondents in the same way for the two modes. For public transport, waiting is said to be endured at a stop, while for the on-demand service, respondents are given a summary of their trip, indicating how many minutes they need to leave their origin (home) in and then possibly walk to a pick-up point. With that in mind, the two different waiting times are shown to respondents in distinctly different ways. For transit, the word "*waiting*" (*wachten* in Dutch) is used and positioned between "*walking*" and "*in-vehicle time*" (*lopen* and *OV tijd* in Dutch respectively), whereas for "*Flex*", the attribute is shown first as "*depart in*" (translated from the Dutch *vertrek over*).

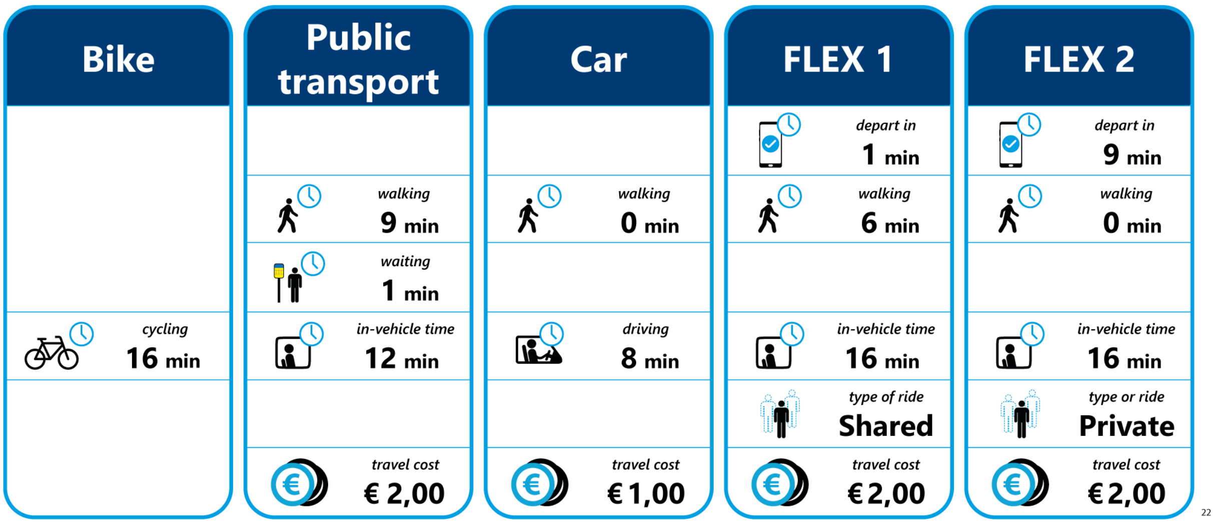


Figure 2.1. Example of the choice set shown to respondents (translated to English)

In addition to the twelve choice tasks, respondents are presented with 16 attitudinal statements (Table 2.3). The goal of the statements is to understand respondents' preparedness to use on-demand mobility services. In investigating the drivers of MaaS and Flex adoption, Alonso-González et al. (2020) used three groups of attitudinal statements, categorized by Durand et al. (2018) into: (1) Mobility integration, (2) Shared mobility modes and (3) Mobile applications. While the goal of this research is to better understand Flex-readiness, a similar setup of attitudinal statements is used, as there are many similarities in the willingness to use of MaaS and on-demand mobility. The formulated attitudinal statements fall into one of four categories:

1. Use of apps
2. Mobility integration
3. Sharing a ride
4. Sharing economy

Table 2.3. Attitudinal statements on pooling rides, travel planning and the sharing economy

Category		Statement
Use of (travel planning) apps	1	I find it difficult to use travel planning apps. [1]
	2	Using travel planning apps makes my travel more efficient. [1]
	3	I am willing to pay for transport related services within apps.
	4	I do not like using GPS services in apps because I am concerned for my privacy.
Mobility integration	5	I am confident when travelling with multiple modes and multiple transfers.
	6	I do not mind infrequent public transport, if it is reliable.
	7	I do not mind having a longer travel time if I can use my travel time productively. [2]
	8	Not having to drive allows me to do other things in my travel time. [2]
Sharing a ride	9	I am willing to share a ride with strangers ONLY if I can pay a lower price. [2]
	10	I feel uncomfortable sitting close to strangers. [2]
	11	I see reserving a ride as negative, because I cannot travel spontaneously.
Sharing economy	12	I believe the sharing economy is beneficial for me.
	13	I believe the sharing economy is beneficial for society.
	14	Because of the sharing economy, I use traditional alternatives (taxis, public transport, hotels,…) less often.
	15	Because of the sharing economy, I think more carefully when buying items that can be rented through online platforms.
	16	I think the sharing economy involves controversial business practices (AirBnB renting, Uber drivers' rights,…).

[1] *adapted from* (Lu et al., 2015)
[2] *adapted from* (Lavieri & Bhat, 2019)
the remaining statements were formulated for the purpose of this study

The first category investigates the understanding and willingness to use smartphone based travel planning applications and certain app features, like making purchases and GPS navigation. Mobility integration, similar to the study by Alonso-González et al. (2020), considers the attitude towards multimodal travel and public transport, as well as the attitude towards not having to drive a car and if that is seen as beneficial or not. Integration with other modes is relevant, as an on-demand service often provides first/last mile connectivity. Previous studies have also found that users of on-demand services tend to be more open to using a variety of transport modes and more often travel long-distance (Alemi et al., 2018). Statements on "Sharing a ride" are meant to capture the social aspect to sitting (close) to strangers. It is also used for a direct comparison to the stated choice survey outcome on the discount required for users to opt for pooled services. Finally, five statements pertaining to the sharing economy are included. As many on-demand mobility services are amongst the most well-known examples of the sharing economy (Uber, Lyft and DiDi being the most prominent), we want to see if there are any links to be made with respect to respondents' attitudes towards the sharing economy and their travel behaviour. Each statement is evaluated on a 5-point Likert scale, and an additional 'No opinion' option is added to each statement. The 'Neutral' and 'No opinion' attitudes are coded as 0, 'Agree' and 'Fully agree' as 1 and 2 respectively and 'Disagree' and 'Fully disagree' as -1 and -2 respectively.

Familiarity with six different shared mobility and sharing economy services is also inquired, with the services and the examples given, shown in Table 2.4. Respondents are asked to indicate their familiarity with the service on a 5-point scale:

1. Never heard of it
2. Familiar with it, but never used it
3. Used it once
4. Used it a few times
5. Use it regularly

As the data is obtained through the Dutch Mobility Panel (MPN – Mobiliteitspanel Nederland), there is no need to ask respondents for basic socio-demographic information, as this is regularly updated for the panel members (Hoogendoorn-Lanser et al., 2015).

Table 2.4. Services for which respondents were asked to indicate their familiarity (including the presented examples)

	Type of (sharing economy) service	Examples shown
1	How familiar are you with car sharing?	Snappcar, Greenwheels, car2go
2	How familiar are you with bike / scooter sharing?	Mobike, OV fiets, Felyx
3	How familiar are you with flexible public transport?	Twentsflex, Bravoflex, U-flex, Delfthopper
4	How familiar are you with ride-hailing?	Uber, ViaVan
5	How familiar are you with food delivery services?	Thuisbezorgd, Deliveroo, Foodora, UberEATS
6	How familiar are you with home rental services?	AirBnB, HomeStay, Couchsurfing

2.3.2 Model estimation

The model is estimated with Biogeme, an open source Python package (Bierlaire, 2020). To analyse respondents' travel preferences, two types of discrete choice models are employed. Firstly, to get an overview of choice behaviour, understand the preferences towards different modes and potential non-linear perceptions of attributes, several different MNL models are estimated. Secondly, to analyse different potential user groups and their respective attitudes and preferences, we perform a market segmentation by means of estimating a latent class choice model (LCCM). All models are estimated under the assumption that users select the alternative with the goal of maximising the utility of their choice (McFadden, 1974).

A generic-parameter model (Equation 2.1) is estimated as a benchmark for the more detailed models that follow. All attributes (*a*) are coded by a single generic parameter (β_a) for the four different modes (*m*), with the exception of waiting time, which is modelled separately for public transport and Flex (see Section 2.3.1 above for the argumentation). The ASP model (Equation 2.2) expands on the GP model by splitting the parameters for each individual mode ($\beta_{m,a}$), allowing a comparison of how the same attribute is perceived across different modes. The DCP model (Equation 2.3) is estimated to uncover and analyse potential non-linarites in the perceptions of attributes. This is done by modelling the utility contribution of each attribute level ($X_{m,a}$) by means of its own parameter ($\beta_{Xm,a}$), with one of the levels being fixed to 0. Based on the outcomes of the three models, other model specifications are tested to obtain the most parsimonious model.

Equation 2.1 GP model formulation

$$V_m = ASC_m + \sum\nolimits_a \beta_a \cdot X_{m,a}$$

Equation 2.2. ASP model formulation

$$V_m = ASC_m + \sum\nolimits_a \beta_{m,a} \cdot X_{m,a}$$

Equation 2.3. DCP model formulation

$$V_m = ASC_m + \sum\nolimits_a \beta_{X_{m,a}} \cdot X_{m,a}$$

To analyse respondent heterogeneity, a latent class choice model is chosen (Greene & Hensher, 2003). Unlike a mixed logit model, a latent class model enables for the estimation of individual parameters for each obtained class, resulting in a straightforward interpretation of the classes and a clear distinction between them. The added value of a latent class model is also the possibility of making a posterior analysis of the attitudinal and socio-demographic characteristics for each of the classes. The model formulation of the LC model is presented in Equation 2.4. The probability of respondent *n* to select alternative *i* is obtained by summing the probability of this alternative being selected, given the different parameter estimates (β) in the different latent classes (*s*). The class specific choice probabilities ($P_n(i|\beta)$) are multiplied with the class allocation probability (π_{ns}). In its simplest form, the class membership function is static (Hess et al., 2008), meaning that only a constant (δ_s) is used. Additionally, the class membership function of the latent class model may include socio-demographic data as a predictor for allocating individuals to different segments of the population. In this study, the goal is to group individuals based purely on their stated preferences, so that travel behaviour preference heterogeneity of individuals within a group is as small as possible, while the difference between groups is as large as possible. A static class membership function is employed in this study. For the individual class formulations, the model which proves as most parsimonious among the

MNL model formulations is used in the LC model, to allow for faster estimation, ease of interpretation and to guarantee that sufficient parameters of interest can be identified.

Equation 2.4. Formulation of the LC model

$$P_n(i|\beta) = \sum_{s=1}^{S} \pi_{ns} \cdot P_n(i|\beta_s)$$

Equation 2.5. Formulation of the class allocation probability

$$\pi_{ns} = \frac{e^{\delta_s}}{\sum_{l=1}^{S} e^{\delta_l}}$$

For the 16 attitudinal statements, an exploratory factor analysis (EFA) is performed, to analyse correlations between the responses to statements, to simplify the interpretation of said responses and also to simplify the interpretation of differences between the latent classes with respect to their attitudes towards ride-sharing and the sharing economy. To perform the EFA, the "factor_analyzer" package for Python is used (Briggs, 2019).

To obtain socio-demographic information for the different latent classes, a posterior probability analysis is carried out. Individuals are probabilistically allocated to each of the classes, based on how well the class-specific parameters capture the respondent's observed choices. Based on this probability, the socio-demographic, attitudinal and travel behaviour characteristics are aggregated per class.

2.3.3 Data collection

The survey was administered to the participants of the Netherlands Mobility Panel (MPN) (Hoogendoorn-Lanser et al., 2015), between February 10th and March 1st in 2020. In total, 1.200 respondents took part in the survey, which was reduced to 1,063 after processing and cleaning the raw data. This was done by removing:

1. Responses with incomplete choice tasks
2. Responses that were completed within fewer than three minutes
3. Respondents with the same answer to all attitudinal questions

The socio-demographics of the sample and the Dutch population are shown in Table 2.5 (Centraal Bureau voor de Statistiek, 2020). The sample is largely representative of the Dutch population. We do note a slight overrepresentation of older individuals in the survey compared to the population. Household income differs as well, which can partly be explained by respondents having the option to not disclose their income in the survey, while the census data has a complete overview of everyone's incomes.

With respect to COVID-19, the first patient in the Netherlands was diagnosed on the 27th of February (Rijksinstituut voor Volksgezondheid en Milieu (RIVM), 2020) and the first lockdown measures announced on March 12th (NOS, 2020). We therefore believe that it is unlikely that the pandemic influenced the decision-making of the respondents.

Table 2.5. Comparison of socio-demographic variables for the survey sample and the Dutch population. Source for the population data: (Centraal Bureau voor de Statistiek, 2020)

Variable	Level	Sample	Population
Gender	Female	52%	50%
	Male	48%	50%
Age	18-34	21%	27%
	35-49	20%	23%
	50-64	30%	26%
	65+	29%	24%
Education[1]	Low	30%	32%
	Middle	41%	37%
	High	29%	31%
Urbanisation level	Very highly urban	23%	24%
	Highly urban	32%	25%
	Moderately urban	17%	17%
	Low urban	20%	17%
	Not urban	8%	17%
Household income[2]	Below average	24%	26%
	Average	50%	47%
	Above average	12%	27%
	Unknown	14%	0%
Employment status	Working	50%	51%
	Not working	50%	49%
Household size	One person	22%	17%
	2 or more	78%	83%

2.4 Results

Outcomes of the four different MNL model specifications, as well as the latent class model, are shown in Table 2.6. The 4-class latent class model significantly outperformed the other three models. Of the MNL models, the DCP model achieves the highest model fit and adjusted rho-squared value. Surprisingly, the ASP model performs relatively well compared to the DCP model, with a final log-likelihood only 13 points lower and essentially no difference in the value of the adjusted rho-squared. Performing a likelihood ratio test, the DCP model is found to be superior to the ASP model. Considering the BIC value on the other hand, the ASP model is superior, as it achieves a similarly high model fit with fewer parameters. Testing different model specifications resulted in an additional model (labelled the LC-base model), which is also reported in Table 2.6. It improves the model fit of the GP model by 28 LL-points with a single parameter. The improvement from the LC-base to the ASP model is 124 LL-points, utilising eight additional parameters. While the BIC and LRT both prove the ASP model is superior to

[1] Low: no education, elementary education or incomplete secondary education
Middle: complete secondary education and vocational education
High: bachelor’s or master’s degree from a research university or university of applied sciences

[2] Below average: below modal income (< €29,500)
Average: 1-2x modal income (€29,500 – €73,000)
Above average: Above 2x modal income (> €73,000)

the LC-base model, the marginal contribution of the additional estimated parameters is less than the LC-base model achieves. Given these outcomes, the following section will focus primarily on the interpretation of the LC-base model results. The respondents' familiarity with shared services and their replies to the 16 statements are also discussed. In Section 2.4.3, the latent class model is then analysed and each of the four classes is discussed on their respective taste parameters, attitudinal statements, socio-demographic characteristics and current travel behaviour.

Table 2.6. Outcomes of models with different parameter specifications

	GP model	LC-base model	ASP model	DCP model	Latent class model
Number of estimated parameters	10	11	19	31	47
Final log-likelihood	-11,595.91	-11,568.26	-11,443.90	-11,430.83	-6,653.10
Adjusted Rho-squared	0.4201	0.4220	0.4272	0.4273	0.6652
BIC value	23,286.35	23,240.52	23,067.42	23,154.72	13,633.73

2.4.1 Results of discrete choice model

The parameter estimates of the LC-base model are presented in Table 2.7, with the outcomes of the ASP and DCP models shown in Appendix A in Table 7.1 and Table 7.2. With the exception of the Flex waiting time parameter, all other are highly significant. This parameter turns out insignificant in all estimated MNL models, while in the DCP model, a waiting time of 5-min seems to be perceived more negatively than a 9-min waiting time. One possible explanation for this is in the way Flex waiting time was specified in the survey: waiting at home, which can be seen as hidden waiting time. A 5-minute duration can be seen as period of time that cannot really be spent on doing anything – just waiting – while nine minutes could already be enough time to accomplish a quick errand at home, meaning the 'waiting' time is well spent and therefore does not have such a high disutility. A 1-min waiting time is still most preferred, meaning that respondents still preferred the shortest possible waiting time.

In the ASP model, the in-vehicle time parameters for all motorised modes (car, public transport, Flex) are insignificant. This could be due to the relatively small variation in the in-vehicle time attribute levels (8, 12 or 16 min), indicating that respondents do not care about the travel time when the differences are relatively small and only the mode which is used appears to be important. In the LC-base model, the in-vehicle time for all three motorised modes is combined into a single parameter, distinguishing it only from the cycling time parameter. Distinguishing two in-vehicle time parameters (cycling and motorised modes) is also the only difference between the GP model and LC-base model, showing that estimating a separate cycling time parameter significantly improves model fit. This is in part due to the fact that the cycling alternative has no other attributes apart from travel time. Cycling time is thus perceived far more negatively than in-vehicle time in motorised modes: six times more.

The mode specific constants capture all other factors not included in the modelled attributes, which are associated with a specific mode, with all other attributes being equal. Table 2.7 reveals that the ASC for bike (fixed to 0) is the highest, followed by car, PT and the Flex ASC having the lowest value. This is mostly in-line with findings reported in the literature (Frei et al., 2017; Y. Liu et al., 2018), although most did not include cycling and the one that did (Yan et al., 2019) found cycling to have the lowest ASC. This likely has to do with the survey being set in Michigan, USA, where the cycling conditions and culture are very different from those in the

Netherlands. (Choudhury et al., 2018) found car to have a lower ASC than the PT alternatives, but they also state that this is due to the survey being conducted in Lisbon.

Comparing the ratios of different travel time components, walking time is perceived four times more negatively than in-vehicle time, whereas waiting time for PT is seen as more than three times as negative. This is higher than expected and higher than reported in research (Wardman, 2004), but could be a consequence of the relatively low disutility associated with in-vehicle time, partly due to the limited differences in travel time attribute levels.

Table 2.7. Model estimation results of the LC-base model

	Parameter estimate	Robust t-stat	Significance
Constant [bike]	0 [fixed]		
Constant [car]	-1.216	-9.56	***
Constant [Flex]	-3.172	-21.66	***
Constant [PT]	-2.303	-17.33	***
Cost	-0.148	-17.86	***
In-vehicle time [bike]	-0.070	-11.15	***
In-vehicle time [other]	-0.011	-2.02	**
Walking time	-0.047	-9.59	***
Waiting time [Flex]	-0.014	-1.24	
Waiting time [PT]	-0.039	-4.22	***
Sharing [Flex]	-0.215	-2.82	***
Leisure trip * cost	-0.022	-2.53	**

**** p ≤ 0,01, ** p ≤ 0,05, * p ≤ 0,1*

Of prime interest for this research is the willingness-to-share on-demand services. Sharing is explored both as a dummy variable (as seen here) and by interacting it with in-vehicle time, as a perceived in-vehicle time multiplier. A superior model fit is achieved when the former model specification is used. From the parameter ratios in the case of the alternative-specific model, we can see that respondents are willing to pay up to €1.45 (*Sharing [FLEX] / Cost*) more for a private trip, which is higher than the 0.41€ reported by Alonso-González, Cats, et al. (2020) for respondents' willingness to pay to avoid sharing with one or two other people, but less than over $6 reported by (Y. Liu et al., 2018). The former study analysed sharing in more detail (different parameters for different numbers of co-riders) and the penalty for only up to two additional passengers is likely less than for a full vehicle. The difference from the latter study could be due to the difference in cultural context (survey carried out in the USA, as opposed to the Netherlands for this study). Respondents are also willing to walk almost 5 min farther for a private ride (*Sharing [FLEX] / Walking time*), or travel up to 20 min longer in a private ride as opposed to a shared ride (*Sharing [FLEX] / In-vehicle time [other]*).

Several different model specifications are also explored with respect to trip purpose (commute and leisure). The trip purpose is interacted with all estimated parameters separately. The best model fit and a highly significant parameter estimate is obtained when the trip purpose is interacted with trip cost. In line with other findings (Alonso-González, van Oort, et al., 2020b; Choudhury et al., 2018), respondents are more cost-sensitive in leisure trips than in their commute trips. Respondents seem to be approximately 15% more cost sensitive when making leisure trips as opposed to commute trips, meaning they are willing to pay less when travelling for leisure.

2.4.2 Service familiarity and Exploratory Factor Analysis

As shown in Figure 2.2, respondents are mostly familiar with sharing economy and shared transport services. Flexible public transport services on the other hand are much less well known than any of the other services, with 51% of the respondents never having heard of it and only 2% using it at least once. Ride-hailing and bike sharing services are most familiar to respondents, although still only around 10% of them have ever used it. Food delivery is the most used sharing economy service, with over 40% having used it at least once before.

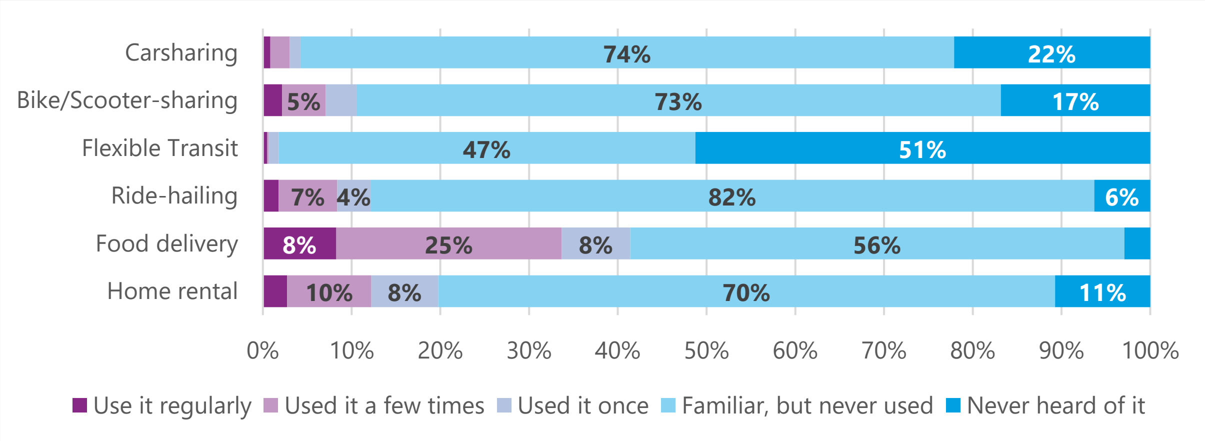
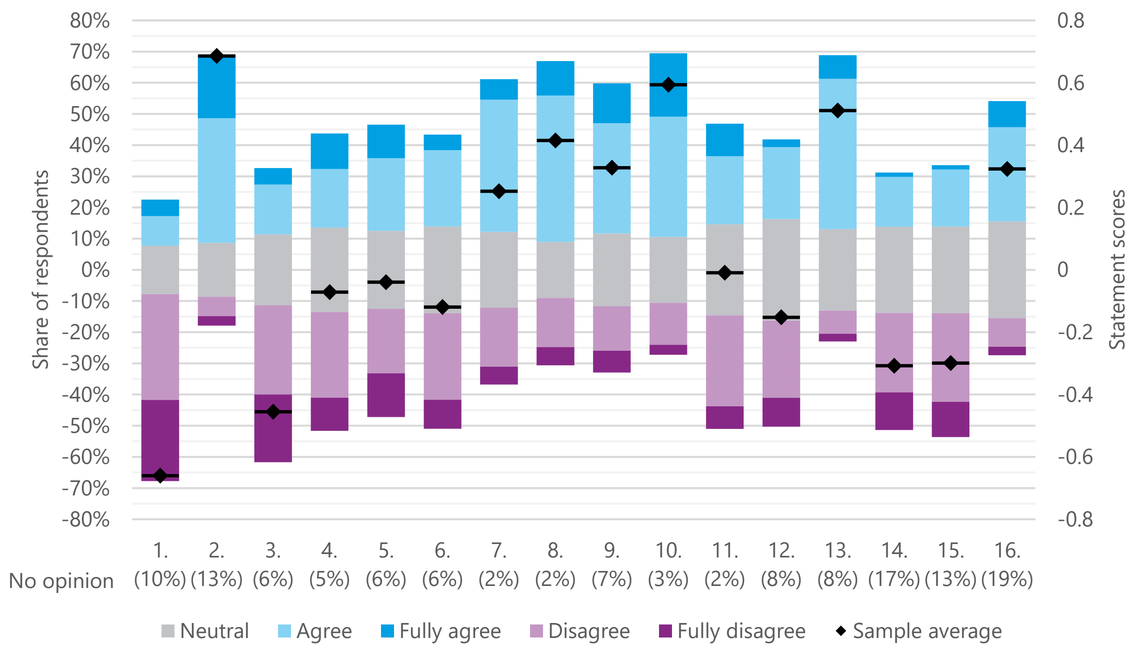


Figure 2.2. Familiarity and frequency of use w.r.t. different shared transport and sharing economy services (values below 5% are not labelled)

The 16 attitudinal statements (Figure 2.3) are used to elicit respondents' readiness to use shared on-demand services. In general, respondent agree that apps are easy to use and make travel more efficient, they prefer not making in-app purchases. Participants overall agree that not having to drive gives opportunities to better spend one's travel time and are also willing to travel longer, if that means they can better use their travel time. Respondents are largely in agreement that they are willing to use a shared service only if they receive a discount (statement 9). There is also a clear indication that they feel uncomfortable sitting close to strangers (statement 10). Attitudes towards the sharing economy reveal that respondents are quite optimistic for what the sharing economy has to offer to society, but for the most part, do not see many direct benefits for themselves. They do however, believe that in some cases, the sharing economy can lead to controversial business practices.

For an easier interpretation of the attitudinal statements, an exploratory factor analysis is performed. A KMO score of 0.78 is obtained, indicating that an EFA can indeed be performed (Ledesma et al., 2021). As mentioned in Section 2.3.1, the statements had 6 possible answers, including a 5-point Likert scale and a "No opinion" option. The latter present a potential issue for performing the EFA. It is decided that for the sake of the EFA, "No opinion" answers are converted to the "Neutral" opinion in the 5-point Likert scale. While this is not ideal, and we certainly cannot state that they represent the same sentiment of the respondents, removing all replies with a "No opinion" answer results in a loss of almost 40% of observations (from 1,063 to 660). It also severely impacts the interpretation of the outcomes.



1. I find it difficult to use travel planning apps.
2. Using travel planning apps makes my travel more efficient.
3. I am willing to pay for transport related services within apps.
4. I do not like using GPS services in apps because I am concerned for my privacy.
5. I am confident when travelling with multiple modes and multiple transfers.
6. I do not mind infrequent public transport, if it is reliable.
7. I do not mind having a longer travel time if I can use my travel time productively.
8. Not having to drive allows me to do other things in my travel time.
9. I am willing to share a ride with strangers ONLY if I can pay a lower price.
10. I feel uncomfortable sitting close to strangers.
11. I see reserving a ride as negative, because I cannot travel spontaneously.
12. I believe the sharing economy is beneficial for me.
13. I believe the sharing economy is beneficial for society.
14. Because of the sharing economy, I use traditional alternatives (taxis, public transport, hotels,...) less often.
15. Because of the sharing economy, I think more carefully when buying items that can be rented through online platforms.
16. I think the sharing economy involves controversial business practices (AirBnB renting, Uber drivers' rights,...).

Figure 2.3. Responses to the attitudinal statements, including the average score for each of the statements

To determine the number of factors to estimate, a scree plot is generated. From the plot five factors seem to be the optimal number for the analysis. However, one of the five factors has only one statement with a strong load. Because of that, a 4-factor EFA is seen as preferred. The factor loadings for the four factors are presented in Figure 2.4. The four factors largely reflect the four topics which the statements were formulated to capture. S16, unlike the other four sharing-economy-related statements does not seem to load strongly onto any factor. Similarly, S6 and S9 are not very strongly associated with the other statements pertaining to »Mobility integration« and »Sharing a ride« respectively. Finally, it is interesting to notice that S5 loads stronger onto F2, along with the app-related statements, as opposed to F3, with the other mobility-related statements. Given the statements and factor loadings, the four factors have been given the following names:

- **F1: Sharing economy support**
  Statements 12-15 asked respondents to consider the added value the sharing economy has for them and soceity, and if they do in fact use traditional services and products less often because of the rise of the sharing economy
- **F2: App savvy**
  Statements 1-4 all pertain to the use of apps, the difficulty respondents find in using them and the usefulness of apps that the respondents belive they offer
- **F3: Travel time use**
  Statements 7 and 8 both discuss the duration of travel time, putting forward to respondents the notion of having a potentially longer travel time in exchange for a more effective use of that travel time.
- **F4: Dial-a-ride opposition**
  Statements 10 and 11 deal with sitting in close proximity of strangers and having to pre-book a ride, both of which can be associated with shared on-demand services, but more specifically dial-a-ride services, as the former do not necessarily have prebooking requirements.

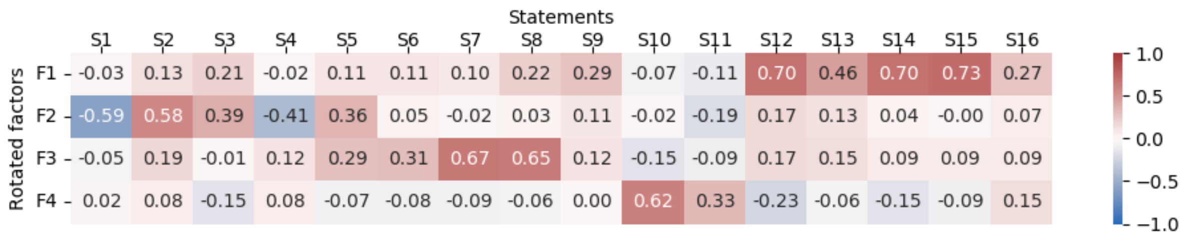


Figure 2.4. Factor loadings from an exploratory factor analysis on the 16 attitudinal statements

2.4.3 Results of the latent class model

The model outcomes of a 4-class latent class model are shown alongside the different MNL models in Table 2.6. In total, models with between two and six classes are estimated. A 6-class latent class model is rejected because two of the classes are too small to serve as a meaningful representation of a market segment (both accounting for only 4% of the population). A 5-class model is rejected because of the very limited interpretability of the classes' characteristics. Models with 2 and 3 classes produced valid and interpretable results, but a model with 4-classes provides insights into a larger number of user groups, while maintaining the interpretability of the results. A latent class model with four classes is therefore chosen for both numerical and interpretation reasons. The MNL model used in the estimation is the LC-base model. The parameter estimates of the four latent classes, along with the class sizes, are presented in Table 2.8. The classes were given names based on their choice behaviour characteristics and the outcomes of the posterior analysis of the EFA for the 16 attitudinal statements:

- Sharing-ready cyclists (55%)
- Tech-ready individuals (27%)
- Flex-sceptic individuals (9%)
- Flex-ready individuals (9%)

The classes are compared on their parameter estimates and the corresponding willingness-to-pay (WTP) in the following paragraph in Table 2.9. Each of the four classes is then presented in more detail in the following subchapters. Their attitudinal, travel behaviour and socio-demographic information is discussed and presented in Figure 2.5, Figure 2.6 and Table 2.10 respectively. These were obtained using the posterior probability analysis.

Table 2.8. Model estimation results of a 4-class latent class model

	Latent class 1 *Sharing-ready cyclists*			**Latent class 2** *Tech-ready individuals*			**Latent class 3** *Flex-sceptic individuals*			**Latent class 4** *Flex-ready individuals*		
Class size	55%			27%			9%			9%		
	Value	Robust t-stat		Value	Robust t-stat		Value	Robust t-stat		Value	Robust t-stat	
δ_s	1.76	15.95	***	1.07	8.84	***	0	fixed		-0.04	-0.23	
Constant [car]	-5.659	-5.04	***	-2.094	-7.02	***	11.343	3.85	***	2.937	2.83	***
Constant [Flex]	-8.412	-6.22	***	-4.279	-12.12	***	-0.021	-0.01		1.806	1.68	*
Constant [PT]	-6.330	-5.65	***	-3.310	-10.80	***	3.063	1.45		1.349	1.28	
Cost	-0.243	-3.38	***	-0.217	-8.85	***	-0.326	-2.33	**	-0.424	-8.52	***
In-vehicle time [bike]	-0.179	-3.76	***	-0.221	-12.03	***	-0.260	-2.50	**	-0.172	-2.26	**
In-vehicle time [other]	-0.016	-0.43		-0.040	-4.12	***	-0.084	-1.63		-0.037	-2.57	**
Walking time	-0.152	-4.68	***	-0.088	-8.61	***	-0.100	-1.50		-0.092	-5.15	***
Waiting time [Flex]	0.095	0.90		-0.024	-1.06		0.025	0.41		-0.021	-1.17	
Waiting time [PT]	-0.111	-1.87	*	-0.061	-3.87	***	0.016	0.27		-0.017	-0.92	
Sharing [Flex]	-0.154	-0.24		-0.234	-1.65	*	-0.207	-0.37		-0.223	-1.64	
Leisure trip * cost	-0.099	-0.99		-0.068	-2.30	**	-0.307	-4.63	***	0.005	0.13	

**** p ≤ 0,01, ** p ≤ 0,05, * p ≤ 0,1*

The '*Sharing-ready cyclists*' seem to be the most sensitive to out-of-vehicle time components, but at the same time the in-vehicle time for motorised modes is found insignificant for them. They also have a fairly strong preference for the bicycle over other modes, with all ASCs being highly significant. The highest WTP for in-vehicle time can be observed for the '*Flex-sceptic individuals*', aligning with the high value of the ASC for car. They do however show the most difference in cost sensitivity for leisure trips, with the WTP for the latter being almost twice as high as for commute trips, whereas it is either insignificant or up to 30% higher for the other three classes. Interestingly, the '*Flex-sceptic individuals*' have the lowest ratio of cycling time to in-vehicle time, meaning that they perceive cycling time relatively less negatively than the other classes. In combination with other parameter estimates however (particularly the ASCs), this lower ratio of travel time does not contribute to a higher likelihood of the '*Flex-sceptic individuals*' to choose the bicycle.

Table 2.9. Willingness-to-pay for travel time components and ratio of cost sensitivity for different trip purposes [2]

	Sharing-ready cyclists	**Tech-ready individuals**	**Flex-sceptic individuals**	**Flex-ready individuals**
In-vehicle time [€/h]		€ 11.15	€ 15.46	€ 5.24
Walking time [€/h]	€ 37.48	€ 24.39		€ 13.09
PT wait time [€/h]	€ 27.42	€ 16.79		
In-vehicle time ratio [cycling/motorised]		5.48	3.10	4.66
Trip purpose cost ratio [leisure/commute]		1.31	1.94	

[2] Parameter ratios are only shown in both parameters are significant at the 90% level

❖ Sharing-ready cyclists

This class is the most enthusiastic about cycling, strongly preferring it to all other modes. This class is not particularly sensitive to the in-vehicle time of motorised modes, but what makes the bike so attractive compared to any of the motorised modes is the price and the absence of walking and waiting times. The trip purpose does not play a role on their cost-sensitivity. Whether a Flex service is shared or private is also not relevant for their decision-making process.

This class has an above average positive opinion of the sharing economy and its merits, and they also see benefits in productively spending their travel time, even if it is not the shortest possible travel time. Their views on sharing and pre-booking a ride (F4) and on the use of apps are very much aligned with the sample. These results indicate that they seem to be (at least) partially ready to adopt Flex services.

'*Sharing-ready cyclists*' are by far the most frequent bike and E-bike users, using them almost twice as often as any of the other classes, whereas their car use is the lowest among the classes (Figure 2.6). They have the highest bike ownership, with 67% owning a bicycle and 34% an E-bike. They tend to be slightly younger, highest educated and most affluent. They are slightly more often found in highly urbanised areas, living without children (Table 2.10).

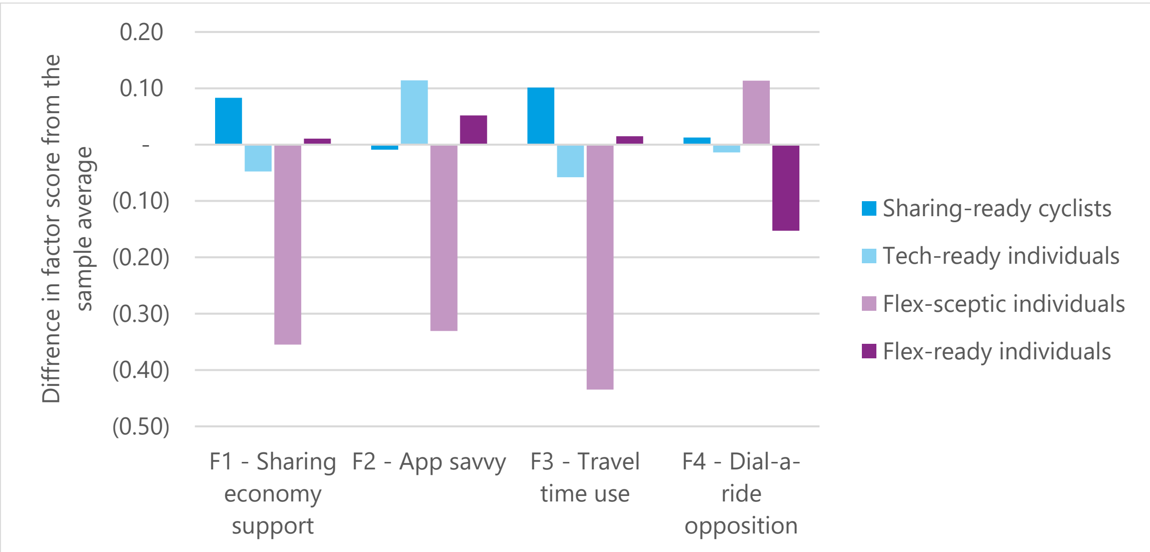


Figure 2.5. The differences between the sample average and the average of each of the four classes

❖ Tech-ready individuals

Based on the SP experiment, the bicycle seems to be the most preferred mode for them, but less so than for the former class. '*Tech-ready individuals*' are more time-sensitive for in-vehicle time and are therefore prepared to pay more for a shorter travel time. For motorised modes, they have a willingness-to-pay ratio of 11.15 €/h. The ratio of cycling time to motorised mode in-vehicle time is also the highest of any class, meaning they perceive cycling time most negatively, making motorised modes comparatively more attractive. They are not as time-sensitive when it comes to out-of-vehicle time (walking and waiting), meaning they are willing to trade-off in-vehicle and out-of-vehicle time. '*Tech-ready individuals*' do not like sharing and are willing to pay €1.08 more to avoid it. They are also more cost-sensitive when making leisure trips, compared to commute trips, with a leisure trip WtP of 8.49 €/h.

This class is considered tech-ready, as they score highly on app-related statements, but low with respect to other factors. Interestingly, they have an above average familiarity with sharing economy services, being either most or second most familiar on all six examples, particularly in the frequency of using food delivery services.

'*Tech-ready individuals*' are frequent car users, with 86% using it on a weekly basis, with 53% using it daily. They also have the highest household car ownership, at 1.27 vehicles per household and only 11.5% of households have no car (compared to the 17% average). They have an above average bike ownership and are the second most frequent cyclists. Members of this class have a middle-to-high level of education (slightly above average) and have an above average household income. They are the youngest class, live more often in suburban areas and have the largest average household size, mostly living as a couple with children or a single parent with children.

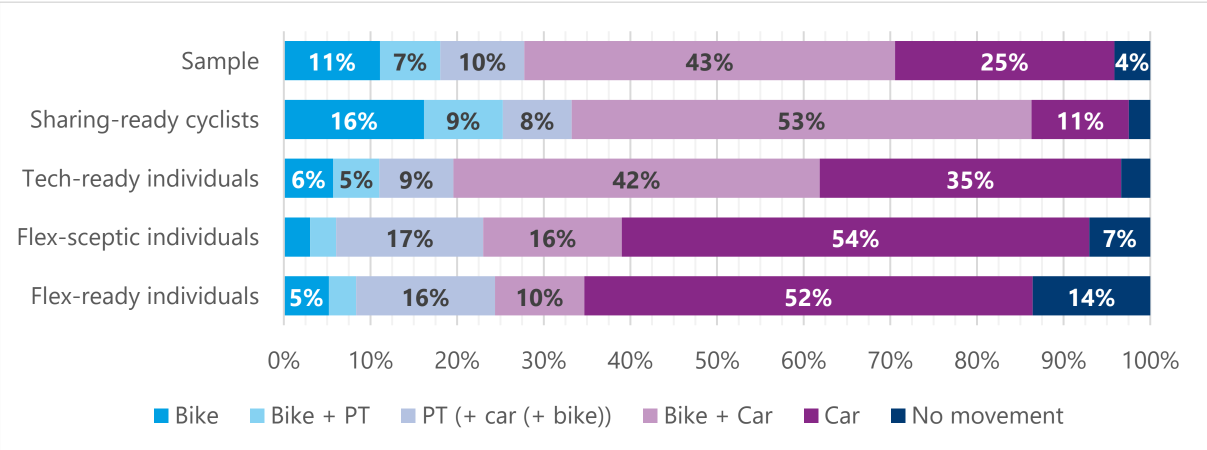


Figure 2.6. Weekly travel pattern of modes being used at least once per day, for the four latent classes (values below 5% are not labelled)

❖ Flex-sceptic individuals

This class has a very strong preference for using the car, scoring well above all other modes. '*Flex-sceptic individuals*' are willing to spend most to reduce their travel time out of any of the classes, with a WtP of over 15€/h, whereas walking and waiting do not seem to play a role in their decision making (all three parameters insignificant). Sharing a Flex trip also does not appear to play a role in their mode choice. Their high time-sensitivity is only observed for commute trips however, as their WtP for leisure trips is only 7.96 €/h.

'*Flex-sceptic individuals*' have the most distinctive profile of the classes. They are strongly opinionated and quite strongly negative on all four factors resulting from the EFA (note that F4 is reversed, so an above average score indicates stronger opposition than the sample average).

Similar to their preferences in the survey, '*Flex-sceptic individuals*' are frequent car users, but with an average car ownership rate. They are less enthusiastic cyclists than the average and have the lowest bike ownership, with only 43% having a bike (low for the Dutch context), compared to the average of 62%. This class is on average the lowest educated and has the lowest income. They also live in less urbanised areas. The latter likely contributes to their above average preference for car, as other modes are comparatively less attractive in such a context. Although a below average income and high car preference may be counterintuitive, their car ownership rate is average for the sample, meaning they seem to be pragmatic in their car ownership. '*Flex-sceptic individuals*' are more likely to live alone, rather than with a partner (either with or without a child). The members of this class have an above average likelihood to be pensioners: 30%, compared to the sample average of 26%.

❖ Flex-ready individuals

Members of this class seem to have an overall minor preference for car over the other modes and also a clear, though less significant (p=0.092) preference for Flex over PT or bike. They are also the most cost-sensitive of the four classes. This makes '*Flex-ready individuals*' the most multimodal of all the classes: selecting a motorised mode when it is cheap and opting for bike when the others are too expensive. They do not like to walk, having the highest ratio of walking time to in-vehicle time in the sample at 2.5-times higher. Sharing Flex is barely significant for this class (p=0.10), with respondents willing to pay only as much as €0.53 more for a private ride, again highlighting their high cost sensitivity.

'*Flex-ready individuals*' are the strongest supporters of dial-a-ride-style services, as they do not seem to be too bothered by sitting close to strangers or having to pre-book a ride. They also seem to be fairly comfortable using apps, and score slightly above average in their favourable opinions towards the sharing economy and the use of travel time.

'*Flex-ready individuals*', like the '*Flex-sceptic individuals*', have an above average use of the car and below average use of bike. They have the lowest bike ownership of any class, at only 39%. Interestingly, they are also the most likely to not travel regularly on a weekly basis. This class has a both a slightly below average income and a slightly below average level of education. Given that many class members are young however, this may be because they have not yet completed their education. While the average age of this class is above the sample average, it has an above average share of both younger (below 25) and older individuals (above 60). They live in more urbanised areas in small households and more often live either alone or as a couple (without children).

Table 2.10. Socio-demographic characteristics of the sample and the four distinct latent classes

		Sample	Sharing-ready cyclists	Tech-ready individuals	Flex-sceptic individuals	Flex-ready individuals
Gender	Female	52%	51%	52%	43%	66%
	Male	48%	49%	48%	57%	34%
Age	18-34	21%	22%	23%	16%	16%
	35-49	19%	18%	23%	23%	14%
	50-64	30%	31%	27%	23%	39%
	65+	29%	29%	26%	38%	30%
Education	Low	30%	29%	29%	36%	37%
	Middle	41%	38%	44%	47%	45%
	High	28%	33%	27%	17%	18%
Household income	Below average	24%	25%	22%	26%	25%
	Average	23%	24%	18%	29%	22%
	Above average	40%	40%	45%	25%	35%
Employment status	Employed	50%	50%	52%	44%	47%
	Student	5%	6%	6%	3%	4%
	Retired	26%	27%	23%	30%	26%
	Other non-employed	19%	18%	19%	23%	24%
Urbanisation level	Very highly urban	23%	25%	20%	23%	24%
	Highly urban	32%	31%	33%	34%	29%
	Moderately urban	16%	16%	16%	13%	21%
	Low urban	20%	20%	20%	18%	22%
	Not urban	8%	8%	10%	12%	4%
Household size	1	22%	23%	22%	22%	23%
	2	36%	38%	32%	34%	38%
	3+	42%	40%	46%	44%	39%
Household car ownership	average	1.14	1.07	1.27	1.11	1.19
	0	17%	20%	11%	17%	18%
	1	56%	56%	56%	59%	55%
	2	23%	22%	28%	20%	19%
	3+	4%	2%	5%	4%	9%

2.5 Discussion

Sharing an on-demand trip is often associated with two main differences compared to taking a private trip: physically sharing the vehicle with other passengers (close presence of strangers) and potential additional travel time. To compensate for this, a discount (financial incentive) is offered for sharing, but the discount necessary to attract different user groups varies based on their preferences. In Figure 2.7, we show the discount needed for shared and private trips to be equally attractive (have the same utility) for the four user groups, given additional travel time. Although the variation of in-vehicle time due to detours was not studied, preliminary research in the field reports that additional travel time has an equal or lower VOT than the promised travel time at the start of the trip (Alonso-González, van Oort, et al., 2020b), meaning that our outcomes (Figure 2.7) are more likely overestimating the necessary discount rather than underestimating it.

For larger travel time differences, two classes with a lower VOT and two classes with the higher VOT can be easily distinguished. Attracting '*Tech-ready individuals*' and '*Flex-sceptic individuals*' to a pooled alternative will therefore require a substantially larger discount than for '*Sharing-ready cyclists*' and '*Flex-ready individuals*'. This is also in-line with their attitudes towards sharing and sitting close to strangers, where '*Sharing-ready cyclists*' and '*Flex-ready individuals*' are more likely to not mind the proximity of strangers.

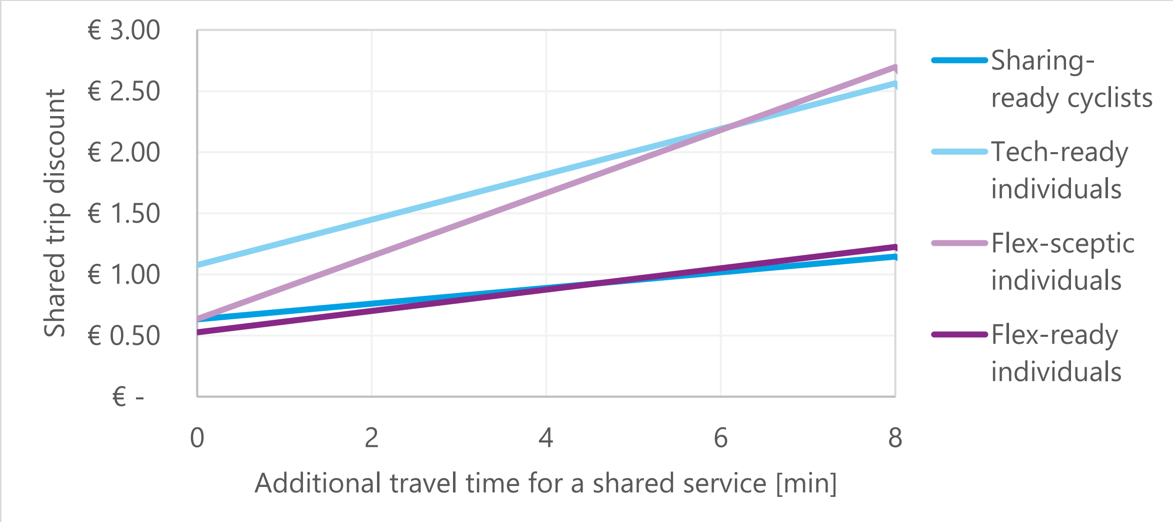


Figure 2.7. Discount required for a shared Flex ride to be equally attractive as a private ride

From Figure 2.7, we would assume that '*Sharing-ready cyclists*' and '*Flex-ready individuals*' should be the target of Flex services, but that only compares shared and private Flex services, without yet positioning them in the wider mobility context. To that end, we perform a sensitivity analysis, mimicking a typical urban trip (Figure 2.8), with a potential market share of a private or shared Flex service, based on a varied Flex trip cost. The findings are presented in Figure 2.9.

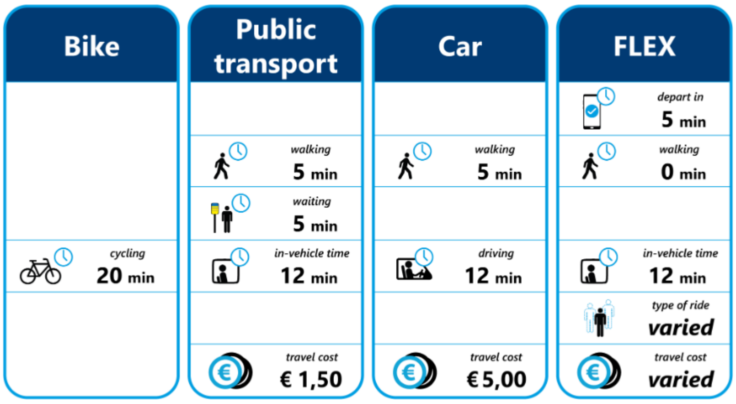


Figure 2.8. Example choice situation

'*Flex-ready individuals*' show the largest potential for using on-demand services. For them, the main competing modes are public transport and car, but as they are highly cost sensitive, Flex is a viable alternative as long as it is sufficiently cheap. '*Sharing-ready cyclists*' show almost no potential to use Flex in an urban environment. As their name suggests, cycling is their mode of choice and for short urban trips, they are unlikely to choose any other mode. Cycling only starts being less viable when it takes more than 30 min. The same can be said for '*Flex-sceptic individuals*', except in their case, the main competitor is the car. Given their strong preference for the car, it would have to be very strongly penalised (high fuel cost, parking cost, limited access,…) for any of the other modes to be a viable alternative. Because they also have a very negative perception of sharing, they may be the least likely to adopt a Flex service. '*Tech-ready individuals*' however, while not very open to sharing, are potential Flex users. Time and privacy are quite important to them so Flex needs to be fast, private and preferably also door-to-door. This is a premium that they are willing to pay for. Sharing on its own would not be a major issue, but since it would likely entail a longer travel time, it is out of the question for them.

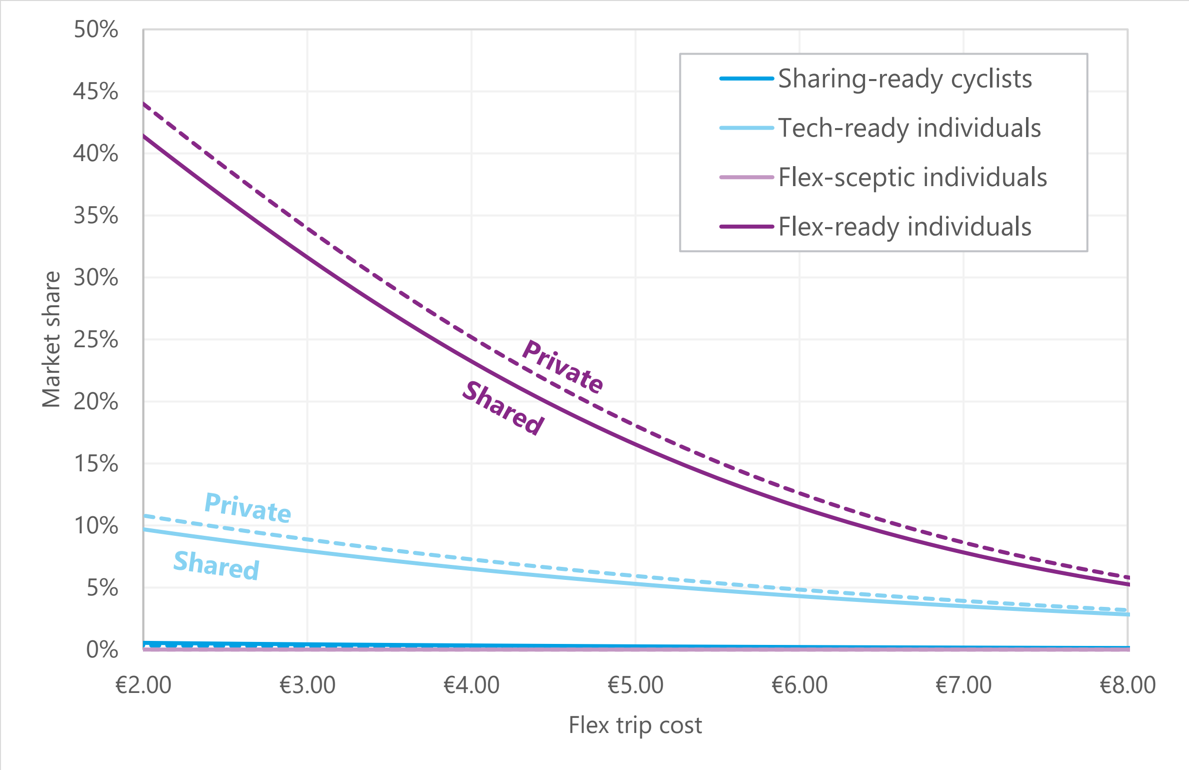


Figure 2.9. Market share of Flex (private or shared, compared to a bicycle, car and PT alternative) among different classes when Flex trip cost is varied ceteris paribus

2.6 Conclusion

This study analyses the role of on-demand transport services, both private and pooled, and their adoption potential within the context of competition for urban trips alongside alternative modes. A survey was carried out in the Netherlands, yielding 1,063 valuable responses. To the best of our knowledge, this is the first study to compare the expected use of on-demand services to car, public transport and bicycle transport and allow for the monetary evaluation thereof. Our survey took place in the Netherlands where the cycling conditions and culture differ greatly from most previous studies which were set in North America, where cycling plays a much smaller role and where cars and (to a lesser extent) public transport carry the majority of urban travellers.

In a highly cycling-oriented environment, Flex services do not seem to offer a highly attractive alternative for (short) urban trips. In line with literature (Choudhury et al., 2018; Hyland et al., 2018; Y. Liu et al., 2018; Yan et al., 2019), on-demand services fall behind cycling, the car and public transport, both in the overall mode perception as well as in the perception of cost. While cycling is not attractive over longer distances, most cities in the Netherlands and the wider region (Central and Western Europe) are relatively small and thus urban trips are usually not longer than five kilometres (de Graaf, 2015). The rise of e-bikes is also extending the range for a journey by (e-)bike. While not of interest for commuting, Flex services are used more commonly around the world for leisure trips, mostly in the evenings and during the night (King et al., 2020; Mohamed et al., 2019; Young & Farber, 2019). Our findings also support this, as the attractiveness of Flex – when compared to other modes – is found to be higher for leisure trips. Respondents are found to be more cost-sensitive when making leisure trips by car or PT, but not when choosing Flex.

To better understand market segmentation and how perceptions vary with respect to on-demand mobility, a latent class choice model is used in which four distinct market segments are uncovered. While being the smallest class (at 9% of the sample), the "***Flex-ready individuals***" have by far the highest propensity to choose a Flex service for an urban trip. With a relatively high cost-sensitivity and refraining from cycling, they are well positioned to adopt on-demand services if / when they become more commonplace. They are quite open to sharing a Flex ride and would only use a private service if it costs only a fraction more. The largest class of the sample (55%), the "***Sharing ready cyclists***" are also very open to sharing, exhibiting similar attitudes and behaviour with respect to sharing, but do not present a high potential for using Flex. As their name implies, they are avid cyclists, and for short urban trips there is virtually no alternative for them. A higher adoption potential can be observed among the "***Tech-ready individuals***" (27%), for whom time is of the essence. If Flex can provide them with a comparatively fast service, they are more than happy to use it. They are more averse to sharing, but if they do not lose much time, they would still consider it they receive a significant discount for sharing. For the final class, the "***Flex-sceptic individuals***" (9%), on-demand services do not seem like a viable alternative. They display a dislike towards sharing, technology and use of public transport, while at the same time highly prioritising their car. Given these results, public transport – and to a lesser degree cars – will likely suffer the biggest impact of an increased presence of Flex in cities. Cycling will likely not be impacted greatly, as the most frequent cyclists do not perceive Flex as a viable alternative for them.

Recently, a few other studies identified latent clusters in the Dutch population, with respect to MaaS, shared, autonomous and on-demand mobility (Alonso-González et al., 2020, 2020; Alonso-González, van Oort, et al., 2020a; Winter et al., 2020). Certain parallels can be drawn between their findings and ours. About half of the population seems to fall into a mostly-ready category with respect to MaaS and Flex, being both ready at the technology level, as well as the sharing and mobility aspect. They tend to cycle a lot, use the car below the average, are younger and higher educated. Around a quarter of the population is found to be so called 'technological car lovers', a group that is technologically advanced and neutral on sharing. Their main characteristic is they are very time-sensitive and are prepared to pay a lot. Two smaller classes (10-20% each) round off the population, with very opposing views. One class are confident in making multi-modal trip and for the most part ready to adopt MaaS. They live in urban areas, have a lower car ownership and are fairly cost-sensitive. On the other side is the class most negative about most things regarding technology and innovation, sticking to the privacy of their car. They tend to be middle-aged or older, predominantly male and middle educated.

A limitation of this study is the hypothetical bias that comes with using stated preference methods. Although some studies found limited bias, most conclude that respondents display a higher willingness-to-pay in the hypothetical setting of an SP survey (Loomis, 2011; Murphy et al., 2005) and that actual behaviour may differ. The transferability of the results to other contexts is also limited. While cycling plays a dominant role for most short trips in the Netherlands, the attitude towards public transport may be lower in rural areas due to its lower quality and the perception of car more positive. While the former could make Flex comparatively more attractive to users, the latter could have a negative impact. Although great care was taken when selecting the attribute levels, to make sure a sufficiently large range of possible values is captured, they may still influence the model outcomes. Specifically with respect to the travel times of car, public transport and on-demand services, the range, although broad for the analysed context of an urban trip, does not vary greatly (between 8 and 16 minutes) and thus may have influenced the model estimation, wherein the parameter for the travel time of those modes was insignificant. The Dutch (north-west European) environment, with its high quality public transport and extensive cycling infrastructure also means that the results cannot be directly translated to other geographic areas with minimal cycling and/or public transport use. With respect to the market segmentation, the "*sharing-ready cyclist*" group is likely (much) smaller and the three remaining classes larger, the extent to which varying depending on local cycling, traffic and public transport conditions.

In contexts where the use on-demand mobility services rises, policymakers need to make sure that active modes stay attractive and especially that public transportation does not start suffering from a decline in ridership due to travellers shifting modes. Municipalities should cooperate with Flex service providers, to stimulate Flex as a complementary service to existing public transport services, by acting as a feeder, providing services in areas and at times of day with poor public transport services. To encourage pooling as much as possible, financial incentives (discounts) should also be offered to travellers for pooling their trips.

In future research, a mixed logit model can provide an alternative interpretation of the heterogeneity of users and their perception of Flex services. Furthermore, a latent class model with a class membership function that incorporates attitudinal and socio-demographic data or directly interacting this data with parameter estimates in the model can help in further identifying potential user groups for Flex services. Future research should also evaluate the potential of Flex for other trip types. An often cited case for (autonomous) on-demand services is for access/egress to/from train stations or other high capacity public transport (P. (Will) Chen & Nie, 2017; Clements & Kockelman, 2017; Hall et al., 2018; Ma, 2017; OECD, 2015; Tirachini & del Río, 2019) and how such a service can impact access mode and station choice – potentially increasing the catchment area of stations. Another potential use of shared Flex services could be on medium-distance (up to 100 km) inter-city trips. Research should also consider how Flex services can aid the attractiveness of MaaS bundles, to complement public transport services by offering first/last mile access and accessibility at times of the day when public transport service are limited or non-existent, offering MaaS users a greater variety of alternatives. Finally, if / when Flex becomes more commonplace, its impact on road congestion, public transport ridership, vehicle ownership etc. needs to be evaluated, along with potential policies on how to increase its level-of-service while securing its affordability and financial viability and minimizing the negative externalities of transportation.

Chapter 3:

Waiting time variability of on-demand mobility services in urban areas

In the previous chapter, people's mode choice behaviour and preferences for on-demand mobility services in an urban setting was analysed, directly comparing on-demand services with other modes. In this chapter, we expand on the knowledge and role of on-demand mobility, by analysing the behaviour of travellers with respect to service variability, studying the perception of waiting time variability for on-demand mobility services. As services are rarely fully reliable and the extent of their variability is likely to vary, the scale of variability may have significant consequences on people's travel behaviour and attitudes towards on-demand mobility. Studying reliability and its impact on future decision-making is enabled by expanding on the approach known as Instance-Based Learning (IBL), to better understand how past experiences of using on-demand services may influence travellers' future choices and how quickly these experiences, be it good or bad, fade over time.

Section 3.1 provides an overview of different types of information influencing an individual's decision-making, the role of past experiences, and how all this can relate to On-Demand mobility services. Section 3.2. outlines how the survey was designed, models estimated and the data collected. Key findings are presented in Section 3.3, with Section 3.4 providing a discussion of the findings, their implications and the outlooks for future research.

This chapter is based on the following article:

Geržinič, N., Cats, O., van Oort, N., Hoogendoorn-Lanser, S., Bierlaire, M., & Hoogendoorn, S. (2023). An instance-based learning approach for evaluating the perception of ride-hailing waiting time variability. Travel Behaviour and Society, 33.

3.1 Introduction

In recent years, ride-hailing services like Uber, Lyft, DiDi etc. have become commonplace around the world and have thus garnered significant attention within the scientific community. Several mode choice studies, predominantly with a stated preference (SP) approach, aimed to evaluate their role and potential within the wider mobility ecosystem (Choudhury et al., 2018; Frei et al., 2017; Geržinič et al., 2022; Y. Liu et al., 2018; Yan et al., 2019). Of particular interest is the relation with public transport, as ride-hailing seems to be abstracting most of its passengers from mass transit (Henao & Marshall, 2018). Whether they compete with each other for passengers or complement each other is still subject to discussion and seems to be quite context-specific (Cats et al., 2022; Erhardt et al., 2022; Phun et al., 2019; Tirachini & del Río, 2019).

In terms of their service characteristics, ride-hailing (and other on-demand services like micro-transit and taxis) shares similarities with public transport (i.e. travellers do not need to own a car and drive themselves) as well as with a private car (i.e. offering a high level of flexibility, not being bound by spatio-temporal operations). Services do not operate according to a predefined schedule or route and may therefore be prone to a certain level uncertainty, most notably in the variability of waiting and in-vehicle time. And while all the aforementioned modes (car, public transport and ride-hailing) can be impacted by external factors such as congestion, the endogenous factors impacting them differ. For ride-hailing for example, drivers' ride acceptance behaviour (Ashkrof et al., 2021), repositioning tactics (Ashkrof et al., 2022) and platforms' fleet management and matching algorithms (Wang & Yang, 2019). may all have a significant impact on the variability of service.

Understanding how users perceive this variability is crucial for the future implementation of ride-hailing and its potential integration with fixed public transportation. Some aspects of ride-hailing waiting time could suggest that it might be perceived differently than wait time for public transport. Firstly, travellers know they are opting for an on-demand based service, not a scheduled service, which could already alter their expectations with regard to service variability. Secondly, passengers tend to wait for public transport at stops/stations, which are designated public locations. For ride-hailing on the other hand, pick-up is usually at a specified address, meaning that potential passengers could wait in private establishments. Thirdly, they may reasonably also assume that the vehicle would wait for them or contact them when it is ready, thereby reducing waiting anxiety.

Despite the inherent uncertainty associated with on-demand services, little is known about the impact of their service variability on decision-making. To the best of our knowledge, Bansal et al. (2019) and Alonso-González et al. (2020b) were the only ones to study the effect of waiting time variability of ride-hailing services. The former performed a stated preference experiment wherein they presented respondents with two unlabelled ride-hailing services, each with its own estimated waiting time and an average pick-up delay. One service was fully reliable (average pick-up delay of 0 minutes) but had a longer expected waiting time. They report that the more unreliable the service is, the higher the percentile of the displayed waiting time should be, to avoid overly optimistic waiting time estimates with large potential pick-up delays. In a second experiment, they presented respondents with a hypothetical past experience, given a certain wait time and pick-up delay, and asked the respondents if they would switch to a different company after this experiment or not. In their sample, the majority chose to switch, with a binary model showing the propensity to switch increasing with the relative pick-up delay

(delay/waiting time). Alonso-González et al. (2020a) carried out three separate SP experiments, investigating the perception of variability in travel time, waiting time at the origin and waiting time at a transfer point. Similar to Bansal et al. (2019), the reliability was stated explicitly, but instead of giving respondents an average delay, three equally likely travel/wait times were presented. This gave respondents more insight into the variance of a service. Using a latent class approach, they identified four distinct groups in the population, although they differed mainly in their time valuation, while the reliability perception was similar across the segments. For all three experiments, the value of reliability was found to be lower than that of the planned waiting/travel time, with the ratio between time and reliability at around 0.5.

In contrast to the ride-hailing services context, the perception of travel time variability has been heavily researched for other modes of transport (Noland & Polak, 2002). Measuring the perception of variability through stated preference (SP) experiments is challenging, and two overarching approaches have emerged in literature; providing the information **explicitly** or **implicitly**. Presenting reliability information explicitly means that respondents are given information on the variability of potential outcomes upfront, before making a choice. Variability is therefore an attribute, that can be presented in different ways: providing a mean and standard error, an average value, a certain number of equally-likely-to-occur values or images of distributions. Both aforementioned studies on the reliability perception for ride-hailing services (Alonso-González, van Oort, et al., 2020b; Bansal et al., 2019) apply this approach.

Alternatively, the information on variability can be given implicitly, with the respondents receiving an indication of the expected level of service and then receiving feedback on the outcome, i.e. how their selected alternative performed. By repeating this choice task several times, respondents get a more realistic experience of variability, and can thereby internalise it and form their own assessment of the reliability associated with each alternative. These experiments can be differentiated based on:

1. **Level of information provided** to the respondent, presenting only the outcome of the selected alternative or of all options (Bogers et al., 2007)
2. **Addition of a "memory aid"** for the respondent, showing them the last few outcomes (Bogers et al., 2007)
3. **Incentives / Penalties** for respondents, linked to the performance of their choices (e.g. making them wait proportionally longer if they chose an alternative with a comparatively poorer outcome (Bogers et al., 2007) or offering financial compensation based on their performance (Ben-Elia et al., 2013) in order to make the experiment more realistic). Studies may include this because there is no real "suffering" from making poor decisions in an SP experiment, and the respondents might thus not be incentivised to make choices in the same way.
4. **Number of repetitions** of such a choice task (varying from 25 (Bogers et al., 2007) up to 120 (Yu & Gao, 2019))

This type of experiment has so far predominantly been applied to car-route choice (Avineri & Prashker, 2006; Ben-Elia et al., 2008, 2013; Ben-Elia & Shiftan, 2010; Bogers et al., 2007; Tang et al., 2017; Yu & Gao, 2019) and to the best of the authors' knowledge, has not yet been used to analyse ride-hailing waiting time.

When taking part in such a survey, respondents learn the reliability of each alternative through experience. It is therefore important to consider the different types of information provided to and used by the respondents in the decision-making process. According to Ben-Elia & Avineri (2015), there are three types of information that respondents may make use of:

1. **Descriptive**: Providing the respondents with information on the state of the system
2. **Prescriptive**: Giving advice to respondents on how to decide
3. **Experiential**: The respondent's own information from the outcomes of previous choices

While descriptive and prescriptive information tends to be choice-set-specific, relevant at the time of the decision-making, experiential information is gathered over a longer period of time and has the potential to influence future decisions. Experience tends however to fade over time (Daneman & Carpenter, 1980), with more recent experiences having a stronger presence in our minds and thus a stronger influence on our decision-making (Anderson et al., 2004). Decay functions are commonly used to capture memory fading, with the most prominent example being the power function (Anderson et al., 2004; Kahana & Adler, 2002). The power function based on the work of Anderson et al. (2004) was adapted for the field of transportation by Tang et al. (2017), integrated into the instance-based learning approach and operationalised in the context of car route choice.

There is evidence to suggest that an additional and potentially contradictory effect might also inter-play, namely human tendency to form and stick to habits, as well as our resistance to change (Gao & Sun, 2018). Many choices we make in our everyday life are habitual and not every situation is thoroughly evaluated, purely to conserve mental effort. When faced with a similar choice situation several times, people will often forego the mental effort of re-evaluating the alternatives in detail and simply keep with the alternative they are more used to. While this repeated selection of the same option can start because of better performance, people are likely to stick to it after a while, even when it is less advantageous, purely because of their habitual behaviour or inertia (Cherchi & Manca, 2011; Gao et al., 2021; Gao & Sun, 2018; González et al., 2017; Ramadurai & Srinivasan, 2006; Rashedi et al., 2017). Choice inertia is the additional value travellers assign to an alternative solely because they are used to it and the perceived mental effort required to re-evaluate the available options exceeds the perceived benefit that could be gained from a thorough analysis thereof. There is a certain threshold, above which people will still re-evaluate their choices and potentially switch, but the benefit needs to be worthwhile for the mental effort to be induced.

The goals of this study are twofold. Firstly, we identify the value travellers place on unexpected outcomes of ride-hailing trips. We focus on the variability of waiting time, as it tends to be perceived more negatively than in-vehicle time (Wardman, 2004), meaning its variability is likely to have a stronger impact on the behaviour of travellers. We also include the possibility of cancelled trips in our study, as they may have a profoundly important impact on respondents future choices. Understanding travellers' behaviour is important for operators, authorities and policymakers to know how to design such services and which aspects to prioritise. Secondly, related to the first goal, our ambition is to evaluate existing and test novel theoretical formulations of both memory decay and choice inertia, to determine how best to explain traveller behaviour in our survey, as well as in future studies on experiential learning.

3.2 Methodology

3.2.1 Survey design

To evaluate the perception of waiting time variability for ride-hailing services, behavioural data of travellers is required. Our study utilises an SP experiment, as (1) revealed preference (RP) data for ride-hailing is scarce and (2) the applied model estimation approach requires a panel structure of the data (multiple observations per individual), which may be difficult to procure through RP data. We employ a survey design similar to what has been applied by Ben-Elia et al. (2013) and Bogers et al. (2007). The survey structure is presented in a flowchart in Figure 3.1, and described below.

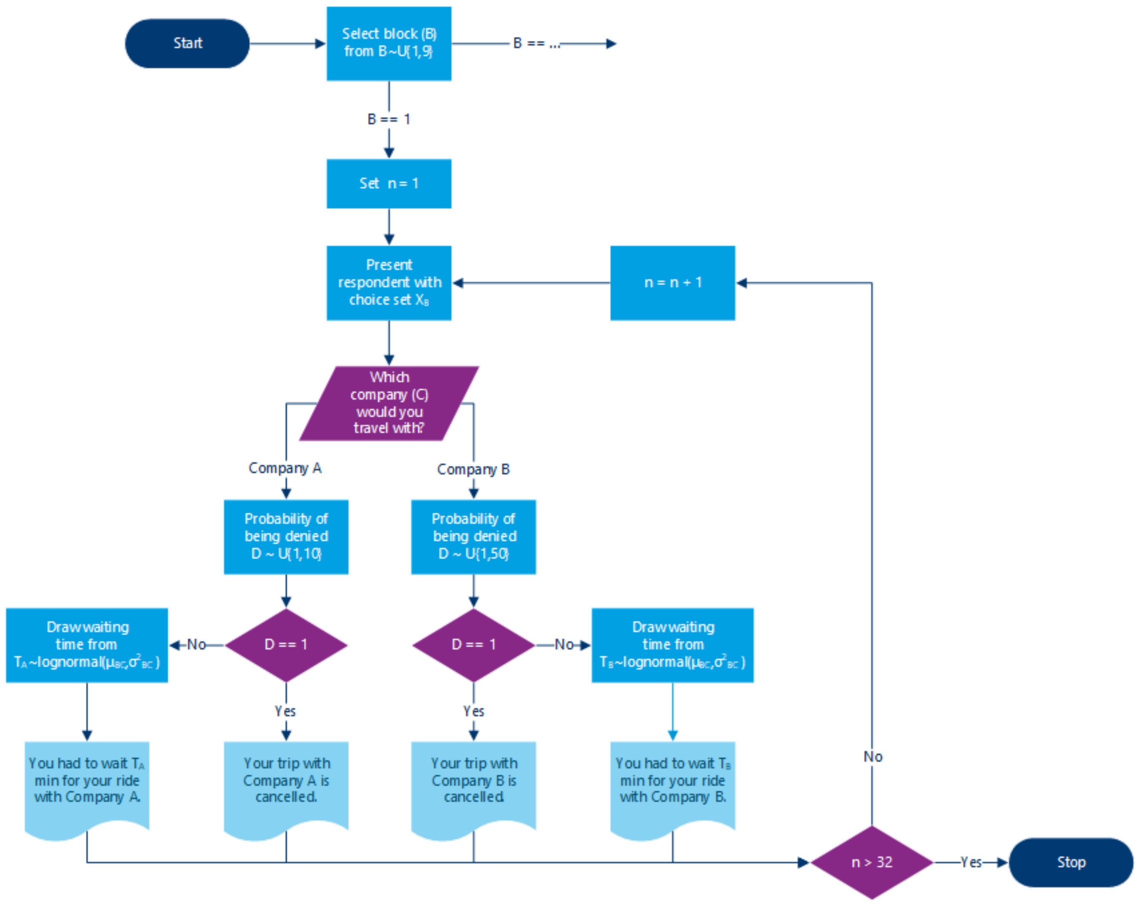


Figure 3.1. Flowchart of the SP experiment focused on experiential learning

In line with previous studies in this field (Ben-Elia et al., 2013; Bogers et al., 2007), we choose to limit the scope of the survey to only include alternatives of the same mode. This is done to avoid overwhelming the respondents with too much information and to focus their trade-off behaviour on the key question that we wish to address in this research. With respect to this respondents are presented with two alternatives, including descriptive information on two independent ride-hailing companies; referred to as Company A and Company B to avoid any bias. The descriptive information includes **expected waiting time**, **travel time** and **trip cost**. Travel time is included for context purposes and is equal for both companies (20 min) to ensure that the trade-off behaviour is limited to the cost and waiting time aspects. Respondents are asked to choose one of the companies and are then shown their experienced waiting time. The experienced waiting times are randomly drawn from an underlying distribution, specific to each company. This process is repeated for 32 instances.

Experiential learning experiments range in length from 25 (Bogers et al., 2007) to 120 repetitions (Yu & Gao, 2019), to ensure that the experiment is sufficiently long for the respondents to learn the reliability of each alternative. In this study, great care was also taken to make sure that the survey is not too long, to avoid overwhelming or exhausting the respondents. A pilot survey with 50 repetitions was carried out. At the start and after every ten repetitions, the respondents were asked a series of fatigue-related questions. Given the outcomes and comments from the respondents of the pilot, we limit the survey to 32 repetitions.

For the underlying distributions, a log-normal distribution is chosen as the most appropriate (Alonso-González, van Oort, et al., 2020b; Cats et al., 2022; T. L. K. Liu et al., 2019). To add sufficient variability to the experiment, we specify three log-normal distributions and three different price levels, resulting in a total of nine combinations (Table 3.1). In all cases, Company A is the cheaper, but more variable alternative, while Company B is more expensive but more reliable. To determine the parameters of the log-normal distribution and the price levels, we use the results reported by Alonso-González et al. (2020b), as their work is both recent and carried out in the Dutch context, making it suitable for our study. We specify the mean and variance for the log-normal distributions, which are then constructed using the μ and σ parameters (see Equation 3.1 and Equation 3.2). The mean of all distributions is set to 10 minutes, to focus on waiting time variation. The descriptive information on the expected waiting time is based on the median of each distribution. As the medians differ between the three utilised distributions, this enables us to test the also the perception of expected waiting time against the variation from it.

Equation 3.1. Definition of μ parameter

$$\mu = \ln\left(\frac{mean}{\sqrt{var + mean^2}}\right)$$

Equation 3.2. Definition of σ parameter

$$\sigma = \ln\left(\frac{var}{mean^2} + 1\right)$$

Table 3.1. Log-normal distribution parameters and price levels for Company A and Company B

mean = 10	var_A: 40 var_B: 10 *median: 8*	var_A: 40 var_B: 1 *median: 9*	var_A: 10 var_B: 1 *median: 10*
$Cost_A$: €12.00 $Cost_B$: €13.50	**Block 1**	**Block 4**	**Block 7**
$Cost_A$: €12.00 $Cost_B$: €15.00	**Block 2**	**Block 5**	**Block 8**
$Cost_A$: €13.50 $Cost_B$: €15.00	**Block 3**	**Block 6**	**Block 9**

In addition to the waiting time variability, we also study passengers' reaction to cancelling the ride-hailing trip altogether. The probability of the trip being cancelled is handled separately from the waiting time. Both companies are associated with a fixed cancellation probability, irrespective of the blocks, namely a 10% cancellation probability for Company A and a 2% cancellation probability for Company B. This way, service cancellation is decoupled from the waiting time distribution, while keeping with the notion of an overall more (B) and less (A) reliable company. Respondents are informed of the possibility that a trip might be eventually cancelled as part of the introduction to the survey. If the trip is cancelled, they are informed of this after having made their decision for Company A or Company B, with a message saying that "the trip could not be performed by your selected company".

Additionally, respondents are presented with certain context information for the choice at the start of the survey. The trip is presented as returning home from a leisure activity (restaurant, cinema, visiting family/friends) in the evening. It is decided to avoid providing additional information on the waiting location and rather ask respondents at the end of the survey how they imagined the situation while answering the survey: was that indoors or outdoors and sitting or standing. A fifth option of "Did not really think about it" is also added. Furthermore, to compare the outcomes of the survey with the direct opinion of the respondents, they are asked which company they found more reliable. For the event of a cancelled service, we ask the respondents how they would have gotten home in real life and how their behaviour with respect to these services would change in the future. Finally, to evaluate if experience has a role in behaviour, we present the respondents with different types of services from the sharing economy (ride-hailing, car sharing, food delivery, home rental,…) and ask them whether they are aware of them and how often they make use of them. The full list of questions and possible answers can be seen in Geržinič et al. (2021).

3.2.2 Model estimation

The specific nature of experiential learning data means it violates one of the principal assumptions of MNL discrete choice models (Ben-Elia & Shiftan, 2010): the error terms are not identically and independently distributed (i.i.d.). This is because the observations are interdependent and thus correlated. To circumvent this issue, we apply the Panel Mixed Logit (ML) model on our data, which relaxes the i.i.d. assumption by accounting for the panel structure of the data. Using an ML model also allows us to capture respondent heterogeneity by allowing parameters to vary between respondents.

The structure of the utility function is based on the design of the survey and how respondents were presented with the alternatives. The function consists of three main parts: (1) descriptive information, (2) experiential information and (3) the error term (shown in Equation 3.3). Descriptive information is formulated following the linear-additive utility. We consider the attributes that are presented to the respondents before making their choice. These include the estimated waiting time and travel cost. Travel time is not included as it is a context variable and thus equal for all alternatives (Equation 3.4). The error terms are assumed to be i.i.d. extreme value across all dimensions.

Equation 3.3. Specification of the systematic utility

$$U_{n,j,t} = D_{n,j,t} + E_{n,j,t} + \varepsilon_{n,j,t}$$

where:

$U_{n,j,t}$	Total utility observed by respondent *n* for alternative *j* in choice situation *t*
$D_{n,j,t}$	Descriptive information for respondent *n* for alternative *j* in choice situation *t*
$E_{n,j,t}$	Experiential information for respondent *n* for alternative *j* in choice situation *t*
$\varepsilon_{n,j,t}$	Error term associated with respondent *n* for alternative *j* in choice situation *t*

Experiential information is accumulated as respondents gain experience and is based on the feedback they receive upon making their choice (Equation 3.5). The two direct experiences from the survey are actual waiting time and cancelled service. The latter is coded as a binary variable, where 0 means the travel service was performed and 1 means that the trip was cancelled. The experience of waiting time is coded as the difference from the expected waiting time, meaning it can take a negative (shorter than expected waiting time) or a positive value (longer waiting time).

Equation 3.4. Specification of the descriptive information part of the utility

$$D_{n,j,t} = ASC_j + \beta_c \cdot c_{n,j,t} + \beta_{\overline{w}} \cdot \overline{w}_{n,j,t}$$

where:

ASC_j	Alternative specific constant, associated with alternative *j*
β_c	Taste parameter associated with attribute c
$c_{n,j,t}$	Cost experience by respondent *n*, for alternative *j* in choice situation *t*
$\overline{w}_{n,j,t}$	Estimated waiting time

In the survey, respondents make repeated choices over a period of time and the number of experiences increases. According to the instance-based learning theory (IBLT), the more recent and more frequent instances / experiences are more prominent in one's memory (Gonzalez et al., 2003; Gonzalez & Lebiere, 2005). In other words, the importance of an experience decays over time. Mathematically, this memory decay can be captured by a decay function (Equation 3.6), specifically the power decay function is often cited as a good approximation for modelling memory decay (Kahana & Adler, 2002; Tang et al., 2017; Yu & Gao, 2019). By incorporating the decay function into the utility function and parameterising it, it is possible to estimate the rate of memory decay for a particular situation. Most theories (including IBLT) consider the most recent experience to be the most important for the next choice situation.

Equation 3.5. Specification of the experiential information part of the utility function

$$E_{n,j,t} = \beta_w \cdot \sum_{t'}^{H_{n,j,t}} \left((w_{n,j,t'} - \overline{w}_{n,j,t'}) \cdot m_w(t,t') \right) + \beta_x \cdot \sum_{t'}^{H_{n,j,t}} \left(x_{n,j,t'} \cdot m_x(t,t') \right) +$$
$$+ \beta_b \cdot b_{n,j,t} + \beta_i \cdot i_{n,j,t}$$

where:

$w_{n,j,t'}$	Waiting time experienced by respondent *n* for alternative *j* in experience *t'*
$\overline{w}_{n,j,t'}$	Expected waiting time for respondent *n* in alternative *j* and experience *t'*
$x_{n,j,t'}$	Binary variable indicating a cancelled service, experienced by respondent *n* for alternative *j* in experience *t'*
$m_w(t,t')$	The weight related to memory decay of attribute *w*, in choice situation *t* for experience *t'*
$H_{n,j,t}$	The set of accumulated experiences, obtained by respondent *n* for alternative *j*, when making the decision in choice situation *t*
$b_{n,j,t}$	Binary variable indicating the barrier to entry, for respondent *n*, alternative *j* in choice situation *t*
$i_{n,j,t}$	Binary variable indicating the inertia (habit), for respondent *n*, alternative *j* in choice situation *t*

When modelling the impact of multiple instances on the current choice, the mathematical formulation used by Tang et al. (2017) employs an averaging approach. In other words, each individual weight of an experience is divided by the sum of all weights associated with the specific alternative. This means that the sum of all weights applied to the experiences associated with a specific alternative (not accounting for the actual utility contribution) is always equal to one (Equation 3.6). We refer to this as the "Relative weights" formulation. In addition, we propose and test the "Absolute weights" formulation. The notion behind this is that having more equally bad experiences should weigh more negatively and thus result in a higher disutility than a single bad experience of the same magnitude. Applying the relative weights approach, the contribution of both is equal. We amend this by removing the denominator from Equation 3.8, resulting in the mathematical formulation presented in Equation 3.7. This straightforward change means that while (for the same value of d_z) the ratios between weights remain the same, their total contribution to the utility changes.

Equation 3.6. Specification of memory decay with relative weights of experiences

$$m_z(t,t') = \frac{(t-t')^{-d_z}}{\sum_{t' \in H_{n,j,t}} (t-t')^{-d_z}}$$

where:

d_z	Memory decay parameter associated with attribute *z*

Equation 3.7. Specification of memory decay with absolute weights of experiences

$$m_z(t,t') = (t-t')^{-d_z}$$

In addition to testing relative and absolute weights of experiences, we also test how experiences may be 'stored' in a decision-maker's memory. In the formulation of Tang et al. (2017), an experience is linked to the moment in time when it is obtained. This means that the weight associated with a given experience decreases over time, regardless of any new experiences obtaining afterwards. We refer to this as the "Time-based" formulation. To that end, we propose an "Event-based" formulation for the set of gained experiences. The notion behind this is that the most recent experience may stay at the top of the decision-maker's mind, largely irrespective of how long ago it happened. In this formulation, the only thing that may decrease the weight of an experience is obtaining a new, more recent experience with the same company. To accommodate this, the formulation of memory decay weight is adapted as indicated in Equation 3.8. The main difference is decoupling the power function from a time-based approach and associating it with the number of experiences *t* in a ranked order of experiences with a specific alternative. For numerical reasons, one is added to the equation, so that the most recent experience is associated with an absolute weight of 1.

Equation 3.8. Specification of memory decay with an Event-based ordering of experiences

$$m_z(t,t') = \left(\left|H_{n,j,t}\right| + 1 - h'\right)^{-d_n}$$

where:

$\lvert H_{n,j,t} \rvert$	Total number of experiences of decision-maker *n*, with alternative *j* when making the decision in choice set *t*
h'	The order number of the experience (1 if it is the first experience, 2 if it is the second,...) obtained at time t'

To highlight the four different approaches and how the weights differ amongst them, they and their relative importance for the overall utility contribution are presented in Figure 3.2. Note that this assumes the alternative to which these weights apply was chosen at instances t=1 and t=3, therefore their impact on the choice only appears in the first following choice task. The weights are based on d=1.

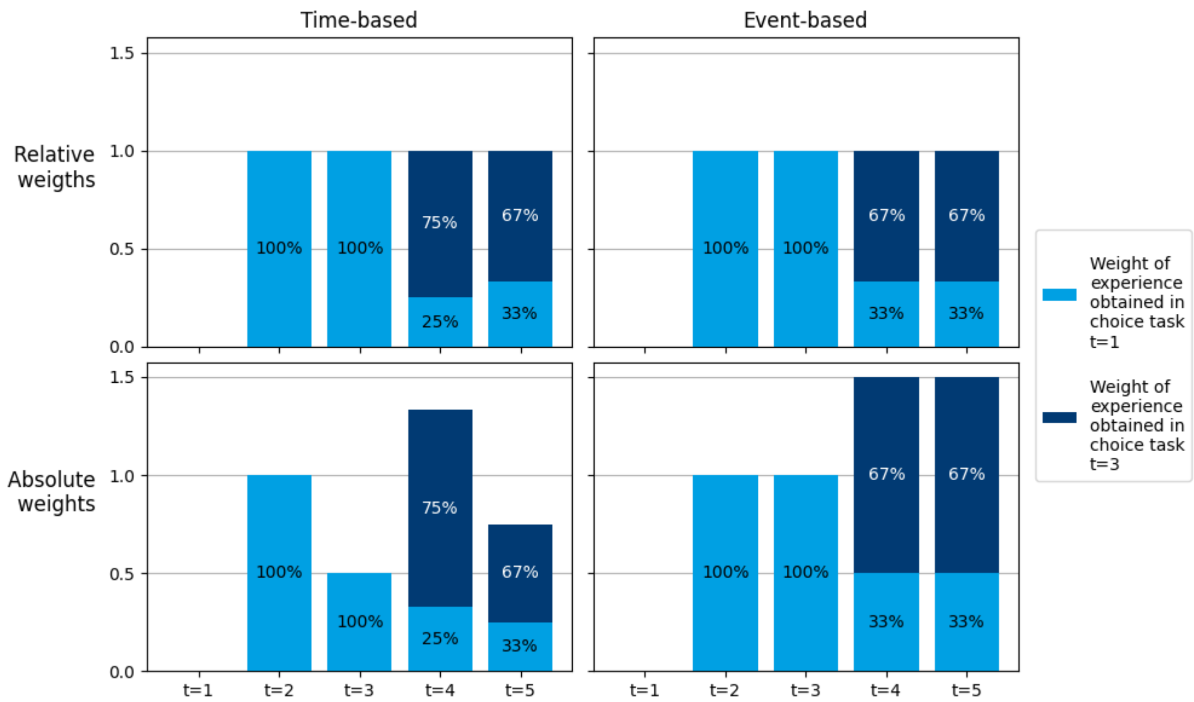


Figure 3.2. Weights and their relative importance at a specific choice situation.
This specific alternative was chosen at instances t=1 and t=3, with an assumption of d=1.

Two further experience-related attributes are specified and tested in the model estimation. Firstly, we add two simple binary variables (one per alternative) that mimic the "barrier-to-entry" for using new products and services. Both variables have a value of 1 at the start, as the respondent has no experience with either company. When a company is chosen for the first time, this variable changes to 0 and remains so for the remainder of the scenarios. This allows us to analyse a potential perceived barrier-to-entry that people experience before trying out a service for the first time.

The second experience-based attribute we include is inertia. By incorporating it into the utility function, the inertia parameter captures the value of not having to engage in a serious mental process of decision-making (Cherchi & Manca, 2011). Cherchi & Manca (2011) summarised and tested eight different specifications of choice inertia, from a simple binary specification, to using the performance (attribute level) of the chosen alternatives in previous experiences. Given that the performance of past experiences is already captured through the experiential variables paired with a decay function, we do not test those further. We focus instead on the specifications considering what the previous choices were. These are specifications 1 and 2 according to Cherchi & Manca (2011), which we refer to as "one" and "sum" respectively. "One" is a binary variable, taking the value of 1 if the alternative was chosen in the previous instance and 0 otherwise. "Sum" counts how many times an alternative has been chosen up till that point. To that end, we propose and test three more specifications. Firstly, we formulate a combination of the "one" and "sum" specifications, which we refer to as "reset". Like the "sum" specification, it keeps increasing with the number of times the same alternative is chosen repeatedly. Once the decision-maker switches to a different alternative, the inertia value resets to 0, similar as in the "one" specification. The other two specifications we test are natural logarithms of the "sum" and "reset" specifications. This is to test if the marginal contribution of inertia decreases with an increasing number of repeated choices. For numerical reasons, we add one before applying the logarithm, as a logarithm of zero cannot be defined. Together, the five specifications can be defined as shown in Equation 3.9. To highlight how the five specifications differ in scale, we plot them in Figure 3.3. The x-axis indicates which alternative is chosen at a given instance. Note that the inertia is based on a past choice and therefore lags by one choice task. The y-axis shows the value of different inertia variables for alternative A.

Equation 3.9. Specifications of choice inertia

One: $$i_{j,t} = \begin{cases} 0, & q_{j,t-1} = 0 \\ 1, & q_{j,t-1} = 1 \end{cases}$$

Sum: $$i_{j,t} = \begin{cases} I_{j,t-1}, & q_{j,t-1} = 0 \\ I_{j,t-1} + 1, & q_{j,t-1} = 1 \end{cases}$$

Reset: $$i_{j,t} = \begin{cases} 0, & q_{j,t-1} = 0 \\ i_{j,t-1} + 1, & q_{j,t-1} = 1 \end{cases}$$

Log-Sum: $$i_{j,t} = \ln\left(i(sum)_{j,t} + 1\right)$$

Log-Reset: $$i_{j,t} = \ln\left(i(reset)_{j,t} + 1\right)$$

Where:

$i_{j,t}$ Choice inertia of alternative *j* in choice situation *t*

$i_{j,t-1}$ Choice inertia of alternative *j* in choice situation *t-1*

$q_{,t-1}$ Binary variable if alternative *j* was chosen in choice situation *t-1*

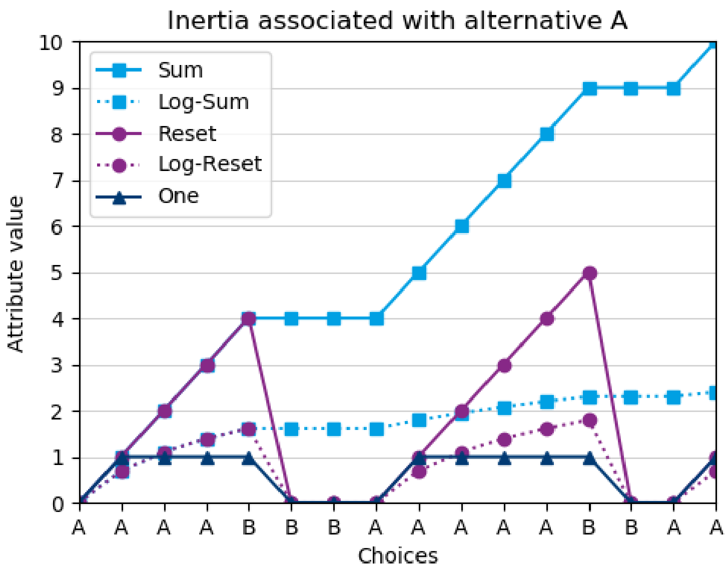


Figure 3.3. The contribution of the five different inertia specifications

3.2.3 Data collection

The full survey was administered to members of the Dutch Mobility Panel (MPN) (Hoogendoorn-Lanser et al., 2015), with the responses gathered between 17-29 of August, 2021. At the time of data collection there were limited regulations regarding the COVID-19 pandemic in the Netherlands, with manageable case and hospitalisation numbers and a sizeable part of the adult population being vaccinated (Rijksoverheid, n.d.-a). Respondents were reimbursed with a flat rate for completing the survey, rather than based on their performance (Ben-Elia et al., 2013), to avoid them focusing exclusively on their financial gain.

In total, 1,304 respondents filled-in the survey, of which 1,023 responses were complete. The data is cleaned based on a minimal and maximal response time. Removing all responses below a certain answering time is standard practice, to remove respondents who rush through the survey without actually reading and considering the task. We set this lower boundary at three minutes. Given the specific nature of our study, a maximum response time is set as well. The MPN allows respondents to stop at any point during the survey and continue at a later time from where they left off. In our experiment, the memory of previous experiences is crucial and by stopping midway and continuing for example a day later, respondents will likely not remember much of what they had seen. We therefore set the maximum cut-off time to 30 min. This reduced the number of observations to 936. We do not apply any answer-based validation, as it might be perfectly possible for a respondent to choose one or the other alternative for all 32 choice sets. The 936 responses are fairly evenly distributed among the nine blocks, with the blocks receiving between 88 and 111 observations. The description of the dataset can be found in Geržinič et al. (2021).

Socio-demographics of the 936 valid responses are presented in Table 3.2. The sample is well representative of the Dutch population on most of the presented characteristics. We do observe a slight overrepresentation of older individuals, single-person households and non-urban individuals. The differences in household income can be explained with the respondents in our survey having the option not to disclose their income. Adjusting for that, we see a slight overrepresentation of middle-income households and an underrepresentation of high-income households.

Table 3.2. Socio-demographic characteristics of the collected sample and the Dutch population. Source for population data: Centraal Bureau voor de Statistiek (2022)

Variable	Level	Sample	Dutch Population
Gender	Female	52%	50%
	Male	48%	50%
Age	18-34	22%	27%
	35-49	25%	23%
	50-64	29%	26%
	65+	24%	25%
Education [1]	Low	25%	29%
	Middle	41%	36%
	High	34%	35%
Gross household income [2]	Below average	20%	24%
	Average	48%	47%
	Above average	17%	29%
	Prefer not to say / Don't know	15%	0%
Employment status	Employed	55%	50%
	Retired	22%	21%
	In education	5%	5%
	Other [3]	18%	24%
Household composition	Single person	26%	18%
	Two or more (with kids)	40%	50%
	Two or more (no kids)	33%	32%
Urbanisation level [4]	Very highly urban	23%	24%
	Highly urban	29%	25%
	Moderately urban	16%	17%
	Low urban	23%	17%
	Not urban	9%	17%

1 Low: no education, elementary education or incomplete secondary education
Middle: complete secondary education and vocational education
High: bachelor's or master's degree from a research university or university of applied sciences

2 Below average: below modal income (< €29,500)
Average: 1-2x modal income (€29,500 – €73,000)
Above average: Above 2x modal income (> €73,000)

3 Includes unemployed, unable to work, stay-at-home, volunteer and unknown

4 Very highly urban: > 2,500 inhabitants/km^2
Highly urban: 1,500 – 2,500 inhabitants/km^2
Moderately urban: 1,000 – 1,5000 inhabitants/km^2
Low urban: 500 – 1,000 inhabitants/km^2
Not urban: < 500 inhabitants/km^2

3.3 Results

The model estimation outcomes, including both the model fit and the parameter estimates, are presented in Table 3.3. In addition, Willingness-to-Pay (WtP) trade-offs are presented in Table 3.4. The presented model achieved a model fit of almost 0.6, with all 13 parameters being highly significant ($p<0.01$). Four parameters (both waiting time parameters, cost and cancelled service) are specified as random parameters in the ML model, allowing us to capture how their perception varies within the population. The remaining five parameters are estimated as fixed.

Table 3.3. Model outcomes

Parameters	13
Null LL	-20,761.14
Final LL	-8,370.43
Adjusted Rho-square	0.596
BIC	16829.8

	Parameter	**Robust t-stat [parameter]**	**σ**	**Robust t-stat [σ]**
Constant [*company B*]	-1.220	*-5.30*		
Trip cost	-0.625	*-5.21*	0.867	*13.70*
Waiting time [*early pick-up*]	-0.277	*-7.86*	0.289	*6.00*
Waiting time [*late pick-up*]	-0.189	*-21.60*	-0.173	*-11.30*
Cancelled ride	-2.780	*-27.30*	1.500	*11.30*
Barrier-to-Entry	-1.240	*-12.50*		
Inertia	0.058	*9.14*		
Memory decay parameter [*waiting time*]	1.670	*-8.76*		
Memory decay parameter [*cancelled service*]	1.660	*-10.40*		

Waiting time is specified as the difference between the expected and experienced waiting times, with a positive value indicating a late pick-up (waiting longer than expected) and a negative value representing an early pick-up. A separate parameter for estimated waiting time is tested, but resulted in a minimal improvement in model fit (five log-likelihood points), so it is not considered further. By specifying separate parameters for early and late pick-ups, we can see a significant difference in their perception. The results indicate that a minute of saved waiting time (earlier than expected) is equally as positive as 1.5 minutes of longer-than-expected waiting time is negative. In terms of monetary trade-off (Table 3.4), travellers are willing to pay €0.44 for each minute of saved travel time if the pick-up is realised earlier than planned, or €0.30 for each minute if it is later. This is somewhat counterintuitive, as a higher penalty (and thus higher WtP) would be expected for longer-than-expected waiting times. We discuss this further in the following section. Both parameters are modelled as random, and we can see from Figure 3.4 that although waiting times with an early pick-up are perceived more negatively, their perception is also subject to greater variability, whereas a longer-than-expected waiting time is more consistent across the sample.

If the ride is cancelled by the driver or platform, after the traveller has already made their decision, this results in quite a strong penalty, equal to a price increase of €4.45. Or in other words, this is the discount needed in the following travel instance for the traveller to consider this company for their travel choice.

Barrier-to-Entry is added as an attribute to mimic the initial hesitation of trying a new product or service. Our model estimates show that this barrier is equal to approximately €2.00, meaning that such a discount may prove sufficient to entice users to try this new service provider.

To test for the impact of socio-demographics (income, car ownership, frequency of car use), service familiarity and situation perception (Geržinič et al., 2021), several models with interaction effects are also specified. As no interaction yielded a significant improvement in model fit and, in most cases, also no significant parameter estimates, interactions are not included in the final model specification.

Table 3.4. Willingness-to-Pay for aspects of the trip

Attribute	**WtP**
Waiting time with early pick-up	26.59 €/h
Waiting time with of late pick-up	18.14 €/h
Cancelled ride	4.45 €
Barrier-to-Entry	1.98 €
Preference for company B	1.95 €
Marginal value of inertia*	0.09 €

**per additional experience*

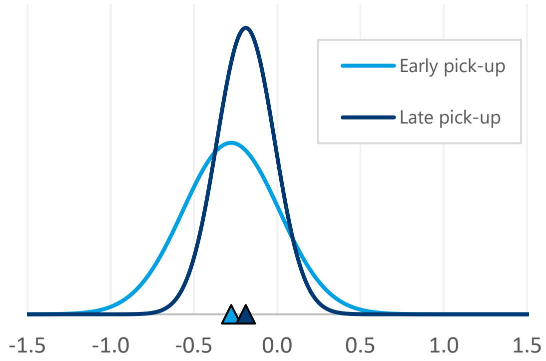


Figure 3.4. Distribution of waiting time parameters

Turning to memory decay and how it is captured, we test four different approaches, as detailed in Section 3.2.2. In Table 3.5, we summarise the outcomes for the four different specifications[3]. We observe that an event-based formulation with absolute weights seems to perform best for our sample, followed closely by the time-based relative weights formulation, as specified by Tang et al. (2017).

Given the best-performing model specification, the power decay function estimated in the model is presented in Figure 3.5. Although we estimate two separate decay functions, one for waiting time and one for a cancelled ride, the estimates are nearly identical, so this figure shows a single line for clarity. What is striking is that the relevance of past experiences seems to decay rapidly, with the second instance already having only a third of the impact of the latest. The fourth instance has a weight of ~0.1 and by the 7th, the weight drops below 0.05. This seems to indicate that respondents only kept a handful of the most recent instances in mind and discarded the rest, with the most recent experience weighing by far the most. As this is the absolute-weight formulation, it is interesting to consider the cumulative weight of all past experiences except for the first one. Given the sharp decline in importance, a large number of experiences would be required to cumulatively weigh more than only the first. Figure 3.5 shows that nine experiences (2-10) give a combined weight of 0.8 (44% of the total weight), compared to the most recent instance (always taking a value of 1). And even considering 31 instances (the maximum in our experiment), the combined weight of all experiences bar the first sums up to 0.967.

[3] The model fit in Table 3.5 differs slightly from the model fit reported in Table 3.3, as the specification of memory decay (absolute and relative weights; time- and event-based formulation) was tested first. Once the best approach was obtained, different specifications of taste parameters were tested.

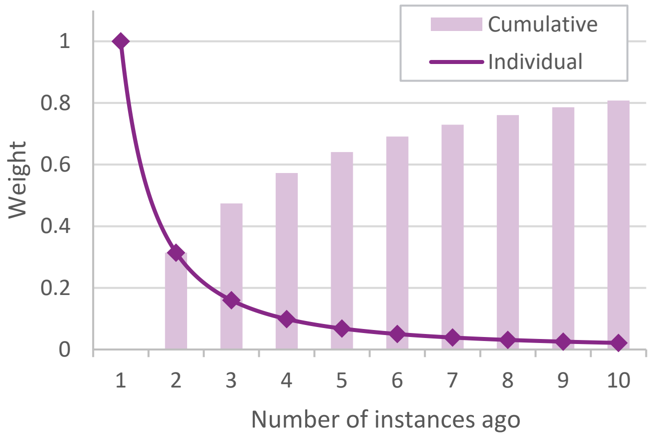


Figure 3.5. Power decay function

Table 3.5. Model fits (log-likelihood and adjusted rho-squared) of different memory decay specifications

	Time-based	Event-based
Relative weights	-8,776.15 *(0.5914)*	-11,581.78 *(0.4417)*
Absolute weights	-9,920.75 *(0.5217)*	-8,445.46 *(0.5927)*

Lastly, we comment on the various inertia formulations. The best performing on our dataset is the reset specifications, where the variable increases by a value of one each time the same option is chosen, then drops to 0 once the respondent switches to a different alternative. This is followed by the log-sum and log-reset specifications, although the reset specification is significantly better performing. Table 3.4 shows that each additional experience adds a value of €0.09. In other words, said alternative could get €0.09 more expensive after each instance and the respondent would still not switch to a different alternative (ceteris paribus). It also means that a potential competing company would need to offer a discount of the same magnitude for each additional experience the traveller has with their rival.

3.4 Conclusion

This paper presents novel insights into the behaviour of individuals in response to unexpected outcomes and how such experiences impact future decision-making. We perform a stated preference experiment on the topic of ride-hailing waiting time on a representative sample of the Dutch population. Mixed logit models are used to quantify the valuation of reliability and capture the heterogeneity within the sample.

3.4.1 Discussion of model outcomes

Our findings show that unexpected waiting time is valued at approximately 20-25€/h. This is somewhat higher than the roughly 15€/h which was uncovered by Alonso-González et al. (2020a). Both studies are based on SP data obtained in the Netherlands, although the works differ in their approach for studying reliability, which is where the difference may originate from. Alonso-González et al. (2020a) provided reliability information explicitly (upfront), whereas in our survey, respondents learned the reliability of a service implicitly, through trial-and-error (as explained in more detail in Section 3.2.1). The only other study to have considered waiting time reliability of ride-hailing (or other forms of on-demand mobility) does not allow for WtP comparison, as no cost component was included in the survey (Bansal et al., 2019). Comparing our findings by means of a ratio between waiting time and travel time is not feasible. To limit the cognitive burden for respondents, we did not vary travel time, meaning we cannot estimate it. Typically, waiting time tends to be perceived 2-3 times more negatively than in-vehicle time (Wardman, 2004). Considering the approximate value-of-time for the Netherlands of 10 €/h, as reported by de Jong & Kouwenhoven (2019), our findings seem to be well within the expected range.

Considering the different valuation of early (26.59 €/h) and late pick-ups (18.14 €/h), our results may seem somewhat counterintuitive. We expected the deviation from the estimated waiting time to be perceived as a dissatisfier (Van Hagen & Bron, 2014), meaning that travellers expect the promised level of performance. There is no benefit associated with performing as expected (on-time) or better (early), but it results in disutility if the performance is below expectations (late). This was also tested by means of a random regret minimisation model (Van Cranenburgh et al., 2015), which is able to discern such effects, but was not found for our dataset. A possible explanation is that waiting time is not seen as a dissatisfier, and that travellers are (very) positively surprised by an early arrival which may make the overall experience more enjoyable. This latter interpretation means that service providers should always strive to be as early as possible, regardless of the displayed waiting time. This however may be troublesome for multiple reasons. As passengers know that the vehicle will wait for them (contrary to traditional public transportation services), some may not arrive at the pick-up location earlier than the displayed departure time, resulting in the vehicle and therefore driver and potential co-riders needing to wait, making their experience less enjoyable (Kucharski et al., 2020). It is also fairly easy to manipulate the upfront information, with service providers displaying a very "safe" expected waiting time and then regularly performing better than expected. However, Alonso-González et al. (2020b) indicate that waiting time variability is perceived less negatively than the initially displayed waiting time, meaning that a balance between low anticipated waiting time and striving to achieve it is required. Further experiments, possibly enriched by RP data, will hopefully shed more light onto this topic.

The valuation of cancelled services has, to the best of our knowledge, not yet been investigated, making is thus difficult to validate. A value of €4.45 or 10-15 waiting-time-equivalent minutes may seem on the low end, especially considering that in our hypothetical case, a cancellation notice is only given after the estimated waiting time has elapsed. This somewhat low value may be a consequence of the SP nature of our data, as respondents did not truly experience the downsides of the cancellation. Another potential cause may be the attribute levels of cost used in the experiment (varied between €12.00 and €15.00). However, parallels can be drawn with the perception of denied boarding in public transport. Yap & Cats (2021) looked at the perception of waiting time pre and post denied boarding and found them to be 1.6 and 2.7 times the value of in-vehicle time respectively. Calculating the fixed penalty from the relative waiting time penalty reported by Yap & Cats (2021) shows that our service cancellation would be on the high end, equating to a waiting time of 20 to 25 minutes[4].

Future studies could therefore study both the waiting time and in-vehicle time variability, to further expand on the knowledge obtained in this research and to establish what is the relation between the two travel time components. As our study did not include mode choice, results would likely be different if alternative modes, such as conventional/fixed public transportation, would also be included. Additionally, including public transportation as an alternative with its

[4] Depending on the waiting time the users would experience after being denied boarding, the penalty would be roughly between €1 and €3 for waiting times of 5 min and 15 min respectively.

own associated variability, future studies could analyse to what extent the perception of variability differs among different types of services and modes.

With respect to the barrier-to-entry estimate, as it was not directly introduced in the survey, it can be seen only as a proxy for such an effect. That also means that comparison with other values is difficult. However, the parameter is (highly) significant and approximate value does point to a potentially necessary discount to entice new users to try a service, which is often similar to what many new market entrants utilise to generate demand (trial periods with a discount, first-time use free,...).

Additionally, socio-demographic information – coded through interaction effects – can often aid in the understanding and interpretation of the differing preferences amongst individuals. In our model, none of the socio-demographic parameter estimates was found statistically significant, indicating that in our case they had an insignificant impact on the choices of decision-makers.

3.4.2 Discussion of model formulation

A major contribution of this paper is also testing different memory decay specifications as well as showcasing the relative importance of past experiences. The power function parameter obtained a fairly high value of 1.67 and 1.66 for the waiting time and cancelled service respectively. As is highlighted in Figure 3.5, this means that the importance of past instances decreases quickly, but it also means that comparatively, the most recent experience carries a lot of weight. Service providers are therefore required to offer significant concessions to customers after a particularly bad experience if they wish to retain them. That bad experience will fade quickly however, once newer (better) experiences are gathered. Albeit in a different context, Tang et al. (2017) report a very similar value of the decay parameter, namely 1.64, in their "uninformed" group of respondents. They split the respondents into "informed" (receiving real-time updates throughout the trip) and "uninformed" (only receiving static information before the trip). The "uninformed" group is therefore essentially identical to our experiment, showcasing that in a similar setup, the context does not seem to have a significant impact on the rate of memory decay. It is interesting to observe that Tang et al. (2017) report a much lower value of only 1.11 for the "informed" group, meaning that the last experience carries much less weight and a larger set of experiences are likely considered when making a choice if the respondent is kept up-to-date when travelling.

It is also interesting to compare the four different memory decay specification, mainly with the two that performed far better. The fact that they are on the diagonal in Figure 3.2 indicates that they are the most different from each other and thus capture distinctive aspects of memory decay in different ways. The time-based relative-weights approach has continuously decreasing weight value with each new instance, but due to the relative nature of the weights, only the ratio between them changes, which is logical as when experiences are further away, it is less relevant if it happened say 14 or 15 days ago, as opposed to 1 or 2 days ago. On the other hand, this approach does not allow for differentiating between a different number of experiences (be it good or bad). Considering an individual had 10 equally bad experiences with one company and only 1 bad experience of equal magnitude with another, the averaging of weights means that the overall disutility contribution is equal. This is what the absolute-weight approach solves, but by staying with a time-based memory specification would mean that the sum of all weights can drop below 1. This is solved by the event-based approach, where there is always an instance that is valued with a weight of 1. The downside of this approach is that over time, the ratio between experiences does not change. Even though our results indicate a superior performance of an event-based absolute-weight formulation, this may very well be experiment-specific. The nature of SP experiments also makes it difficult to make a strong differentiation between what we characterise as time-based or event-based memory. Given that in our survey respondents answered all 32 scenarios in one go, it is difficult to say for certain which specification is better. Utilising RP data, where the passage of time is much more evident and also clearly recorded may provide relevant further insight into this topic and the role of elapsed time.

A point of attention in IBL, that is present in both specifications, but may be particularly prominent in the absolute-weight formulation, is serial correlation. IBL uses past instances to predict future choices of respondents, and information on past instances is only recorded for the selected alternatives. This is then exacerbated in the absolute-weights approach, as the contributions of past experience accumulate for a single alternative, meaning the utility of said alternative will grow in magnitude and a substantially larger offset (bad experience) will be required for another alternative to become appealing. This is less of a concern in the relative-weight scenario, as all the weights for all alternatives always equal one and only the magnitude of the experiences may differ.

The specification of memory decay likely also has a strong influence on the performance of different inertia (habit) specifications. The additive nature of the absolute-weights approach means that by continuously selecting the same option, more weight is put onto it, resulting in an ever larger (dis)utility. The reset specification is able to offset this additional (dis)utility. It is striking that all three of the specifications developed in this research outperformed the “one” and “sum” specifications. We do note that Cherchi & Manca (2011) also test specifications utilising the actual performance of alternatives, which we do not test, as those are indirectly included through the memory decay function. As with the memory decay, the inertia specification may also be influenced by the SP nature of the experiment and thus data based on revealed behaviour may result in a different specification performing best.

3.4.3 Implications

These insights – both the taste related findings on time valuation, ride cancellation and barrier-to-entry, as well as the memory decay and inertia workings of decision-makers – are potentially valuable insights for policymakers, authorities and operators for designing, governing and regulating on-demand services. When providing travellers with a waiting (and also travel) time estimates, a balance between the descriptive (upfront displayed waiting time) and experiential (actual waiting time) information is necessary. Research has shown that reliable waiting time estimates can be obtained and provided to users (R. Chen et al., 2022; Kontou et al., 2020). Combining this with existing knowledge on users’ WtP (Alonso-González, van Oort, et al., 2020b; Bansal et al., 2019; Buchholz et al., 2020) and the impact of past experiences, presented in this research, will allow operators to provide users with a much better service.

Secondly, analysing the barrier-to-entry shows the advantage that the first entrants to the market will have, as they do not have to entice users from a competing service to try out their own. However, their position may be even more difficult, as a switch between different providers of the same type of service may be easier for individuals than trying a completely new service in the first place. Here, existing providers of a different service (in particular public transport operators) could have the upper hand, being more familiar to the local population, or at the very least by its existing users, and thus may find it easier to launch a new type of service within its existing portfolio.

Finally, in order to retain users, it is key for the operators to offset bad experience immediately after they occur, ideally through financial incentives, as their impact on other relevant attributes (travel and waiting time) is limited. The upside is that if carried out correctly, a good experience will quickly balance out the bad and operators do not have to suffer the consequences of a single bad instance for a long time.

Data from experiential learning surveys, analysed by means of an instance-based learning approach is also highly valuable for future work. As past research has shown, and is further confirmed in this study, past experiences of passengers have an important and significant impact on their future decision-making, yet the magnitude of it and its persistence in the decision-maker's subconscious may vary. They could be different for different level-of-service indicators, modes etc. and last but not least, they likely also differ among individuals. This opens up a broad new area within travel behaviour research that is yet to be explored.

Chapter 4:

Mode and station choice in the presence of on-demand mobility services for medium distance intercity trips

Chapters 2 and 3 investigated the role of on-demand mobility services for unimodal trips in an urban setting, which is one of the most common cases highlighted for the potential for on-demand mobility services. The second frequently cited case is that of providing an access or egress (first/last mile) solution for longer public transport trips. This chapter studies the potential of using on-demand mobility services to improve train station access. By means of a three-step sequential stated choice approach, on-demand mobility services are compared with the bicycle, car and public transport for accessing two different train stations, with a different access distance and different level-of-service. This gives insight into station access mode preferences, station choice and, through sample segmentation, enables the analysis of the decision-making order of individuals.

Section 4.1 summarises existing studies on both on-demand services and train station access behaviour, highlighting the unanswered research questions. Section 4.2 elaborates on the survey design approach, the model specification and estimation and the data collection process. Key results and uncovered market segments are presented in Section 4.3. Section 4.4 demonstrates four different scenarios of introducing on-demand mobility services and how they could impact the modal split. The findings are then summarised and their policy implications discussed in Section 4.5.

This chapter is based on the following article:

Geržinič, N., Cats, O., van Oort, N., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2023). What is the market potential for on-demand services as a train station access mode? Transport Metrica A: Transport Science.

4.1 Introduction

Train travel is acutely affected by the first/last mile problem. With a significant number of people not living within walking distance of a train station, it is clear that train travel is heavily dependent on how well travellers can access and egress the train station (Brons et al., 2009). The most common train station access mode (on the home-end) in the Netherlands is the bicycle, representing almost half of all trips (Shelat et al., 2018), with walking and local public transport (bus, tram and metro or BTM) accounting for around 15% each and the rest being either as a car driver, car passenger or other modes. Similar to walking, cycling is strongly impeded by distance, with the attractiveness decreasing significantly for distances above three kilometres (Keijer & Rietveld, 2000), at which point motorised modes like public transport and car become comparatively more attractive.

In recent years, on-demand services (both flexible public transport and ride-hailing services like Uber or Lyft) have begun operating, also as first/last-mile access to mass transit (Phun et al., 2019), with the advent of smartphone technology further boosting the rapid emergence and deployment of such services. Several studies assert that on-demand services both attract passengers from public transport services and at the same time act as an access/egress providers to public transport stations (Alemi et al., 2018; Clewlow & Mishra, 2017; Deka & Fei, 2019; Hall et al., 2018; Sikder, 2019; Tirachini, 2019; Tirachini & del Río, 2019; Young et al., 2020; Young & Farber, 2019).

Research shows that the longer their trip, the longer travellers are willing to travel on their access mode. According to Krygsman et al. (2004), access and egress time can account for up to 50% of total travel time. While for longer trips the overall access and egress times are longer, they account for a lower share of the total trip time. Travel time spent travelling with access modes is predominantly found to be valued higher (perceived more negatively) than travel time on the main leg of the trip (Arentze & Molin, 2013; Bovy & Hoogendoorn-Lanser, 2005; La Paix Puello & Geurs, 2014). Travel time on the access leg is also found to be a key determinant, both for station access mode choice (Halldórsdóttir et al., 2017; van der Waerden & van der Waerden, 2018) as well as for airport ground access (Jou et al., 2011), where both in-vehicle and out-of-vehicle time components were found to be crucial in mode choice. In order to increase the catchment area of train stations beyond the current range of active modes, improving the quality of (public/shared) motorised access modes is therefore essential.

Past findings based on transit ridership data (Hall et al., 2018), household travel behaviour surveys (Clewlow & Mishra, 2017) and intercept surveys (Rayle et al., 2016; Tirachini & del Río, 2019) suggest that on-demand services generally reduce the ridership of local bus and light rail transport and increase the ridership of longer-distance rail services. Tirachini & del Río (2019) find that for every user that accesses public transport with a ridesourcing service, eleven users switch from public transport. The authors argue that this is not necessarily entirely negative, as in the latter case, travellers are infrequent public transport users and the trips happen at the edges of the day, when public transport services are often limited. In contrast, findings by Dong & Ryerson (2020) on airport ground access suggest that the entry of Uber and Lyft onto the market has primarily impacted taxi trips, with transit ridership seeing a very limited impact based on the trend.

Ridesharing and ridesourcing services have the potential to provide first/last mile connectivity to public transportation. The potential of the former is explored by Stiglic et al. (2018), who analysed peer-to-peer ridesharing (different from ride-hailing from an organisational perspective, but very similar for the passenger) where drivers (themselves commuters) would pick up passengers along the way and drop them off at a train station, potentially also parking there and taking the train themselves. They report an improvement in the matching rate both when ridesharing is offered as station access instead of only for the entire trip, as well as by allowing the driver to pick up two passengers, instead of just one. On-demand services could be subsidized to make them more affordable, increase their attractiveness and thereby also the attractiveness of public transport. Reck & Axhausen (2020) find that the travel time saved by using ridesourcing rather than walking does not outweigh the additional cost and transfer. This could be due to the rather short access distances in the data (with an average of 1-1.5 km). The authors suggest that over longer access distances and especially if a transfer can be saved on the public transport leg, using ridesourcing as an access mode could prove beneficial. Taxi (on-demand) services were also found to be attractive for a majority of people accessing high speed railway stations in Taiwan (Wen et al., 2012).

Access mode choice is often only one part of a larger choice process, as passengers may be located in the vicinity of more than one train station and therefore also have to choose which station to access for their trip. The attractiveness of stations is determined on one hand by their facilities (e.g. parking availability, shops, ticket counters) and on the other hand by the rail service quality. The latter was defined by Debrezion et al. (2009) as the Rail Service Quality Index (RSQI), which is based on the (1) frequency of the service / waiting time at the station, (2) connectivity of that station in the network (number of transfers needed to destinations), (3) location in the network (travel time to destinations) and (4) the price to reach those destinations. They then used this RSQI to estimate a combined access mode and station choice based on revealed preference (RP) data from the Netherlands. With respect to station characteristics, they conclude that indeed both rail services and (parking) facilities at stations significantly increase the station’s attractiveness. For access mode choice, their findings are in line with the literature in that cycling and especially walking are highly affected by the access distance, with public transport being least sensitive to the distance. Joint mode and station choice was also researched by Bovy & Hoogendoorn-Lanser (2005), who characterised the train services based on the travel time, number of transfers and the type of service as either InterCity (IC) or local trains only. While the former two attributes were determined to be significant, the latter was not. The authors speculate that this is a consequence of their focus on shorter trips. Comparing the travel time estimates, in-vehicle time (IVT) on the train was found to be perceived less negatively than access time by private modes (bike and car), but more negatively than public transport access time. The respective weights for the two access IVT components were reported as 1.6 and 0.8 compared to the train IVT. Transfers were also found to have a significant impact, with higher frequency (>6x/h) transfers having a lower impact than low frequency (≤6x/h) transfers. Travel time, service frequency and parking availability were also found to be significant predictors of station choice by Chakour & Eluru (2014) and by Fan et al. (1993). Chakour & Eluru (2014) concluded that improvements in access time (especially for public transport and active modes) largely impacts mode choice and not station choice. (Fan et al. (1993) modelled car and public transport access separately, reporting that travellers who travel by car, perceive travel time less negatively and attach greater value to the frequency of train services compared to travellers who access train stations by public transport.

When modelling the joint access-mode-and-train-station choice, a nesting structure is often included in the model specification. This enables the model to capture correlations between (unobserved) utilities of alternatives which are modelled in the same nest. With the estimation of access and station choice, two possible nesting structures can be formed, where either the station is chosen first (station-based nesting) or the access mode is chosen first (mode-based nesting). Studies report mixed outcomes, with some finding that station-first models achieve a better model fit (Bovy & Hoogendoorn-Lanser, 2005; Chakour & Eluru, 2014), whereas others concluding that mode-first models prove superior (Debrezion et al., 2009; Fan et al., 1993). Interestingly, in a study of joint access mode and airport choice in the New York City area (Gupta et al., 2008), a model without any nesting structure was found to be superior. While these results are also influenced by the exact context of the SP and RP data, most studies find the differences between the models to be relatively small.

The behavioural characteristics of passengers' choices in the context of accessing larger transportation hubs, i.e. a train stations, airports etc. has been widely studied. More recently, advancements have also been made in understanding how on-demand services impact travel behaviour in both urban and rural areas, due to their on-demand nature, potential pooling with other passengers, detours and time variability etc. Notwithstanding, to the best of our knowledge, the intersection of these two topics, i.e. the behavioural preferences of accessing public transportation by means of on-demand mobility, remains unknown, despite their growing relevance in the urban mobility landscape worldwide. Although this topic has been somewhat studied for airport ground access, Gupta et al. (2008) state that airport access trips are highly specific and differ significantly to typical commute trips, making the generalisation of their results difficult.

Our study fills the aforementioned research gap, providing insight into how on-demand services can be utilised as an access mode for train stations, as well as how this may impact station choice of travellers. We carry out a stated preferences survey of joint access mode and train station choice. The contributions of this study are threefold: (1) highlighting the preferences of travellers associated with on-demand mobility services, (2) estimating how the characteristics of the access leg and the train leg are traded off and (3) segmenting the population based on their preferences towards on-demand mobility, train station access and the nesting structure that best captures the joint mode-station choice.

4.2 Methodology

To analyse the potential impact of on-demand services on passenger train station choice, a stated preference survey is carried out in which both access mode choice and station choice are evaluated. The design of the survey is outlined in Section 4.2.1. Several choice models are then estimated, to gain an understanding of the respondents' travel behaviour preferences, as described in Section 4.3.2. Finally, the data collection is presented in Section 4.2.3.

4.2.1 Survey design

Although several smaller scale on-demand services are operating in the Netherlands (Bronsvoort et al., 2021), most people are not yet familiar with this type of service. Thus, a stated choice experiment is chosen to obtain travel preference information. To capture both the access mode and train station choice, a three-step sequential stated preference survey is carried out (Choudhury et al., 2018), as shown in Figure 4.1. In the first two steps (Choice 1 and Choice 2), respondents choose one of five available modes to access stations A and B (four modes if they do not have a driving licence and access to a car). The third choice then integrates information on the access modes for each station as chosen by the respondents and the train service characteristics of that particular station. This choice process is repeated for a total of six hypothetical trips. Examples of the choice sets for all three choices are also shown in Appendix B.

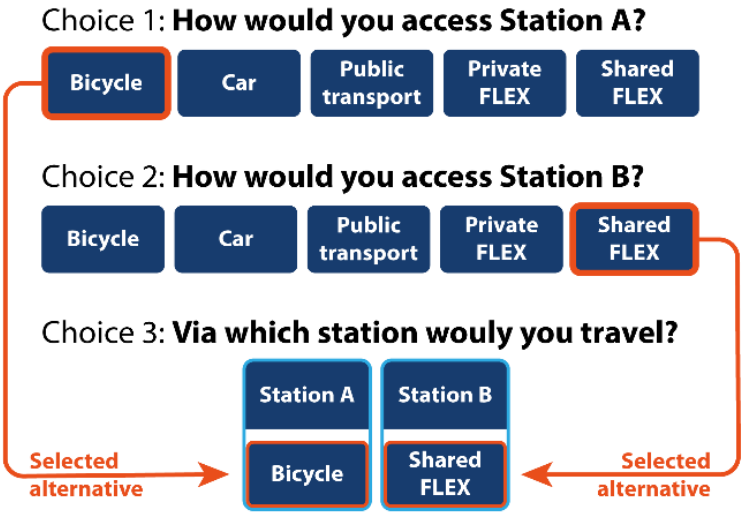


Figure 4.1. Survey outline for the three choices within one choice set

Train station access/egress trips can be on the home-end or activity-end of the train journey. Activity-end trips are interesting for the potential of shared modes as travellers commonly do not have a private mode available and thus must use a shared mode of transport. The most common activity-end modes in the Netherlands are walking and public transport (MRDH, 2016; Stam et al., 2021), with shared/micro- mobility becoming a more and more attractive alternative. Home-end trips can be interesting from the perspective of on-demand mobility, as these trips tend to be longer than activity-end trips (MRDH, 2016; Stam et al., 2021), meaning people are less likely to walk and therefore more likely to choose a bicycle or a motorised mode of transport. While the availability of private modes on the home-end reduces the attractiveness of on-demand mobility, it can become more attractive when coupled with policies that restrict car use, such as higher parking cost and fewer car parking spots. Although both sides of a train trip are interesting from an on-demand mobility perspective, this study looks into the home-end of the train trip.

To that end, the survey includes three of the most frequently used access modes at the moment: bicycle, car, public transport (specified as either bus, tram or metro) (MRDH, 2016; Stam et al., 2021) and two on-demand service options, a private and a shared service. The on-demand service is branded as FLEX, to ease communication and because this name is often used in the Netherlands for such services (Bronsvoort et al., 2021). Each of the access modes is characterised by three attributes: (1) cost, (2) (in/on-vehicle) travel time and (3) out-of-vehicle (OVT) time. Cost refers to the trip cost (car, PT, FLEX) and parking cost (bicycle, car). In-vehicle time is the time spent on the move and only includes time in (on-board) the vehicle. Out-of-vehicle time is defined as (a) "*parking search time and time walking to the station*" for bicycle and car, as (b) "*walking to a nearby PT stop and waiting*" for public transport and as (c) "*waiting (at home)*" for the two FLEX alternatives. The attributes and their corresponding levels are presented in Table 4.1.

The station choice is the third and final step of the choice process, where the respondents are shown their selected access modes and attributes, along with four characteristics of the train services at the respective station. The access distance used to determine the attribute levels for the two stations are approximately five and ten kilometres from the trip origin (home). As five kilometres is the average access distance to the nearest train station in the Netherlands (CBS, 2011), this is an appropriate access distance to assume. The inclusion of a second, more distant station, is made with the goal of testing if respondents are willing to travel further for a different train service and if different access modes are offered. According to the Dutch Statistics Bureau (CBS, 2011), the average distance to the nearest interchange station (offering potentially a more direct service) in the Netherlands is 10.5km. To avoid respondents having an inherent preference for either of the stations, they are only labelled as "*Station A*" and "*Station B*" in the experiment. Given the access distances, we refer to them from here on as the "*Local station*" and "*Distant station*" respectively. Based on results from literature (Debrezion et al., 2009; van Mil et al., 2021), we characterise the train stations and services by (1) the trip cost (only for the train leg), (2) total travel time on the train(s), including the transfers, (3) train service headway and (4) the number of transfers on the train leg of the trip. The attributes and levels are summarized in Table 4.1.

Table 4.1. SP survey prior values and attribute levels

Access leg prior		Train leg priors	
Cost	-0.6	Cost	-0.6
In-vehicle time	-0.1	In-vehicle time	-0.1
Out-of-vehicle time	-0.2	Headway	-0.1
		Transfer	-1.2
		InterCity station label	0.7

	Cost		In-vehicle time		Out-of-vehicle time	
	Local station	InterCity station	Local station	InterCity station	Local station	InterCity station
Bicycle	€ 0.00	€ 0.00	12 min	30 min	1 min	1 min
	€ 1.00	€ 1.00	16 min	35 min	5 min	5 min
	€ 2.00	€ 2.00	20 min	40 min	9 min	9 min
Car	€ 1.00	€ 2.00	8 min	12 min	1 min	1 min
	€ 5.00	€ 6.00	12 min	21 min	5 min	5 min
	€ 9.00	€ 10.00	16 min	30 min	9 min	9 min
Public transport	€ 0.50	€ 1.00	8 min	12 min	1 min	1 min
	€ 2.00	€ 3.00	12 min	21 min	5 min	5 min
	€ 3.50	€ 5.00	16 min	30 min	9 min	9 min
Private FLEX	€ 5.00	€ 8.00	8 min	12 min	1 min	1 min
	€ 10.00	€ 13.00	12 min	21 min	5 min	5 min
	€ 15.00	€ 18.00	16 min	30 min	9 min	9 min
Shared FLEX	€ 2.00	€ 2.00	8 min	12 min	1 min	1 min
	€ 5.00	€ 6.00	12 min	21 min	5 min	5 min
	€ 8.00	€ 10.00	16 min	30 min	9 min	9 min

	Cost	In-vehicle time	Headway	Transfers
Local station	€ 17.00	60 min	10 min	1
	€ 20.00	75 min	15 min	2
	€ 23.00	90 min	30 min	3
InterCity station	€ 20.00	75 min	10 min	0
			15 min	1
			30 min	

A D-efficient design with six choice sets is constructed in Ngene (ChoiceMetrics, 2018), with prior parameter values obtained from the literature. The prior values (found in Table 4.1) are determined based on the value of travel time of 10 €/h in the Netherlands (Kouwenhoven et al., 2014a). From that, we specify the IVT prior as -0.1 and the cost prior as -0.6. Priors for other attributes are based on IVT-equivalent minutes (multipliers) reported in the literature (Arentze & Molin, 2013; Bovy & Hoogendoorn-Lanser, 2005; Frei et al., 2017; Wardman, 2001, 2004). With respect to mode specific constants, we found a large range of preferences (Arentze & Molin, 2013; Bovy & Hoogendoorn-Lanser, 2005; Choudhury et al., 2018; Currie, 2005; Frei et al., 2017; Paleti et al., 2014; Rose & Hensher, 2014), differing not only in their relative preference (compared to IVT), but also in the order of which modes are preferred over others. Hence, we decide not to specify any prior values for the Alternative Specific Constants (ASCs).

To get insights into the attitudes towards new mobility services, respondents are asked to respond to 16 Likert-type questions (shown in Table 4.2). The statements are associated with different characteristics of FLEX services, based on the categories defined by Durand et al. (2018): (1) Use of smartphone apps, (2) Mobility integration, (3) Sharing a ride and (4) Sharing economy. They are also asked to indicate their familiarity with six service of the sharing economy, four of which are in the mobility domain (found in Table 4.3). Additional socio-demographic and travel behaviour information is obtained from other surveys in the Dutch Mobility Panel (Hoogendoorn-Lanser et al., 2015).

Table 4.2. Attitudinal statements on FLEX-related characteristics

Category		Statement
Use of (travel planning) apps	1	I find it difficult to use travel planning apps. [1]
	2	Using travel planning apps makes my travel more efficient. [1]
	3	I am willing to pay for transport related services within apps.
	4	I do not like using GPS services in apps because I am concerned for my privacy.
Mobility integration	5	I am confident when travelling with multiple modes and multiple transfers.
	6	I do not mind infrequent public transport, if it is reliable.
	7	I do not mind having a longer travel time if I can use my travel time productively. [2]
	8	Not having to drive allows me to do other things in my travel time. [2]
Sharing a ride	9	I am willing to share a ride with strangers ONLY if I can pay a lower price. [2]
	10	I feel uncomfortable sitting close to strangers. [2]
	11	I see reserving a ride as negative, because I cannot travel spontaneously.
Sharing economy	12	I believe the sharing economy is beneficial for me.
	13	I believe the sharing economy is beneficial for society.
	14	Because of the sharing economy, I use traditional alternatives (taxis, public transport, hotels…) less often.
	15	Because of the sharing economy, I think more carefully when buying items that can be rented through online platforms.
	16	I think the sharing economy involves controversial business practices (AirBnB renting, Uber drivers' rights…).

[1] *adapted from* (Lu et al., 2015)

[2] *adapted from* (Lavieri & Bhat, 2019)

the remaining statements were formulated for the purpose of this study

Table 4.3. Service of the sharing economy, including examples, as presented to respondents

	Type of (sharing economy) service	Examples shown
1	How familiar are you with car sharing?	Snappcar, Greenwheels, car2go
2	How familiar are you with bike / scooter sharing?	Mobike, OV fiets, Felyx
3	How familiar are you with flexible public transport?	Twentsflex, Bravoflex, U-flex, Delfthopper
4	How familiar are you with ride-hailing?	Uber, ViaVan
5	How familiar are you with food delivery services?	Thuisbezorgd, Deliveroo, Foodora, UberEATS
6	How familiar are you with home rental services?	AirBnB, HomeStay, Couchsurfing

4.2.2 Model estimation

We analyse the obtained SP observations by estimating a series of choice models using the PandasBiogeme package for Python (Bierlaire, 2020). The data is analysed under the assumption that respondents make decisions by maximising their perceived utility (McFadden, 1974). Given the nature of the 3-step stated choice experiment, different model specifications were tested for how to include the alternatives of the different choice steps in the model estimation. In the end, the most realistic option, capturing the characteristics of all available alternatives, is used. The model is made up of 10 alternatives, consisting of 5 alternatives for each of the 2 train stations (8 alternatives in total for respondents without a driver's licence or an access to car).

We estimate a series of Multinomial logit (MNL) models with varying parameter specifications, ranging from fully generic parameters (common taste parameters for the same attribute across alternatives) to fully alternative specific parameters (independent taste parameters per alternative and attribute) and dummy coded parameters, to capture potential non-linear perceptions of attributes.

As highlighted in Section 4.1, the joint access-mode-and-train-station choice is likely to be nested, with research being inconclusive on the overall preferred nesting structure (mode-first or station-first). Given the structure of our data (considering all ten alternatives in a single choice set), nesting of alternatives is also likely to occur. To capture potential nesting and cross nesting effects, we estimate a series of nested logit (NL), cross-nested logit (CNL) and Error component panel mixed logit (ML) models.

In addition, MNL models are also unable to capture unobserved taste heterogeneity in the sample, nor can they account for the panel effect. Two different modelling approaches are frequently used in research, which are able to mitigate these shortfalls: the panel random parameter mixed logit (ML) model and the latent class choice model (LCCM). The former extends the MNL model by allowing the taste parameters to be drawn from a distribution, acknowledging that different respondents may use different weights for the respective attributes. The latter model creates several discreet (latent) segments, each with their own parameter estimates. Both modelling approaches have their benefits and drawbacks. ML models are more parsimonious, capturing the sample heterogeneity with a relatively small number of parameters. By means of error components, the ML model is also able to capture nesting effects, as mentioned previously. LCCMs on the other hand require a larger number of parameters to be estimated, but result in a discreet number of classes, which provide a straightforward interpretation of the different population segments (Greene & Hensher, 2003; Hess, 2014) allowing us to distinguish segments within the population, each with its own mode preferences, time- and cost-sensitivity etc.

Another benefit of LCCMs is that the class membership function (used to determine the probability of each individual belonging to a specific segment) may include socio-demographic and attitudinal information of the respondents (Greene & Hensher, 2003). The class membership function aims to divide the population into segments that are as different from each other as possible, in order to capture the heterogeneity in the obtained SP data. By including socio-demographic information in the class membership function, more information is available on the influence of socio-demographics on class membership.

As our goal is to identify distinct user groups within the population, based on their train station access behaviour and the potential use of FLEX services, we opt for the Latent class choice model structure. Given the present nesting structure, a nested logit model is also applied within each of the segments. For capturing nesting, the NL specification is chosen over the ML for its closed-form and ease of interpretation. The resulting nesting parameter μ gives information on the level of nesting of the alternatives within the same nest. A lower value indicates the alternatives are largely independent from one another, whereas a higher value (upper bound set to 10 in models) indicates a strong nesting effect. Based on insights from the various MNL, NL and ML models estimated, a Latent class choice model with nesting structures is specified and estimated, the results of which are elaborated on in the following section.

For the class membership function of the LCCM, both socio-demographic and attitudinal information is used in the class membership. To simplify and narrow down the number of parameters, as well as to test for possible correlations between the various attitudinal statements, an exploratory factor analysis (EFA) is performed. This also allows us to test the attitudinal categories which were used when formulating the statements. The EFA is performed using the "factor_analyzer" package for Python by Briggs (2019).

4.2.3 Data collection

The survey was distributed to participants of the Dutch Mobility Panel (MPN) (Hoogendoorn-Lanser et al., 2015) between February 10th and March 1st in 2020, resulting in a total of 1,193 responses. The data was then processed and responses that were either (1) incomplete, (2) completed in fewer than five minutes or (3) chose the same response to all attitudinal statements, were removed from the dataset, leaving a total of 1,076 responses.

The sample is largely representative of the Dutch population (Table 4.4). The sample displays a slight overrepresentation of older individuals, those having a higher level of education and single-person households. The difference in household income is largely due to respondents having the option not to disclose their household income (not knowing or not wishing to share that information). We believe these slight disparities to not significantly influence the model outcomes.

With respect to COVID-19, the first patient in the Netherlands was diagnosed on the 27th of February (Rijksinstituut voor Volksgezondheid en Milieu (RIVM), 2020) and the first lockdown measures were announced on March 12th (NOS, 2020). We therefore believe that it is unlikely that the pandemic influenced the decision-making of the respondents.

Table 4.4. Socio-demographics of the sample and the Dutch population (Centraal Bureau voor de Statistiek, 2020)

Variable	Level	Sample	Population
Gender	Female	53%	50%
	Male	47%	50%
Age	18-34	22%	27%
	35-49	22%	23%
	50-64	30%	26%
	65+	26%	24%
Education[5]	Low	25%	32%
	Middle	39%	37%
	High	36%	32%
Household income[6]	Below average	21%	26%
	Average	48%	47%
	Above average	6%	27%
	Did not disclose	25%	0%
Employment status	Working	51%	51%
	Not working	49%	49%
Urbanisation level	Very highly urban	23%	24%
	Highly urban	31%	25%
	Moderately urban	17%	17%
	Low urban	21%	17%
	Not urban	8%	17%
Household size	One person	22%	17%
	2 or more	78%	83%

4.3 Results

In this section, we report the survey results, outcomes of the model estimation and the interpretation of individual population segments obtained through the latent class choice model estimation. We start by summarising the descriptive statistics of the choices made by respondents in section 4.3.1. Then, we analyse the attitudinal statements and familiarity of the respondents with services of the sharing economy. We perform an Exploratory Factor Analysis (EFA) on the attitudinal statements, to uncover potential correlations between them, as well as to narrow down the number of attributes for the following step. This is outlined in Section 4.3.2. In Section 4.3.3, we present the results of the latent class choice model and describe the taste, attitudinal, behavioural and socio-demographic characteristics of each segment.

[5] Low: no education, elementary education or incomplete secondary education
Middle: complete secondary education and vocational education
High: bachelor's or master's degree from a research university or university of applied sciences

[6] Below average: below modal income (< €29,500)
Average: 1-2x modal income (€29,500 – €73,000)
Above average: Above 2x modal income (> €73,000)

4.3.1 Descriptive statistics

The most commonly selected access modes are the bicycle and public transport (bus, tram or metro), each being selected in 36% of the cases for both the local and distant station categories. As expected, cycling dominates for accessing the local station, representing half of all choices, whereas public transport is the preferred access modes of respondents for accessing stations that are further away (beyond a comfortable cycling distance for many). All other modes (car, private and shared FLEX) are also more popular for the more distant stations. Private FLEX does not seem to be very popular as an access mode, regardless of the distance. This is not entirely surprising, given the relatively high travel cost. Shared FLEX on the other hand, seems to be reasonably attractive for accessing more distant stations, reaching a share of about 10%.

In Figure 4.2, we compare the modal split for access modes that are chosen initially (inner ring), and access modes for when the corresponding station is actually chosen. The differences seem to be quite minor, with the local station seemingly being more appealing when accessed by bike, whereas the distant station was more often chosen if a motorised means of transport was selected as the access mode. Aggregating the choices between the two stations, the access mode split between the initial choices and final choices is almost identical.

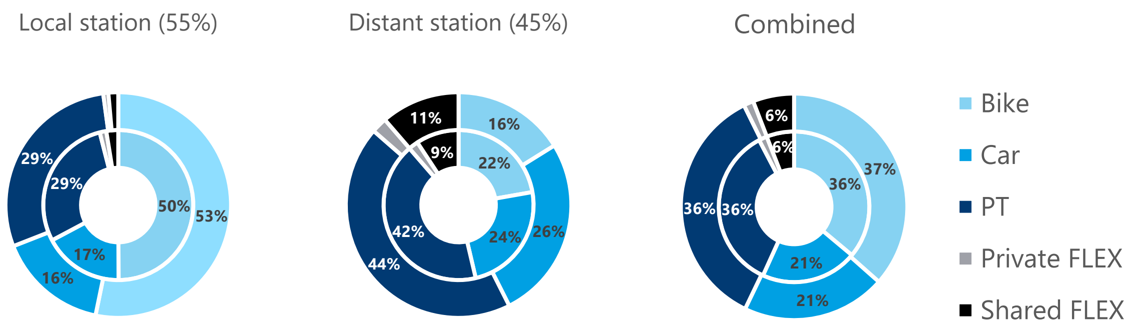


Figure 4.2. Modal split of the initially selected access modes (inner ring) and access modes selected for the actually chosen station (outer ring), for the local and distant station separately and combined

4.3.2 Attitudinal statements and service familiarity

The distribution of responses and the average of each of the 16 statements, relating to the use of on-demand services, are presented in Figure 4.3. The first four statements capture the technology- and app-related attitudes, showing that the biggest barrier seems to be making purchases with smartphones, with the majority not willing to do so. The travel-related attributes (statements 5-8) show that people generally do not mind travelling a bit longer, provided they can use that time productively. Regarding their willingness to share (statements 9-11), respondents say they are willing to share a ride only if they get a discount, yet the proximity of strangers does not seem to be an obstacle for sharing. This could mean that sitting next to strangers is not the key reason for not pooling, but rather other aspects such as a longer and more uncertain travel (and waiting) time. For the statements on sharing economy in general (statements 12-16), people seem to be less optimistic about it for themselves, but think of it as very beneficial for society, while also seeing it as potentially leading to controversial business practices.

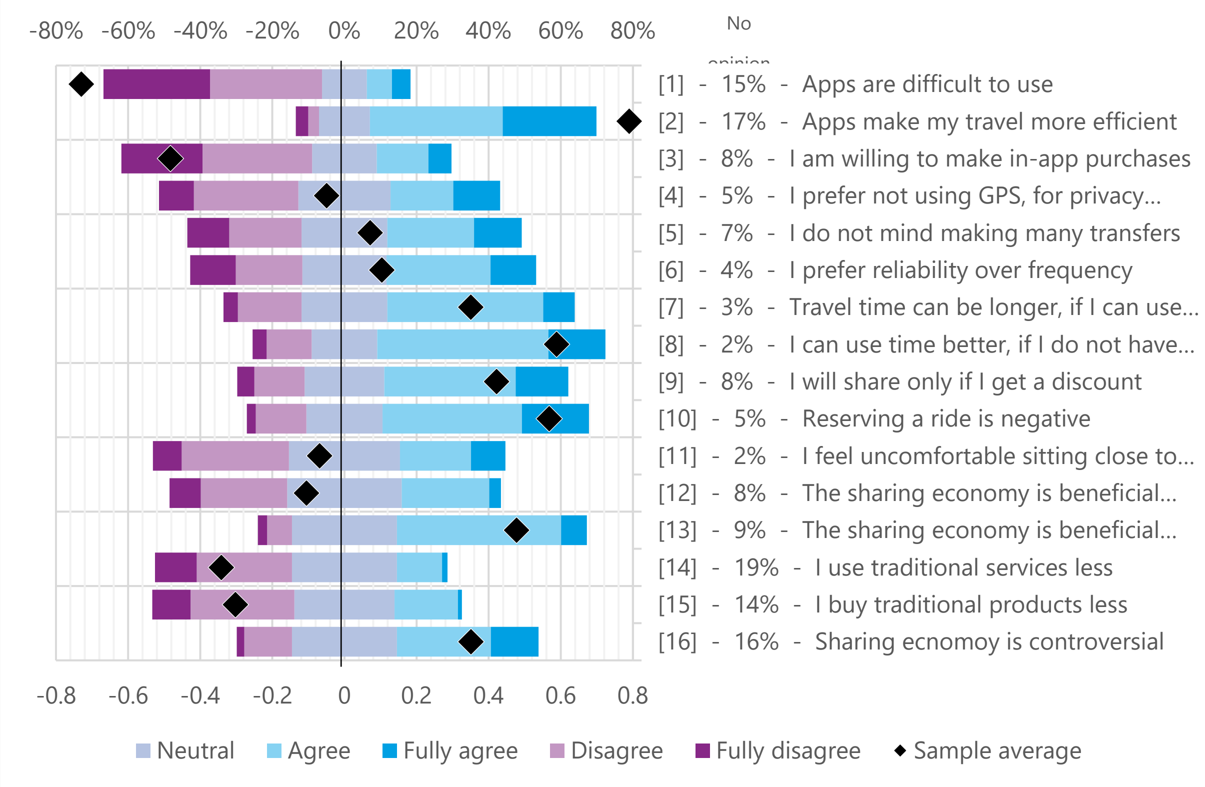


Figure 4.3. Results of the attitudinal statements

Similarly to what was found by Geržinič et al. (2022), the most known and often used sharing economy service in the Netherlands is food delivery, with almost half of the sample having used it at least once (as seen in Figure 4.4). Ride-hailing services such as Uber are familiar to most respondents, but have only ever been used by few. Most striking is that flexible public transport services, although present in several areas around the Netherlands, are unfamiliar to over half of the population. Similar results have been reported in other studies on the topic of flexible public transport (Arendsen, 2019; Bronsvoort et al., 2021).

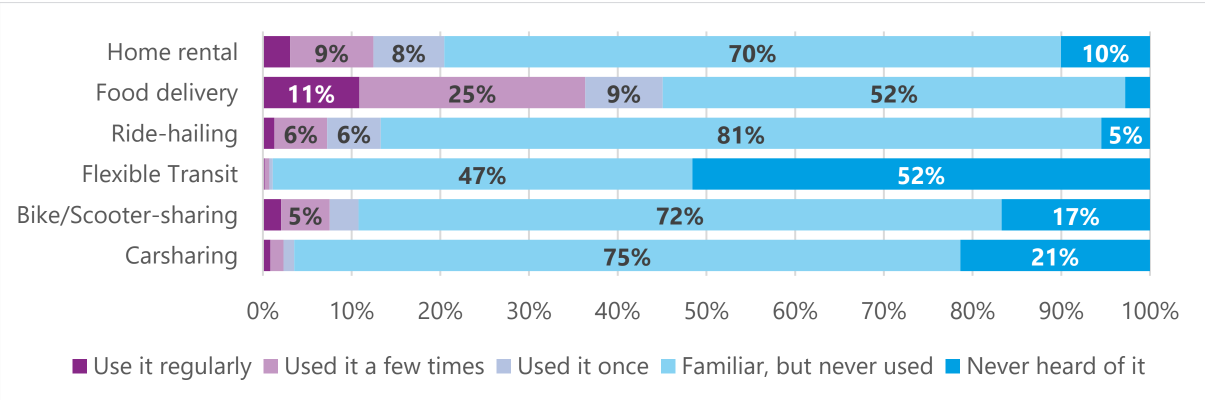


Figure 4.4. Familiarity with different sharing economy services (values below 5% are not labelled)

An exploratory factor analysis is performed on the 16 attitudinal statements. “No opinion” responses are recoded to match the “Neutral” response, to ease the performance of an EFA. This is not ideal and it is not possible to state that those responses are equivalent. Performing an EFA would thus require the removal of all respondents who at least once chose the “No opinion” response. This results in reduction in sample size of over a third and it also inhibits the use of these factors in the class membership function of the latent class choice model. From the recoded data, we compute the KMO score to be 0.733, which indicates the sampling is middling, but still sufficient to perform an EFA (Ledesma et al., 2021).

Using a scree plot, we determine the optimal number of factors to be four. The resulting factor loadings onto the four corresponding factors are presented in Figure 4.5. The grouping of statements is largely in line with their category as indicated in Table 4.2. Interestingly, S5 (on making transfers) seems to be more correlated with statements on the use of travel planning apps rather than the travel related statements of S6-S8. Statement 9 (willingness to share only for a discount) and Statement 16 (controversial business practices of sharing economy) load overall weakly onto any of the four factors. The four factors can be described as "**Support for sharing economy**" (F1), "**App savviness**" (F2), "**Efficient travel time use**" (F3) and "**Dial-a-ride scepticism**" (F4).

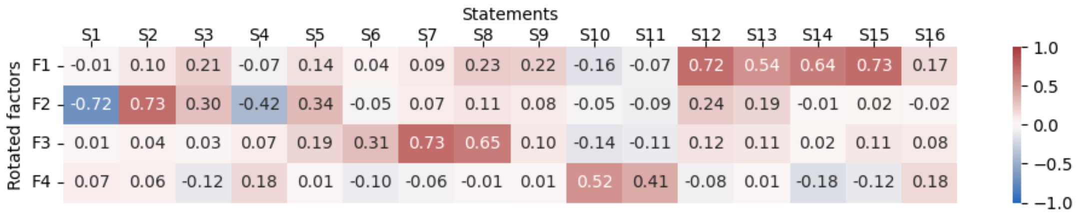


Figure 4.5. Exploratory factor analysis factor loadings for the four factors

Based on the results of the EFA, a confirmatory factor analysis (CFA) is also performed. Factor loadings of above 0.3 (below -0.3) from the EFA are considered. The outcomes (loadings) of the CFA are used to calculate the factor values for each respondent.

4.3.3 Market segmentation

To understand how people's preferences differ, we estimate a series of latent class choice models. We choose to present a model with two sets of taste parameters, dividing the population into two segments. To capture different possible nesting structures, we further divide each of the two segments into two more, where one is given a mode-based nesting structure and the other a station-based nesting structure. Both structures are presented in Figure 4.6. This results in a total of four segments, with two pairs sharing the same taste parameters (segments 1 and 2 vs. segments 3 and 4), and two different pairs sharing the same nesting structure (segments 1 and 3 vs. segments 2 and 4). Unlike with taste parameters, we do not restrict the nesting parameters (μ) to be the same across the segments that share a nesting structure, but allow them to be estimated independently, resulting in four groups of nesting parameters, two for mode- and two for station-based nesting. This allows us to observe the different levels of correlation within the same nesting structure but among respondents with different tastes. The segmentation structure is shown in Table 4.5. The full set of outcomes from the model, including the model fit, taste parameters, nesting parameters and class allocation parameters are shown in Table 4.6. A brief overview of some estimated nested and cross-nested logit models is presented in Appendix C.

Table 4.5. Segmentation structure and corresponding segment sizes

	Higher WtP	Lower WtP	Σ
Mode-based nesting	*Segment 1* **21.6%**	*Segment 3* **30.2%**	**51.8%**
Station-based nesting	*Segment 2* **25.9%**	*Segment 4* **22.3%**	**48.2%**
Σ	**47.5%**	**52.5%**	**100.0%**

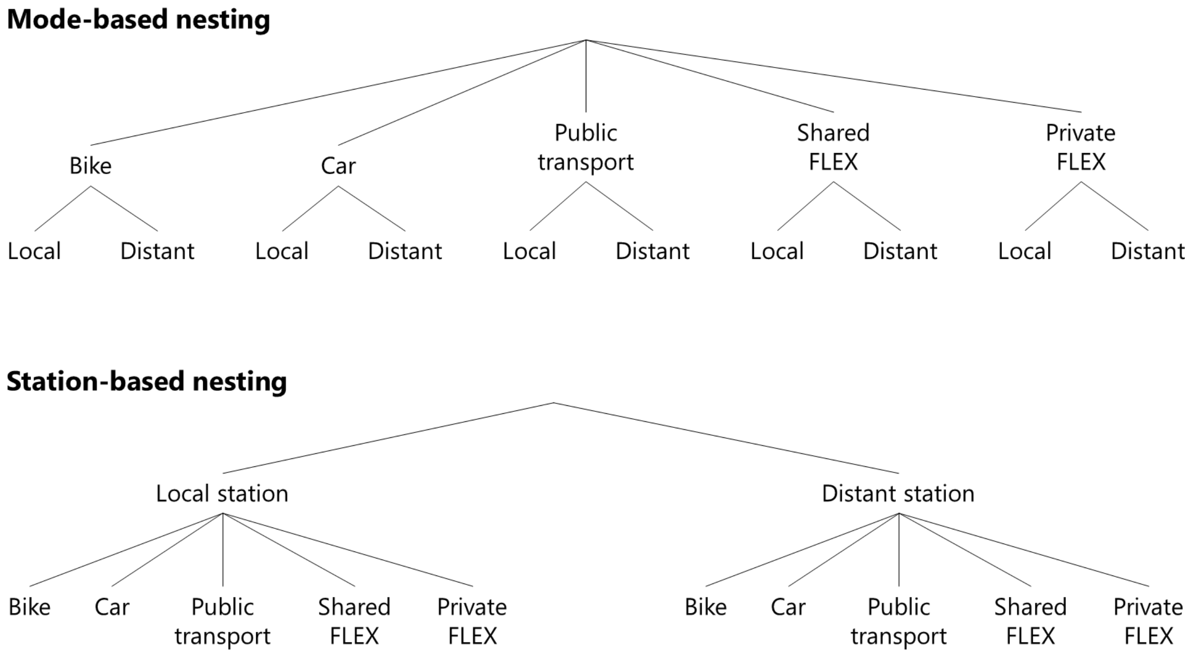


Figure 4.6. Mode-based and station-based nesting structure of choices

The utility function used in the LCCM model is determined based on various different MNL model specifications. It is decided to use a single cost parameter for both the access leg and the train leg. In-vehicle times on the access sections of the journey are modelled as generic (common parameter for bike, car, PT and FLEX), with a second in-vehicle time parameter for the train leg. Out-of-vehicle times (OVT) are modelled using three parameters; for (1) bike and car (parking search time and walking time), (2) public transport (walking and waiting time) and (3) FLEX (waiting at home). Most of the estimated taste parameters are highly significant, with the only major exception being the waiting time for FLEX services, which is highly insignificant for all segments. It should be noted that this is the case in all the tested model specification, indicating that almost all respondents are largely indifferent to it. Similar results are also reported by Geržinič et al. (2022). This may be due to the waiting taking place at home and thus may be similar to hidden waiting time, where individuals undertake other activities at home (quick errands) while waiting. The only other insignificant parameter is the ASC for Shared FLEX for Segments 3 and 4, indicating that for them, there does not seem to be significant inherent (dis)preference for Shared FLEX over the bicycle.

Estimating the class membership parameters, an initial 4-class model with several factors and socio-demographic variables is estimated. As this results in many insignificant parameters, the characteristics which result in insignificant parameters for all classes are removed one by one, until only those remain, where a significant parameter is obtained for at least one class.

Through this approach, education level, household income, urbanisation level, car ownership and train usage are removed, as well as the app savviness factor.

Table 4.6. Model fit, estimates of the taste, nest and class allocation parameters

Model fit	
Null LL	-14,627.17
Final LL	-9,699.74
Adj. Rho-square	0.3327
BIC	19,825.31

Taste parameters				
	Segments 1 & 2		**Segments 3 & 4**	
Class size	**47.5%**		**52.5%**	
	Est.	t-stat	Est.	t-stat
Constants				
Bike	0 (fixed)		0 (fixed)	
Car	-2.08	-9.79 ***	1.17	3.43 ***
Public Transport	-1.56	-11.30 ***	0.85	3.81 ***
Shared FLEX	-3.27	-7.70 ***	-0.06	-0.36
Private FLEX	-6.43	-6.58 ***	-0.75	-2.44 **
Local station	0 (fixed)		0 (fixed)	
Distant station	-0.56	-2.73 ***	-0.44	-2.10 **
Common parameters				
Cost	-0.28	-7.71 ***	-0.18	-8.22 ***
Access leg				
In-vehicle time	-0.10	-8.89 ***	-0.04	-6.84 ***
Park & walk [bike, car]	-0.07	-7.60 ***	-0.08	-5.37 ***
Walk & wait [PT]	-0.04	-1.97 **	-0.02	-2.03 **
Wait time [FLEX]	0.03	0.64	0.00	0.27
Train leg				
In-vehicle time	-0.06	-10.20 ***	-0.04	-5.84 ***
Headway	-0.04	-7.61 ***	-0.04	-7.11 ***
Transfer	-1.02	-7.58 ***	-0.85	-4.77 ***

Nesting parameters and class allocation parameters								
	Segment 1		**Segment 2**		**Segment 3**		**Class 4**	
Class size	**21.6%**		**25.9%**		**30.2%**		**22.3%**	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Nesting parameters								
Bike nest	10.00	4.65 ***			1.57	4.32 ***		
Car nest	1.45	3.04 ***			1.00	14.30 ***		
PT nest	7.43	1.01			10.00	3.43 ***		
Private FLEX nest	1.00	0.38			1.04	3.42 ***		
Shared FLEX nest	2.18	2.62 ***			2.82	4.77 ***		
Local station nest			2.03	7.46 ***			2.38	6.73 ***
Distant station nest			1.00	5.15 ***			3.11	5.05 ***
Class allocation param.								
Constant	4.08	5.07 ***	2.94	4.35 ***	2.22	3.13 ***	Baseline	
Age	-0.57	-3.38 ***	-0.19	-1.55	-0.42	-3.13 ***		
BTM use	-1.12	-5.58 ***	-0.74	-4.78 ***	-1.24	-6.86 ***		
Car use	-0.23	-1.43	-0.38	-2.64 ***	0.64	3.50 ***		
DRT averse	-0.01	-0.10	0.14	1.81 *	0.00	0.00		
SE positive	0.39	2.92 ***	0.24	2.31 **	0.11	1.03		
TT use	-0.21	-1.80 *	0.00	-0.01	-0.30	-2.79 ***		

**** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$*

Each segment is presented in more detail in the following sections. For ease of interpretation, parameter trade-offs (such as the Willingness-to-Pay) are summarised and presented in Table 4.7. To better characterise the different segments and distinguish them from each other, their weekly travel behaviour and overall socio-demographic characteristics are presented in Figure 4.7 and Table 4.8, respectively.

❖ Segments 1 & 2: Higher WtP

Members of these segments tend to have a stronger sensitivity to travel time, particularly to in-vehicle time (IVT). They see the in-vehicle time on the access leg particularly negatively and are willing to travel more than 1.5 min longer by train to save 1 min on the access leg. Out-of-vehicle times (OVT) on the access leg does not seem that undesirable, with the walking, waiting and parking search times being seen as less negative than the access IVT. Compared to the other segments, they seem to be less sensitive to other aspects of train travel, as frequency and transfers are perceived less negatively, with a transfer equalling a similar penalty to 17min of travel by train or €3.66. Overall, members of these segments prefer the bicycle, followed by PT, the car and the two FLEX options at the end.

Respondents in Segment 1 tend to form fairly strong nests for the bicycle, PT and to a lesser extent Shared FLEX services, with their μ's corresponding to 10, 7.4 and 2.2 respectively. The two private motorised modes (car and private FLEX) on the other hand tend to be less strongly correlated, meaning that the nesting structure is weak.

For a station-based nesting structure, the nesting effect of the local station is somewhat strong (μ = 2), indicating some level of correlation between access modes. This means that a new access mode will largely result in a redistribution of travellers among the modes and attract a limited number of new users to the station. Alternatively, the modes accessing the more distant station do not seem to be correlated at all, forming independent alternatives.

Table 4.7. Parameter trade-offs for different segments

		Segments 1 & 2	Segments 3 & 4
In-vehicle time			
	Access IVT [€/h]	20.62	13.86
	Train IVT [€/h]	13.14	12.71
	Ratio access/train IVT	1.57	1.09
Access segment			
	PT Walk + Wait [€/h]	9.33	6.88
	Car & Bike Walk [€/h]	15.89	27.93
Train segment			
	Frequency [€/h]	8.95	12.81
	Transfer [€]	3.66	4.80
	Transfer [min]	16.69	22.64

◆ Segment 1: Young professionals

From the class membership function, we see that this segment is composed of younger individuals, who are average car users and not likely to use BTM. Interestingly, from Table 4.8 we can see that they seem to have a fairly positive opinion about DRT and the sharing economy, yet they do not see the benefits of not having to drive themselves. Considering other socio-demographic characteristics and mobility patterns, members of this segment seem to be overall quite similar to the sample. They are, nevertheless, somewhat higher educated and tend to use the bicycle more often.

◆ Segment 2: Middle-aged neutrals

Class allocation parameters for Segment 2 indicate that their members tend to be older, infrequent car users and more frequent BTM users. Similar to Segment 1, they are positive about the sharing economy, but in contrast, they do see the benefits of not having to drive themselves, yet are more DRT averse. Other factors indicate they are more digitally challenged and less experienced with using services of the sharing economy. They tend to live in more urban areas and are on average lower educated and the least affluent of the segments. They also have the lowest car ownership of any segment, with only 1.04 vehicles per household and 21% living in households without a car at all. Logically, they are also the least frequent car users and thus use public transport or cycle more often. They are also the most likely to not travel at all regularly on a weekly basis.

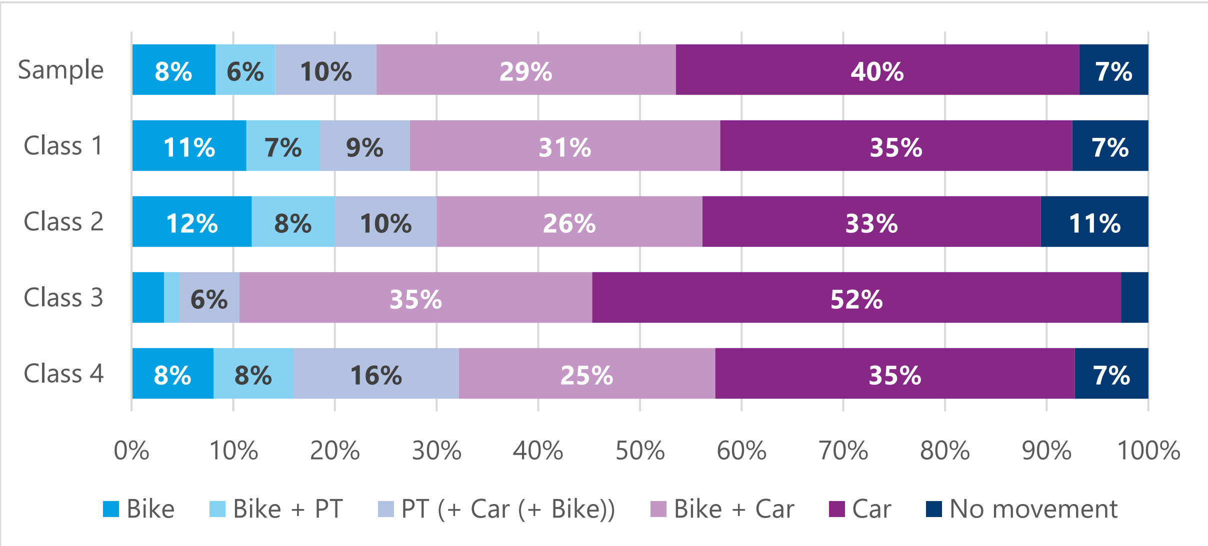


Figure 4.7. Weekly mobility patterns of the entire sample and the 4 classes (values below 5% are not labelled)

❖ Segments 3 & 4: Lower WtP

Compared to the first two segments, members of these tend to be slightly more cost sensitive, especially when it comes to access IVT. They do not perceive the access and train-leg IVT very differently, meaning that they would prefer to minimise their overall travel time and do not have a particular preference for one leg or the other. They are however very strongly averse to the parking search time for bike and car, seeing it twice as negative as access IVT. They are also less tolerant of transfers than the other segments, being willing to travel 5min or paying over €1 more compared to the other segments. Their overall access mode preferences lie with the car and PT. Cycling and Shared FLEX are seen as roughly equal, whereas Private FLEX is again least preferred.

Similar as with Segment 1, the nesting of PT and Shared FLEX alternatives in Segment 3 is quite strong, indicating that the users of these modes would likely keep using them, even if a new station opened. Car and Private FLEX are also, like in Segment 1, highly uncorrelated, meaning that multiple alternatives (train stations) are independent of one another when considering these modes. The key difference however, is for the cycling alternatives, which do not seem to be very strongly correlated in Segment 3 (μ = 1.6), as opposed to the very strong nesting structure in Segment 1 (μ = 10).

In Segment 4, nesting for both station alternatives tends to be reasonably strong, with both having a μ of over 2. The correlation of access modes to the local station is similar as in Segment 2, whereas much stronger nesting for the distant station can be observed in Segment 4.

◆ Segment 3: Exurban car drivers

Members of Segment 3 tend to be very frequent car users and thus infrequent BTM users. They are the most DRT averse, digitally challenged, least positive about the sharing economy and also see the least benefits in not having to drive themselves. They are predominantly young adults, with the largest share of individuals obtaining a middle education and an average to above average income per household. They are also the most likely to live in large household (three or more people). Being the least likely segment to live in an urban area (rather living in suburban and rural areas), it is logical that they are the segment with the highest car ownership (almost 1.4) and only 5% do not have a car at all. 62% also drive their car daily, compared to 40% in the sample average. This last also corresponds to their very low use of other travel modes.

◆ Segment 4: Urban PT enthusiasts

Conversely to the previous, members of Segment 4 are frequent BTM users and less frequent car users. They are also more SE averse, but tend to be positive towards DRT and the use of travel time for other activities. They are overall the oldest of the four segments, with an average income and a below average level of education. Corresponding to their lower car use, their car ownership is below average and almost 19% do not own a car at all. In addition to being the most frequent BTM users (20% on a weekly basis, compared to 11% in the sample), they are also above average train users, making them the overall strongest PT users.

Table 4.8. Average factor scores and socio-demographic characteristics of the sample and each segment

		Sample	Segment 1	Segment 2	Segment 3	Segment 4
Factors	Digitally challenged	-	-0.11	0.03	0.05	-0.00
	DRT averse	-	-0.13	0.10	0.12	-0.16
	Unfamiliar with SE	*Normalised*	-0.01	0.00	0.01	-0.00
	Positive about SE	-	0.24	0.12	-0.24	-0.05
	Effective use of TT	-	-0.03	0.21	-0.34	0.24
Gender	Female	53%	55%	55%	49%	53%
	Male	47%	45%	45%	51%	47%
Age	18-34	22%	29%	19%	22%	16%
	35-49	22%	25%	20%	26%	16%
	50-64	30%	28%	31%	32%	30%
	65+	26%	18%	30%	20%	37%
Education level	Low	25%	21%	27%	23%	28%
	Middle	39%	39%	37%	43%	37%
	High	36%	40%	36%	34%	35%
Household income	Below average	21%	21%	24%	17%	22%
	Average	48%	47%	47%	51%	48%
	Above average	16%	17%	15%	17%	16%
	Did not say	14%	15%	14%	15%	14%
Employment status	Employed	51%	55%	44%	61%	40%
	Student	6%	8%	6%	4%	6%
	Retired	24%	17%	28%	18%	34%
	other	20%	20%	21%	17%	20%
Urbanisation level	Very highly urban	23%	22%	25%	17%	30%
	Highly urban	31%	31%	32%	31%	32%
	Moderately urban	17%	17%	17%	17%	16%
	Low urban	21%	22%	19%	26%	16%
	Not urban	8%	8%	7%	10%	7%
Household size	1	22%	21%	25%	17%	25%
	2	36%	31%	37%	34%	41%
	3+	42%	48%	38%	49%	34%
Household car ownership	Average	1.17	1.17	1.04	1.38	1.06
	0	15%	17%	21%	5%	19%
	1	56%	53%	56%	57%	59%
	2+	29%	30%	23%	38%	22%

4.4 Model application: Scenario analysis of market potential

In the following we evaluate how the introduction of FLEX and the variation if its service level impacts modal split and travel behaviour. Firstly, we look at different FLEX introduction scenarios and how the market shares between modes shift due to this introduction. Secondly, we vary several attributes of the trip, including (1) the distance of the more distant station, (2) the average speed of FLEX and (3) the number of transfers saved by travelling via the distant station. We evaluate the impact of this on the individual class level and at an aggregate level. As a baseline, we take a typical medium-distance trip with two possible stations to access and four access modes for each. The attribute levels are presented in Figure 6.4 in Appendix D. The assumed average travel speeds for calculating the travel times of the access modes are 15km/h for the bicycle, 24km/h for the car and 18km/h for public transport and 20km/h for FLEX.

We also carry out a sensitivity analysis, the full results of which are reported in Table 7.4 in Appendix E. Overall, we observe that demand (market share) is largely inelastic. Individuals seem to be most sensitive to the access leg in-vehicle time. Interestingly, the ticket price of a longer public transport access trip is quite elastic, resulting in a shift in demand that is greater than 0.1 for many modes. Demand for existing transport modes (bike, car, PT) tends to be more sensitive to time, whereas the demand for FLEX seems to be more sensitive to price. It should be noted that the biggest changes in demand occur for alternatives that have an initially small market share, as a slight increase in demand means a big proportional change in market share.

4.4.1 Introducing an on-demand service

We apply the outcomes of the choice model to examine how the existing modal split is affected in four introduction scenarios of FLEX. Two scenarios model a "*Competition*" style entry of FLEX, acting as a direct competitor to existing services. The other two scenarios consider a "*Substitution*" setting in which FLEX replaces PT services in the study area. As our interest is also the interaction of access mode and station choice, we also consider if a more distant station becomes a new alternative and its opening coincides with the introduction of FLEX, or if it is already present when FLEX is launched. The impacts of the scenarios on the modal shift are presented in Figure 4.8.

In all four scenarios, we can observe that FLEX obtains a fairly small market share; approximately 7% in the *Competition* scenario and 12% in the *Substitution* scenario. In the former, the split between the two stations is about equal, whereas in the latter, almost two thirds of the FLEX trips are made accessing the local station, despite the distant station having an overall higher market share. Interestingly, in the case of a new station opening, most FLEX users are former PT users, whereas if both stations are already present, they are primarily former car drivers (specifically distant station car drivers). In either case, cyclists do not really shift in large numbers to using FLEX. Considering the impact of FLEX on overall station market share, it is almost insignificant, only marginally adding to the attractiveness of the local station (change in market share is less than one percentage point).

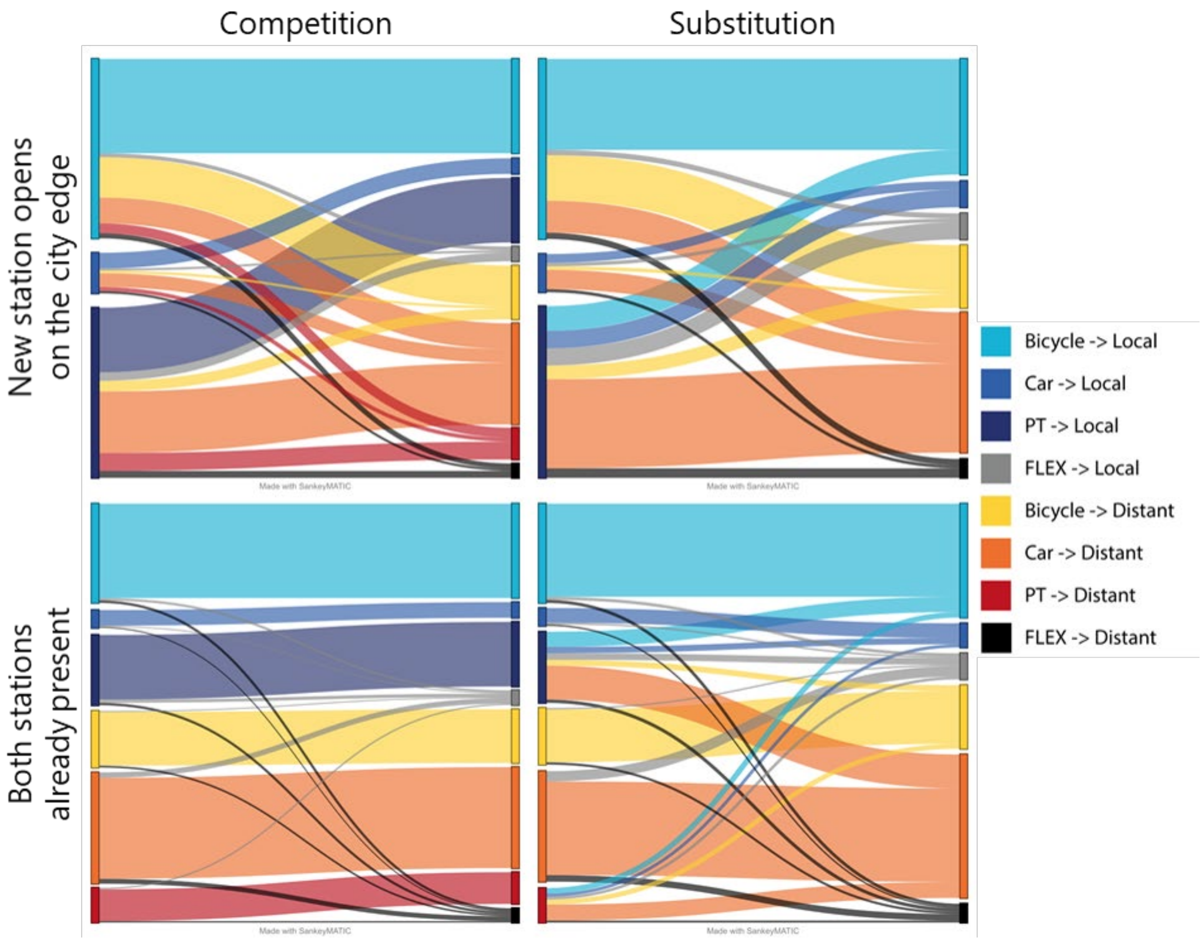


Figure 4.8. The impact of the Introduction and Substitution scenarios on modal split for train station access

Turning next to the impact of PT substitution, the first and clear impact is an increased share of both car (10 percentage points) and, to a lesser extent, bike use (six percentage points), with FLEX providing an alternative for only a small number of former PT users. Despite it often being touted as a PT replacement, our results seem to suggest that this is not as straightforward. When only one station is present at the start, most FLEX passengers are former PT users (approximately 60%). In the case of both stations already being present, most FLEX users (again) switch from their car however (45%), with limited correlation between the local and distant stations. Looking at where former PT users shift to, it is mainly to the car (especially to access the distant train station), with cycling to the local station being an attractive option primarily for travellers already using the local station.

Mode and station market shares used in this example are heavily dependent on the selected attribute levels. Nevertheless, we can see that FLEX is not a highly competitive alternative, capturing only a small share of the market. If a new station opens some distance away from the existing one, where cycling becomes too strenuous for most, FLEX can provide a viable alternative, although still representing a small share, compared to the car, which dominates as the access mode to the new station. The impact of distance on the attractiveness of FLEX, along with varying other operational characteristics, is investigated in the following section.

4.4.2 Level-of-service variation

Figure 4.9 and Figure 4.10 show the scale of changes in the market share when varying FLEX travel speed, number of transfers saved and access distance. The latter requires some further clarification. We fix the access distance to the local station at 3km from home and then vary the additional travel distance to the distant station. The Δ distance in both Figure 4.9 and Figure 4.10 thus indicates the extra distance (varied from 0 to 7km farther), meaning that the total access distance is varied between 3 and 10km. The trip characteristics are identical to what is shown in Figure 6.4 in Appendix D, where the distant station is 8km away from home (5km farther than the local station).

In both figures, we see that FLEX is less attractive for shorter distances, becoming an increasingly attractive alternative with the distance becoming too long for most to cycle, plateauing somewhere around 7-8 km away from home (4-5 km farther than the local station). Segment 3 (Exurban car drivers) seems to be most likely adopter of FLEX services, with a market share of around 15%, whereas the remaining three segments at around 5% market share. In terms of sensitivity to the distance, Segment 1 (Young professionals) seem to be the most affected by it, switching almost entirely to the local station if saves them 5km or more of travelling. The least sensitive on the other hand are members of Segment 4 (Urban PT enthusiasts). Looking at the combined market share of the distant station, an interesting observation can be made at around 4-5km of extra travel distance. That seems to be the tipping point for the overall population on which station to choose. A likely reason is that at that point, cycling becomes too unattractive to access the local station and bike nesting individuals (Segments 1 and 3) make the switch to the local station at roughly that distance.

Considering the varying FLEX speed, a higher speed does increase overall FLEX market share, although not more than one percentage point. Because the speed increases for accessing both stations, the impact on station choice is very limited, with only a marginal increase for the distant station at higher speeds. We assumed an average speed of 20km/h, slower than car as FLEX has to potentially make additional stops and detours to pick up other passengers, yet we still consider it faster than PT, as it does not stop that often. The average FLEX speed can be influenced by allowing the vehicles to use PT lanes, giving them priority at traffic lights and by determining the longest allowed detours for picking up additional travellers. Given the relatively minor changes to market share, it may be more beneficial to pick up additional passengers rather than use more vehicles to guarantee a quicker trip, for a marginal improvement in attractiveness.

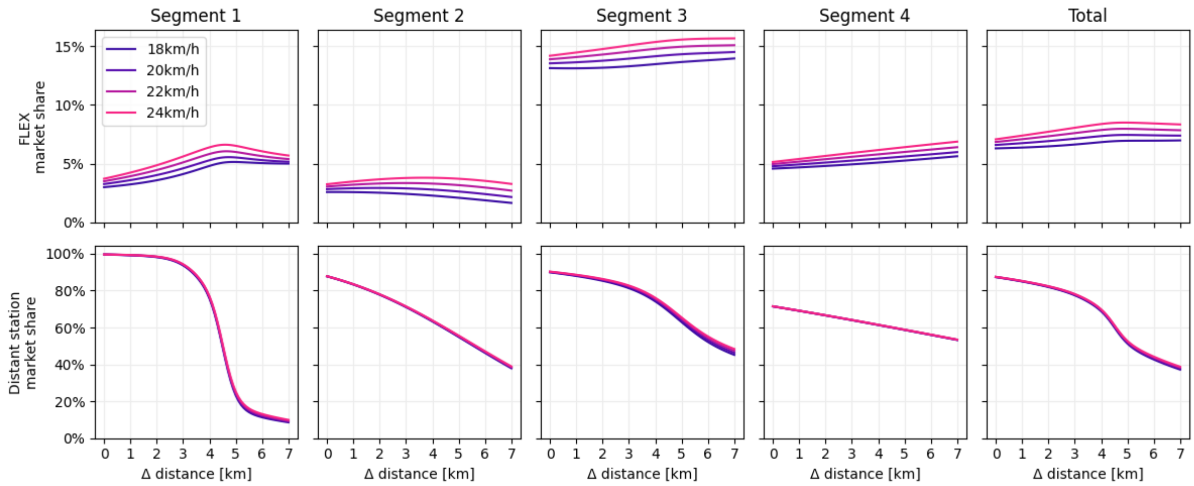


Figure 4.9. Market share for FLEX and Distant station when varying the average travel speed of FLEX and the distance between the two stations

The second analysis focuses on saving transfers on the train leg of the trip. Transfer provide a significant barrier in train travel for many passengers. Our results also support this notion, with a transfer being perceived equally as 15-25min of travel time or €3-5 of trip costs. FLEX market share seems to overall decrease when the local station has additional transfers, which is somewhat logical, given that the local station was more attractive for FLEX users. The change in market share is again quite limited, although an interesting pattern can be observed for Segment 1. The attractiveness of FLEX peaks at a greater distance if more transfers can be saved. The market share also increases with distance, which likely due to the bicycle becomes a less viable alternative. Turning to the station market shares, we see the impacts are quite significant. As in Figure 4.9, Segment 1 is highly sensitive to distance, with the number of transfers saved only influencing at what distance they would shift. The results indicate that for saving a transfer, they are willing to travel approximately 3km farther. Big differences (of at least 20% points per transfer saved) can also be observed for other segments, although their sensitivity to distances is less pronounced. A particularly high sensitivity can be observed in Segment 3, where saving two transfers makes a difference of almost everyone or no one from that segment using the distant station.

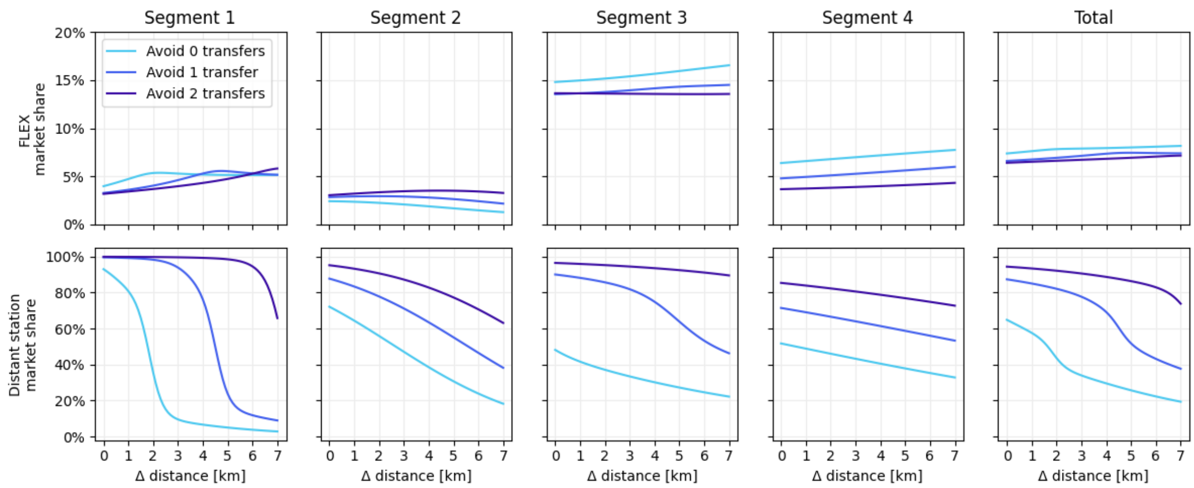


Figure 4.10. Market share for FLEX and Distant station when varying the number of transfers saved by travelling via the distant station and the distance between the two stations

4.5 Conclusion

In this paper, we explore the potential of using on-demand mobility services (FLEX) for home-end first/last mile train station access in the Netherlands. Improving station access is an essential aspect in increasing train use and is as important as improving the train service itself. We analyse the joint choice of access mode and train station, by applying a sequential stated preference survey design, disseminating it through the Dutch Mobility Panel (Hoogendoorn-Lanser et al., 2015). We estimate several choice models in order to examine the prominence of access station versus access mode choice, user heterogeneity and market segments. Here, we first present and discuss the main findings (Section 4.5.1). This followed by policy implications of introducing FLEX services in Section 4.5.2, before finalising with the limitations of this research and outlining the future outlook (Section 4.5.3).

4.5.1 Discussion and key findings

Model estimates show that respondents prefer the existing access modes, such as the bicycle, car and public transport, over on-demand services. This is in line with other studies analysing the potential of on-demand mobility (Frei et al., 2017; Geržinič et al., 2022; Y. Liu et al., 2018), possibly due to the unfamiliarity of respondents with novel services. A generic IVT parameter for the access leg shows that respondents perceive it more negatively than the main leg travel time (Arentze & Molin, 2013; Bovy & Hoogendoorn-Lanser, 2005; La Paix Puello & Geurs, 2014), although we show that the scale of the difference in perception varies between users. A somewhat unexpected finding is the perception of waiting time for on-demand service, which seems to be insignificant. Arguably, this is due to a combination of its description in the survey - as waiting time is presented as waiting at home - and the small attribute levels used, ranging between one and nine minutes. A similar result was found in our previous study on on-demand services for urban travel (Geržinič et al., 2022). The potential to have more time to get ready or to run a quick errand before leaving is presumably the reason for such an estimate. We suspect that a negative perception would be observed if longer waiting times would have been used or if the waiting would have to occur at the pick-up location on the street.

By means of a latent class model, we uncover and characterise four distinct user groups, based on their taste heterogeneity (time-cost trade-offs), nesting structure, socio-demographic characteristics, mobility patterns and attitudinal statements. Of the uncovered segments, the lower WtP segments, in particular the mode-based-nesting segment (*Exurban car drivers*) seems to be the most likely to adopt FLEX services for station access. Although they prefer the car and PT for station access, shared FLEX is not seen as significantly inferior to the bicycle for example. Their aversion to transfers on the train leg, higher sensitivity to train frequency and an almost identical weighing of IVT on the access and main leg also make them more likely to opt for a more distant station if it provides a superior service. The two segments with a higher WtP seem to be less likely FLEX adopters. Although they use their cars less intensely and have a higher value of time, they have a strong preference for cycling and a strong dispreference for FLEX. In addition, their stronger penalty for the access leg IVT means they are more likely to access a nearby station if possible and are willing to tolerate more travel time and transfers while traveling by train. This means they are more likely to opt for a local station, which, in combination with their high cycling preference, means that they are much more likely to cycle overall.

With respect to the two possible nesting structures, we show that both are almost equally prevalent amongst respondents, with the segments modelling mode-based nesting representing roughly 52% of the population, whereas the station-based nesting segments account for 48%. This is largely in line with previous literature, which reports mixed results (Bovy & Hoogendoorn-Lanser, 2005; Chakour & Eluru, 2014; Debrezion et al., 2009; Fan et al., 1993). As the difference between the two segments is fairly minor in our results, a small change in context is likely to tilt the model performance and favour one or the other nesting structure.

With the two-level segmentation structure (two pairs of segments sharing the same taste parameters and then two more based on mode nesting), it is interesting to see similarities in attitudes and socio-demographics in segments with similar WtP and with the same nesting structures. When grouping segments based on their taste parameters, individuals with a higher WtP tend to have a more positive view of the sharing economy. When analysing similar nesting structures, respondents who tend to nest alternatives based on the train station tend to be older, have a slightly lower level of education, more urban dwelling and living in smaller households. They also see the benefit of not having to drive themselves and being able to use that time productively. Interestingly, there are some similarities that can also be observed between two diagonal segments that have both different taste parameters and nesting structures; Segments 1 (high-WtP, mode-nesting) and 4 (low-WtP, station-nesting) as opposed to Segments 2 and 3. The former two nests tend to have more experience with services of the sharing economy, are more tech savvy and have a more positive view towards DRT services.

The four clusters show similarities to other studies looking into market segmentation with respect to new mobility solutions (Alonso-González et al., 2020, 2020; Geržinič et al., 2022; Winter et al., 2020). Most of these studies report at least one group that is largely ready to adopt mobility innovations and is currently fairly multimodal in their travel behaviour. In our study, this is somewhat split between Segments 1 and 4, where the former is more ready to adopt mobility innovations, whereas the latter is the most multimodal of any. These two segments also relate strongly to two further often uncovered groups, with one being a technologically-savvy car driving segment also shows potential for innovation adoption, but they tend to be time-sensitive (comparable to Segment 1). The other typical segment is a public transport supporting cluster, which tends to be more cost-sensitive and largely willing to adopt innovation, but are somewhat limited due to their cost-sensitivity (largely in line with Segment 4). Finally, most studies also find a segment in the population that is more negative/reluctant towards the adoption of innovations and also prefers to drive a car (very similar to Segment 3). It is interesting to point out however, that despite these characteristics of Segment 3, they seem to be a strong contender for FLEX adoption, based on our findings. The aforementioned studies are all based on separate data collection efforts, samples and models estimated, hence the uncovered parallels to these studies further support the findings of this research.

4.5.2 Policy implications

Applying the model estimates, we show that introducing an on-demand service will not have a significant impact on any existing mode, with most users coming from the car if FLEX is added as an additional service. Although not directly resulting from our study, we speculate that some travellers would likely not travel at all if public transport was entirely substituted by on-demand services.

If implemented, on-demand services would capture a fairly niche market, attracting users away from PT and car as an access mode to train stations. To limit the modal shift from public transport as much as possible, the planning of fixed (traditional) and flexible (on-demand) public transport should be integrated. Pinto et al. (2020) show that both the users and the operators could benefit from jointly planning (re-designing) a public transport network made up of fixed lines and flexible services. The greatest benefits of replacing fixed lines are likely to stem from current low-demand areas, where PT is operated at low-frequencies and is therefore less attractive to users. Notwithstanding, the results of Pinto et al. (2020) and also those of Narayan et al. (2020) suggest that ridership of fixed PT would nevertheless decline.

With respect to operational characteristics, FLEX services should aim at bundling multiple travellers into a single vehicle, reducing the overall vehicle miles travelled. This can however lead to more stops and detours, increasing the overall trip time and reducing the average speed. To counteract that, services can be given priorities reserved for public transport, such as the use of dedicated lanes and priority at traffic lights. Our results show that the travel speed does not have a significant impact on the attractiveness of the service and thus on the market share. Orienting the service to pick up a larger number of passengers, at the expense of a few minutes of travel time might therefore be reasonable. Designated pick-up and drop-off locations, with potentially similar amenities as bus stops, may also help reduce the scale of detours necessary to pick-up passengers and thus decrease travel time, but would result in travellers having to walk a certain distance, reducing the attractiveness of the service. Given the limited sensitivity to waiting at home, pick-up and drop-off locations may be best avoided, with the higher attractiveness of waiting at home possibly compensating for the slightly longer travel time.

In terms of joint access mode and station access, we show that on-demand services do not have a significant impact on the share of one particular station, with FLEX being an equally attractive service to both more local and more distantly located stations. It is important to note however, that when serving more remote stations, FLEX tends to compete primarily with the car as the access mode, whereas when serving a local station, the key competitor is public transport.

4.5.3 Limitations and future research

Our research utilises a stated preference approach, which allows us to investigate the attitudes and perceptions of travellers towards services that are not yet widespread and/or commonly known by the local population. However, this does bring with it the limitations associated with SP studies, namely hypothetical bias and a potentially high willingness-to-pay displayed by respondents (Loomis, 2011; Murphy et al., 2005). All respondents were also presented with two train stations to choose between, however some may not have any choice at all in reality, whereas others may have even more options to choose among, making the survey less realistic for some.

Future research can also test for the transferability of our market segmentation results to other contexts, particularly the size and composition of the segments, which we expect to differ depending on the trip purpose and geographical area. Our results are based on the attitudes of the Dutch population and Dutch context, meaning there is a high prevalence for cycling to the station and often limited car parking availability.

To understand how on-demand service can help in attracting more train travellers, an alternative to the main trip leg (train) should also be studied. It is likely that many participants would not have travelled by train if given the option, yet they were forced to choose an access mode and train station. This may have skewed the results towards a particular mode or attribute. However, it does show the preferences of the entire population, providing us with knowledge on attributes that require attention to attract all types of travellers.

Our study also did not take the activity side of the trip into account. While there is likely limited impact of the activity-end mode choice on the home-end mode choice, we cannot be certain and studying the complete trip would allow one to state with more certainty whether or not this is the case. The activity-end is also interesting to study in and of itself. As travellers rarely have their own means of mobility available on the activity side of the trip, shared mobility services may prove highly attractive and could potentially increase the share of train users.

Finally, a highly relevant characteristic of station access is reliability, both of the travel time and parking search time. If train services are not very frequent, this may be a key deciding factor for many travellers, choosing an alternative that is reliable and gives them the best chance of making their connection. Including this variability was beyond the scope of our research, but could provide invaluable insight into future service design.

Chapter 5:

Mode choice in the time of COVID-19 for long-distance international trips

In the previous Chapter, train services (in combination with station access mode) for regular medium-distance intercity trips were compared. This Chapter considers trips that are even longer and performed irregularly, investigating mode choice for long-distance trips. Long-distance / International travel is a topic within travel behaviour research that has seen limited attention in the past, largely due to the irregular and sporadic nature of such trips. And yet, a single long-distance trip can amount to a distance equivalent to a year's worth of commute trips, resulting in a similar, if not worse, environmental footprint. In recent years, international travel has been severely impacted by the COVID-19 pandemic, with the abundance of national and regional pandemic-related safety measures playing a significant role in this effect. While not their primary goal, these measures may play a role in passengers' perception of safety and risk of infection. This aim of this Chapter is thus to evaluate the impact of COVID-19-related safety measures on mode choice for long-distance trips.

Section 5.1 summarises the key research in the field of long-distance trips, discussing both the Hierarchical Information Integration approach and the impact of COVID-19 on travel behaviour. In Section 5.2, the survey design is discussed first, including the risk-of-infection perception experiment and the bridging mode choice experiment, followed by the modelling approach for both the Weighted Least Squares (WLS) regression and the Latent Class Choice Model (LCCM). Additionally, Section 5.2 also discusses the data collection and relevant COVID-19 situation. Results of the final model are presented in Section 5.3, while the implications, application and trade-off behaviour showcased in Section 5.4. Section 5.5 sums up the key findings, discusses the limitations and provides an outlook for future research.

This chapter is based on the following article:

Geržinič, N., van Dalen, M., & Cats, O. (2023). COVID-19 risk-perception in long-distance travel. (*Under review*).

5.1 Introduction

In recent years, long-distance travel has been gaining prominence in both political and scientific discussions (particularly in Europe), with many new services, proposals and policies being passed or put forward, aimed at fundamentally reshaping how we travel (euronews, 2023; Steer, 2021; Witlox et al., 2022). What ties them all together is their emphasis on improving rail travel. In recent years, night trains have been experiencing a revival in Europe (de Kemmeter, 2021; Heufke Kantelaar et al., 2022). France and Austria have banned short-haul domestic flights on routes with good (high-speed) rail alternatives (Ledsom, 2022; Morgan, 2020). Proposals from several organisations have also been put forward for Europe-wide (high-speed) rail infrastructure and service enhancement, with the most high-profile case being the TEE 2.0 project (German Federal Ministry of Transport and Digital Infrastructure, 2021).

To support the evaluation of proposed policies and investment projects, there has been a fair amount of research on long-distance travel and high-speed rail. An extensive literature review on research concerning long-distance travel is given by Sun et al. (2017), providing a good overview of the state-of-the-art. As most studies have a specific case-study focus, it is difficult to obtain a clear and straightforward understanding of individuals' long-distance travel behaviour. The consequences of introducing high-speed rail (HSR) differ greatly per country, based on the implementation, service pattern, policies and regulation of the air, rail and road markets etc. Jiang et al. (2021) acknowledge that trains are certainly a more sustainable alternative, but due to induced demand, the environmental benefits may not be as high as anticipated.

With respect to long-distance travel behaviour, most studies (both revealed (RP) and stated preference (SP)) report a Willingness-to-Pay (WtP) for in-vehicle time and access/egress time to HSR train stations, with the former being in the range 10-30 €/h and the latter at 20-50 €/h (Bergantino & Madio, 2018; Ortúzar & Simonetti, 2008; Román et al., 2014; Román & Martín, 2010). Other frequently evaluated attributes are frequency/headway, waiting time, reliability and comfort, with the results between studies being highly inconsistent. Frequency and waiting time essentially analyse the same travel aspect, but the perception of this is fundamentally different in long-distance travel and thus cannot be compared to values of waiting time reported in studies on daily commute behaviour. The context-specific nature of the studies (Spain, Italy, Chile) further exacerbates these differences.

5.1.1 Risk perception

Contrary to the core attributes of travel time and travel cost, other attributes are often more complex and it is often difficult to capture them using a single objectively measurable metric. Typical examples are safety/risk, comfort and reliability. Risk, for example, can refer to many different things and situations. In essence, risk infers a potential a harmful or undesirable outcome in a future state. The risk can be related to safety, health, operations, financial state, legal state etc. In the domain of travel behaviour, the perception of safety risk can related to the likelihood of an accident occurring, an operations-related risk can be linked to the reliability of travel and a health risk could be the seen as the potential to get ill or injured.

The perception of risk has been shown to influence travel behaviour, with travellers tending to behave in a way which reduces the level of perceived risk (thus increasing perceived safety and security) (Fyhri & Backer-Grondahl, 2012). Molin et al. (2017) investigated the risk perception of airline safety, following the crash of Malaysia Airline Flight MH17 in eastern Ukraine. They report that the airline safety index, number of fatal crashes (in the past ten years) and flying over conflict areas are all highly influential on people's perception of risk, with the subjective level of risk often being associated with the respondent's age. When linking risk perception to willingness-to-pay, the authors show that risk perception is perceived as non-linear (logarithmic), with travellers willing to pay substantially more when the initial situation is perceived as less safe. In other words, using a subjective 6 point scale, people are willing to pay more to increase the level of safety from level 1 to level 2, than from level 5 to level 6.

In recent years, a major influencing factor for risk perception has been the covid-19 pandemic. With travel heavily restricted and several measures in place, the effect of perceived safety for mode and route choice became a prime interest. Shelat et al. (2022) devised a stated preference survey, where they assessed the impact of a variety of measures and characteristics on a subjective risk perception of getting infected with covid-19, such as infection rate, lockdown status, face mask policy etc. and how this risk perception affected people's route choice when travelling with public transport. As expected, the authors find that crowding and infection rate increase the level of risk, while mandatory mask wearing and enhanced cleaning reduce risk. Analysing the trade-offs between risk factors and cost, the authors observed a relatively low willingness to pay, i.e. only €1.60 to halve the occupancy, only around €0.50 for increased sanitisation and less than €1.00 for trips with mandatory masks.

5.1.2 COVID-19 pandemic

With the outbreak of the covid-19 epidemic, the perception of safety and infection risk has become a key decision factor for many travellers. Since the outbreak in late 2019, our travel behaviour has fundamentally altered. The most notable change happened during the first lockdown, when all but essential activities were cancelled, leading to drastic reductions in travel demand, with public transport (PT) seeing the biggest drop in usage (Currie et al., 2021; de Haas et al., 2020; Shamshiripour et al., 2020). According to Currie et al. (2021), the fear of infection remained a key factor for travellers to continue avoiding the PT in subsequent lockdowns. Crowding was also high on the list of influential factors, due to the higher likelihood of virus spread in crowds. To combat the spread of covid-19, numerous measures were introduced on PT around the world (Shelat et al., 2022; Shortall et al., 2022; Tirachini & Cats, 2020), such as enhanced cleaning policies, increased ventilation, mask mandates, travel and country entry regulations, adapted operating strategies etc.

Long-distance and particularly international travel were especially strongly impacted by the outbreak of the epidemic, with most countries implementing strict entry requirements or closing their borders entirely. This meant that most international trips had to be cancelled or rescheduled if possible (Fatmi et al., 2021; Mary & Pour, 2022). Due to both the safety perception (infection risk) and a reduced level of service, mode choice was affected (Li et al., 2021), with more people choosing to travel by car (Kamplimath et al., 2021; Shamshiripour et al., 2020) rather than train or air. Similar to what was reported for commute behaviour by Currie et al. (2021), hygiene became a top priority for individuals when selecting their travel mode for long-distance trips (Kamplimath et al., 2021). In terms of future prospects, researchers propose mixed outcomes, with some studies reporting people flying less after the pandemic (de Haas et al., 2020; Shamshiripour et al., 2020), with the shift being mainly towards the private car (Shamshiripour et al., 2020), whereas others reported the train being perceived as less safe than flying, with the latter being perceived as no less safe than the car (Kamplimath et al., 2021). Nevertheless, Burroughs (2020) and Tardivo et al. (2020) both speculate that, particularly in Europe, the railway sector could come out of the covid-19 epidemic far stronger. They attribute this in part due to the ever more important environmental concerns of society, large investments into railways during the epidemic in the form of economic relief packages and partially due to lower risk of infection on trains as opposed to aircraft.

The impact of the covid-19 epidemic on long-distance travel and the associated behaviour of individuals is therefore uncertain. Despite a large array of measures being passed, little is known about the subjective perception of their efficacy. Although policymakers highlight the importance of measures and their benefits, it is ultimately the perceived efficacy which underlies users' decision making. To the best of our knowledge, this has not yet been looked into with respect to the long-distance travel market. With many international travel markets nearing pre-pandemic levels and some already surpassing those results (Harper, 2023; Railway Gazette International, 2023) and the covid-19 epidemic seemingly fading in large parts of the world, research suggests that future pandemics are becoming increasingly likely (Marani et al., 2021; Michael Penn, 2021), meaning that our understanding of the perception of public safety is just as important now, if not more, than during an ongoing pandemic.

The contributions of this paper are twofold. Firstly, we evaluate the perception of various COVID-19 measures aimed at limiting the spread of the virus, through an HII variant type SP survey. The rating experiment includes eight attributes associated with the perception of infection risk. This infection risk is then carried into the bridging experiment, along with travel cost, time and comfort level, where respondents choose their preferred travel mode for a long-distance trip of approximately 500km and 1000km. Secondly, upon modelling the bridging experiment by means of an LCCM, we estimate several weighted least squares (WLS) regression models to uncover the different perceptions of infection risk as experienced by different population segments that are obtained from the LCCM. Using a WLS regression, as opposed to the commonly applied ordinary least squares (OLS) regression, the analyst is able to obtain segment-specific perceptions from the rating experiment of HII for any analysed context, providing more information on how the perception of a construct differs among individuals.

5.2 Methodology

In this section, we outline the steps undertaken in this research: how the survey was constructed and thereafter, the obtained data modelled. The chapter starts by describing the Hierarchical information integration (HII) approach, which was used to collect the data. As the HII experiment is formed of two separate experiments (the rating and bridging experiments), they are each discussed separately, both in the survey design section (5.2.2) as well as in the model estimation section (5.2.3). Section 5.2.4 then presents the data collection approach and the sample characteristics, with Section 5.2.5 outlining the COVID-19 circumstances under which respondents were filling in the survey.

5.2.1 Hierarchical information integration

When making decisions, people often analyse a variety of attributes. In addition to the most frequently evaluated attributes (such as travel time and cost), people consider many other aspects when making decision about long-distance travel which can be difficult to capture, or there may simply be too many to consider. To overcome this issue, some studies employ the Hierarchical Information Integration (HII) approach. It enables the analyst to capture a broader array of attributes and grouping them based on a common denominator. Respondents first evaluate these groups of attributes (i.e. comfort, safety, reliability, convenience,…) individually, giving them a subjective ranking on a Likert-scale. These rankings are then presented to respondents in a bridging experiment, which is able to couple the different attributes and disentangle how they are traded-off (Louviere, 1984). Since its introduction, different version of HII have been proposed and implemented. Molin & Timmermans (2009) present a review of HII studies and classify the studies into three categories: (1) Conventional HII, as defined by Louviere (1984), (2) HII variant that was first introduced by Bos et al. (2004) and (3) an Integrated Choice experiment, proposed by Oppewal et al. (1994). The HII variant differs from the main approach in the setup of the bridging experiment, with some attributes representing the subjective construct evaluations, alongside conventional objective attributes such as travel time or cost. The Integrated Choice experiment on the other hand, includes attributes of other constructs in the sub-experiments as well, giving more context to the decisions being made.

5.2.2 Survey design

As outlined in the Introduction, safety perception with respect to covid-19 infection risk is arguably a complex construct, associated with a large number of possible influencing factors. To capture their impact on individuals' mode choice, we devise an HII experiment, specifically the HII variant, developed by Bos et al. (2004) which has been applied in past studies by Molin et al. (2017) and Heufke Kantelaar et al. (2022). We design two separate experiments: (1) a rating experiment that captures respondents' perception of infection risk and (2) a bridging experiment, where the infection risk rating is included as one of the attributes. The experiments are administered sequentially, starting with the rating experiment, where the respondents get acquainted with the infection ratings and different attribute levels, subsequently followed by the bridging experiment where those subjective ratings are contextualised in a full mode-choice experiment. The design of each experiment is described in more detail in the following sections.

❖ Rating experiment

In the rating experiment, attributes pertaining to a common topic are joined and their attributes are varied in order to obtain the influence of each individual factor onto the overall perception of that construct. A single rating experiment is administered in our experiment, where respondents report their perceived risk of infection with COVID-19 in relation to a long-distance trip.

Individuals may consider a wide variety of factors and mitigation policies when evaluating their perceived risk of infection. Numerous studies measured reported perceived risk directly (asking respondents about their risk perception) to understand its relation to other factors (Dryhurst et al., 2020; Kroesen et al., 2022; Mertens et al., 2020). However, there is lack of knowledge concerning the underlying determinants of the perceived risk. An SP survey on mode-choice in Santiago, Chile was carried out by Basnak et al. (2022), in which the authors test respondents' sensitivity to mask-wearing compliance (% of passengers wearing a mask), crowding and cleaning policy. Utilising an HII experiment, Shelat et al. (2022) analysed infection risk perception and its impact on train route choice in the Netherlands. In the risk perception experiment, they tested on-board crowding, number of transfers, face mask policy, sanitisation, current infection rate and lockdown status. Crowding has also been recognised as a major influencing factor on mode choice by Currie et al. (2021). None of the above has been conducted in the context of long-distance travel, where train and aircraft are the main passenger transport alternatives.

We devise an experiment with eight attributes, based on three groups as defined by Shelat et al. (2022): *trip-specific* (partial control by the operator), *policy-based* (set by the government or operator) and *pandemic-context* (information on the state of affairs at the time). The attributes and associated attribute levels are summarized in Table 5.1.

Regarding the *trip-specific* attributes, we include **on-board crowding**, which is one the most frequently cited influencing factor on the risk perception (Basnak et al., 2022; Currie et al., 2021; Shelat et al., 2022). As standing is a rare occurrence on long-distance travel and in many cases not even permitted, we include this as a share of occupied seats in the vehicle.

With regard to *policy-based* attributes, we include **face mask policy**, which is one of the more recognisable policies adopted by governments and operators around the world (Shortall et al., 2022; Tirachini & Cats, 2020). We also test for **cleaning policy** and **air circulation**. Although the efficacy of the former is contested (Thompson, 2020), it may still have a profound impact on travellers risk perception (Basnak et al., 2022), and it is therefore included. Many airlines were quick to emphasize their commitment to hygiene and have put out statements on their enhanced cleaning policies and the use of HEPA filters in air-conditioning units (Wichter, 2020). Ventilation has also been a frequent piece of advice to the public as an easy and efficient way of reducing infection risk.

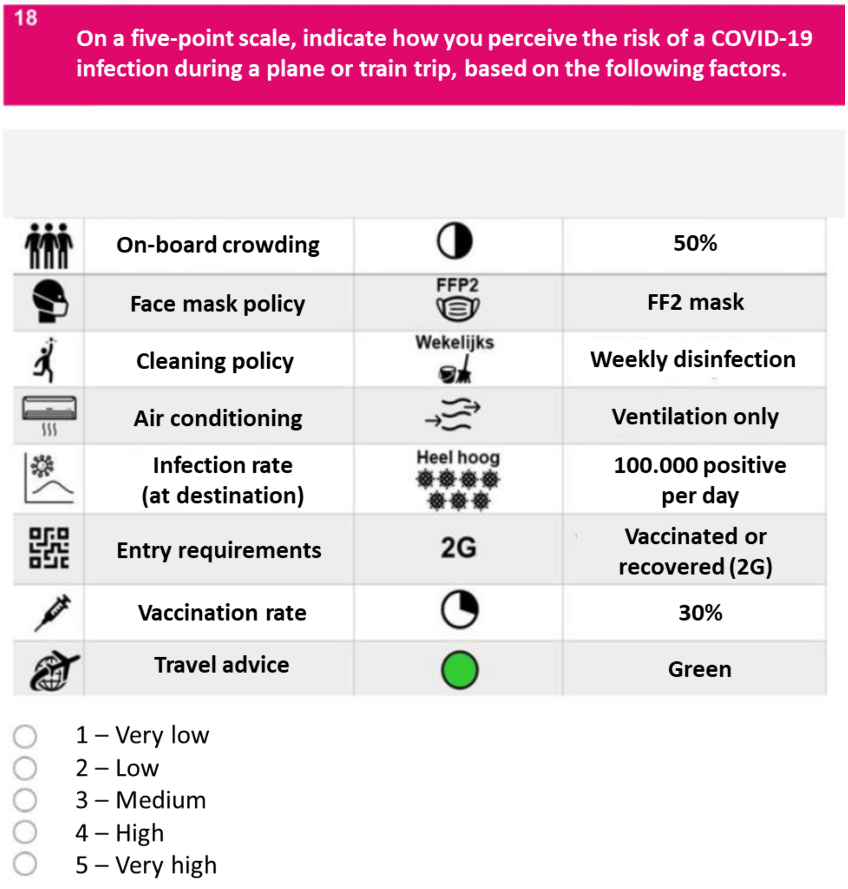
We test two more policy-based attributes, which are specifically aimed at international travel: **government travel advice** and **entry requirements**. In the Dutch context, long-distance travel mostly implies international travel. The Dutch government keeps a regularly updated list of countries and a simple colour-coded travel advice (green, yellow, orange, red) for each country, based on the risk associated with traveling there (Rijksoverheid, n.d.-b). During the pandemic, this list was updated given the epidemiological situation at the time (case numbers, local regulations etc.). For many travellers, it is a first point of information and a good indication of the associated risks. At the time of the data collection (February and March, 2022), testing and vaccination had already become widespread across Europe and with the introduction of the QR-code system (European Commission, 2021), many countries adopted this as a means to allow for some international travel while keeping with national containment policies. Depending on the government policies and the severity of the pandemic at the time, different combinations of certificates could be required to enter a country (vaccination, recovery, testing).

Finally, the *pandemic situation* at the decision moment is an important consideration individuals make. Initially, this primarily meant the **infection rate** (Shelat et al., 2022), with the most frequent metric being number of cases (although hospitalisations, ICU admittance or virus reproduction rate have also been reported by governments). With vaccination becoming more widespread and the concept of herd immunity, the **vaccination rate** in a society can also be a predictor of overall infection risk perception.

As prior values are not available for some of the included attributes, an orthogonal (fractional factorial) design is utilised to construct the experiment. The resulting design contains 20 rows. By applying blocking, each individual was asked to evaluate five choice sets, indicating their perceived level of infection risk on a Likert-scale between 1 and 5. An example choice set can be seen in Figure 5.1, with the design obtained by utilising Ngene software (ChoiceMetrics, 2018) and the full design can be seen in Table 7.5 in Appendix F.

Table 5.1. Attributes and attribute levels used in infection risk rating experiment

Category	Risk factor	Attribute levels
Trip-specific	**On-board crowding**	- 25% of seats occupied - 50% of seats occupied - 75% of seats occupied - 100% of seats occupied
Policy-based for travel	**Face mask policy**	- No mask mandatory - Mandatory face mask (can be any kind) - Mandatory surgical face mask - Mandatory FFP2 mask
Policy-based for travel	**Air circulation**	- No ventilation or air-conditioning - Only ventilation - Air-conditioning without HEPA filters - Air-conditioning with HEPA filters
Policy-based for travel	**Cleaning policy**	- The same cleaning policy as before COVID-19 - Enhanced cleaning (touch points) - Weekly full-vehicle disinfection - Daily full-vehicle disinfection
Policy-based for international travel	**Travel advice**	- Green - Yellow - Orange - Red
Policy-based for international travel	**Entry requirements**	- No entry regulations - Tested, recovered or vaccinated (3G) - Vaccinated or recovered (2G) - Vaccinated or recovered + tested (2G+)
Pandemic-context	**Infection rate**	- 100 positive tests per day (summer 2020 & June 2021) - 10.000 positive tests per day (autumn 2020 & July 2021) - 25.000 positive tests per day (November 2021) - 100.000 positive tests per day (fictitious extreme high)
Pandemic-context	**Vaccination rate**	- 15% fully vaccinated (Bulgaria) - 30% fully vaccinated (Romania) - 70% fully vaccinated (Netherlands & EU average) - 90% fully vaccinated (Portugal)


18 On a five-point scale, indicate how you perceive the risk of a COVID-19 infection during a plane or train trip, based on the following factors.

On-board crowding		50%
Face mask policy	FFP2	FF2 mask
Cleaning policy	Wekelijks	Weekly disinfection
Air conditioning		Ventilation only
Infection rate (at destination)	Heel hoog	100.000 positive per day
Entry requirements	2G	Vaccinated or recovered (2G)
Vaccination rate		30%
Travel advice		Green

- 1 – Very low
- 2 – Low
- 3 – Medium
- 4 – High
- 5 – Very high

Figure 5.1 Example question of the rating experiment

❖ Bridging experiment

To link the perceived infection risk with other travel-related attributes, a bridging experiment is designed. Based on the HII variant (Bos et al., 2004), this experiment contains both the rating experiment attribute value, and directly included objective attributes. This bridging experiment is designed as a mode choice experiment, wherein respondents can choose among car, train or aircraft options, as these are the most widely available and have also seen most attention in research (Bergantino & Madio, 2018; Cascetta et al., 2011; Ortúzar & Simonetti, 2008; Pagliara et al., 2012; Román et al., 2014; Román & Martín, 2010). Despite the growth of long-distance bus services (such as Flixbus) in Europe in the years before the pandemic, those are still primarily seen as a low-cost alternative, and are therefore excluded from the survey. The aircraft alternative is defined as a “flag carrier”, to avoid respondents making assumptions on the type of service offered. For train, no distinction is made between conventional rail and high-speed rail, as the interior comfort level is often indistinguishable and travel time is the only indicator of the travel speed.

The most important attributes, included in past research are **travel time** and **cost**. We define travel time as the door-to-door travel time, including the main leg travel time, the terminal dwell time (time spent at the airport/train station) and the access/egress time. The latter is often included in studies, because long-distance/international trains serve only a single or a handful of stations in a city, resulting in a significant role of access/egress time in the decision-making process. This is even more pronounced for airports, as they tend to be located outside of the city, sometimes far away, resulting in long access times. Different travel time components are merged into a single attribute to avoid overwhelming respondents with too many attributes. Transfers are not included, as in long-distance travel, they tend to be highly case dependent. Frequency and time-of-day information is also left out, to minimise the amount of information that respondents need to process and evaluate.

In addition to the **perceived infection risk**, the fourth and final attribute included in the survey is **travel class (comfort level)**. The travel class can have a strong impact on the perception of travel time and with more personal space and often lower occupancy in first/business class, some may choose it as a safer travel alternative.

To capture a broader scope of potential long-distance trips, two separate experimental designs, with two distance categories are used: a shorter trip of approximately 500km and a longer trip of approximately 1000km. These distances are used primarily to determine appropriate travel time and travel cost attribute levels. The attribute levels for all three modes in both distance categories can be viewed in Table 5.2. Example destinations from Amsterdam are also given to respondents as an indication of the travel distance:

- 500km trip: London, Paris, Zurich, Berlin, Copenhagen
- 1000km trip: Bordeaux, Barcelona, Milan, Warsaw, Stockholm

Additionally, trip purpose was included implicitly in the stated choice experiment. Prior to the discrete choice portion of the experiment, respondents were asked to elicit their main trip purpose when making international trips (most trips). This was then to be used as the context for their mode choice in the discrete choice experiment.

A Bayesian D-efficient design in Ngene (ChoiceMetrics, 2018) is generated for the bridging experiment. An advantage of an efficient design is that it results in far fewer choice sets. Using the approximate willingness-to-pay (WtP), the design maximises the number of choice tasks within this trade-off area and avoids dominant alternatives. As we can never be fully certain about the priors, especially when stemming from different sources, we apply a Bayesian efficient design. This allows us to specify a standard error for each prior value, indicating our level of certainty. The priors for the travel time and cost are based on the study by Kouwenhoven et al. (2014b), who carried out a detailed value-of-time (VOT) study for the Dutch Government. The values tend to be around 10 €/h, which we use as a base. For risk perception, we set the prior at a WtP of €5 per risk level reduction, based on the result of Shelat et al. (2022), who found a value of ~€4 per risk level reduction for trips up to one hour long. Finally, we use a WtP for a higher level comfort (business/first class) of €50, based on the findings of Ortúzar & Simonetti (2008) and also on the values observed when determining the price levels. The standard errors of the priors are set at half the value of the prior. Given the assumed normal distribution, this means that we are 0.975 certain that the prior has the correct sign (negative for travel time, cost and perceived infection risk & positive for comfort). The priors and their respective standard errors can be found in Table 5.2, with an example choice set shown in Figure 5.2. The final designs for both distance scenarios are presented in Table 7.6 and Table 7.7 in Appendix F.

Table 5.2. Prior parameter values, attributes and attribute levels per mode and distance category

	Prior values	Train		Aircraft		Car	
		~500km	*~1000km*	*~500km*	*~1000km*	*~500km*	*~1000km*
Travel time	*-0.1 (0.05)*	- 3h - 4.5h - 6h	- 6h - 9h - 12h	- 3h - 4h - 5h	- 4h - 5h - 6h	- 4.5h - 6.5h - 8.5h	- 10h - 13h - 16h
Travel cost	*-0.01 (0.005)*	- €30 - €65 - €300	- €50 - €200 - €350	- €50 - €175 - €300	- €50 - €225 - €400	- €80 - €115 - €150	- €100 - €150 - €200
Comfort level	*0.5 (0.25)*	- 1st class - 2nd class		- Business - Economy		/	
Perceived risk of infection with COVID-19	*-0.05 (0.025)*	- 1 (very low) - 3 (medium) - 5 (very high)		- 1 (very low) - 3 (medium) - 5 (very high)		*1 (very low)*	

Figure 5.2 Example question of the bridging experiment

❖ Additional questions

In addition to the rating and bridging experiments, respondents were presented with travel-related and socio-demographic questions. To get a better idea of respondents' long-distance travel characteristics, we asked them (1) how many times they had travelled to European destinations in 2021, (2) what was the most frequent purpose of those trips, (3) who paid for those trips and (4) who they travelled with. We also asked them to state their preferred travel mode for both the shorter (~500km) and longer (~1000km) context trips. As the Omicron variant had just become the dominant strain of covid-19 a month before the survey took place, we included a question on the perception thereof; whether they are more, equally or less worried about it, as compared with the previously dominant Delta variant. Regarding the socio-demographic information, respondents were asked to elicit their age, gender, income, completed level of education, working status, household composition and access to a car. This last question was included by asking if respondents have access to a car at all times, in agreement with other members of their household, with people outside of their household or not at all.

5.2.3 Model estimation

The separate rating and bridging experiments, forming the complete HII dataset, are modelled separately. In both Conventional HII and the HII variant, rating experiments are modelled by means of a multiple linear regression and the bridging experiment as a discrete choice model (DCM). As mentioned in the introduction, we apply an LCCM to account for respondent heterogeneity in the bridging experiment. By doing so, we obtain information on the probability of each individual to belong to a certain latent group in the population, which is subsequently used to estimate a weighted least squares (WLS) regression for the rating experiment. As the class allocation probabilities are a prerequisite for WLS regression, we firstly explain the LCCM estimation for the bridging experiment, before proceeding with the regression analysis for the rating experiment. The choice model bridging experiment is modelled with the help of the PandasBiogeme python package (Bierlaire, 2020) and the rating experiment with IBM SPSS Statistics (Version 26).

❖ **Bridging experiment: Latent class choice model**

The bridging experiment is a discrete choice experiment and is therefore modelled using a DCM. The decision rule that respondents used to make their decisions is assumed to be utility maximisation (McFadden, 1974). As a point of departure, different MNL models are estimated, testing for different parameter specifications, capturing potential interaction and non-linear effects. The model is then extended to also capture respondent heterogeneity, which gives more detailed insights into individuals' choice behaviour.

As shown in the Introduction section, the perception of risk can vary substantially among travellers. To capture this respondent heterogeneity, several different DCM specifications exist. Two of the most prominent are the Panel Mixed Logit (ML) and latent class choice model (LCCM) approaches (Greene & Hensher, 2003). The benefits of ML models is that they are able to capture heterogeneity with a fairly small number of parameters, making them very parsimonious in the estimation. For attributes deemed to vary in the population, a second parameter (standard error) is estimated, giving information on the width of the (normal) distribution of the attribute's perception in the population. In HII experiments, the perception of the rating attribute is then linked with a regression analysis, meaning that a single (normally distributed) parameter is a good way of achieving this. Both studies by Molin et al. (2017) and Heufke Kantelaar et al. (2022) utilised the ML approach to capture respondent heterogeneity.

In contract to ML models, LCCMs capture heterogeneity by estimating several distinct MNL models, to which individuals are allocated to in a probabilistic fashion, based on the likelihood of their observed choices (Equation 1). In this manner, each MNL model represents a distinct class or segment of the population, making their interpretation very straightforward. Another benefit of LCCMs is that the class allocation function, used to classify individuals, can be extended with socio-demographic information, providing valuable insight into the composition of each class. Specifically, this information can be included in the class allocation utility Cn,s (Equation 2). However, applying LCCMs to HII data is challenging, as the perception of the subjective ratings in the bridging experiment will result in different parameters for each class. However, if the rating experiment is modelled with a regression function as is common practice now, that means there is no distinction between classes in their perception of the different influencing attributes. Intuitively, this subjective perception should differ between the classes, yet to the best of the authors' knowledge, latent class segmentation has not been attempted in HII variant experiments.

Equation 5.1. Formulation of the LC model

$$P_n(i|\beta) = \sum_{s=1}^{S} \pi_{n,s} \cdot P_n(i|\beta_s)$$

where:

$P_n(i|\beta_s)$ Choice probability of respondent *n* selecting alternative *i*, given a set of parameters β_s

$\pi_{n,s}$ Probability of respondent *n* belonging to class *s*

Equation 5.2. Formulation of the class allocation probability

$$\pi_{n,s} = \frac{e^{C_{n,s}}}{\sum_{l=1}^{S} e^{C_{n,l}}}$$

where:

$C_{n,s}$ Utility of respondent *n* belonging to class *s*

❖ Rating experiment: Regression

The results of the rating experiments in HII are analysed using a multiple linear regression approach, to capture the impact of each individual aspect onto the scoring of the attribute. As we aim to capture the different underlying perceptions of risk by different population segments, we propose to estimate *S* number of regression models, one for each segment obtained from the LCCM. To differentiate between the models, we apply a WLS regression, as opposed to the ordinary least squares (OLS) regression. In OLS, each data point contributes equally to the estimation of the regression model. WLS is a generalisation of OLS, wherein a weight is added for each individual data point, indicating the accuracy or trust of the researcher into that specific data point. The weight is an additional input parameter in the regression function that takes a values between 0 and 1, indicating how much it should contribute to the model estimation. When all data points have a weight of 1, the WLS reduces to an OLS regression. This approach provides a great opportunity to estimate separate regression models for each individual population segment. LCCMs allow for the calculation of a class allocation probability for each individual ($\pi_{n,s}$), which can be used as the weight in WLS. Based on this, the WLS formulation is adapted as shown in Equation 5.3.

Equation 5.3. Formulation of the class allocation probability

$$WSS_s = \sum_{n=1}^{N} \left(\pi_{n,s} \cdot \left(y_n - \sum_{k=1}^{K} x_{n,k} \cdot \beta_{s,k} \right)^2 \right)$$

where:

WSS_s	Weighted sum of squares for segment *s*
y_n	Observed value of perceived risk for respondent *n*
$x_{n,k}$	Attribute level of attribute *k*, evaluated by respondent *n*
$\beta_{s,k}$	Parameter capturing the sensitivity of parameter *k* in segment *s*

5.2.4 Data collection

The survey was administered to the respondents of the online panel managed by the Dutch Railways (NS) (NS, 2020). It should be stressed that the panel is not limited to train users. In total, 938 responses are obtained between 8th of February and 8th of March 2022. This data is filtered based on a minimal response time of five minutes and maximum of 30 minutes, resulting in 705 fully valid responses. A lower boundary is set to remove speed runners from the data. As the connection between the rating and bridging experiments is crucial, an upper boundary is also set for the response time, to guarantee that respondents are still conscious of this connection.

The sample's socio-demographics characteristics are compared to those of the Dutch population and presented in Table 5.3. The sample is skewed with regard to the overall Dutch population, consisting of an above average share of older individuals and therefore a larger share pensioners. Additionally, the sample has a higher than average level of education, with 63% having bachelor's degree or higher. While it can be seen that the sample is not representative of the Dutch population, we cannot be certain how representative it is of the Dutch long-distance-travelling public, our target population. The respondents are members of the Dutch Railways panel, indicating a potential preference towards train travel. However, as regular train travel is not a prerequisite for joining the panel, this may not necessarily be the case. The impact of the sample characteristics on the model results are examined in Section 5.5.

Table 5.3. Sample and population socio-demographic characteristics

		Population	Sample
Gender	Female	50 %	49 %
	Male	50 %	50 %
	other		2 %
Age	18-34	27 %	12 %
	35-49	22 %	13 %
	50-64	26 %	27 %
	65+	25 %	48 %
Education	Low	29 %	14 %
	Middle	36 %	23 %
	High	35 %	63 %
Income	Below average	40 %	21 %
	Average	52 %	50 %
	Above average	8 %	8 %
	Did not say		21 %
Working status	Working	66 %	45 %
	Retired	23 %	42 %
	other	11 %	13 %

5.2.5 COVID-19 situation and survey context

With the survey being undertaken during the COVID-19 pandemic and various government measures in place, it is important to understand the context under which the respondents have been answering the survey. An overview of the situation and implemented measures can be seen in Figure 5.3. At the start of the year in 2022, around 70% of the Dutch population was fully vaccinated and half have also received their booster shot (Rijksoverheid, 2022b). The first cases of the Omicron variant of COVID-19 had been diagnosed in the Netherlands in mid-November 2021 (Seveno, 2021), with the government announcing new lockdown measures not long after, on December 18th. Through the course of January 2022, the Omicron variant of COVID-19 became dominant in the Netherlands, representing 47% on the 3rd and reaching 98% by the 31st of January. At the same time, with hospitalisations and ICU admissions declining, the most restrictive measures had been lifted, namely the reopening of schools and (non-essential) shops on January 15th. This was followed by the reopening of bars and restaurants on January 26th, although a proof of vaccination, recovery or testing was still required and special occupancy limits were still in place, to comply with social distancing norms. Halfway through the survey collection stage, on February 25th, a mask mandate in public indoor areas and social distancing norms (1.5m distance) had been lifted, with the exception of masks on PT (Rijksoverheid, 2022a). Mask were no longer required on PT as of March 23rd, with widespread testing of the population ending on April 11th (NOS Nieuws, 2022).

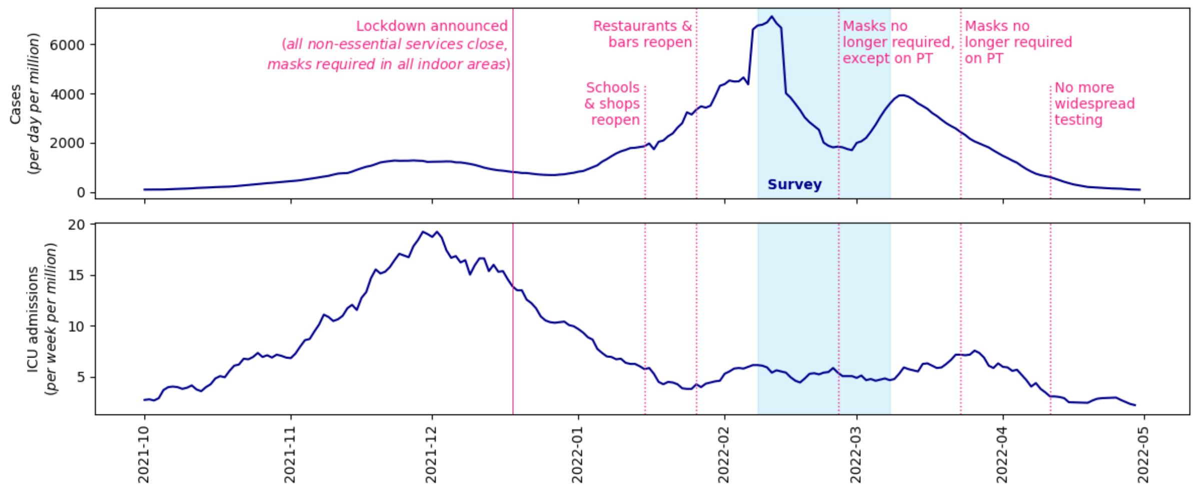


Figure 5.3. COVID-19 situation (cases and ICU admittance) in the Netherlands, from October 2021 until May 2022. The data collection period is indicated by the light blue shade.

5.3 Results

From the bridging experiment, we obtain a 4-class latent class model, with a loglikelihood of -4,030, yielding an adjusted rho-squared of 0.34. Using the sample segmentation, we estimate four weighted least squares regression models – one per market segment – which achieve R^2 values ranging from 11.3% to 15.9%. The full model outcomes, with parameter estimates and t-values are shown in Table 5.5 and Table 5.6, for the bridging experiment and rating experiments, respectively.

For the bridging experiment, multiple model specifications are tested to obtain more detailed information, particularly for the infection risk perception attribute. The final model is specified with mode-specific risk perception parameters (for air and train, the risk for car is fixed to 1 – low). Each mode is also associated with two separate risk parameters: (1) a fixed penalty that is associated with its respective mode and (2) and a time-based penalty. This allows us to test if individuals' (and different segments) perceived risk is time-dependent or not. In other words, do people feel less safe if they spend a longer time in a higher-risk situation or not. Our modelling approach also allows us to capture situations where travellers assign both a fixed and a time-based penalty to a travel mode. To retain consistency between the rating and bridging experiments, we treat perceived risk as an interval variable. We refer the interested reader to Heufke Kantelaar et al. (2022) for a detailed deliberation on why this is preferable. Considering the comfort attribute, we apply the same "fixed and time-based penalty" approach, but keep it generic across the rail and air modes. Travel time and cost are also assumed to be generic and thus perceived equally for all three modes. The impact of trip purpose, which respondents elicited prior to the choice experiment, is also tested in various specifications, however none resulted in significant parameters or improvements in model fit. Trip purpose is thus not included in the final model specification.

Estimating the LCCM models, we start by determining the optimal number of segments by means of a static class membership function (constant only) (Hess et al., 2008). In order to determine the most suitable number of classes for the latent class choice model, we consider several criteria (Table 5.4). Weighing the model fit against the number of estimated parameters, we calculate the adjusted rho-squared and BIC, where the former should be as high as possible, whereas the latter as low as possible. For both, we see that a model with seven segments is the best performing one. The size of the segments should also be sufficiently large, to guarantee a meaningful representation of the segment. For this, we apply a rule-of-thumb size of at least 10% of the sample for the smallest segment. Applying this rule, results in excluding models of six segments or more. Finally, we consider interpretability and the number of significant parameters. With the latter, we observe hardly any change between the four and five segment models. Additionally, in the five segment model, two segments are nearly identical in terms of their parameter estimates. We therefore choose to continue our analysis with an LCCM with four specified segments.

All socio-demographic information is incorporated into the class membership function, to improve the predictive capabilities of the model. If the parameters for all three segments (one segment serves as the baseline) are insignificant ($p > 0.1$), the socio-demographic is removed. This is done iteratively, until only significant socio-demographics remain in the class membership function.

Table 5.4. Number of segments and their respective model fits and characteristics

Number of segments	Adjusted Rho-squared	BIC	Number of significant parameters ($p < 0.05$)	Size of the smallest segment
1	0.1798	10,230	7 (70%)	100%
2	0.2612	9,252	10 (48%)	49%
3	0.2975	8,851	15 (47%)	16%
4	0.3131	8,709	19 (44%)	16%
5	0.3217	8,652	20 (37%)	12%
6	0.3286	8,617	21 (32%)	8%
7	0.3346	8,592	26 (34%)	6%

In the regression models, capturing the infection risk perception, all attributes are dummy coded. For nominal and ordinal attributes, this (or effects coding) is the only option. For the three ratio attributes (share of occupied seats, number of daily infections and vaccination rate), we also apply dummy coding to capture any potential non-linear effects that may be present in the perception of risk.

In the following sections, each of the four segments is described, based on their travel preferences, infection risk perception and socio-demographic characteristics. The implications of their preferences on modal split are then discussed in the following section, by means of a sensitivity analysis. The four segments are:

- Segment 1: Time-sensitive travellers (30% of the sample)
- Segment 2: Prudent travellers (36% of the sample)
- Segment 3: Frequent train-loving travellers (15% of the sample)
- Segment 4: Cautious car travellers (19% of the sample)

5.3.1 Segment 1: Time-sensitive travellers

Time-sensitive travellers are, as the name implies, the most sensitive of the four segments to travel time, with a Willingness-to-Pay (WtP) of 72€/h compared to a sample average of 40€/h.

Figure 5.4 shows the impact of perceived risk on modal preferences (fixed penalty) in the top row, whereas the bottom row displays the impact on WtP (time-based penalty). Equation 5.4 and Equation 5.5 show the approach used to calculate the WtP values. We can see that Time-sensitive travellers perceive risk as time-dependent only (sensitivity to travel time increases with risk, resulting in a higher WtP for higher risk) and do not associate any fixed penalty for risk (modal preferences are constant). Further, we observe that time sensitivity doubles for Time-sensitive travellers if the level of perceived risk jumps from low (level 1) to high (level 5). Mode-specific constants indicate a strong preference for train and the largest aversion towards the private car (all else being equal) amongst all segments. Comfort (both risk and time-dependent) is insignificant for this segment.

Table 5.5. Model fit, parameter estimates and class allocation parameters of the mode choice model

Model fit								
Null LL	-6,196							
Final LL	-4,030							
Adj. Rho-square	0.34							
BIC	8499							
Taste parameters								
	Segment 1		Segment 2		Segment 3		Segment 4	
	Est	t-val	Est	t-val	Est	t-val	Est	t-val
Constants								
Air	1.3500	3.59 ***	-1.1500	-2.74 ***	-2.2500	-2.97 ***	-3.3500	-4.24 ***
Train	2.7300	3.89 ***	0.0592	0.21	2.5600	6.02 ***	-0.0568	-0.13
Common parameters								
Cost [€]	-0.4500	-6.89 ***	-0.6120	-8.36 ***	-0.5330	-5.22 ***	-0.9220	-7.43 ***
Travel time [min]	-0.3250	-3.92 ***	-0.3100	-7.03 ***	-0.2000	-4.18 ***	-0.1400	-3.16 ***
Comfort [baseline]								
Comfort [time-based]	0.0411	0.72	0.0867	2.64 ***	0.1040	1.43 *		
Risk parameters								
Train Baseline			-0.6990	-2.86 ***	-0.5240	-3.15 ***	-0.2700	-1.34 *
Train Time-based	-0.0767	-4.50 ***	-0.0015	-0.07			-0.0620	-3.04 ***
Air Baseline	-0.0113	-0.06	-0.3480	-1.57 *	-0.1070	-0.14		
Air Time-based							-0.0344	-0.47
Class allocation parameters								
Constant	-1.3600	-1.79 **			-1.4500	-1.56 *	-0.4090	-0.43
Age [years]	0.0249	2.66 ***			0.0283	2.37 **	0.0140	1.29 *
Car ownership	-0.7260	-2.03 **			-1.3600	-3.61 ***	-0.1550	-0.45
Travel frequency	-0.1800	-0.93			0.1850	1.00	-0.3700	-1.84 *
Female	0.5350	2.22 **	*Baseline*		0.2490	0.76	0.2570	0.92
Air for short trips	0.2750	0.61			-7.5300	-7.55 ***	0.6630	0.65
Car for short trips	-1.4600	-3.65 ***			-1.9400	-2.79 ***	0.4860	1.06
Air for long trips	0.2320	0.51			-4.4700	-1.09	-2.6300	-5.53 ***
Train for long trips	0.1930	0.40			1.1400	2.41 **	-0.4030	-0.90

**** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.2$*

Turning to the perception of infection risk, members of this segment seem to be strongly influenced by the infection and vaccination rates, as well as the mask requirements. Figure 5.5 shows the impact of the different attributes on perceived risk. Official advice, like government travel advise and entry requirements do not have a strong influence on the perceived risk of Time-sensitive travellers. This seems to indicate that they prefer making their own informed decision rather than rely on the government travel advice. Curiously, all segments associate yellow advice with lower risk and red with higher risk, compared to the green. A possible explanation for this could be that people believe yellow (and orange) advise will deter enough people from travelling to that destination to make it somewhat safer, offsetting the possible higher risk which substantiated the advice. A red advice on the other hand seems to indicate to members of all segments that the risks are simply too great.

Members of this segment are quite representative of the sample as a whole in terms of income, education and gender. They have a fairly low car ownership (only 50% have their own) and are the least frequent long-distance travellers of the four, with 68% not making a single long-distance trip in 2021, compared to the 61% sample average. Those who did travel, travel above average for work, indicating that they primarily travel only when they have to (limited leisure trips). As for the stated modal preferences, they prefer train or air for shorter and only air for longer trips. This last can also be observed in the ternary chart in Figure 5.6. The ternary chart indicates the market share for each of the three available modes. The altitude of the triangle indicates the market share; the closer to the corner, the higher the market share for each of the three modes and their corresponding corners. The preference based on the ASCs is determined assuming all other attributes are equal / zero (i.e. ceteris paribus), and only ASCs enter the utility function.

5.3.2 Segment 2: Prudent travellers

Similar to Time-sensitive travellers, the Prudent travellers are also quite sensitive to time, but slightly less so, with a WtP of 50€/h. Contrary to the previous segment, Prudent travellers perceive risk primarily as both mode-dependent and time-independent, with train and car being equally preferred at low risk, with train decreasing rapidly in preference to the point where even an aircraft is preferred over a train when the perceived level of risk is very high. They are also willing to pay for a class upgrade: based on the duration of their travel, they are willing to pay an additional 14€/h to travel in first/business class.

Similar to the Time-sensitive travellers, Prudent travellers are also strongly influenced by the infection rate, vaccination rate and masking requirements. While government travel advise is also less relevant, they do consider the entry requirements more than other classes do, namely more stringent regulations make them feel safer.

Describing the demographics of this segment, Prudent travellers tend to be the youngest and most male dominant (59%) of the segments. Members of this class are also most likely to be employed and least likely to be retired of any segment. In 2021, they travelled slightly more than the average survey respondent, with 10% making four or more long-distance trips. In terms of their modal preference (Figure 5.6), they prefer using their car for shorter trips and flying for longer trips.

5.3.3 Segment 3: Frequent train-loving travellers

Contrary to the previous two segments, who exercise a considerable trade-off behaviour amongst different travel attributes, the second two segments have stronger mode-related preferences, and are thus not easily swayed to try a different travel mode. As their name implies, Train-loving travellers have a strong preference for train travel, although this diminishes in case of higher perceived risk. They are also strongly averse to flying: all else being equal, they are willing to travel 24 hours longer by train than air. According to our findings, they perceive risk primarily as time-independent and associate a fixed penalty with each mode. The parameter for comfort is borderline significant ($p = 0.15$), but indicates quite a high WtP for an upgrade of almost 20€/h or over 50% more compared to economy class (with a WtP for second class of 38€/h). This is the biggest relative WtP for an upgrade (the previous two segments have a relative WtP of 13% and 28% respectively).

Table 5.6. Model fit and parameter estimates of the risk perception regression models

	Model fit							
	Segment1		Segment2		Segment3		Segment4	
R^2	14.02%		15.85%		12.04%		11.30%	
BIC	10,751		10,635		19,300		11,686	
	Parameter estimates							
	Est	t-val	Est	t-val	Est	t-val	Est	t-val
Constant	3.2769	54.68 ***	3.2481	48.75 ***	3.2085	49.78 ***	3.2048	56.97 ***
No mask required								
Any mask			0.1752	2.20 **				
Surgical mask	-0.3019	-2.44 **						
FFP2 mask	-0.3439	-4.44 ***	-0.3618	-5.24 ***	-0.2499	-4.91 ***	-0.2424	-5.00 ***
Status quo								
Increased	0.3252	3.40 ***	0.4331	4.24 ***	0.2436	3.34 ***	0.2387	4.81 ***
Weekly disinfection	0.2315	2.61 ***	0.4534	4.82 ***	0.3296	4.67 ***	0.2444	4.95 ***
Daily disinfection								
Nothing								
Ventilation only								
AC w/o HEPA filters	-0.2530	-5.19 ***	-0.3550	-5.52 ***	-0.3236	-5.15 ***	-0.3773	-7.28 ***
AC w/ HEPA filters	-0.2997	-6.47 ***	-0.2974	-6.21 ***	-0.1343	-2.60 ***	-0.2519	-5.79 ***
None								
3G					0.1953	2.38 **		
2G			-0.2586	-3.56 ***	-0.1903	-3.42 ***	-0.1265	-2.50 **
2G+	-0.2073	-4.60 ***	-0.2923	-5.60 ***			-0.1113	-2.49 **
Green advice								
Yellow advice	-0.2240	-2.37 **	-0.1639	-2.03 **	-0.3295	-3.54 ***		
Orange advice					-0.4432	-4.64 ***		
Red advice	0.3667	3.79 ***	0.4587	5.04 ***	0.3791	6.60 ***	0.5234	10.65 ***
25% seats full								
50% seats full			0.1951	2.25 **				
75% seats full					-0.2507	-4.31 ***		
100% seats full	0.2707	5.31 ***	0.3594	7.38 ***	0.6007	9.28 ***	0.3139	6.27 ***
100 cases								
10.000 cases	0.3878	3.17 ***						
25.000 cases	0.5764	7.42 ***	0.4363	7.53 ***	0.1511	2.43 **	0.3105	5.85 ***
100.000 cases	0.3078	4.68 ***	0.2623	3.06 ***	0.2538	4.18 ***	0.2723	5.16 ***
15% vaccinated								
30% vaccinated	-0.2331	-3.12 ***	-0.3830	-5.15 ***			-0.2234	-3.03 ***
70% vaccinated	-0.1939	-2.06 **	-0.3598	-4.69 ***			-0.2369	-3.08 ***
90% vaccinated	-0.5056	-6.58 ***	-0.5679	-6.76 ***	-0.1854	-3.09 ***	-0.2763	-4.78 ***

**** $p \le 0.01$, ** $p \le 0.05$, * $p \le 0.2$*
Baseline attribute levels shown in bold italic

Frequent train-loving travellers also perceive risk differently, compared to the two previously described segments. The key differentiating factor is that they seem to base their risk primarily on the government travel advice, showing the strongest sensitivity to both the yellow and orange warnings (Figure 5.5). Along the same lines, they have the lowest sensitivity to vaccination and infection rates. This seems to indicate that they trust the official travel advice takes this into account and they do not have to concern themselves with any additional information. They exhibit mixed behaviour when it comes to entry requirements and crowding with no clear linear trend. They are nevertheless the most sensitive in refraining from traveling in full vehicles (100% occupied).

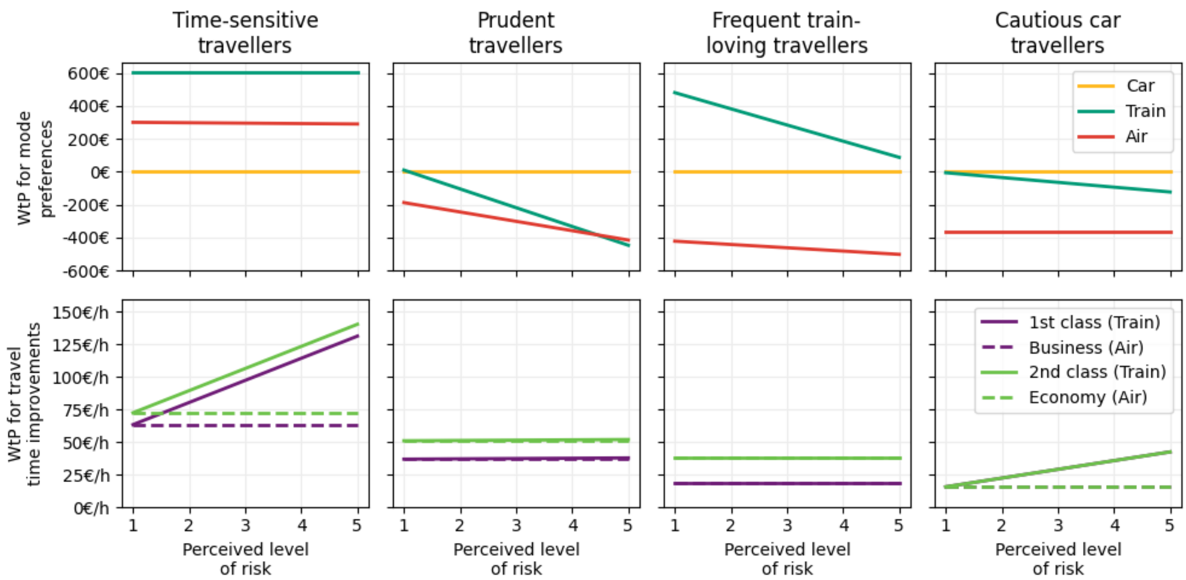


Figure 5.4. Mode preferences and WtP for travel time improvements, given different levels of perceived infection risk

Frequent train-loving travellers are, as one may expect, the most frequent long-distance travellers in 2021: 15% travelled four or more times. Their train-loving nature also corresponds to the lowest car ownership of any class, with only 35% having their own car and 37% having no car access at all (compared to the sample averages of 57% and 23% respectively). In terms of modal preferences, they exhibit a strong anti-flying and anti-car attitude, with most preferring to take train for short as well as long trips (Figure 5.6). They are the oldest, most female dominated segment (57%), having on average the highest level of education.

Equation 5.4 Willingness-to-Pay for individual modes

$$WtP_{mode} = \frac{ASC_{mode} + \beta_{risk,mode} \cdot Risk}{\beta_{cost}}$$

Equation 5.5. Willingness-to-Pay for travel time savings

$$WtP_{time} = \frac{\beta_{time} + \beta_{risk,mode,time} \cdot Risk}{\beta_{cost}}$$

5.3.4 Segment 4: Cautious car travellers

The last segment we uncover has the lowest WtP towards travel time improvements: 15€/h. Interestingly, cautious car travellers seem to experience risk both as a fixed penalty and time-dependent. Although, judging based on the parameter significance, time-dependence is more important to decision-makers. In relative terms, they are the most sensitive to increasing risk on a train, as the sensitivity to travel time in high risk situations is almost three times (2.77) as high as in low risk situations. This perhaps also explains their strong preference for car, as it is perceived as safer (and was also presented as such in the survey).

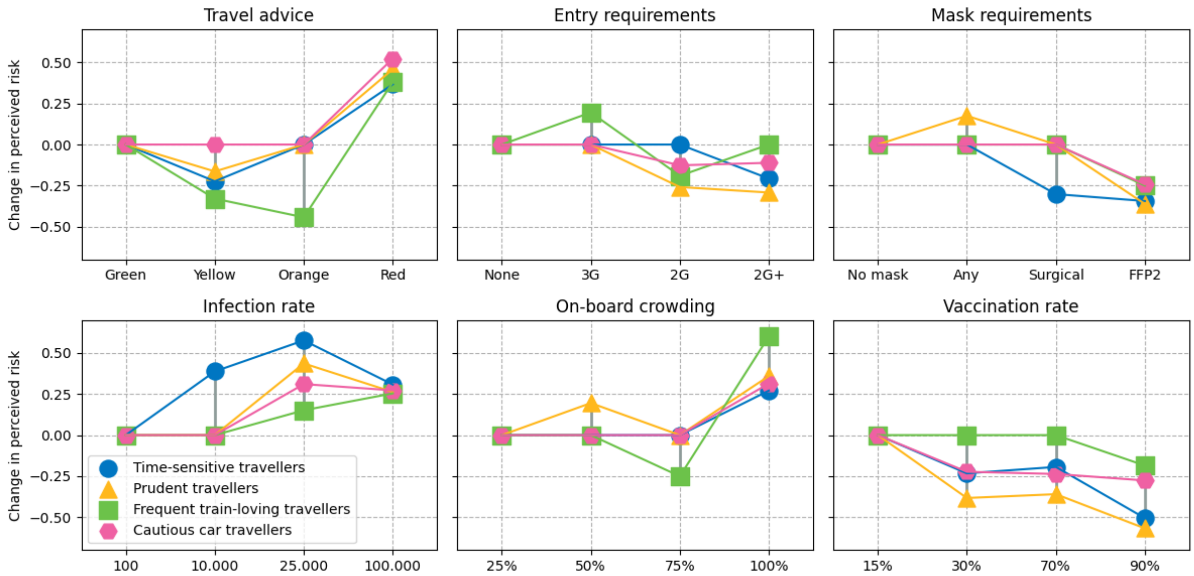


Figure 5.5. Sensitivity to different risk factors for the four market segments

Moving to what influences their perceived level of risk, they seem to exhibit the most average perception of the different attributes. However, they are the only class to not see a yellow travel warning as lowering risk. They also perceive a red warning as the most risky out of any class.

Conversely to the previous segment and analogous to their name, this segment has the highest car ownership, with 68% owning their own car and only 15% not having it at all. Their high car ownership likely influences their modal preferences, as they strongly prefer to use their car for making any kind of long-distance trips. When they travel, it is usually not alone, but with their partner or family.

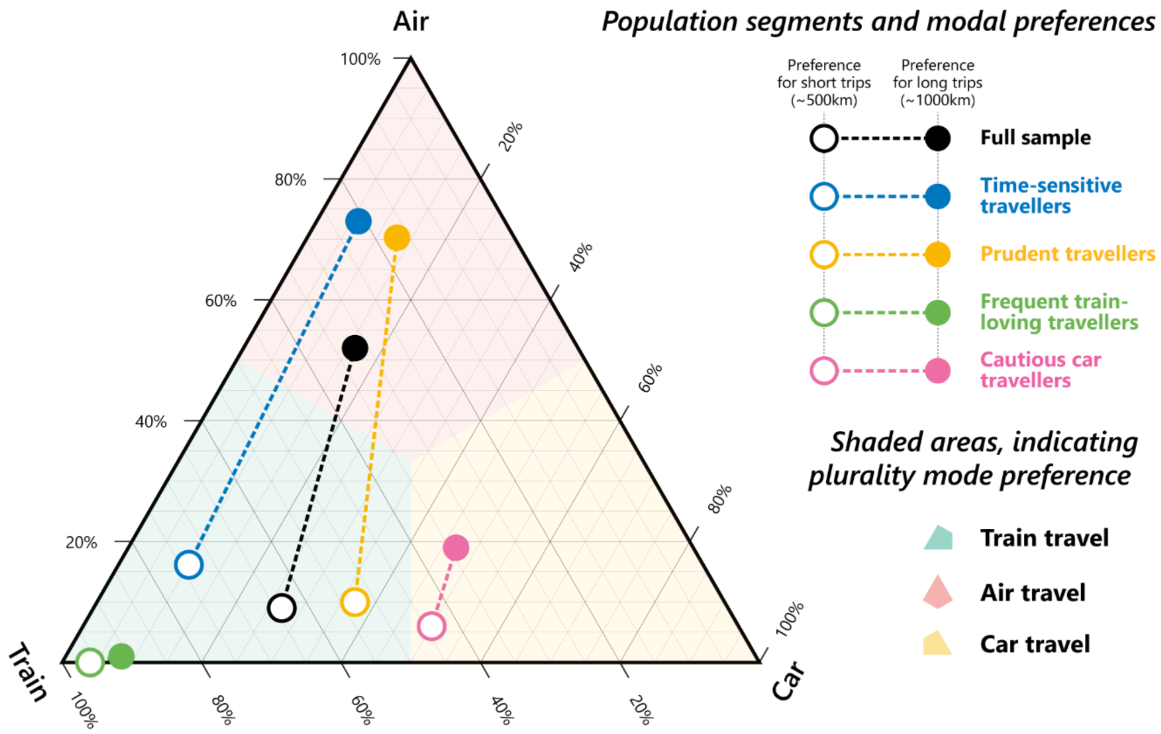


Figure 5.6. Market share of different modes, based on segments' modal preferences

5.4 Implications

To better understand how the obtained parameter estimates impact mode choice, we perform a sensitivity analysis, wherein we explore how the modal split is affected for different trip lengths and different levels of perceived risk. As the sample is not representative of the Dutch (travelling) population, the sizes of the individual segments are thus also not assumed to be representative. Hence, we do not present a joint "population" modal split in the analysis, but rather analyse changes at the level of the individual segments. The results are presented in Figure 5.7.

In the analysis, the level of perceived risk is only varied for the train, Levels 1 (low risk), 3 (medium risk) and 5 (high risk). As can be seen from Figure 5.4, the impact of perceived risk on flying is minimal, both with respect to time and overall. We therefore decide to fix the perceived risk for flying to Level 3. Remaining consistent with our survey, the perceived risk of car is fixed to Level 1.

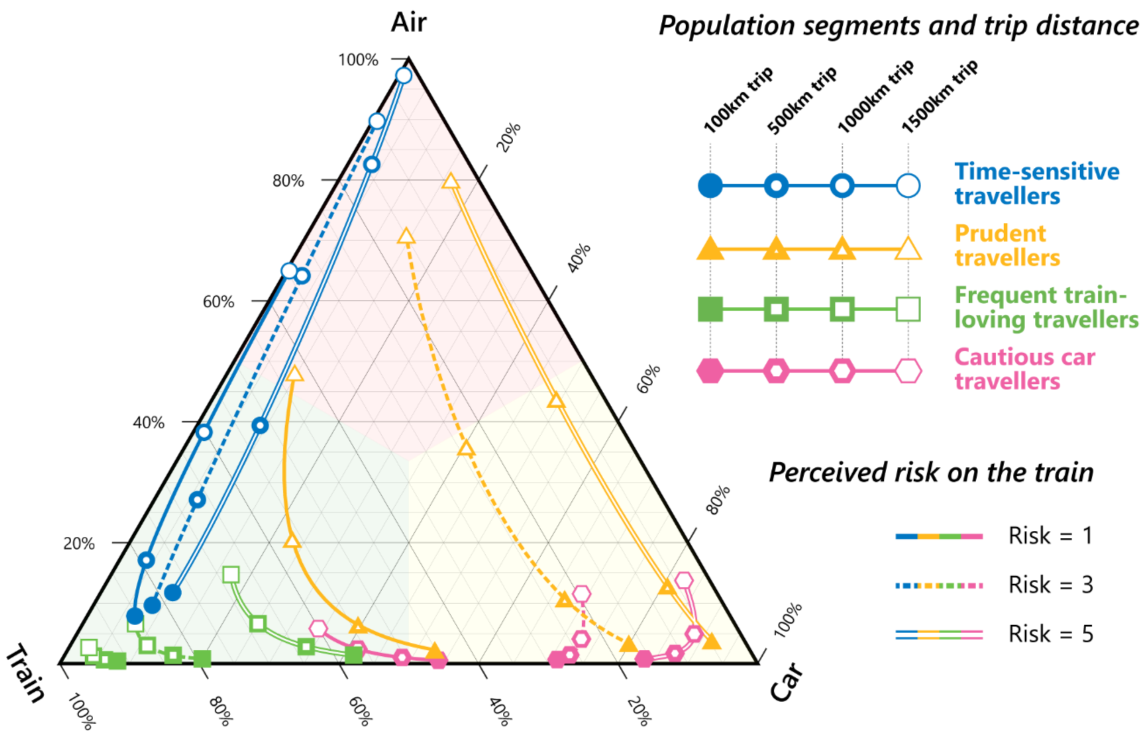


Figure 5.7. Market share of different modes and the sensitivity of market segments to the variation of the level of perceived risk when travelling by train

To obtain a value for travel time based on travel distances, we apply a linear function (Figure 6.5 in Appendix G) where each mode is associated with an average travel speed and a constant (intercept) that corresponds to the time spent waiting at the airport/train station. For the train, Figure 6.5 shows multiple different speeds; for this analysis, we assume an average speed of 160km/h, which corresponds to a partial use of high-speed rail infrastructure. For a more detailed analysis, where the variation of average train speed on market share is investigated, we refer the reader to Appendix H.

Determining price is done in a similar manner to the travel time. Based on pricing data of long-distance trips in Europe (Tanner & Provoost, 2023), we obtain a linear function for price based on distance for all three investigated modes. The functions can be seen in Figure 6.5 in Appendix G.

From the results, the first thing we notice - as is already alluded to the previous section, through the names of the segments – is that the first two segments (Time-sensitive and Prudent travellers) tend to display more trade-off behaviour, with the shifts between modes being much more pronounced. Interestingly, they each seem to have their preferred land-based mode for short-/medium-distance trips, i.e. train and car, respectively - and flying for longer trips. With respect to Time-sensitive travellers, we further observe their strong aversion to using the car, by the fact that with increasing risk on a train, they almost exclusively shift to air. For example, for a trip of ~1000km, with the risk increasing *low-medium-high*, the share of trips by train decrease *60%-30%-15%*, whereas the share of people choosing to fly increases *40%-65%-80%* and while the car sees a small increase *0%-5%-5%*.

Prudent travellers are the most mode-agnostic, exhibiting the strongest shifts between modes given the varying distance and risk. When risk is perceived low for the train (lower than for air travel), the train actually becomes the dominant mode for distances between 200km and 1,500km, with the peak observed between 500km and 1,000km. This train ridership peak also sees the biggest drop if perceived risk increases. For 500km-trips, it drops from 55% to 25% to 5% for low, medium and high risk respectively.

Moving to the second two segments, the more mode-fixed ones, they predominantly shift between land-based modes, with both largely refraining from flying: less than 15% choose it even for trips of 1,500km. For the competition between the train and car, a lower perceived risk on the train naturally leads to a higher share for the train. Interestingly, if the risk of train and car is equal, Cautious car travellers would actually use train more than car, if the trips are over 500km. However, this drops to below 30% for a medium level of risk and below 15% for high risk.

Frequent train-loving travellers seems to be least affected by this, highlighting their dedication to the train and that even very risky situations will not persuade them to shift modes, with the lowest train share of 60%, observed for short high risk trips (100km).

With respect to policies and factors affecting the level of perceived risk, their somewhat low magnitude means their impact on market shares is also not as substantial. Vaccination rate and travel advice for example both reduce or increase risk by roughly 0.25 to 0.5 points on the risk perception scale. This usually translates to a difference in market share of up to 5 percentage points, with lower risk situations benefiting the train and higher risk being in favour of the car or plane.

These results clearly indicate that making passengers feel safer on the train will result in them using it more often. And while this is an important benefit, lowering travellers' perceived risk is beneficial in its own right, as it makes the travel less stressful and more enjoyable. It may also convince more travellers to try the train. If train is perceived as less safe however, air and car travel both benefit from it, offering a modal substitution. As the sizes of the segments within the population are not known, it is difficult to determine which sees more shifting travellers. Time-sensitive travellers shift almost exclusively to air, Frequent train-loving and Cautious car travellers shift predominantly to car, whereas Prudent travellers seem to shift to both.

5.5 Conclusion & Discussion

This research investigates the subjective perception of risk, within the context of long-distance (international) travel. A Hierarchical Information Integration (HII) approach is applied to measure the perceived risk and the mode choice behaviour for trips of approximately 500km and 1,000km. The data obtained through the Dutch Railways' panel is analysed by means of a Latent Class Choice Model (LCCM). To analyse the subjective perception obtained through the rating experiment, we present a novel approach to analyse this for different population segments. We apply a Weighted Least Squares (WLS) regression model (as opposed to the commonly applied Ordinary Least Squares), and integrate therein the individual class membership probabilities obtained in the LCCM.

Based on the estimated LCCM, we uncover four distinct segments with respect to their varying travel behaviour preferences. Two segments, dubbed the *Time-sensitive travellers* and *Prudent travellers*, have an above average value of time: 72€/h and 50€/h, respectively. They also each have their preferred land-based mode for shorter trips of (train and car, respectively) and flying for longer distances. The two segments with lower values of time, the *Frequent train-loving travellers* and *Cautious car travellers*, are more tied to their respective mode of choice (as their names imply), switching to other modes only in extreme circumstances (very low/high risk and or a very long trip).

With respect to risk, some seem to perceive it as based on time (a longer exposure time results in a higher disutility), whereas others see it as a fixed penalty, dependant on the level of risk and the travel mode, but not on travel time. In cases when the risk is time-based, that is the case only for the train, but not for the flight. *Time-sensitive travellers* tend to perceive risk as time-dependent, with the difference in travel time penalty almost doubling (a 95% increase) when increasing the level of perceived risk from a low to high. *Prudent travellers* and *Frequent train-loving travellers* on the other hand tend to perceive risk as time-independent. In both segments, travellers associated a bigger penalty per train travel-minute than per air travel-minute. Finally, *Cautious car travellers* tend to see it as a mix of both, a fixed and a time-based penalty.

Surprisingly, only a single segments showed some degree of sensitivity, yet low, to risk while flying (*Prudent travellers*), that being the time-independent perception. And even then, the significance level of the parameter is quite low. One possible reasoning could be that flying is perceived equally risky, no matter the level of risk, a preference which is captured not in the risk-perception parameters, but rather by the mode-specific constant. This could also explain why air (including the time spent at airports which is an integral part of the air travel experience) had the lowest overall preference amongst all four segments.

What is considered risky tends to differ among segments, however they do generally tend to impact it in the same direction, with the main difference being in magnitude. *Time-sensitive travellers* and *Prudent travellers*, seem to prefer analysing the data themselves, being the most sensitive to infection and vaccination rates, while simultaneously being less affected by government travel advice. *Frequent train-loving travellers* and *Cautious car travellers* on the other hand, exhibit the opposite behaviour, with the official advice being an important deciding factor.

Comparing the impacts of different risk factors, it can be seen that certain policy measures (mask wearing, entry requirements etc.) can help in reducing the level of perceived risk, but their contribution to reducing perceived risk tends to be lower than the increase caused by external factors. Some factors, i.e. crowding and travel advice, contribute to reducing risk at some levels while increasing for other levels (for the same traveller segment), which seems counterintuitive. A possible explanation could be that in the case of travel advice, a green level may indicate to people that there is no real risk and thus travellers may perceive that too many people will travel, making it less safe. With yellow and orange, this may seem safer as there is some warning, reducing the traveling public and making it somewhat safer. Then at the red level, it becomes riskier again as it is the highest possible level and travellers may perceived it as very unsafe.

Curiously, the impacts of cleaning and air circulation are very inconclusive. With respect to air circulation, the model shows that three of the four segments see the addition of HEPA filters as more negative. This likely stems from the fact that the majority do not know what HEPA filters are or how they work, as this was not explained during the survey. Regarding the cleaning policy, travellers' expectations of the current norm seems to be a daily disinfection, as all four segments saw no difference between the two. Furthermore, performing only weekly disinfection or merely increased cleaning of touchpoints was perceived as more risky than the status quo by all segments.

It is also important to note that risk perception and safety measures can have a profoundly different impact on travellers on long-distance trips as opposed to commute trips. From previous work, crowding is often cited as a major concern from travellers on commute trips. In our results however, this does not seem to be the case. While we can see a penalty for 100% occupancy, this is not very high, whereas occupancy levels below 100% have a mixed and negligible impact. This could potentially stem from a higher traveller density typically observed on commute trips, with people often standing. In contrast, long-distance trips tend to have more space for passengers, with people standing being a very uncommon sight. The much longer exposure time experiences on long-distance trips (up to several hours) could also contribute to a lower reduction in risk perception of safety measures, as travellers may perceive the measures not (as) effective to mitigate exposure during such a long time.

With that in mind, it is apparent that policy measures, while not fully mitigating the increase in risk due to high infection numbers, do still help in making travellers feel more at ease. It is important to clarify however, that while some policies may reduce the perceived risk of individuals, these do not necessarily coincide with measures which tend to be perceived as actually reducing the rate of transmission. There may be measures which make people feel safer, but have no noteworthy impact on the viral transmission, whereas others may not be perceived as relevant at all, they may have a significant role in reducing transmission. And, as can also be observed from our results, the perception of measures also varies between people. Hence, a measured and balanced combination of measures is likely needed.

The Weighted Least Squares regression proved to be a good approach to distinguish the perception of risk among different travellers. Especially for factors such as infection, vaccination and travel advice, we see a clear trend for each of the segments. Nevertheless, a key outlook for future research is to develop a model, which is capable of segmenting the sample based on both the rating and bridging experiments simultaneously. In our study, this is done purely on the bridging experiment, meaning that differences in travel behaviour are the dominant driving force behind the segmentation, and the key differentiator among travellers. If segmentation would be done exclusively on the rating experiment or ideally on both, we would expect to see a more pronounced difference in risk perception as well.

Our results are based on a sample that is obtained through the Dutch railways' panel which might be representative of the travelling population, however, this cannot be empirically verified. With that in mind, it is important to not generalise the conclusions of our study onto the population. By estimating an LCCM, this issue can be somewhat mitigated, as each individual group of travellers is allocated to a different MNL model. We therefore do not make any claims in regard to the sizes of the segments in the sample. Given our fairly large sample, and the decent representation of all groups, we believe however that we do capture the key traveller segments present in the population while their shares remain unknown.

Additional studies on long-distance travel and safety and risk perception, in different contexts and trip purposes, should further expand on the findings from our work. A dataset based on a representative sample of the population could offer information on the sizes of different traveller segments as well, to benchmark against our results. Additionally, including an opt-out option would also allow concluding on what is the tolerance (for price, time and risk) that travellers are willing to accept on such trips, as they tend to be less essential than commute trips: for leisure trips for example, the decision order of choosing the destination first and then the mode/route is likely to be inverted, and thus the threshold to opt-out may be lower. Business travel, while much less flexible in the past, has also seen a fundamental shake-up with online meeting becoming the norm.

Chapter 6:

Conclusion

The impact of disruptors on individuals and their travel behaviour has been significant and is expected to continue shaping the way people move. Aiming to quantify the impacts of present-day disruptors on the public transport industry, this thesis advances the methods employed to study travel behaviour to get a better understanding of behaviour to improve policymaking, modelling and enabling the design of transport systems that better reflect the needs and desires of travellers. By applying these methods, the thesis also provides insights into the effects of internal and external disruptors on travel behaviour and modal shift of the traveling public in the context of different trip types.

6.1 Main findings and conclusions

This chapter summarises the main methodological and substantive contributions and findings and thereby provides answers to the research questions formulated in Section 1. By answering these questions, the overarching goal of quantifying the behavioural impact of disruptors on public transport has been fulfilled.

How would the introduction of on-demand mobility services impact everyday trips in urban areas? (Chapter 2)

Trips in urban areas are some of the most common that people make on a daily basis, be it for work, education, errands, leisure, etc. In the Netherlands, more than half of all trips are performed in urban areas and are shorter than five kilometres. Urban areas are also where on-demand mobility services like ride-hailing first made their appearance around a decade ago. To have a good idea of how on-demand mobility services impact everyday trips, understanding the behaviour of people in the urban context is vital. To that end, we carried out a stated preference survey throughout the Netherlands (including residents of rural areas, for trips in an urban environment), where respondents had to select their preferred travel mode for six hypothetical work/education trips and six hypothetical leisure trips. This data was analysed by means of a latent class choice model, allowing us to get a better understanding of different user groups within the population, analysing their specific travel preferences, attitudes, and experience with similar services.

Our results identify four distinct traveller groups for urban trips in the Netherlands, two of which may be potential users of on-demand service. The segment showing most potential to take up these services are the so-called **Flex[7]-ready individuals** (roughly 9% of the population). They are the most mode-agnostic (no strong preference for a specific mode) of the four segments and the only ones to show a positive (albeit weak) preference towards Flex compared to any of the other investigated modes, namely bicycle, car and public transport. Their high Flex-use potential also manifests itself through their low value-of-time, opting for Flex only when it is relatively affordable. The second segment are the **Tech-ready individuals**, who are also fairly mode agnostic (although still perceiving Flex most negatively) but have – in contrast to Flex-ready individuals – a high value-of-time. Both groups show positive attitudes towards technology and the use of smartphones, with the former group also having a positive view of sharing and seeing the benefits of not having to drive oneself. This last point highlights their key difference in the type of service they would most likely opt for, with Flex-ready individuals opting for shared Flex (pooling a ride with other passengers), while Tech-ready individuals opting for private Flex (a private ride, not dissimilar to a taxi). The two remaining segments, showing limited potential for adopting Flex for urban trips are **Sharing-ready cyclists** and **Flex-sceptic individuals**. While the former do not have negative views towards Flex and sharing, their fondness of the bicycle means they will hardly use any other mode for their everyday urban travel. The latter group on the other hand, show a very negative view towards anything new and innovative, sticking to their car for most of their travel.

These findings have implications for public transport. By analysing the existing travel behaviour of the user groups, we were able to assess which modes are more likely to be substituted by

[7] "Flex" is a term used to refer to services resembling on-demand mobility in the Netherlands and was used throughout the survey and research for the sake of respondent clarity.

on-demand mobility, should it be introduced. Given that Flex-ready individuals are the most likely on-demand mobility adopters and the most frequent users of public transport, this suggests that the primary modal shift would be from public transport to on-demand services. Sharing-ready cyclists are also fairly frequent users of public transport, yet there seems to be limited impact of on-demand mobility on their travel behaviour. Considering the type of public transport services used, Flex-ready individuals are particularly frequent users of local public transport (buses, trams, metros), whereas Sharing-ready cyclists mainly use the train (for medium-distance trips between urban areas). This further reinforces the notion that particularly urban public transport may be highly affected by the arrival of on-demand mobility services.

Given that the performance of any kind of transport service is inherently variable, how does this variability impact the perception of said service? (Chapter 3)

Transport services of any kind are subject to variability in their performance (level-of-service). On-demand mobility services are no exception and may even have their own unique set of variability to contend with. Waiting time and in-vehicle variability are most reminiscent of the same variabilities in other types of transport: they may occur due to the stochasticity of road traffic, the passenger(s) and the driver. What is perhaps more unique to on-demand mobility and ride-hailing in particular, is ride cancellation. Ride-sourcing drivers are (to a certain extent) independent decision-makers and may accept or reject the rides allocated to them. Waiting time variability and potential ride cancellation both occur in the same phase, namely pre-trip. We conducted a stated preference survey and analysed it by means of an instance-based learning approach to evaluate how passengers internalise service variability through trial-and-error and how that impacts their future decision-making. We also tested for different types of habitual behaviour and inertia.

We find that respondents' memory fades relatively quickly, with the most recent experience having by far the strongest impact on their next choice: with two experiences, the more recent one makes up 75% of the total weight. Even with a total of ten experiences, the most recent experience alone contributes 55% to the decision. Having the ride cancelled is valued as a penalty of roughly €4.45 or in other words, the passenger would have to be offered a discount of that scale in the next decision-making moment to still consider said company ceteris paribus. In terms of the valuation of time, we differentiate between an early pick-up (earlier than anticipated) and a late pick-up (later than anticipated). Counterintuitively, an early pick-up weighs more than a late pick-up of the same magnitude. For example, passengers seem to be willing to pay around €0.44 for each minute of saved waiting time prior to the expected pick-up time. For saving a minute of waiting time after the estimated pick-up time, this willingness to pay is at €0.30.

This information is vital for operators of on-demand services, who need to provide travellers with upfront information on the expected outcome of the trip. Based on the results obtained in this research, it would seem most beneficial for operators to indicate a fairly long waiting time (at a high percentile of the distribution), resulting in exceeding the passenger's expectations. This however may not always be optimal. In this research, the planned waiting time was not varied and thus not evaluated. Similar studies from the field suggest that planned waiting time is weighted equally, if not more negatively than unexpected waiting time. These findings suggest that although passengers may "reward" earlier-than-planned pick-ups, the long planned waiting time when booking the trip may be unappealing enough for the traveller to not even consider it an option.

In what way and order do users make choices when making a multi-leg public transport trip involving on-demand mobility? (Chapter 4)

Contrary to other trips, trips with public transport (almost) always include multiple legs. This is because public transport stops or stations are rarely located in or immediately next to a passenger's origin and/or destination. A trip on public transport will therefore almost always involve access and egress travel, for which multiple different modes may be used, such as walking, cycling, car or even a more local mean of public transport (e.g. using a bus to access a train station). When passengers are faced with multiple combinations of access modes and stations to access, the question of the order of choices is raised. Do travellers first select their preferred access mode (e.g. cycling) or their preferred station (e.g. the central station of a city)? In the light of multi-modal public transport trip chains, on-demand mobility has frequently been touted as a solution for the first/last mile problem facing public transport. To investigate this relation, we undertook a 3-step stated preference approach, asking respondents to select their preferred access mode to two different (hypothetical) stations. We then showed them the two access modes and their respective characteristics alongside the two stations and their respective level-of-service, asking the respondents to select their preferred combination of access mode and station. We analysed this data by means of a latent class choice model, where we specify different nesting structures for each class. This allowed us to observe if respondents are more likely to be allocated to a class where a "mode-first" nesting structure is specified, or to a class with a "station-first" structure.

Our results show that the population is almost evenly split, between choosing the mode first (51.8%) and choosing the station first (48.2%). In the mode-first segment, the mode was specified to have its own nest, with on-demand mobility showing a significant, yet weak nesting structure. In general, the strongest nesting structure was observed for public transport and the weakest (essentially no nesting) for the car as an access mode. Analysing the differences between travellers based on their choice order, we observe that "station-first" individuals tend to be older, are more likely to live in smaller households in urban areas and are somewhat lower educated than average. In terms of their attitudes, they are more likely to be Flex-positive, meaning they are more comfortable sharing and also see the benefits of not having to drive themselves and being able to use that time more effectively.

Evaluating the impact of introducing Flex services shows that if nothing else changes, they obtain a minor market share in the station access domain. A positive result is that they seem to attract an above average share of car users. Flex services, however, cannot be a substitution for fully fledged public transport services. If a public transport service is fully replaced by Flex, only a minority of its users would indeed shift to Flex, with the majority switching to either car or bicycle, depending on the access distance to the station and the parking cost.

What was the impact of the COVID-19 pandemic and the restrictions across countries on travel behaviour for long-distance cross-border travel? (Chapter 5)

The COVID-19 pandemic has had a profound impact on travel behaviour, with short-, medium- and long-distance trips all being severely impacted. Due to the international nature of long-distance trips in Europe, these perhaps saw the most drastic change, with various national policies effectively halting any non-essential international travel. Once national borders started re-opening, with certain regulations in place, many travellers were still hesitant to travel. To analyse the impact of perceived risk on long-distance travel and mode choice, we carried out a stated preference survey with a hierarchical information integration element, allowing us to study the perception of risk and how it affects behaviour. We then estimated a latent class choice model to uncover different user groups within the population. To obtain the perceived risk of each individual group, we applied a novel approach by estimating a weighted least squares regression model on the respondents' risk perception. To get a deeper understanding of how this perception varies for train and air travel, we specified separate parameters for each mode, and also investigated if this perception is influenced by the amount of time spent travelling, i.e. is the perceived risk height, if the trip is longer due to longer exposure time.

Based on their responses, we uncovered four types of long-distance travellers with respect to COVID-19 infection risk. Two groups (**Time-sensitive travellers** and **Cautious car travellers**) seem to perceive risk as time-dependent, while the other two as independent of the journey duration. Time-sensitive travellers have the highest willingness-to-pay and are also the most time-sensitive to infection risk, with travel time perceived twice as negatively in a very high-risk situation as opposed to a very low risk situation. Prudent car travellers have a similar penalty ratio between low and high risk, but have the lowest willingness-to-pay (15€/h, compared to 72€/h for Time-sensitive travellers – both in the very low risk case). The other two groups (**Prudent travellers** and **Frequent train-loving travellers**) associate risk more with the specific travel mode. Both perceive train travel as marginally the riskiest (the increase in penalty per risk level). In terms of the influencing factors, infection and vaccination rate in the destination country are strong predictors of perceived risk.

With respect to the impact of different policies on perceived risk, the impact is varied. Yellow and orange travel advice reduced risk (compared to green), while red universally increases the risk (compared to green). In terms of mask mandates, only FFP2 masks seem to have a clear impact on reducing perceived risk, while other types (cloth and surgical) see mixed results. The same can be said about entry requirements, with testing and vaccination proof having some, albeit mixed impact on travellers' perception of risk. Finally, on-board crowding only has an impact if the vehicle is full (100% of seats occupied). If 75% or fewer are occupied, the impact is limited to none.

6.2 Implications for practice

Disruptors are a common occurrence in almost any field, and usually catch the established industry by surprise and unprepared. To properly respond to the emergence of a disruptor in the field of public transport, operators and policymakers need accurate and relevant information about the travellers and their behaviour, preferences, attitudes etc. Through this dissertation, we analysed the travel behaviour of passengers in the light of two different disruptors, namely on-demand mobility services and the COVID-19 pandemic, both of which had and continue to have a significant impact on public transport. In this section, the implications of our findings on the public transport industry are discussed, from the perspective of the three main stakeholders: (1) the public transport operators, (2) providers of on-demand mobility services and (3) policymakers at the local, regional and national levels.

Implications for public transport operators

When they first entered the streets, on-demand services promised to revolutionise transport, promising to offer a service more convenient than the car or public transport. With that notion, some local public transport providers decided to replace lower demand/frequency lines with an on-demand service instead. Our findings show that by replacing the public transport alternative with an on-demand one, only a minority of users will actually make this shift, with the majority shifting to either car or bicycle (*Chapters 2 and 4*). Nevertheless, public transport operators are the prime candidates to introduce on-demand services. Being the ones in charge of the introduction, they can avoid the pitfall of abstracting their own riders and rolling out the service in areas where public transport supply is limited or inexistent at the moment, or where demand may even be exceeding supply. Even though many on-demand users come from public transport, a fair share also switches from the private car (*Chapters 2 and 4*). Integrating public transport and on-demand services (where public transport operators provide on-demand services as a supplement to their existing supply) would prove particularly beneficial for access/egress trips to public transport stops. In the case of medium-distance journeys by train, on-demand services could provide a valuable alternative to many, who currently use their car to access the train station (*Chapter 4*). With respect to COVID-19 and the associated perception of risk, operators of long-distance train services should be aware that their service is likely to be more affected than air travel when factors affecting perceived risk are on the rise. At the same time, risk-reduction measures seem to have mixed and limited impacts on perceived risk (*Chapter 5*) and operators are also not fully independent to select implementation measures but rather have to comply with public health regulations.

Implications for on-demand mobility service providers

In addition to public transport operators, our findings are also relevant for on-demand service providers, both private operators as well as public transport operators offering these types of services. A frequently praised advantage of on-demand services is their ability to transport multiple passenger in a single vehicle at the same time. For this, passengers pay a reduced fare, while the operating costs for the provider/driver are also lower. Our findings suggest that the (perceived) penalty for sharing a ride is not that substantial. In other words, passengers are not willing to pay that much extra for a private ride, compared to a shared one. For example, if a shared trip lasts roughly five min more than private one, passengers are only willing to spend €1-2 extra to get a private ride. Results also show that sharing does not seem to be a time-based penalty, but rather a fixed penalty, irrespective of the trip duration (within the tested range of 8 to 16 minutes) (*Chapter 2*). In the case of waiting time prediction, our findings suggest that operators should show a waiting time that is above average, making sure that most of the likely outcomes are shorter, resulting in a shorter than expected pick-up time (*Chapter 3*). Other research however would suggest that a high initially predicted waiting time would turn away too many passengers – combining the results therefore indicates that a balanced prediction is the most appropriate. Finally, as on-demand services may also be subject to cancellation (due to the driver's decision, vehicle unavailability, etc.), our results also show how negatively this is perceived by passengers and what level of discount they expect at the event of a cancellation. Finally, we also analysed the barrier-to-entry, which is the perceived barrier that users associate with trying a new service for the first time. Based on our findings, the monetary value of such a barrier is roughly equal to €2.00. Putting it differently, new market entrants need to provide a discount of roughly such magnitude to attract new customers more easily.

Implications for policymakers

Finally, we discuss the implications of our findings for policymakers. As the ones with the most leverage over high-level decisions in public transport, their influence is the most far-reaching and potentially also the most significant in the future, especially with respect to achieving a more sustainable transport system. Firstly, as already mentioned for public transport operators, policymakers should be cautious when allowing new on-demand mobility services to enter the market. The results from our research indicate that most of their passengers are former public transport users (*Chapter 2*) and thus do not contribute to reducing congestion or vehicle miles travelled, but actually make the situation worse, increasing air and noise pollution. Instead, a coordinated approach of public transport and on-demand complementing each other is advised, as this can have much more beneficial outcomes (*Chapter 4*). When it comes to replacing fixed public transport services, caution is advised. In the case of low-demand routes, a decision needs to be made, whether replacing it with flexible services is truly the best option. While operating costs may be reduced, ridership will likely decrease as well. If the demand is really to low to warrant any fixed service, a flexible service still provides a bare minimum accessibility for those without other alternatives. In other cases, more appropriate scaling of the fixed service may be more desirable (i.e. smaller vehicles). On-demand services should also not be allowed to replace fixed public transport services, as they will most likely reduce ridership. Secondly, pooling can and should be incentivised to better utilise the available space in existing vehicles. This can be done through an appropriate pricing policy and the additional travel time due to it could be somewhat reclaimed by allowing on-demand vehicles to operate as public transport vehicles (e.g. using dedicated lanes and having signal priority) (*Chapter 4*). In terms of COVID-19, the measures that proved most effective in reducing perceived risk of travellers tend to be those implemented by governments and thus policymakers, rather than individual operators. Although the impact was somewhat mixed, entry regulation (negative test and vaccination proof) and mask mandates did show a risk reduction effect. This is especially important as train travel tends to be more strongly affected when the perceived risk of infection changes (*Chapter 5*).

6.3 Future research directions

In addition to the implications for practice, this dissertation also provides several avenues for future research to be explored. These recommendations are provided in this section for two distinct themes, namely **New behavioural insights** (application-related research directions, aimed at uncovering additional insights into travellers' attitudes, preferences and perceptions) and **Advancement of behavioural models** (methodology-related research directions, advancing the techniques used to obtain behavioural insights).

New behavioural insights

Insights into traveller behaviour are obtained through stated preference data (as done in this dissertation), revealed preference, or a combination of both. As outlined in Section 1.3, each approach has its benefits and drawbacks and depending on the goal and resource availability, one may be preferrable over another. However, solid behaviour understanding can only be obtained through multiple studies, utilising different approaches. With that in mind, more research into shared mobility and specifically on-demand mobility, using also RP data, would be highly beneficial to showcase how travellers actually make use of these services. Over four years on since the start of this research, on-demand services have become more commonplace and thus data may be more readily available.

To get a better understanding of the potential of on-demand services as an access/egress mode to increase ridership on public transport, the main leg of the trip should also be compared with different modes (mainly the private car). In this way, we can obtain a more clear understanding of what the addition of a new alternative would mean and how potential substitution patterns would look like.

Investigating the role of on-demand services on the egress / activity side of a public transport trip would also be advised. Although activity-end trips tend to be shorter in distance and thus favour the use of active modes, travellers tend to not have any of their own means of mobility on the activity end, highly increasing the potential attractiveness of shared modes, including on-demand mobility.

With more of these services present, an analysis of their usage is also warranted, investigating not only the passengers' perception, but the operational characteristics, inferring to both the drivers, but also the operator. Of particular interest is the analysis of services where on-demand mobility replaced fixed public transport services: what were the outcomes of this change, how did it impact ridership, operating costs, vehicle-miles travelled, congestion, accessibility etc.

As the concept of Mobility-as-a-Service is moving from concept and trials to more fully-fledged operations, the role and added value of on-demand services within MaaS should be investigated. MaaS packages include many different types of services and how much of each is offered is crucial for the success of the service. On-demand mobility may be an invaluable service for some users and its addition to the package may just convince them to opt for it. Analysing this potential added value for different user groups would thus be highly beneficial.

In addition to short-distance / urban services, on-demand mobility may also be an interesting alternative for longer trips: medium-distance trips (i.e. inter-city commute) or even long-distance international trips. This may be of particular interest between destinations with limited air and rail connectivity, providing an alternative between long-distance bus services and driving oneself. Such services already exist in an informal nature (peer-to-peer ridesharing), but may be an alternative worth investigating even for an official on-demand mobility service provider.

For long-distance trips in light of external disruptors (such as the COVID-19 pandemic), different trip purposes should also be investigated, to get a better understanding of how this will impact behaviour. We know that travellers tend to have a lower willingness-to-pay in leisure trips as opposed to commute trips, but we do not know how this translated into risk perception. Trip purposes such as business, holiday and visiting friends and family (VFF) may all have different perception of risk as well as other trip-related attributes. In the case of the COVID-19 pandemic, essential and non-essential travel should also be evaluated, with non-essential travel having an additional alternative, namely an opt-out (not travelling at all if the situation is deemed to risky or none of the alternatives are attractive enough).

Finally, long-distance travel (particularly with a holiday trip purpose) can be highly influenced by the accessibility of the destination. So, similarly to what was done in Chapter 4 with a joint analysis of access mode and station choice, a joint evaluation of destination and mode choice could shed light on how holiday travellers make choices. Do they pick easily accessible destinations, choose a specific destination no matter the ease (or difficulty) of accessibility, or most likely, a combination of both.

Advancement of behavioural models

Behavioural insights and preferences in this thesis are based on various discrete choice modelling approaches. All four chapters in this dissertation also apply methods aimed at capturing respondent heterogeneity, with three chapters utilising some form of latent class clustering, with the analysis in Chapter 3 making use of a mixed logit approach. A novel approach of combining latent class clustering with a hierarchical information integration approach was operationalised in Chapter 5, using the obtained sample segmentation on the rating experiment by means of a weighted least squares approach. However, this was done in a sequential manner, meaning that the rating experiment responses did not have an effect on class allocation. Future research could therefore develop a model which would consider both the observed discrete choice behaviour and the rating experiment, combining the model fit of a logit model and a regression model.

In Chapter 3, a novel approach for modelling memory decay was presented. We explored different ways of "memory storage" or in other words, the way past experiences are called upon. In existing literature, the memory of past experiences was modelled to "fade" over time (decrease in importance) – an approach we refer to as time-based memory storage. We propose that while this may be the case, the importance of the most recent experience would not decrease, as long as it was the most recent, and importance would only decrease when a new, more recent experience is obtained. In this sense, time is only important for the sequence of events, but not the actual passage of time; an approach we term event-based memory storage. Our results indicate that event-based storage seems to make the model more likely. However, our results are based on SP data, meaning that the passage of time is not fully realistic and through RP data, these different approaches to memory storage could be put to the test in the real world.

The importance of past experience can, and likely also does, vary between individuals. Future studies should therefore also look into this variation, both in a random parameter approach (mixed logit) and also in a population segmentation approach (latent class choice model).

In our study, we evaluated waiting time and a potentially cancelled ride to evaluate respondents willingness to continue using this service. As discussed in the chapter, other aspects of the trip are also prone to variability, with in-vehicle time being the most apparent one, particularly in pooled on-demand trips, where detours may come about unplanned, when a travel request is paired with a trip that is already underway. The exact time or part of the trip where this detour may occur might also play a role in the way it is perceived: a detour of equal magnitude would likely be perceived more negatively towards the end of the trip, when the passenger can already see themselves completing the trip, as opposed to at the start of the trip. Additionally, the interplay between the variability of waiting time and in-vehicle time would also be very relevant to look into and disentangle the trade-off behaviour.

Finally, the study also considered the impact of habits or inertia in decision-making. As individuals with limited resources, many of our decisions are subconscious and done habitually (the same as in the past, without (re)evaluation). The subconscious trade-off we make here is between mental effort and optimality of outcome. In the context of waiting time variability, we explored three established modelling approaches for inertia and proposed two additional ones, with the "reset" specification performing the best. Future research could test how these different specifications perform on other topic and attributes, if the same specification consistently performs best, or is the specification context and attribute specific. Comparing the outcomes of SP and RP research could also shed light on the differences between the hypothetical and real-world choices individuals make.

Appendices

Appendix A

Model estimates of the Alternative-specific parameter (ASP) model and the Dummy-coded parameter (DCP) model estimated for on-demand mobility in urban areas

In this appendix, the outcomes of the ASP (Table 7.1) and DCP (Table 7.2) models are presented, along with a visualisation of the impact of the parameter estimates on the utility (Figure 7.1). Most parameters seem to have a mostly linear impact on the utility of an alternative, which the ASP model can capture just as well as the dummy-coded model. Adjusting the ASP model parameters to the reference level of the DCP model parameters, the estimated dummy parameters largely follow a linear pattern with only minor deviations from the alternative-specific parameters. With respect to cost, a slight reduction of marginal utility contribution can be seen (each additional euro has a lower impact on utility than the previous one), whereas with all three time-related parameters, a slightly increasing marginal utility contribution (each additional minute of travel/walking/waiting contributes more disutility than the previous one) can be observed. A notable exception here is the waiting time for Flex. As explained in Section 2.2, Flex waiting time and PT waiting time are expected to be perceived and experienced differently (and were therefore presented differently in the survey), and this is indeed confirmed by the model estimation results. What is most striking about the Flex waiting time is that a 5-min waiting time seems to have a more negative impact than a 9-min waiting time. As explained in Section 2.4.1, this could be indicating respondents perceiving waiting at home as hidden waiting time.

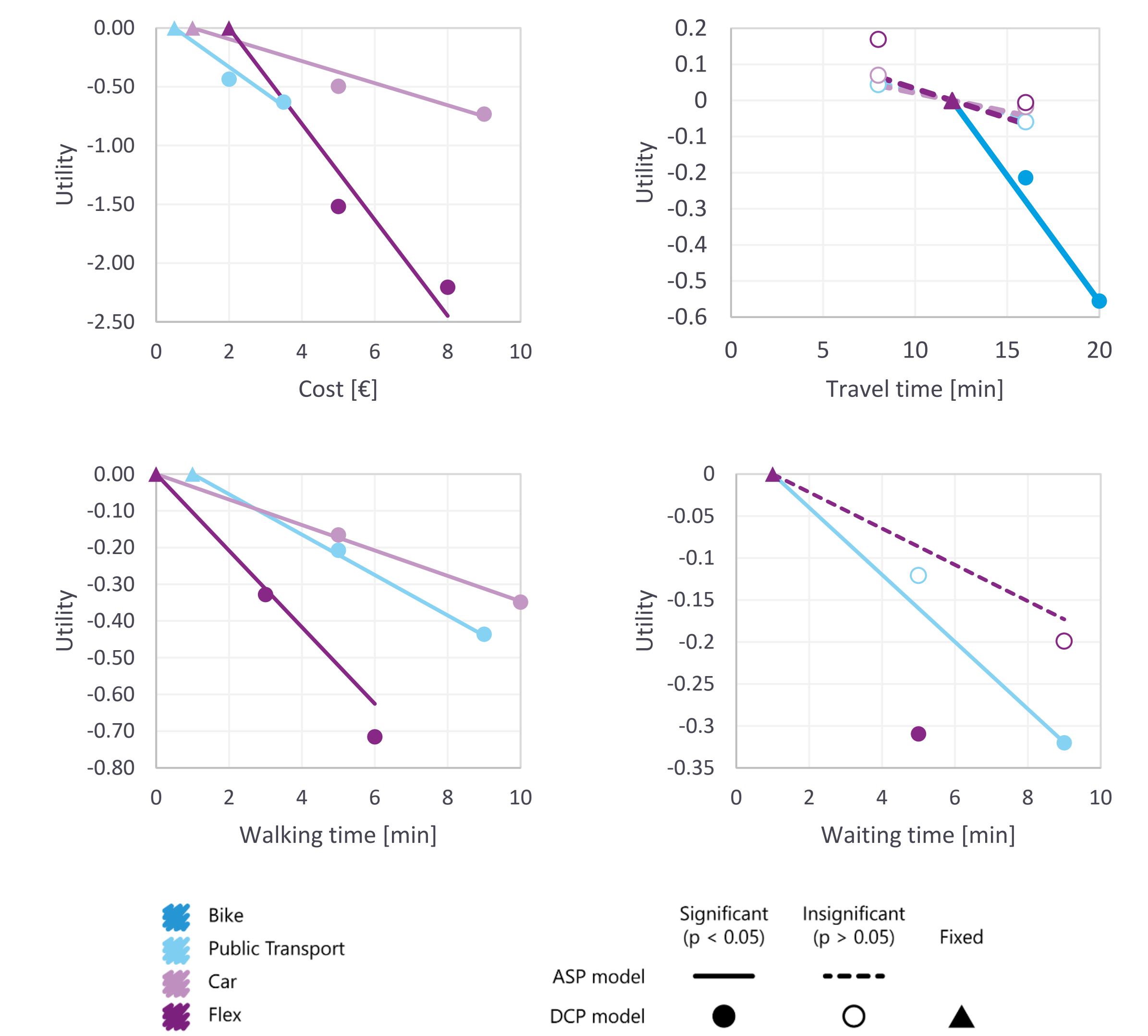
Table 7.1. Model estimation results of the ASP model

	Parameter estimate	Robust t-stat	Significance
Constant [bike]	0 [fixed]		
Constant [car]	-1.498	-10.37	***
Constant [Flex]	-2.044	-9.68	***
Constant [PT]	-2.082	-12.03	***
Cost [car]	-0.094	-10.53	***
Cost [Flex]	-0.408	-16.44	***
Cost [PT]	-0.221	-7.50	***
Leisure trip * cost [car]	-0.024	-2.56	**
Leisure trip * cost [Flex]	0.002	0.11	
Leisure trip * cost [PT]	-0.061	-2.03	**
In-vehicle time [bike]	-0.070	-11.21	***
In-vehicle time [car]	-0.010	-1.38	
In-vehicle time [Flex]	-0.016	-1.34	
In-vehicle time [PT]	-0.012	-1.29	
Walking time [car]	-0.035	-5.73	***
Walking time [Flex]	-0.104	-6.35	***
Walking time [PT]	-0.055	-5.77	***
Waiting time [Flex]	-0.022	-1.73	*
Waiting time [PT]	-0.040	-4.27	***
Sharing [Flex]	-0.198	-2.56	**

**** $p \leq 0{,}01$, ** $p \leq 0{,}05$, * $p \leq 0{,}1$*

Table 7.2. Estimation results of the DCP model

Mode	Attribute	Level	Value	Robust t-stat	Significance
Bike	Constant		*0 (fixed)*	-	-
	In-vehicle time	12 min	*0 (fixed)*	-	-
		16 min	-0.2139	-4.19	***
		20 min	-0.5556	-11.21	***
Public transport	Constant		-1.5765	-18.27	***
	Travel cost	€ 0.5	*0 (fixed)*	-	-
		€ 2	-0.4356	-4.84	***
		€ 3.5	-0.6308	-6.56	***
	Leisure trip (additional impact)	€ 2	-0.0974	-0.87	
		€ 3.5	-0.2097	-1.68	*
	In-vehicle time	8 min	0.0437	0.59	
		12 min	*0 (fixed)*	-	-
		16 min	-0.0591	-0.77	
	Walking time	1 min	*0 (fixed)*	-	-
		5 min	-0.2075	-2.85	***
		9 min	-0.4361	-5.67	***
	Waiting time	1 min	*0 (fixed)*	-	-
		5 min	-0.1207	-1.64	
		9 min	-0.3201	-4.19	***
Car	Constant		-0.8482	-12.32	***
	Travel cost	€ 1	*0 (fixed)*	-	-
		€ 5	-0.4960	-6.90	***
		€ 9	-0.7328	-9.59	***
	Leisure trip (additional impact)	€ 5	-0.1636	-1.83	*
		€ 9	-0.1754	-1.83	*
	In-vehicle time	8 min	0.0698	1.17	
		12 min	*0 (fixed)*	-	-
		16 min	-0.0175	-0.29	
	Walking time	0 min	*0 (fixed)*	-	-
		5 min	-0.1657	-2.81	***
		10 min	-0.3488	-5.74	***
Mobility-on-demand	Constant		-2.1523	-17.87	***
	Travel cost	€ 2	*0 (fixed)*	-	-
		€ 5	-1.5182	-10.79	***
		€ 8	-2.2061	-11.96	***
	Leisure trip (additional impact)	€ 5	0.2414	1.38	
		€ 8	-0.2404	-0.89	
	In-vehicle time	8 min	0.1691	1.81	*
		12 min	*0 (fixed)*	-	-
		16 min	-0.0061	-0.06	
	Walking time	0 min	*0 (fixed)*	-	-
		3 min	-0.3282	-3.35	***
		6 min	-0.7155	-6.61	***
	Waiting time	1 min	*0 (fixed)*	-	-
		5 min	-0.3095	-3.02	***
		9 min	-0.1991	-1.95	*
	Sharing the ride		-0.1549	-1.82	*



** for the sake of claritz, the parameters from the different model specification, the alternative-specific parameters are aligned to 0 at the reference level of the dummy-coded parameters*

Figure 7.1. Utility contributions of the linear alternative-specific parameters and the dummy parameters for the attributes of cost, travel time, walking time and waiting time

Appendix B

Survey example for the mode- and station-choice experiment

In the survey, respondents are asked to make 3 successive choices for making one multimodal trip. Choices 1 and 2 required respondents to choose an access mode to two different train stations at different distances from their trip origin. An example choice set is shown in Figure 7.2. The "Car" alternative was only presented to the respondents who indicated they have a drivers licence and access to a car.

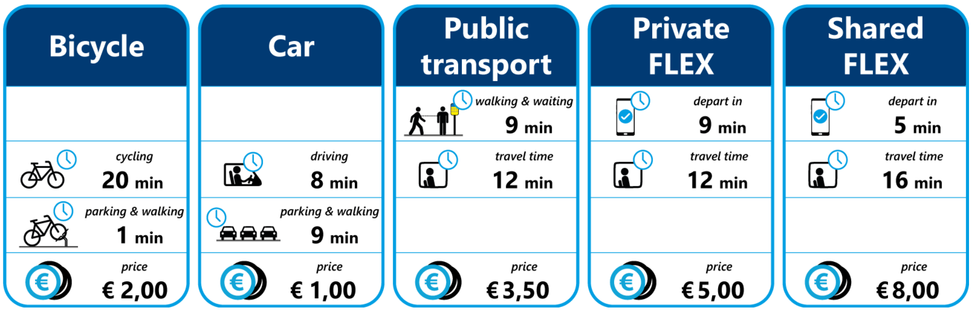


Figure 7.2. Example choice set of Choice 1 (and Choice 2)

Based on the access modes chosen in Choices 1 and 2, a choice set containing those access modes and the train service characteristics are presented to the respondents, as highlighted in Figure 7.3. In this particular case, the respondent has chosen to access Station A (Choice 1) by bicycle and Station B (Choice 2) by Public transport.

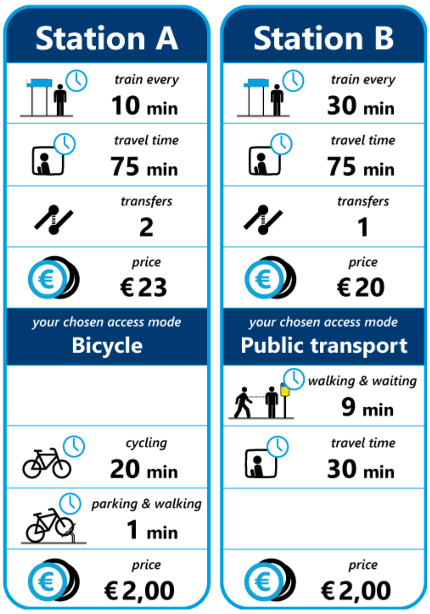


Figure 7.3. Example choice set of Choice 3

Appendix C

Nested and cross-nested logit models for the mode- and station-choice experiment

To better understand and capture the different possible nesting structures, several different cross-nested logit (CNL) models are also estimated. With multiple nesting structures possible in our dataset, CNL models are able show (probabilistically), how the alternatives are allocated to different nest structures. Compared to the MNL and NL models, CNL models are statistically superior (see Table 7.3). However, another possible way of accounting for this cross-nesting structure is by means of a latent class choice model (LCCM), with common taste parameters and two different nesting structures. The benefit of using LCCMs as opposed to CNL models is that we can include socio-demographic characteristics in the class allocation function, to better understand not only how the alternatives are allocated to different nesting structures, but also what are the characteristics of the individuals who form certain nesting structures. Estimating a 2-class LCCM with common taste parameters are results in a statistically superior model fit to the CNL model (see Table 7.3).

Table 7.3. Model fits of non-nested, nested, cross-nested and latent-class nested logit models

	MNL model	**NL model** (station-based nesting)	**NL model** (mode-based nesting)	**CNL model**	**2-class LCCM with nesting**
Final LL	-11,238	-11,134	-11,114	-10,853	-10,768
Adj. rho-square	0.2308	0.2388	0.2389	0.2556	0.2623
BIC	22,590.15	22,408.96	22,394.69	22,014.72	21,689.51

Appendix D

Example options of a the trip for the mode- and station-choice case study

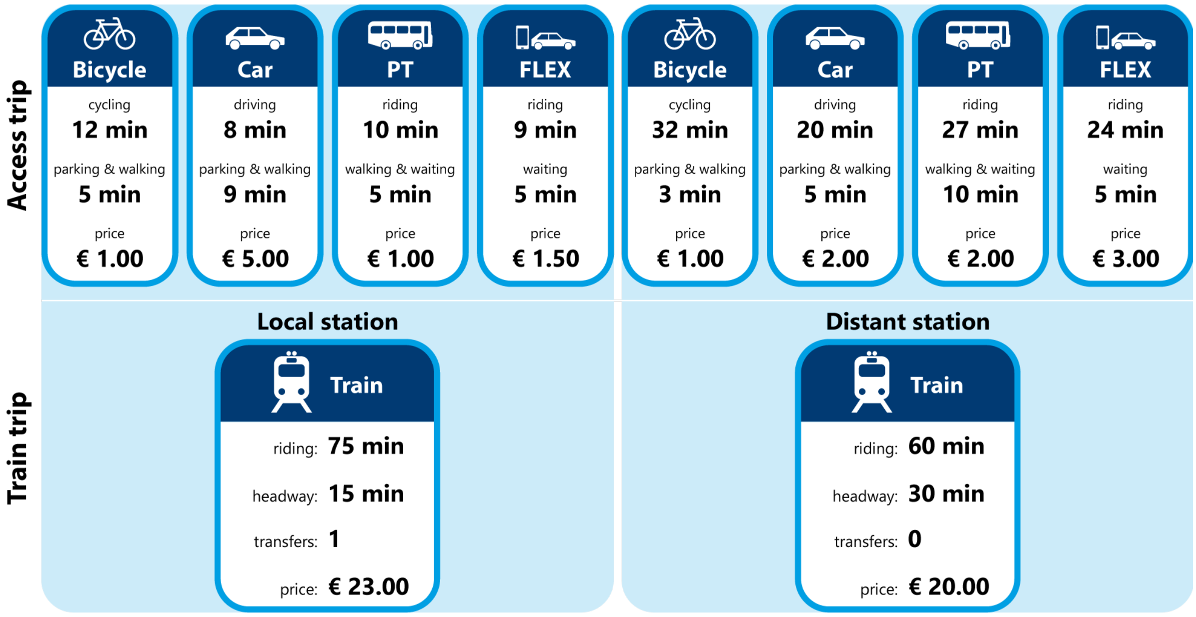


Figure 7.4. Example trip options (left: Via local train station; right via IC train station

Appendix E

Sensitivity analysis of the mode- and station-choice study

Table 7.4. Results of the sensitivity analysis. Coloured cells indicate differences greater than 0.1

		Local station					Distant station				
		Bike	Car	PT	FLEX shared	FLEX private	Bike	Car	PT	FLEX shared	FLEX private
Initial market shares		0.28	0.04	0.40	0.03	0.01	0.01	0.02	0.18	0.03	0.00
Bike to Local station	Access time	-0.08	0.11 *	0.03	0.03	0.02	0.01	0	0.01	0	0
	Parking cost	-0.02	0.02	0.01	0.01	0	0	0	0	0	0
	Parking search time	-0.02	0.02	0.01	0.01	0	0	0	0	0	0
Car to Local station	Access time	0.01	-0.08	0	0.01	0	0	0	0	0	0
	Parking and trip cost	0	-0.05	0	0	0	0	0	0	0	0
	Parking search time	0	-0.06	0	0	0.01	0	0	0	0	0
PT to Local station	Access time	0.03	0.03	-0.05	0.05	0.01	0.01	0.01	0.05	0.02	0.01
	Ticket price	0.02	0.02	-0.04	0.03	0.02	0.01	0.01	0.05	0.01	0.01
	Walking & waiting time	0.01	0.01	-0.01	0.01	0	0	0	0.02	0	0
Shared FLEX to Local station	Access time	0	0	0	-0.1 *	0.01	0	0	0	0.01	0.01
	Ride price	0	0	0	-0.11 *	0.03	0	0	0	0.01	0.02
	Waiting time	0	0	0	0.02	0	0	0	0	0	0
Private FLEX to Local station	Access time	0	0	0	0	-0.08	0	0	0	0	0.02
	Ride price	0	0	0	0.01	-0.16 *	0	0	0	0	0.03
	Waiting time	0	0	0	0	0.01	0	0	0	0	0
Bike to Distant station	Access time	0	0	0	0	0	-0.33 *	0.02	0.01	0.02	0.01
	Parking cost	0	0	0	0	0	-0.04	0	0	0	0
	Parking search time	0	0	0	0	0	-0.09	0	0	0	0.01
Car to Distant station	Access time	0	0	0	0	0	0.02	-0.13 *	0.01	0.01	0.01
	Parking and trip cost	0	0	0	0	0	0.02	-0.16 *	0.01	0.01	0.01
	Parking search time	0	0	0	0	0	0.02	-0.14 *	0.01	0.01	0.01
PT to Distant station	Access time	0.01	0.02	0.03	0.01	0.04	0.12 *	0.13 *	-0.12 *	0.05	0.13 *
	Ticket price	0	0.01	0.01	0.01	0.01	0.07	0.07	-0.05	0.05	0.05
	Walking & waiting time	0	0	0.01	0	0.01	0.02	0.01	-0.02	0.01	0.02
Shared FLEX to Distant station	Access time	0	0	0	0.01	0.01	0.03	0.03	0.01	-0.1 *	0.02
	Ride price	0	0	0	0.01	0.01	0.03	0.02	0.01	-0.11 *	0.03
	Waiting time	0	0	0	0	0	0	0	0	0	0
Private FLEX to Distant station	Access time	0	0	0	0	0	0	0	0	0	-0.15 *
	Ride price	0	0	0	0	0.01	0	0	0	0	-0.38 *
	Waiting time	0	0	0	0	0	0	0	0	0	0
Travel via Local station	Train travel time	0	-0.03	-0.02	-0.06	-0.09	0.06	0.05	0.05	0.06	0.1
	Train ticket price	0	-0.04	-0.03	-0.08	-0.13 *	0.07	0.07	0.07	0.06	0.13 *
	Operating frequency	0	-0.01	0	-0.01	-0.03	0.01	0.01	0.01	0.01	0.02
	Transfers	0	-0.02	-0.01	-0.04	-0.05	0.03	0.04	0.03	0.03	0.05
Travel via Distant station	Train travel time	0.01	0.02	0.02	0.03	0.06	-0.06	-0.04	-0.04	-0.06	-0.1 *
	Train ticket price	0.01	0.03	0.02	0.04	0.07	-0.08	-0.05	-0.06	-0.07	-0.13 *
	Operating frequency	0	0.01	0.01	0.01	0.02	-0.01	-0.01	-0.01	-0.02	-0.03
	Transfers	0	0.01	0	0	0.01	-0.01	0	-0.01	-0.01	-0.02

Appendix F

Survey design of the rating and bridging experiments for the study investigating long-distance travel in time of COVID-19

Survey designs are constructed utilising Ngene software (ChoiceMetrics, 2018). Below, the design for the rating experiment (Table 7.5), shorter context (~500km, shown in Table 7.6) and longer context (~1000km, show in Table 7.7) bridging experiment designs are presented.

Table 7.5. Rating experiment design

Task	On-board crowding	Face mask policy	Air circulation	Cleaning policy	Travel advice	Entry requirements	Infection rate	Vaccination rate	Block
1	25	0	0	0	0	0	0.1	15	3
2	75	0	3	2	3	3	25	30	4
3	25	2	3	1	2	2	100	70	4
4	75	1	0	3	0	3	100	70	4
5	50	3	3	0	1	1	25	70	1
6	50	0	1	3	3	2	0.1	70	1
7	25	1	2	1	3	0	100	30	3
8	50	1	0	0	3	3	10	90	1
9	100	0	1	0	2	1	100	15	2
10	75	2	1	1	1	1	10	90	3
11	25	3	1	3	2	1	0.1	30	4
12	100	1	3	3	1	0	10	15	2
13	100	3	2	1	2	3	0.1	15	2
14	50	3	1	2	0	2	100	30	1
15	50	0	2	3	0	1	25	90	1
16	75	1	3	0	0	2	0.1	90	4
17	100	2	0	1	1	2	25	30	3
18	75	3	0	2	3	0	25	70	3
19	100	2	2	2	2	0	10	90	2
20	25	2	2	2	1	3	10	15	2

Table 7.6. Bridging experiment – Shorter trip design (~500km)

	Train				Aircraft				Car		
Task	**Travel time**	**Travel cost**	**Comfort**	**Risk**	**Travel time**	**Travel cost**	**Comfort**	**Risk**	**Travel time**	**Travel cost**	**Block**
1	6	30	0	5	3	50	1	1	6.5	150	1
2	4.5	300	0	3	3	175	1	1	8.5	80	3
3	4.5	300	0	3	5	175	1	5	4.5	80	1
4	4.5	30	1	3	4	175	0	3	6.5	115	3
5	3	300	1	1	3	175	0	5	8.5	80	1
6	3	165	1	1	5	50	0	5	6.5	150	2
7	6	30	1	1	3	50	0	5	6.5	150	2
8	3	165	0	5	4	300	1	1	8.5	115	2
9	4.5	300	0	3	5	50	1	3	4.5	150	3
10	6	165	1	5	4	300	0	1	4.5	115	1
11	6	165	1	5	4	300	0	3	4.5	80	3
12	3	30	0	1	5	300	1	3	8.5	115	2

Table 7.7. Bridging experiment – Longer trip design (~1000km)

	Train				Aircraft				Car		
Task	**Travel time**	**Travel cost**	**Comfort**	**Risk**	**Travel time**	**Travel cost**	**Comfort**	**Risk**	**Travel time**	**Travel cost**	**Block**
1	12	200	1	5	5	400	0	3	10	200	2
2	9	350	0	3	4	225	1	1	16	100	3
3	12	50	1	5	4	50	0	1	13	200	2
4	6	350	0	1	5	225	1	5	16	100	1
5	6	200	1	1	6	225	0	5	16	150	3
6	12	200	1	3	6	400	0	3	10	100	1
7	9	50	0	5	5	50	1	1	13	150	1
8	9	50	0	5	5	400	1	1	10	150	2
9	12	50	1	1	4	50	0	5	10	200	3
10	6	350	0	3	6	400	1	3	13	100	3
11	6	200	0	3	6	50	1	3	13	150	2
12	9	350	1	1	4	225	0	5	16	200	1

Appendix G

Travel time and travel cost determination for a case study on long-distance travel in time of COVID-19

In order to calculate the travel time and travel cost based on the distance, linear functions with an intercept are constructed. For travel time, average speeds of 100, 160 and 800km/h are chosen for the car, train and aircraft respectively. The intercepts is set to 0, 1 and 3 hours respectively. These capture the time travellers spend at the airport/train station and the slower access/egress times, whereas for car, it is assumed that no such waiting takes place. The relation between travel time, distance and speed can be seen in Figure 7.5. In an additional analysis (Appendix H), train speed is also varied between 70km/h and 300km/h.

With respect to travel cost, a regression analysis is performed on pricing data scrapped from the web (Tanner & Provoost, 2023). This is then used to construct a linear function with the estimated slope and intercept. Curiously, air fares for European flights are found to be fully distance independent, with an average price of €135. Train and car on the other hand seem to have an identical slope of ~€0.12 per kilometre (or 8.33km per €1), with an intercept of €8 and €5 respectively.

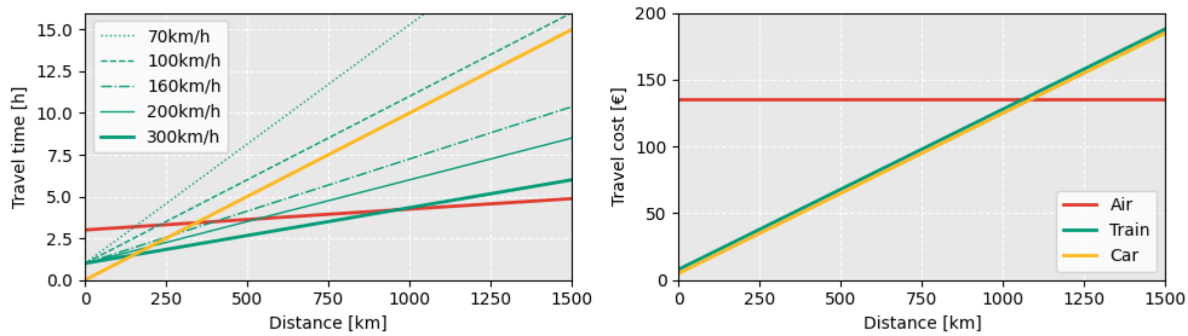


Figure 7.5. Calculation of trip travel time and travel costs for different modes

Appendix H

Sensitivity analysis of the impact of average train travel speed on market share among different user groups

Unlike car or air travel, which tend to have much more consistent average speeds, due to infrastructure between large cities being roughly at the same level, this cannot be said for trains. City pairs connected by high-speed rail (300km/h) are virtually incomparable to pairs connected with conventional rail. In the main sensitivity analysis, we assumed an average speed of 160km/h, which implies that there is some high-speed infrastructure along the way, but not the entire journey. Here, instead of varying perceived risk, we vary the average train speed, to better understand the added value of building out high-speed rail infrastructure and the potential it holds for modal shift.

What we can observe for all four segments (Figure 7.6) is that the difference between average speeds of 70km/h and 300km/h, over a 1,000km distance can be as much as 50 percentage points. In general, the implications of higher train speeds are largely equal to lower perceived risk (see Section 5.4), with Time-sensitive travellers mainly switching from air to train, Frequent train-loving and Cautious car travellers shifting from car and the Prudent travellers substituting both. We also see the same modal preference pattern, with Time-sensitive and Prudent travellers each having their own preferred land-based mode for shorter trips and flying over longer distances, whereas Frequent train-loving and Cautious car travellers predominantly stick to their preferred land-based mode (respectively to their names), even for distances of over 1,000km.

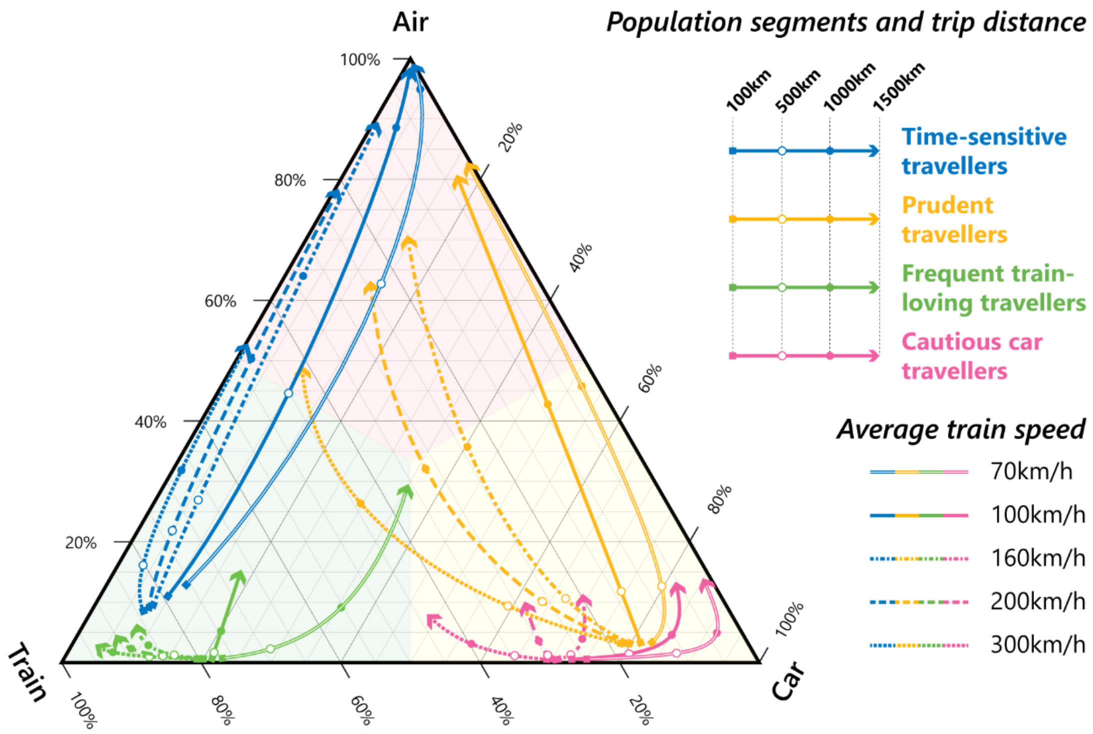


Figure 7.6. Market share of different modes, for different market segments, based on average train travel speeds

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About the author

Nejc Geržinič was born in Ljubljana, Slovenia in 1994. Since early childhood, he showed an interest and passion for (public) transport. In 2016, he completed his Bachelor's degree from the University of Ljubljana, Faculty of Maritime Studies and Transport, finishing the Traffic Technology program. His Bachelor thesis investigated the potential and sustainability of Park-and-Ride facilities in and around Ljubljana. In 2018, he obtained his Master's degree at Delft University of Technology, in the Transport, Infrastructure & Logistics program, with a focus on the design of public transport networks. In his thesis, he investigated the decision-making process in complex ranking experiments, applying it on the topic of park-and-ride facility choice.

Nejc started his PhD in 2019 as part of the CriticalMaaS project, working in the Smart Public Transport Lab (SPTL), the Transport & Planning department, Faculty of Civil Engineering & Geosciences, Delft University of Technology. During his doctoral studies, he was involved in teaching activities and co-supervised five master student graduation projects. During this time, he also became actively involved in a non-governmental organisation of advocates for sustainable transport policy in Slovenia (Koalicija za Trajnostno Prometno Politiko), which also included a proposal for a complete redesign of the public transport system in Ljubljana.

Since July 2023, he is working as a researcher in the both the Smart Public Transport Lab and the Active Mode Lab at the Department of Transport & Planning, conducting research on travel behaviour in multimodal trip chains, focusing on the impact and potential of micromobility as access and egress modes for public transport.

List of publications

Journal articles

1. Bickel, J., **Geržinič, N.**, van Oort, N., de Bruyn, M., & Molin, E. (2023). Heterogeneity in route choice behaviour during unplanned train disruptions considering the possibility of teleworking. (*Under review*).

2. **Geržinič, N.**, van Dalen, M., & Cats, O. (2023). COVID-19 risk-perception in long-distance travel. (*Under review*).

3. Loudon, E., **Geržinič, N.**, Molin, E., & Cats, O. (2023). Determinants of shared moped mode choice. Journal of Urban Mobility, 3.

4. **Geržinič, N.**, Cats, O., van Oort, N., Hoogendoorn-Lanser, S., Bierlaire, M., & Hoogendoorn, S. (2023). An instance-based learning approach for evaluating the perception of ride-hailing waiting time variability. Travel Behaviour and Society, 33.

5. **Geržinič, N.**, van Oort, N., Hoogendoorn-Lanser, S., Cats, O., & Hoogendoorn, S. (2023). Potential of on-demand services for urban travel. Transportation, 50(4), 1289-1321.

6. **Geržinič, N.**, Cats, O., van Oort, N., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2023). What is the market potential for on-demand services as a train station access mode? Transport Metrica A: Transport Science.

7. Montes, A., **Geržinič, N.**, Veeneman, W., van Oort, N., & Hoogendoorn, S. (2023). Shared micromobility and public transport integration - A mode choice study using stated preference data. Research in Transportation Economics, 99.

8. **Geržinič, N.**, van Cranenburgh, S., Cats, O., Lancsar, E., & Chorus, C. (2021). Estimating decision rule differences between 'best' and 'worst' choices in a sequential best worst discrete choice experiment. Journal of Choice Modelling, 41.

Peer reviewed conference publications

1. **Geržinič, N.**, van Dalen, M., Donners, B., & Cats, O. (2023). The impact of covid-19 on modal shift in long-distance travel. *11th Symposium of the European Association for Research in Transportation (hEART 2023)*, Zürich, Switzerland.

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