Demand for Urban Pooled On-Demand Services: Attitudes, Preferences and Usage

María J. Alonso González

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Dedicated to my mum

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María
Delft, June 2020

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List of Acronyms and Abbreviations

BTM	Bus, tram, metro
DRT	Demand responsive transport
GC	Generalised costs
GJT	Generalised Journey Times
LCCA	Latent class cluster analysis
LCCM	Latent class choice model
MaaS	Mobility as a Service
ML	Mixed logit
MNL	Multinomial logit
PT	Public transport
RG	Research gap
RQ	Research question
RUM	Random utility maximisation
SP	Stated preference
VOR	Value of reliability
VOT	Value of time
WTS	Willingness to share

Chapter 1

Introduction

A new range of tailored, on-demand mobility alternatives are emerging worldwide; amongst these are pooled on-demand services, i.e., shared ride-hailing services such as UberPOOL or ViaVan. Simulation studies have shown the potential benefits of these services in urban areas, yet their ridership is still very limited. This thesis examines the behavioural reasons underlying the adoption of such services. To this end, it includes a series of quantitative studies and suggests a series of policy implications based on the performed analyses. In this thesis, pooled on-demand services are also analysed in the broader context of Mobility as a Service (MaaS).

In this introductory chapter, we first explain the research motivation and the research gaps that underlie the thesis (Sections 1.1 and 1.2, respectively). Then, we outline the research objective and questions (Section 1.3) and describe the theoretical and conceptual frameworks (Section 1.4). We further elaborate on our research approach (Section 1.5) and the main research contributions (Section 1.6), both from a scientific and from a societal perspective. Finally, we explain the context in which this thesis is embedded (Section 1.7) and present the thesis outline (Section 1.8).

1.1 Research Motivation

Cities provide individuals with a wide range of opportunities in a reachable distance, driving economic growth. Notwithstanding, cities' high population densities also bring a series of challenges. One of these challenges is managing congestion. Congestion currently costs the European Union around 1% of its GDP annually (Christidis & Ibáñez Rivas, 2012) (and similar shares apply to other highly developed economies). Urban road transport is also the main cause of air pollution in cities (European Commission, 2018). Another challenge is the spatial footprint of cars. It is not only the traffic lanes in the cities; cars are parked, on average, 95% of the time (Shoup, 2017). This requires a high amount of dedicated parking space. All these aspects strongly influence livability in the cities. Moreover, as a result of the still increasing urbanisation rates (60% of the world's population will live in cities by 2030 (United Nations, 2019)), urban mobility problems are expected to increase if no measures are taken.

The root of urban mobility problems lies in the mismatch between the high modal share of cars in urban areas and the need of dense cities for vehicles with high(er) occupancy rates (the car average occupancy rate amounts to just 1.5 both in the EU (European Environmental Agency, 2010) and in the US (Department of Energy & Renewable Energy, 2018)) and for active mode trips (walking and cycling trips). Ideally, a large share of the urban trips would be performed using public transport and active modes. However, the earlier has fixed routes and schedules, not fitting the mobility needs of many individuals, while the latter is not a feasible alternative for trips that go beyond a certain distance. An intermediate transport alternative between the car and public transport, one which combines the flexibility of the car with the collective nature of public transport, could be an additional key component towards improving urban mobility. That missing piece are pooled on-demand services.

Pooled on-demand services, also referred to as Demand Responsive Transport (DRT) services, are taxi-like services that provide shared rides, matching different users together within a trip. These transport services are not a new invention (they were first offered as early as 1916 in Atlantic City (USA) (Strobel, 1982) and they were already recommended for urban mobility in the sixties (Cole, 1968)), yet only recent ubiquitous internet communication and increased computational power have enabled their real-time large-scale operations. Within pooled on-demand services, we could differentiate two groups: microtransit services (e.g., Bridj, Chariot, Kutsuplus), and ride-splitting/ shared ride-sourcing/ shared ride-hailing/ ride-pooling services (e.g., UberPOOL, LyftLine, OlaShare). While the first group is closer to public transport and tend to operate in minibuses, the latter is closer to taxi services. The same service could be operated with different vehicle sizes and offer different flexibility levels. As a result, there is no clear-cut between the services that belong to each of the groups.

Simulation studies have shown that, indeed, pooled on-demand services can bring large mobility benefits to urban areas, helping reduce their congestion, pollution and parking space problems (ITF, 2016, 2017). Moreover, these large mobility improvements do not come at the expense of substantial travel time increases for the users; Tachet et al. (2017) found that, for very different urban settings, trip matching is possible with very little total travel time increases for the passengers (amounting to less than five minutes per ride). Despite these promising research findings, adoption of pooled on-demand services in real settings is still very limited. Different pooled on-demand providers decided to stop their operations due to the lack of financial viability of their services (Enwemeka, 2017; Het Parool, 2017; Sulopuisto, 2016). And on-demand providers that offer both individual and pooled rides experience that it is their individual alternative that is most requested (Chen et al., 2018; Gehrke et al., 2018; Uber, 2018). Therefore, understanding the user demand for pooled on-demand services is essential in order to capitalise on all the potential benefits that the usage of these services can bring to urban areas. This is the main motivation of the current thesis.

1.2 Research Gaps

This thesis addresses different research gaps (RG) regarding the demand for pooled on-demand services. They relate to three main perspectives: attitudes, preferences and usage. According to the Merriam-Webster dictionary, attitudes are individuals' mental position regarding facts or states; preferences are the act of preferring (i.e., prioritizing), and usage is the action, amount or mode of using. While attitudes are abstract in nature, usage captures individuals' behaviour. Preferences are an in-between perspective. *Attitudes* influence *preferences*, which, in turn, influence behaviour (e.g., *usage*) (McFadden, 1986). And the relations between these aspects is not exclusively one-directional; for example, attitudes and behaviour mutually influence each other over time (Kroesen et al., 2017). Therefore, it is important to understand not only current usage, but also the more intrinsic psychological aspects that affect the demand for pooled on-demand services.

Other than providing a comprehensive view of the aspects that influence demand, our three perspective approach allows us to study our research topic from a more holistic mobility scope (with the study of attitudes), to a more specific scope (with the study of existent behaviour in a specific setting). Including a holistic perspective is especially important given that pooled on-demand services are not the only change currently happening in urban mobility. Rather, they are expected to be an important element within the Mobility as a Service (MaaS) concept, which according to many comprises a new mobility ecosystem. MaaS stands for the integration of all available mobility services (Jittrapirom et al., 2017; Kamargianni et al., 2016). MaaS is offered to the user via an app which enables booking and paying, and which provides travel information both before and during the trip. The MaaS offer includes the new mobility services (also referred to as shared modes; e.g., car-sharing, bike-sharing, ride-hailing) as well as traditional public transport services. Unlike some other conceptualisations, we do not consider price bundles a requisite in MaaS schemes. Figure 1.1 schemes the three perspectives investigated to tackle the research gaps articulated in the remaining of this section and the scope taken when investigating each of them.

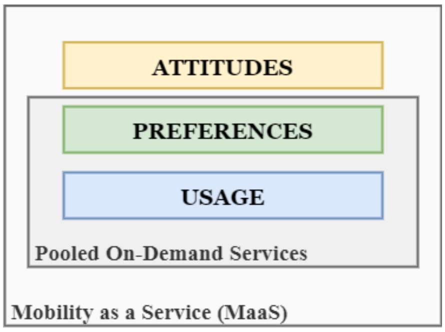

Figure 1.1: Three perspectives investigated in this thesis

Attitudes are acknowledged to be integral to individuals' transport mode choices (Paulssen et al., 2014), which explains why transport attitudinal studies have become established in the past years (Parkany et al., 2004). Specially in settings where behaviour cannot yet be observed (or can only be observed in relation to early adopters), as is the case of the usage of new mobility services, the study of attitudes can bring insights into which mobility changes could be expected. Previous research has included attitudinal statement in their analysis of pooled on-demand services in order to better understand individuals' related preferences and behaviour (e.g., Al-Ayyash et al. (2016); Khattak & Yim (2004); te Morsche et al. (2019)). Previous research has also investigated broader MaaS-related attitudes, such as the attitude towards the private car, towards the integration of mobility options through an app or towards route planning aspects (e.g., Kamargianni et al. (2018); Polydoropoulou et al. (2018); Schikofsky et al. (2020)). However, no previous study analyses attitudes towards pooled on-demand services together with other MaaS-related attitudes (such as the ones just mentioned), even if there is a common understanding that pooled on-demand services need to be understood in the context of the more general new mobility paradigm (RG 1). Next to providing descriptive attitudinal insights, attitudinal indicators can be used to identify different market segments. Mobility-related attitude-based segmentation results in higher predictive power for travel mode choice than other segmentation approaches (e.g., those based on socioeconomic factors) (Redmond, 2000), and they are advantageous as a starting point for related policy interventions (Haustein, 2012; Haustein & Hunecke, 2013). Nevertheless, despite customisation being one of the unique selling points of MaaS, none of the previous mentioned studies has performed any MaaS-related attitude-based segmentation analysis (RG 2).

Preferences is the second perspective investigated in this thesis in relation to the demand for pooled on-demand services. Their study via stated preference experiments provides insights into specific trade-offs. As was the case with the attitudinal indicators, stated preference experiments allow investigating both users and non-users of pooled on-demand services. Two of the most important travel demand trade-offs obtained from stated preference experiments are the time-cost trade-off and the reliability-cost trade-off (i.e., the value of time (VOT) and the value of reliability (VOR)) (Carrion & Levinson, 2012). Previous studies have investigated the VOT of pooled on-demand services in the UK (Ryley et al., 2014), the USA (Frei et al., 2017) or Lebanon (Al-Ayyash et al., 2016). However, none of these has analysed their VOR, despite its importance due to the flexible nature of these services (RG 3). One exception is Bansal et al. (2019). Bansal et al. (2019) considered pick-up reliability in their on-demand SP experiment. However, the cost attribute was not included in their study, and, thus, the corresponding VOR cannot be determined. Also, it would be interesting to analyse how the VOT and VOR in the different trip stages differentiate from each other. Again, no previous study has analysed the different trip stages of pooled on-demand services (RG 4).

Other than individuals' preferences regarding time-reliability-cost trade-offs, it is important to understand individuals' preferences towards sharing their rides. Often, on-demand providers offer individual and pooled ride alternatives simultaneously. In such cases, the large majority of their rides (around 80%) are being requested as individual rides (Chen et al., 2018; Uber, 2018). So, are individuals not willing to share their rides? And if the rides are being shared, what is the effect of different numbers of co-riders? Previous research has investigated this willingness to share either as a mode specific parameter (e.g., Chavis & Gayah (2017); Krueger et al. (2016); Liu et al. (2018); Steck et al. (2018)) or as the effect of different number of co-riders in pooled alternatives (e.g., Al-Ayyash et al. (2016); Yan et al. (2019)). Only one previous study, Lavieri & Bhat (2019), simultaneously considered the preference between individual and pooled alternatives, and the effect of different numbers of additional passengers in the pooled alternative. This was done in the context of autonomous vehicles for the US setting. Other than providing sound behavioural models, it is important to understand the policy implications of the findings. Scenario analyses can help decision makers prioritise mobility policies that steer behavioural change in the desired direction. From the above mentioned studies, Liu et al. (2018) has analysed the shares of individual and pooled rides with the aim to optimise the supply-side parameters as a result of varying fleet sizes and the implementation of a per-ride tax. A similar analysis with a demand (rather than supply) perspective is missing from current literature (RG 5).

It should be noted that pooled on-demand services allow for customisation and service differentiation: different pooled on-demand alternatives can be offered simultaneously, catering for the needs of different individuals. In literature, differentiation of pooled on-demand services has been suggested in Al-Ayyash et al. (2016) and Atasoy et al. (2015). However, previous research has not identified different market segments for pooled on-demand services. Rather than segmenting individuals based on trip purpose or specific socioeconomic characteristics, previous research has found that latent segmentation techniques (latent class choice models in particular) are more suitable in identifying distinct market segments (Teichert et al., 2008). Such techniques have been applied satisfactorily to the railway industry (e.g., Hetrakul & Cirillo (2014); Wen et al. (2012)) and the airline industry (e.g., Seelhorst & Liu (2015); Wen & Lai (2010);

Teichert et al. (2008)). In the context of pooled on-demand services, latent market segments could shed light into differences in time-reliability-cost trade-offs (RG 6), or differences in the willingness of individuals towards sharing rides (RG 7).

Last, let us consider *usage*. Even if attitudes and preferences provide interesting behavioural insights regarding the demand for pooled on-demand services, uncertainties prevail in relation to the extent to which behavioural change will take place. Empirical demand data from current on-demand services can help analyse and evaluate the real usage of these services. Previous assessment frameworks have evaluated pooled on-demand services in isolation from other modes (Morse et al., 2017) or have done so at a high level (Ferreira et al., 2007). However, in order to understand their impact on urban mobility, pooled on-demand services should be evaluated in conjunction with the other available transport alternatives by means of specific key performance indicators. Ideally, pooled on-demand services serve as complement to traditional public transport and active modes (walking and cycling). However, the extent to which pooled on-demand services act as a complement or a substitute to those is still unknown, and it is likely setting dependent. Several studies (we refer the reader to Tirachini (2019) for a good overview) have investigated the complementing/substituting relation between the usage of on-demand services and public transport. Past studies offer conflicting findings: some studies indicate a complementing effect and others a substituting one. These studies, however, have focused mainly on individual on-demand services (due to their higher popularity). Impacts from their pooled alternative could be arguably different, since they are closer in nature to public transport (RG8). When studying the complementarity/substitution effects between on-demand services and public transport, two approaches have been used. In the first approach, individuals (approached with intercept surveys) are asked how they would have made the on-demand trip if that service had not been available. In the second approach, the duration of the on-demand trip is compared to the duration of the public transport alternative. However, individuals do not associate the same disutility to the different trip stages. For example, performing a transfer implies, for the passenger, a disutility by itself (other than the transfer time), and waiting times are usually more heavily penalised that in-vehicle times. Therefore, when assessing the improvements in mobility that (pooled) on-demand services bring to the passenger, a generalised journey time approach may be more suitable than solely comparing total trip time duration. This has not been considered in previous related research, yet it can help better evaluate the usage of operational (pooled) on-demand services (RG 9).

1.3 Research Objective, Scope and Research Questions

The overarching research objective of this thesis is **to identify individuals' attitudes, preferences and usage regarding urban pooled on-demand services while accounting for the (hypothesised) heterogeneity among individuals**. We frame our research objective in the current urban mobility landscape, in which autonomous vehicles are not yet prevalent. As a result, all the on-demand services included in this research are manned and not autonomous. As for the geographical context the present research focuses on urban Dutch settings in particular. Findings are, however, applicable to similar urban settings in developed countries.

In order to achieve our main research objective, and following the research gaps (RG) identified in the previous section, we formulate the following four research questions (RQs):

- RQ 1: What are the drivers and barriers for adopting Mobility as a Service (MaaS) for different (groups of) individuals? (Addressing RG 1 and 2; Chapter 2)
- RQ 2: What are (the differences in) individuals' values of time (VOT) and values of reliability (VOR) for the different stages of pooled on-demand trips? (Addressing RG 3, 4 and 6; Chapter 3)
- RQ 3: What are the determinants of the willingness to share rides in pooled on-demand services? (Addressing RG 5 and 7; Chapter 4)
- RQ 4: What are the temporal and spatial characteristics of the pooled on-demand trips? (Addressing RG 8 and 9; Chapter 5)

1.4 Theoretical and Conceptual Foundation of the Thesis

As explained in the previous section, this thesis aims to identify individuals' attitudes, preferences and usage regarding pooled on-demand services. Our interest in these three pillars stems from the expectation that they all can shed light on the future demand for pooled on-demand services. We rely on psychological theories to underpin our attitudinal study (given its more abstract nature), while behavioural economic theories underpin our studies which focus on preferences and usage. In this section, we explain these theories.

In the attitudinal study (Chapter 2), we focus on Mobility as a Service (MaaS), arguing that the study of attitudes towards pooled on-demand services needs to be embedded in the overarching context of the upcoming urban mobility ecosystem. We claim that not only individuals' attitudes towards pooled on-demand services per-se, but also individuals' attitudes towards the MaaS ecosystem will ultimately influence future demand for pooled on-demand services (given the inherent link between these two).

In MaaS, we make a distinction between two components: a *mobility component* (integration of mobility options, including the new shared mobility alternatives), and a *technological component* (the innovative app that enables MaaS). Therefore, we decide that the most suitable theoretical foundation for our attitudinal study is a combination between the Theory of Planned Behaviour (TPB) (for the mobility component of MaaS) and the Technology Acceptance Model (TAM) (for the technological component of MaaS). In the literature, we find several studies that have combined these theories in their conceptual frameworks in order to cover a broader range of constructs in their analyses (e.g., Chen (2016); Lu et al. (2010); Safeena et al. (2013)).

The Theory of Planned Behaviour (TPB) (Ajzen, 1991) is an extension of the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and considers that an intention to perform a behaviour depends on an individual's intention to engage with this behaviour. This behavioural intention, in turn, depends on the individual's attitude towards the related behaviour, the subjective norm and the behavioural control. We highlight two main mobility attitudes regarding MaaS: individuals' attitude towards mobility integration, and individuals' attitude towards shared modes (towards pooled on-demand services in particular). We only consider the perceived behavioural control and the subjective norm to a limited extent in our research (by means of some of the studied attitudinal statements). One main reason underlies this decision: MaaS is not yet a well-known concept, so it is difficult for individuals to reflect on behavioural control and subjective norm.

The Technology Acceptance Model (TAM) (Davis, 1989a) is one of the most recurrently used models to predict use and acceptance of information systems (Surendran, 2012). This framework considers that the perceived usefulness and the perceived ease of use are the most important determinants to determine the attitude and subsequent use of a new innovation. We study the first via individuals' willingness to pay, and the latter by analysing statements regarding the mobile application itself. Our conceptual framework considers that the intention to adopt MaaS (and subsequent MaaS adoption) depends on both the intention to engage in the integrated mobility that MaaS offers and the intention to use the MaaS app. Also, both TPB and TAM suggest that other external factors affect behaviour indirectly. That is why we consider the role of socioeconomic characteristics, mobility patterns and technology-related characteristics in this part of our research.

There is a third social theory that plays a role in our attitudinal study: the Diffusion of Innovations Theory (Rogers, 1983). This theory explains how new technology adoption spreads and it distinguishes different groups regarding their "readiness" to adopt an innovation. Inspired by this line of thought, we cluster individuals according to differences in the previously mentioned attitudinal constructs, with the aim to obtain groups with different MaaS "readiness" levels.

The second pillar of this thesis, pertaining to preferences (covering Chapters 3 and 4), is underpinned by economic theories. In particular, by the Random Utility Maximisation (RUM) Theory. This theory was first proposed by Marschak (1960), building on Thurstone (1927), and has been widely implemented based on the multinomial logit (MNL) model proposed by Mcfadden (1975). The RUM theory considers that, when faced with a discrete choice, decision makers try to maximise their obtained utility. This utility is made of two components, a representative component which includes the attributes that can be observed by the researcher and a random (unobserved) error term component. We refer the reader to Train (2009) for more information on the RUM theory and its mathematical formulation. The methodological sections of Chapters 3 and 4 include information on the models that, based on the RUM theory, are used in the preference studies.

We consider that there are four main attributes that are determinant to how individuals make choices regarding the offered pooled on-demand services, and model these under the RUM framework. The first two are time and cost, the most essential attributes in transport studies. Third, reliability, especially important given the flexible nature of pooled on-demand services. And last, the number of passengers, which reflects the disutility that individuals associate with sharing their ride. Additionally, socioeconomic and mobility characteristics of the individual are considered as potential additional variables that play a role in the different preferences among individuals.

The preference studies in this thesis (Chapters 3 and 4) are also underpinned by the Economic Pricing Theory. This suggests that profits can be maximised when different pricing levels are set for different segments (Frank et al., 1972), and it is the foundation for market segmentation analyses. We argue that given their tailored nature, pooled on-demand services can offer a portfolio of services, and thus, address the needs and preferences of different segments. In order to identify segments with different trade-off preferences, our search for different market segments is integrated with the discrete choice RUM models.

Finally, the usage perspective, the third pillar in this thesis (covered in Chapter 5). It is based on the notion that "people travel because they want to carry out activities" (van Wee et al., 2013). As a result, when deciding which mode of transport to use for their trip, individuals try to minimise the disutility that they associate with the performed trip. This means that, once again, we consider a theoretical economic underpinning in the decision making process of the individual. We measure the disutility that individuals face in their trips with the generalised journey time and the generalised cost accessibility indicators. The first indicator measures individuals' time disutility in performing the trip (by means of their perceived time), and the second indicator includes individuals' cost-related disutility in addition to their time disutility. The methods used for all three perspectives are introduced in detail in the following section and in the respective chapters.

1.5 Research Approach

This section discusses the main features of the research approach followed in the thesis. We use three main methods in order to answer our research questions, each of them related to one of the three research perspectives (attitudes, preferences and usage).

The two methodologies used for attitudes and preferences are in the domain of cluster analysis and discrete choice modelling (with a market segmentation approach), while the methodology used for analysing usage involves a service assessment framework. The data used for the attitudinal and preference analyses stem from a dedicated survey designed for the purpose of this thesis, while the data for the usage analysis stem from field observations of an operational pooled on-demand service. Figure 1.2 depicts the scheme of the overall research approach.

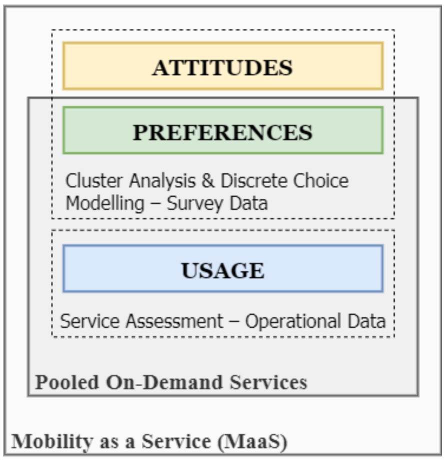

Figure 1.2: Scheme of the overall research approach

For the *attitudinal study (RQ 1)*, we design a series of Likert-scale attitudinal indicators that cover different MaaS-related aspects. In the indicators, special attention is given to attitudes towards pooled on-demand services, the main mobility service studied in this thesis. As research methodologies, we perform a variable reduction technique followed by a cluster analysis. In particular, we use exploratory factor analysis and latent class cluster analysis. The first examines the relationships among the variables, in order to identify a lower number of factors that encompass the main relations between the different variables. These factors are the indicators used in the posterior latent class cluster analysis. They help delve into the latent variable that is behind the different latent classes. Finally, the classes are characterised in detail regarding their socioeconomic, mobility and technology-related characteristics.

For the *preference studies (RQ 2 and RQ 3)*, we design four different stated preference experiments. The first three stated preference experiments (aimed to answer RQ 2) are designed to analyse the time-reliability-cost trade-offs of pooled on-demand services in the waiting stage, the in-vehicle stage, and the transfer stage (when combined with traditional public transport). Care is taken in how reliability is conveyed to respondents, given the many discrepancies existing in literature. The fourth stated preference experiment (aimed to answer RQ 3) presents respondents with two alternatives, an individual and a pooled on-demand service, in order to study the willingness to share of individuals. These experiments are analysed using discrete choice models, and, in all cases, latent class choice models form part of the analysed models. They help identify different market segments and their specific preferences. Additionally, the methodology used to answer RQ 3 includes a scenario analysis, which helps visualise the role of time, cost and the number of passengers on the willingness to share.

The dedicated survey developed to answer RQ 1 to 3 targets individuals living in (sub)urban areas in the Netherlands. The final sample contains 1006 valid respondents. The unique and comprehensive survey design ensures consistency in the results (all data are collected from the same respondents at one moment in time) and allows for a better comparison of the results. Survey respondents belong to the Netherlands Mobility Panel (MPN), a panel designed for the longitudinal study of travel behaviour in the Netherlands (Hoogendoorn-Lanser et al., 2015).

For the *usage study (RQ 4)*, we develop an assessment framework. This framework includes an analysis of the system characteristics and operational features of pooled on-demand services. Based on the latter, the framework proposes the study of several accessibility indicators, aimed at quantifying the accessibility improvements that the pooled on-demand service has brought to their users. Special emphasis is set to help understand whether the relation between pooled on-demand services and public transport is primarily complementary or substitutionary. The framework is applied to BrengFlex, a pooled on-demand service in the Netherlands. We analyse the demand data of its performed (and cancelled) trips in the city of Nijmegen. We also complement this data with the Google Maps Direction API, in order to analyse the characteristics of the public transport rides that could have substituted the pooled on-demand requests.

Note that the research approach undertaken in answering the first three research questions includes a (latent) segmentation methodology (latent class cluster models or latent class choice models). Both MaaS and on-demand services offer individuals a tailored service, and it is therefore important to understand attitude and preference heterogeneity in order to provide services that match the distinct segments. This approach also allows to develop models that better explain the choices made. Given the lack of information on individual characteristics from our usage data, we cannot follow the same approach for the usage analysis. European privacy regulations and business interests limit the amount of demand data that on-demand operators are able or willing to share with third parties. As a result, differences in demand pertaining to real usage are analysed taking into account temporal and spatial considerations.

1.6 Main Research Contributions

The research performed in this thesis contributes to both science and society. The main scientific and practical contributions are discussed in Sections 1.6.1 and 1.6.2, respectively.

1.6.1 Scientific Contributions

Overall, this thesis makes scientific contributions to the understanding and modelling of the demand for pooled on-demand services. Below, we highlight the main specific contribution of each of the individual chapters:

- **Identifying the drivers and barriers playing a role in adopting Mobility as a Service (MaaS) for different individuals (RQ 1, Chapter 2)**

  We identify factors relevant for MaaS adoption: drivers that can stimulate some individuals and barriers that may be holding back others. Using an attitudinal segmentation approach, we identify (latent) clusters regarding individuals' inclination to adopt MaaS, and carefully characterise those based on their (a) socioeconomic characteristics, (b) their mobility characteristics and (c) their technology related characteristics. This analysis provides novel insights into which shifts in mobility patterns are likely to occur as a result of MaaS.

  This contribution has led to the following journal article:

  Alonso-González, M.J., Hoogendoorn-Lanser, S., van Oort, N., Cats, O. & Hoogendoorn, S.P. (2020) Drivers and barriers in adopting Mobility as a Service (MaaS) – A latent class cluster analysis of attitudes. *Transportation Research Part A: Policy and Practice*, 132, 378-401.

- **Quantifying individuals' values of time and values of reliability for the different stages of pooled on-demand trips (RQ 2, Chapter 3)**

  We analyse individuals' time-reliability-cost trade-offs in pooled on-demand trips. We analyse these trade-offs for (i) the waiting stage, (ii) the in-vehicle stage, and (iii) the transfer stage (when pooled on-demand services are combined with traditional fixed public transport). To this end, we designed and conducted a series of stated preference experiments. The simultaneous analysis of the different stages allows for comparisons across the obtained values. Moreover, providing insights into individuals' preferences regarding the reliability of pooled on-demand services is especially important, given that, unlike in traditional public transport, their announced times are trip specific and do not follow a recurrent schedule. Additionally, this study contributes to literature by identifying distinct (latent) classes of travellers with different time-reliability-cost sensitivities for the different trip stages of pooled on-demand trips.

  This contribution has led to the following journal article:

  Alonso-González, M.J., van Oort, N., Cats, O., Hoogendoorn-Lanser, S. & Hoogendoorn, S. P. (2020) Value of Time and Reliability for Urban Pooled On-Demand Services, *Transportation Research Part C: Emerging Technologies*, Volume 115, 102621.

- **Analysing the determinants of the willingness to share rides in pooled on-demand services (RQ 3, Chapter 4)**

  We disentangle the sharing aspect from related time-cost trade-offs (e.g., detours) when choosing between individual and pooled on-demand services. We investigate preference heterogeneity and identify distinct market segments with respect to the willingness to share and the value of time of on-demand services. Modelling results are then applied to a scenario analysis, allowing for a visual inspection of the role of time, cost, and the number of additional passengers in determining the share of pooled on-demand trips that can be attained.

  This contribution has led to the following journal article:

  Alonso-González, M.J., Cats, O., van Oort, N., Hoogendoorn-Lanser, S. & Hoogendoorn, S.P. (2020) What are the Determinants of the Willingness to Share Rides in Pooled On-Demand Services? *Transportation*.

- **Developing a usage assessment framework to evaluate the characteristics of pooled on-demand trips (RQ 4, Chapter 5)**

  We present a framework to assess how pooled on-demand services perform in real settings. In particular, the framework adds to knowledge by providing a series of concrete accessibility indicators to measure the change in accessibility attributed to the pooled on-demand usage (given the existing alternatives), and it can help identify whether pooled on-demand services are used as a complement or a substitute of traditional public transport. We also apply the proposed framework to an urban pooled on-demand system in the Netherlands.

  This contribution has led to the following journal article:

  Alonso-González, M.J., Liu, T., Cats, O., van Oort, N. & Hoogendoorn, S. P. (2018) The Potential of Demand-Responsive Transport as a Complement to Public Transport: An Assessment Framework and an Empirical Evaluation. *Transportation Research Record*, 2672(8), 879–889.

1.6.2 Societal Relevance

This section discusses the societal relevance of this thesis. The stakeholders that can benefit the most from this research are policy makers, on-demand transport providers and public transport providers. We highlight the thesis relevance to each of these three parties as follows:

Relevance to policy makers

We identify distinct clusters regarding individuals' inclinations to adopt MaaS. Based on the characteristics of each cluster, we outline a series of tailored policy recommendations. Their implementation can support the adoption of MaaS schemes that help improve urban mobility. Regarding pooled on-demand services, transport authorities can include the parameters obtained in our behavioural models in their existing assignment models. This implementation can lead to better assessments with respect to the modal shifts that are likely to take place with the introduction of pooled on-demand services. The updated models, can, in turn, help draft future multimodal (public) transport concessions, depending on the observed (and desired) modal shifts. Finally, the key performance indicators proposed in the usage assessment framework help transport authorities evaluate how pooled on-demand services are being used. The suggested indicators can aid them decide on the most suitable subsidy (or tax) level to be applied to these services from an accessibility standpoint.

Relevance to on-demand transport providers

This research offers on-demand providers insights into the existing market segments regarding pooled on-demand services and their preferred time-reliability-cost trade-offs in the different trip stages, as well as the cost disutility they attribute to sharing their rides. These findings allow on-demand providers to assess the impact that service provision decisions can have on users' choices. The identification of different market segments can also help them develop a portfolio of services that addresses the needs and preferences of different individuals, thereby increasing patronage. Additionally, service differentiation can allow them to make a better use of the flexibility nature of these services. Regarding already operating services, our research offers them a framework to evaluate the on-demand services' usage and performance.

Relevance to public transport providers

Due to the collective nature of both pooled on-demand services and public transport, public transport providers need to consider that their demand is likely to be impacted by these new services. The attitudinal study on MaaS offers public transport providers insights into which individuals prefer traditional public transport over new pooled on-demand services (and vice versa). It also investigates which segments of the population are more (and less) likely to adopt MaaS, which can help them assess how MaaS can influence the mobility patterns of their current customers. To address the impact from forthcoming (or eventual) pooled on-demand services, we provide public transport providers with behavioural parameters to introduce in assessment models so as to better forecast modal shifts. Last, to address the impact from already operating on-demand services, we provide them with a usage assessment framework which helps identify whether pooled on-demand services are being used as a complement or as a substitute of public transport. As a result of these findings, public transport providers can better adjust their schedules, routes and types of offered services in order to better fit demand. Public transport providers interested in offering a mix of flexible and fixed services can find additional relevant contributions in the previously discussed 'relevance to on-demand transport providers' subsection.

1.7 Research Context

This thesis is part of the SCRIPTS (Smart Cities Responsive Intelligent Public Transport Services) research project. SCRIPTS is funded by NWO (The Organisation for Scientific Research from the Netherlands), as part of the SURF (Smart Urban Regions of the Future) programme. The project consortium, based entirely in the Netherlands, consists of three academic partners (Delft University of Technology, Eindhoven University of Technology, and Radboud University), the HAN university of applied sciences, and representatives of public transport companies, local and provincial governments, mobility service providers and consultants. The academic partners investigate demand, supply and governance aspects, while the more applied partners focus on implementing a series of related pilot studies.

The main aim of the project is to *'create and disseminate academic and applied knowledge and decision tools in the design, implementation and performance of the envisioned future hybrid public transport systems in the context of the smart city concept'*. The term "hybrid public transport" refers to the idea that future public transport services will not include exclusively traditional fixed (i.e., fixed routes and schedule) public transport, but also encompass different kinds of on-demand services. In line with the overarching project vision, this thesis studies the demand for pooled on-demand services in detail. Thus, this thesis can help in the design and evaluation of these services.

1.8 Thesis Outline

Figure 1.3 presents an overview of the thesis structure. Chapters 2-5 form the core of this thesis and are based on published journal articles. As illustrated in Figure 1.3, these chapters are organised in three main parts, covering the study of attitudes, preferences and usage regarding pooled on-demand services. The data used for the analyses in Part I and II pertains to the survey designed for the sake of this thesis (as explained in Section 1.5). On the other hand, Part III analyses demand data related to the usage of an operational pooled on-demand service.

Part I, comprised of Chapter 2, delves into attitudes. In this chapter, pooled on-demand services are understood as one piece in the new mobility ecosystem in which these services are likely to operate in the future: the Mobility as a Service (MaaS) ecosystem. This chapter analyses this broader mobility ecosystem by means of several Likert-scale attitudinal indicators. Different clusters arise from the analysis, and several policy implications are drawn from the careful characterisation of the found clusters.

Part II focuses on preferences. It contains two chapters, Chapters 3 and 4. Chapter 3 analyses individuals' preferences regarding time, reliability and cost in pooled on-demand trips. It does so for the waiting stage, the in-vehicle stage and the transfer stage (when combined with public transport). Since pooled on-demand services have the potential to offer a range of services that cater for various market segments with different values of time and values of reliability, we also identify distinct segments regarding their time-reliability-cost trade-offs. Chapter 4 models preferences regarding another important aspect of pooled on-demand services: the willingness to share rides with different numbers of additional passengers. Same as in Chapter 3, preference heterogeneity is investigated and different market segments are identified. Additionally, Chapter 4 illustrates via a scenario analysis the role of time, cost and the number of passengers on the willingness to share rides.

After having investigated individuals' attitudes and behaviour regarding pooled on-demand services, Part III addresses the usage of these services. Chapter 5 presents a framework to assess usage and performance of pooled on-demand services. It proposes a series of accessibility indicators to measure the mobility improvements that these services have offered their users, compared to alternative modes. The framework is applied for an operational service in the city of Nijmegen in the Netherlands.

Finally, we draw the overall conclusions of the thesis in Chapter 6, as well as discuss their practical implications. At the end of this last chapter, we also formulate recommendations for future research.

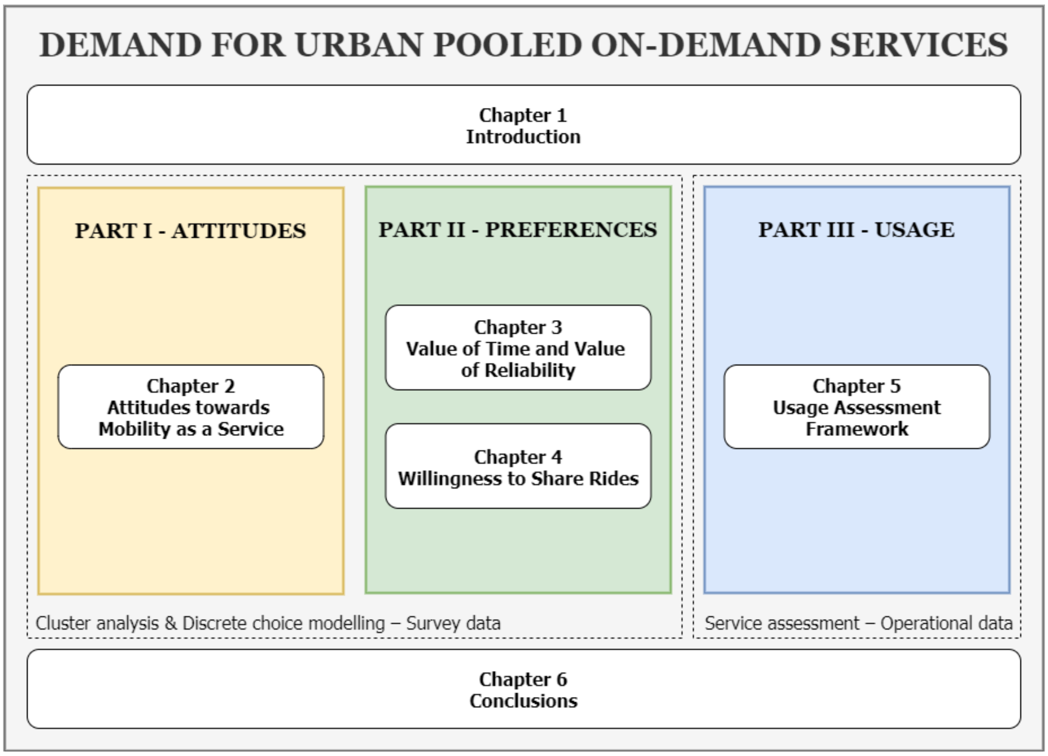

Figure 1.3: Structure of the thesis

Chapter 2

Attitudes towards Mobility-as-a-Service

Pooled on-demand services are likely to be part of the broader new mobility ecosystem, Mobility as a Service (MaaS). In this chapter, we study what the drivers and barriers for adopting MaaS are for different (groups of) individuals (RQ 1). We investigate who is most likely to embrace MaaS and the impacts that this can have in urban mobility. We use an attitudinal approach to be able to go beyond the consideration of early adopters. First, we design a series of MaaS-related Likert-scale attitudinal indicators, giving a special focus to pooled on-demand services, which exemplify the flexibility characteristics of on-demand services, important in MaaS ecosystems. Our final sample comprises of over thousand respondents in urban areas of the Netherlands. Using exploratory factor analysis, we extract factors that stem from the relations between the collected attitudinal data. Subsequently, we perform a latent class cluster analysis, which allows us to identify distinct clusters in relation to individuals' inclinations to adopt MaaS in the context of urban mobility. Finally, based on a detailed characterisation of the clusters found, we propose a series of policy recommendations tailored to the different clusters in the study to support future MaaS adoption.

This chapter is organised as follows: Section 2.1 introduces the background and related literature; Section 2.2 explains the research methodology; Section 2.3 presents the study results and introduces the clusters; Section 2.4 characterises the clusters in detail; Section 2.5 discusses the key results and provides cluster specific policy recommendations, and Section 2.6 provides the final conclusions.

This chapter is an edited version of the following article:

Alonso-González, M.J., Hoogendoorn-Lanser, S., van Oort, N., Cats, O. & Hoogendoorn, S.P. (2020) Drivers and barriers in adopting Mobility as a Service (MaaS) – A latent class cluster analysis of attitudes. *Transportation Research Part A: Policy and Practice*, 132, 378-401.

2.1 Introduction

Urban transportation is changing rapidly, with the emergence of a broad spectrum of on-demand modes such as bike-sharing, car-sharing or ride-sharing appearing in urban areas. Even if these mobility services have been around since the 20^{th} century, only recently their real-time operation in large settings has become a reality. They increase the modal choice set of travellers and their accessibility to different locations, but the wide range of options available also implies some degree of extra complexity for the user. In order to avoid this extra complexity and to maximise the benefits that all these options can bring when integrated, Mobility as a Service (MaaS) is emerging.

MaaS is a service offered to the user in a single mobile app platform, which integrates all aspects of the travel experience, including booking, payment, and information both before and during the trip (Jittrapirom et al. (2017) and Kamargianni et al. (2016) provide an overview of early MaaS schemes). In essence, MaaS brings an individual from A to B regardless of the mode. In dense urban settings in which congestion, liveability and parking space are high on the urban mobility agenda, a robust public transport system would ideally constitute the core of MaaS, with the new on-demand modes acting as first/last mile solutions or to complement public transport for trips for which it does not provide a convenient service (Li & Voege, 2017). The transport integration that has for long been considered a precondition to reduce car use in favour of public transport (Chowdhury & Ceder, 2016; Givoni & Banister, 2010; Janic, 2001) is therefore provided in MaaS.

Previous research indicates that MaaS has the potential to induce modal shifts towards a more public transport and less car oriented lifestyle (Karlsson et al., 2017; mobility, 2015) while it increases users' travel satisfaction (Sochor et al., 2016). As a result, MaaS has recently attracted much attention, to the extent that it is expected to become the drive of a mobility revolution comparable with the introduction of the private car in the $20^t h$ century (Goodall et al., 2017; Shaheen et al., 2018). However, there has been a self-selection effect among individuals participating in the researched early stage MaaS pilots (Strömberg et al., 2016). It is unknown if the general population will replicate the modal shifts of individuals in these MaaS pilots and whether public transport or rather on-demand services will play the mayor role in urban MaaS schemes (car users partly explain their current mode choice decisions by referring to the inflexibility of transit (Clauss & Döppe, 2016)).

In this study, we contribute to the understanding of who will embrace MaaS and which shifts in mobility patterns MaaS is likely to occasion. Limited quantitative research has been done so far on this topic other than the resulting from pilot evaluations, even if MaaS is expected to significantly change our travel patterns. Our study goes beyond the consideration of early adopters and identifies not only the characteristics of potential users of MaaS, but also the barriers that may be holding other individuals from adopting this new mobility paradigm. We also investigate if public transport, or rather other on-demand services are more attractive to the different traveller groups, which indicate which changes in mobility patterns can take place as a result of MaaS. In our study, we focus on urban areas of the Netherlands, and we discuss what the results indicate for other urban settings.

Within the study of the on-demand modes present in MaaS, we pay special attention to pooled on-demand services. They can add flexibility without compromising on sustainability and efficient use of mobility resources. By pooled on-demand modes, we refer to the new generation of taxi-like services (usually booked via an app) that match different travel requests in the same vehicle (usually) in real-time, without these matched trips needing to start or end at the same location. Examples of these services are pooled ridesourcing services such as UberPool or UberExpressPOOL, or micro-transit services such as the services offered by Via or Chariot. Tachet et al. (2017) demonstrated that pooled on-demand services have a high potential in urban settings, given that individual mobility patterns are highly shareable for very diverse urban networks. Moreover, simulation studies show that combinations of pooled on-demand services with traditional public transport (Martinez & Viegas, 2017) or with individual on-demand services (such as bike-sharing (Luo et al., 2018)), lead to drastic reductions in the number of vehicles needed, carbon emissions and congestion, and they improve passenger trip times and accessibility simultaneously. As a result, their contribution can indeed be key in future MaaS schemes.

The main contributions of the present study are the following. First of all, we identify user clusters with respect to their attitudes towards MaaS, identifying which segments of the population are more likely to engage in MaaS (and whether pooled on-demand services also deem apt in them from an attitudinal perspective). Second of all, we investigate if there is a relation between current mobility patterns and the inclination towards MaaS, and interpret what this can mean to future urban mobility. Third of all, we identify barriers that can hold back users from adopting MaaS. Finally, based on the presented new insights, we propose a series of recommendations and policy implications tailored to the different clusters present in the study to support future MaaS adoption.

2.2 Methodology

In this section, we discuss the overall research approach, including the design of the survey and the data analysis approach.

2.2.1 Survey Design

We performed a survey in order to identify potential future users of sustainable MaaS schemes in the Netherlands. Given that the higher densities of urban areas better allow for the economically viable coexistence of a robust transit system and different on-demand services, we exclusively targeted individuals living in (sub)urban areas in The Netherlands in our study. The survey included several attitudinal Likert-scale statements regarding attitudes towards MaaS, with an emphasis on pooled on-demand services. The included attitudinal indicators are explained in detail in the following subsection.

Survey respondents were recruited from the Netherlands Mobility Panel (MobilitieitsPanel Nederland, MPN), which is an annual household panel designed for the longitudinal study of travel behaviour in the Netherlands (Hoogendoorn-Lanser et al., 2015). In addition to the annual panel waves, MPN respondents occasionally take part in specific questionnaires, as is the one designed for the current piece of research.

Attitudinal Indicators

MaaS is still in its first stages. Therefore, the study of transport behaviour in real MaaS settings is still limited to the small number of MaaS pilots currently available. We add to this knowledge by carefully designing a series of attitudinal indicators to better understand the mobility changes MaaS will spark. This methodology is underpinned by previous research which has found a relation between attitudes and behaviour in mode choice (Molin et al., 2016). Moreover, previous research has shown that attitudinal approaches that are used as a base for mobility segmentation are advantageous as a starting point for related policy interventions (Haustein, 2012; Haustein & Hunecke, 2013).

Durand et al. (2018) identified three main aspects relevant when investigating changes in travel preferences that can take place as a result of MaaS: (i) mobility integration, (ii) shared mobility modes, and (iii) mobile applications. In our analysis, we add a category focusing on willingness to pay, to have a notion of the business case for MaaS. Figure 2.1 shows the key aspects of the attitudinal indicators included in the survey, which will be described in detail below. The complete formulation of the attitudinal indicators as well as their source (where applicable) are detailed in Appendix A.

Mobility integration. Individuals need to be willing to integrate different modes of transport as part of their travel patterns in order to exploit the benefits provided by MaaS. This willingness to use different modes can, in turn, be influenced by individuals' attitudes towards public transport and private car. Therefore, we include three subcategories:

(i) Multimodal mind-set. We understand the multimodal mind-set as the willingness to integrate different modes of transport into one's travel patterns. Similarly, we refer to multimodal individuals as those who include different transport modes in their weekly mobility. With regard to the multimodal mind-set, we differentiate two aspects, namely the attitude towards multimodality with the traditional modes, and the openness to innovate in mobility.

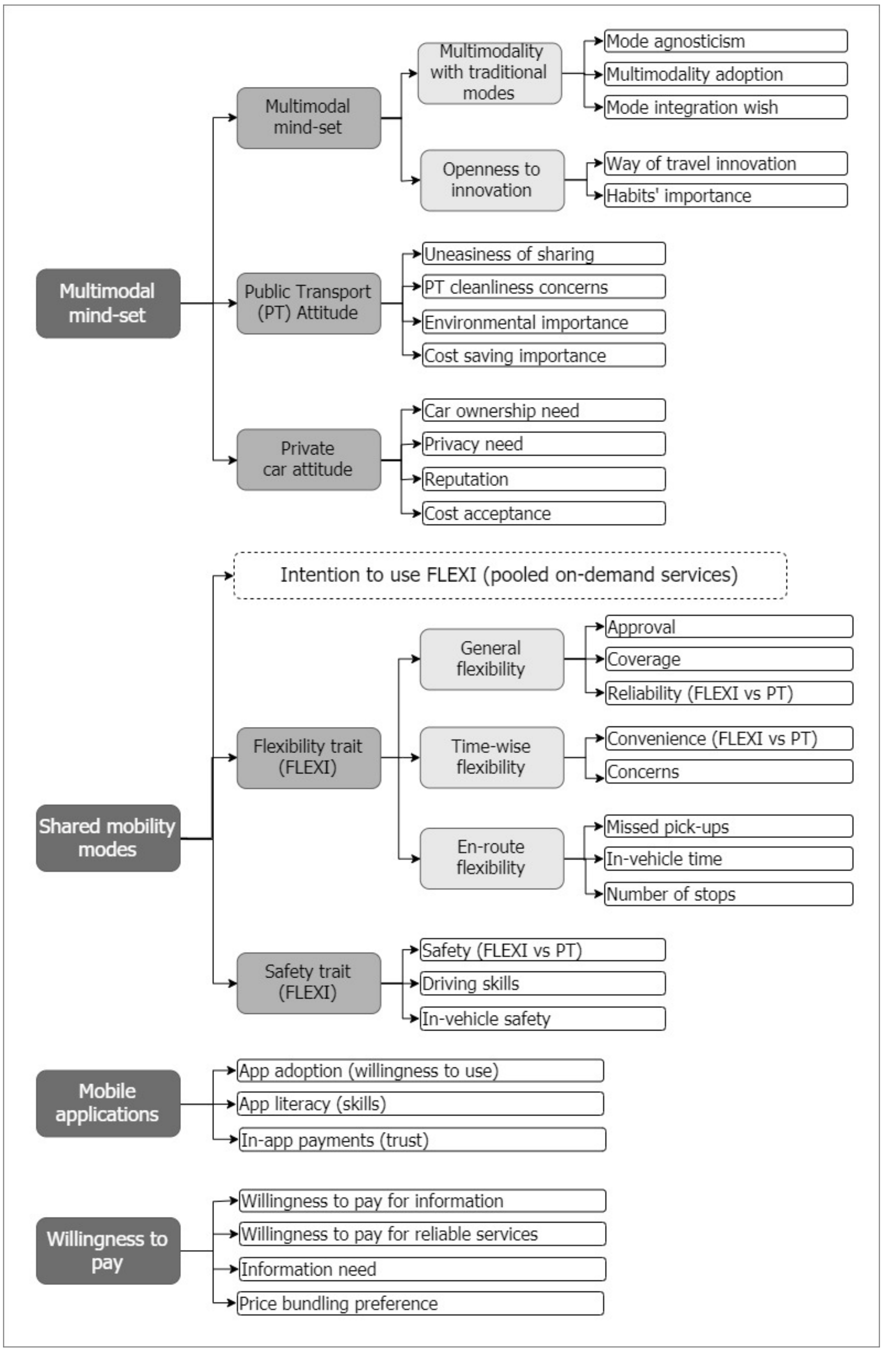

Figure 2.1: Key aspects of the attitudinal Likert-scale indicators

(ii) Public transport attitude. Attitudes towards public transport in the Netherlands are more negative than those towards bike or car (Kennisinstituut voor Mobiliteitsbeleid (KiM), 2018), yet a positive attitude towards public transport is helpful in order to accept a MaaS scheme with public transport as its core. We do not include operational aspects in our statements due to large differences in frequency and reliability between different available services. Rather, we focus on sharing (common characteristic for all public transport modes) and common goals of public transport and MaaS: cost and environmental impact reduction.

(iii) Private car attitude. From a utilitarian perspective, MaaS can offer a good alternative to using a privately-owned car. However, symbolic and affective motives related to car usage have been found more important than utilitarian ones (Steg, 2005). This would make it more difficult to shift from the current mobility paradigm towards MaaS. Therefore, we address these motives in our indicators.

Shared mobility modes. Given the still limited experience of most individuals with these services, we consider novel shared mobility modes independently, and not merged in the attitudes towards the more general mobility integration, as suggested by Durand et al. (2018). In this study, we focus on pooled on-demand services as an example of shared mobility modes. These services do not only provide the flexibility of on-demand services, but they also offer a collective service, fitting the needs of congested urban areas.

Pooled on-demand services (referred to as FLEXI when presented to respondents) were described in detail in the questionnaire. It was introduced as a mobility service which could have a maximum of six people in a vehicle and was bookable in real time via an app (or via a mobile phone for those not owning a smartphone). The pick-up point was assumed to be 1-minute walking distance from their location, and detours could take place to pick up or drop off other passengers. Before being presented with the related attitudinal indicators, respondents also completed two stated preference experiments focusing on reliability of these pooled on-demand services. This way, respondents had a better understanding of both the flexibility (+) and the variability (-) associated with flexible route and schedule services and could form an opinion towards these services prior to indicating their attitude towards the envisaged service. In turn, this allowed us to ask respondents about their intention to use pooled on-demand services.

Within pooled on-demand services, our main interest is to analyse their flexibility trait. Flexibility is the common characteristic of all on-demand services, and is arguably the fundamental difference between these services and traditional public transport. Therefore, even if only pooled on-demand services are explicitly addressed, the outcomes of some of the indicators included can (at least partially) be transferred to other on-demand services. We cover aspects that address both temporal and spatial flexibility.

Additionally, we analyse the safety construct. Adequate safety is the (non-performance related) most basic transportation need (Peek & van Hagen, 2002) and a point of concern of some individuals for pooled on-demand services specifically (Sarriera et al., 2017). Traffic safety and social safety are covered in the indicators.

Mobile applications. Given that individuals interact with MaaS services via an app interface, it is necessary to investigate their willingness to adopt the app. Even in countries where mobile phone adoption is almost ubiquitous, attitudes and skills can widely differ among individuals. Potential users need to not only have a smartphone and internet connection to operate the app, they also need to be willing to install the app, have enough skills to operate it, and have trust in the app. These three aspects are covered in our study.

Willingness to pay. The added value of MaaS lies in its integration of all modes of transport and travel stages, and in its real-time information functions, which enable both better services and better information. Under this category, we want to better understand respondents' willingness to pay for improved mobility, as well as their perceived need for improvements. Some studies consider bundling packages (i.e., having monthly subscriptions instead of paying per individual trip) a key aspect in MaaS. MaaS, as is considered in this study, does not require bundles. However, we also include a statement regarding bundling preferences to obtain a first impression on this aspect. We refer the reader to Ho et al. (2018) and Matyas & Kamargianni (2018) for those looking for studies regarding MaaS willingness to pay in bundling options.

All attitudinal indicators are presented to respondents as 5-point Likert-scale statements (strongly disagree / disagree / neutral / agree / strongly agree). Moreover, respondents are also given the 'Not applicable' answer option. Indicators are presented to respondents in blocks of either 4 or 5 statements. The order of the statements is randomised within each block.

Habits and Current Behaviour

Since habits and current behaviour are important predictors of future transportation behaviour (Lanzini & Khan, 2017), we complemented the previous attitudinal indicators with questions related to respondents' experience with aspects relevant to MaaS.

We inquire respondents' adoption of mobile technology (needed to operate any MaaS app) and their usage experience with the predecessor of the MaaS app: the journey planners (multimodal journey planners are considered Level 1 MaaS apps (Sochor et al., 2017)). Also, we look into individuals' current mobility patterns. We already had information regarding individuals' travel patterns from the 2017 wave of the MPN general annual survey. We add to this information by inquiring about respondents' familiarity with on-demand services. Additionally, to better understand what drives respondents while shaping their transport mode choices in their trips, we ask them for their motives in this decision process.

2.2.2 Analysis Framework

Figure 2.2 provides a step-wise overview of the main steps of the analysis. First, the data is cleaned. Respondents who require an unrealistically low time to complete the questionnaire, recurrently straight line (i.e., do not differentiate in ratings) and repeatedly select the 'not-applicable' option are considered invalid. Following, exploratory factor analysis and latent class cluster analysis are performed for variable reduction and clustering purposes.

Even if segmentation in transport literature often stems from differences in socioeconomic characteristics or current travel behaviour, previous research has identified

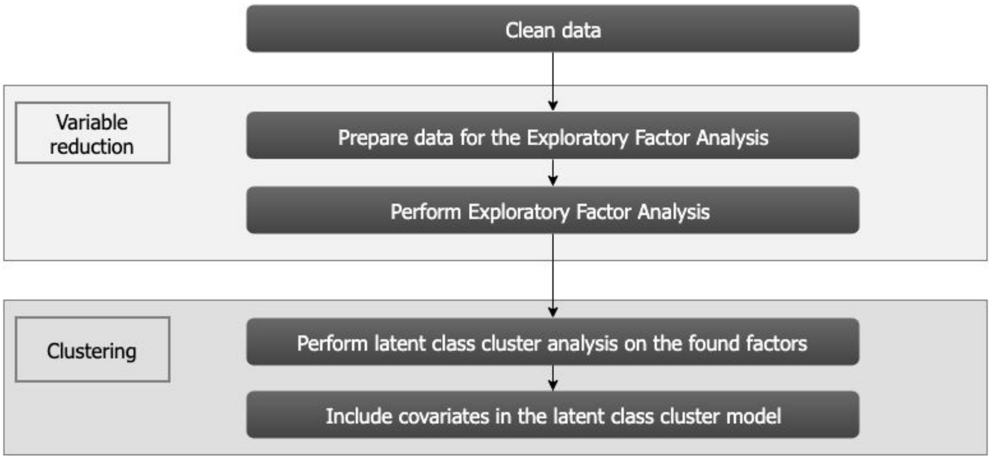

Figure 2.2: Step-wise scheme of the analysis framework

attitudes as important predictors of travel behaviour (Pronello & Camusso, 2011). For example, Hunecke et al. (2010) found mobility-related attitude-based segmentation to yield greater differences in mobility behaviour than those based on socioeconomics, and Redmond (2000) found it to result in the highest predictive power for travel mode choice. Research into attitude-based segmentation has significantly increased in recent years. The common methodology, as the one followed in this chapter, is composed of a variable reduction technique and a subsequent cluster analysis. We refer the reader to Anable (2005), Haustein & Hunecke (2013) or Pronello & Camusso (2011) for further literature on previous research regarding mobility attitude-based segmentation. The following subsections explain the methodology used in our research in more detail.

Exploratory Factor Analysis

In this study, we look for relationships among the variables that may be different from the prior expectations of the categories presented in Figure 2.1. Therefore, Exploratory Factor Analysis (EFA; (Williams et al., 2010)) is the variable reduction technique used in this study. EFA accounts for the common variance among the variables (and is not to be confused with principal component analysis) (Suhr, 2005).

EFA can be performed exclusively on interval or ratio level variables (Suhr, 2005). Equidistance is often assumed between the different levels of Likert-scales, which allows us to perform EFA on our data. To identify if a considerable number of respondents does not feel addressed by some of the statements, we included the 'non-applicable' option. However, this option introduces data that falls out of the Likert-scale. We remove from the analysis any variable with a considerable number of non-applicable responses from the posterior analysis (not-applicable responses are not distributed at random). Low recurrence of non-applicability in a variable (<5.5%) is accepted and this data is treated as missing at random. This data is imputed using expectation maximisation, which produces the maximum likelihood estimation of parameters using all observed information (Acock, 2005). We impute the correlation matrix (using the SPSS add-on module presented in (Weaver & Maxwell, 2014)) instead of imputing the variables themselves, to overcome SPSS shortfall in including standard errors in the expectation maximisation imputation (von Hippel, 2004).

Factor scores are then calculated using a non-refined method. These methods are more stable across different samples than refined methods (Distefano et al., 2009). If factor loading differences among the indicators of the different factors are small, the 'non-weighted sum score method' will be used. Otherwise, the 'weighted sum score method' will be preferred. Both methods allow for a direct interpretation of the factor value in relation to the 5-point Likert scale presented to respondents.

Latent Class Cluster Analysis

We aim at identifying respondents that share similar attitudes on the researched indicators. We hypothesise that attitudes on these indicators are to some extent related to each other, encompassed in their attitude towards MaaS. To this end, we perform latent class cluster analysis (LCCA). LCCA models, also referred to as finite mixture models, group individuals in different classes according to an unobserved (latent) class variable that explains their responses on a set of observed indicators (Molin et al., 2016).

Figure 2.3 shows the conceptual latent class model used in the analysis. The EFA factors are the indicators of the model that help delve into the latent variable that is behind the differentiation of the latent classes. The covariates, represented in the lower part of Figure 2.3, help characterise the different classes. Covariates on socioeconomic, mobility and technology-related characteristics are added to the model after a model without covariates with adequate model fit has been identified. Whenever the covariates do not improve the model, they are only included as passive covariates, to aid cluster identification.

The mathematical formulation of the model with the covariates takes the following form (Vermunt & Magidson, 2016):

$$f(y_i \mid z_i^{cov}) = \sum_{x=1}^{K} P(x \mid z_i^{cov}) \cdot \prod_{m=1}^{M} f(y_{im} \mid x) \tag{2.1}$$

where x is the latent variable with its K categories, z_i^{cov} individual's i set of covariates and y_{im} individual's i response to indicator m (M being the number of indicators). The first factor of the equation refers to the probability of belonging to a certain latent class given the individual's covariates, and the second factor is the probability density of y_i given x. This mathematical formulation holds assuming that the indicator variables are independent of each other conditional on the latent variable x (Vermunt & Magidson, 2016). A violation of this assumption in our model, which can be measured by means of the bivariate residuals, would indicate that the model lacks local fit and that it cannot be trusted (Oberski, 2016). We therefore examine this assumption by

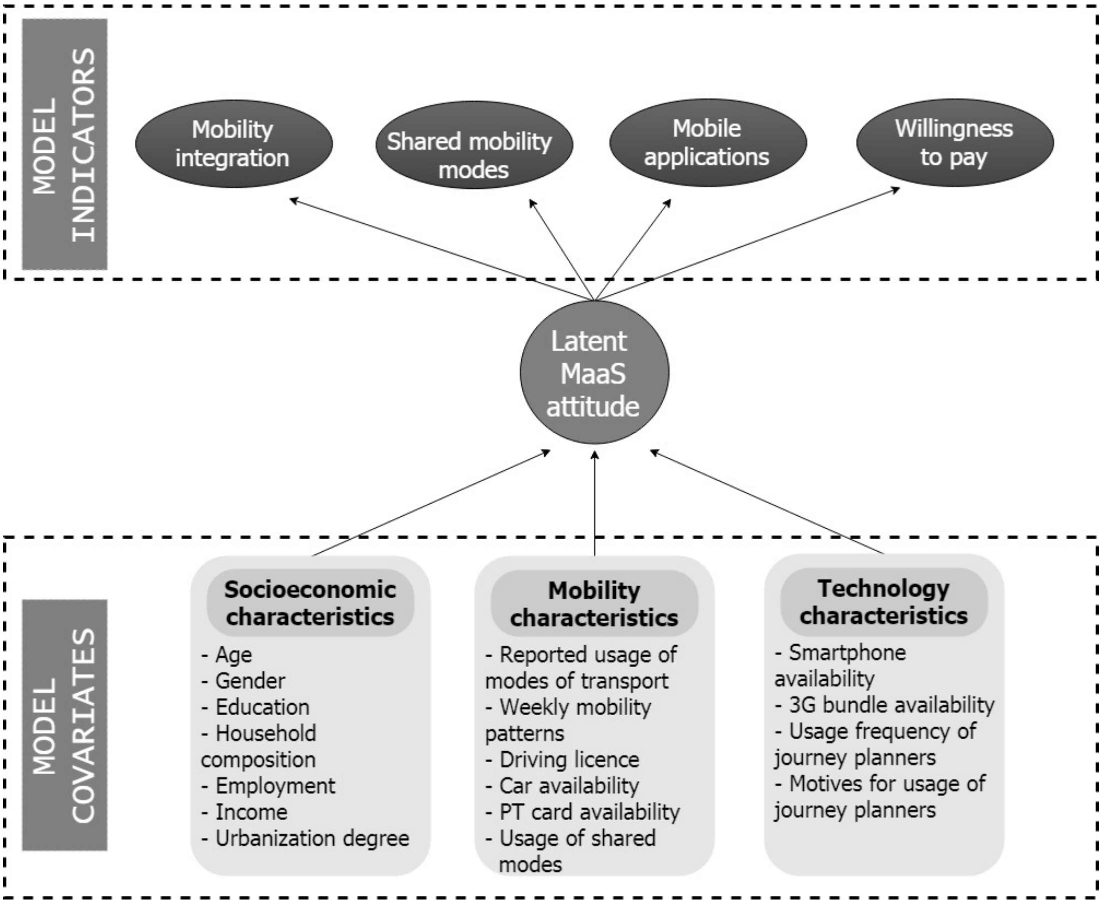

Figure 2.3: Scheme of the latent class cluster model with the investigated covariates

studying the bivariate residuals (BVR). Applied research often considers BVR to be chi-squared distributed, yet this approach does not always work satisfactorily (Oberski et al., 2013). Instead, Oberski et al. (2013) suggest to analyse the BVR p-values of the parametric bootstrapping. We follow this procedure in combination with the study of the bootstrapped L^2 of the overall model, as done in Oberski (2013).

Some of the variance present in the initial data of the attitudinal indicators is lost by using the obtained factors as only model indicators in the LCCA. Additionally, this approach treats the EFA factors as observed variables in the LCCA, ignoring the uncertainty that arises from the measurement of the factors through its attitudinal indicators. Still, the large number of statements included makes this double approach (variable reduction and subsequent cluster analysis) the rule in attitude-based segmentation studies, as previously mentioned in Section 2.2.2.

2.3 Results

The analysis and modelling approach detailed in the previous section has been applied to a dataset representative of the urban Dutch population. Figure 2.4 indicates the research questions that are answered in the different sections of the analysis and interpretation of the results. Data collection and descriptive statistics are first presented (Section 2.3.1) followed by the Exploratory Factor Analysis (Section 2.3.2) and the Latent Class Cluster identification (Section 2.3.3). These clusters are further characterised in Section 2.4.

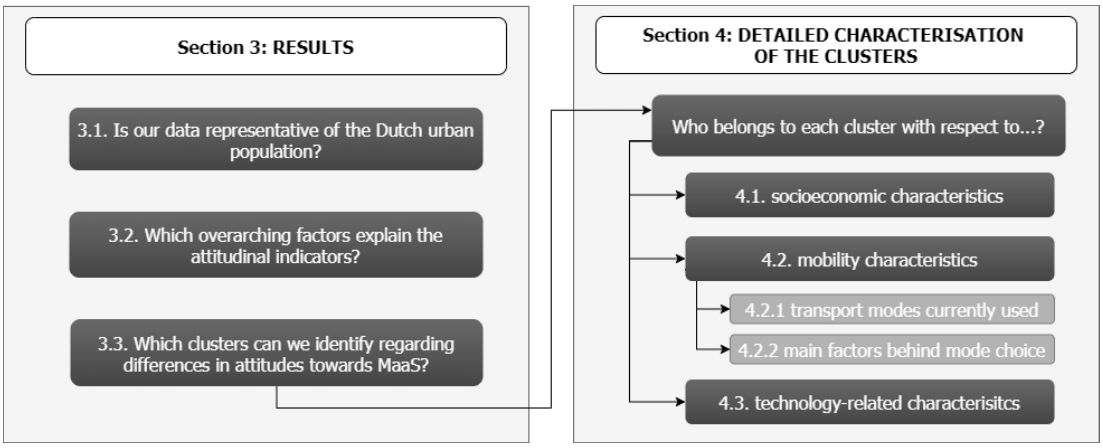

Figure 2.4: Research questions answered in the analysis and interpretation of the results

2.3.1 Data Collection and Sample Description

To test our questionnaire, an on-line pilot was performed on April 2018. No modifications of the attitudinal indicators used in this study were needed after the pilot. Our final questionnaire (conducted on-line and in Dutch) was distributed on May 2018. A total of 1077 respondents finished the questionnaire, of which 1006 (93%) were considered valid respondents after data cleaning. Only individuals aged 18 and older in possession of a mobile telephone took part in the questionnaire. We targeted respondents living in areas with more than 1,500 inhabitants/km^2 (highly urbanised areas according the 'urbanity degree' indicator used in the Netherlands (Centraal Bureau voor de Statistiek (CBS), 1992)), and all respondents belonged to different households. The socio-economic characteristics of the sample, as well as the Dutch values (both for (very) high urbanised areas and for the whole of The Netherlands) are included in Table 2.1.

Our sample satisfactorily represents the shares between the two levels of urbanisation levels (high urbanised areas and very high urbanised areas) and gender. Regarding age, middle aged adults are a bit underrepresented and the elderly population slightly overrepresented. We can observe some differences between the age shares of the urban areas exclusively and the average of the Netherlands. As expected, younger adults are more prominent in urban environments. This is well represented in our sample.

We do not have values regarding education level, working status and household composition for the urbanised areas, only for the average of the Dutch population. Differences between our sample and the national average are as expected: a higher proportion of highly educated respondents and working individuals as well as a higher share of single person households than the national average. In general, we consider the representativeness of our sample to the shares of the target population to be adequate.

Table 2.1: Comparison between the sample and Dutch population for different socio-economic variables. Sources for the population data: Centraal Bureau voor de Statistiek (CBS) (2018d,c,a,b).

Socio-economic variable	Category	Total sample (N=1006)	Dutch (very) high urbanised areas	Dutch 2018 shares
Gender	Male	48.2%	48.9%	49.6%
	Female	51.8%	51.1%	50.4%
Age	18* to 39	38.1%	38.1%	31.8%
	40 to 64	35.6%	42.0%	44.0%
	65 and above	26.3%	19.8%	24.2%
Education	Low	25.2%		31.5%
	Average	32.5%		37.8%
	High	42.0%		29.2%
	Unknown	0.2%		1.4%
Employment status	Working	59.9%		50.9%
	Not working	40.1%		49.1%
Household	1 person household	49.0%		38.2%
	> 1 person household	51.0%		61.8%
Urbanisation level	Very high urbanised (>2500 inhab./km²)	46.9%	48.2%	23.3%
	High urbanised (1500-2500 inhab./km²)	53.1%	51.8%	25.1%

* 18 to 39 for the share sample, but 20 to 39 for the Dutch 2018 values

2.3.2 Exploratory Factor Analysis of MaaS indicators

2.6% of the total data from the attitudinal indicators was marked as 'not applicable', a high share of which is present in three out of the 31 indicators. These three indicators are not considered for the EFA analysis. The remaining missing values (1.4% of the total data) were imputed using expectation maximisation. We performed the EFA employing the Principal Axis Factoring extraction method (unlike other methods it does not require the multivariate normality assumption (Fabrigar et al., 1999)) with oblimin oblique rotation (which allows for correlation among factors and thus better replicates human behaviours (Williams et al., 2010)). We investigate the suitability of the data for EFA with the Kaiser-Meyer-Olkin's (KMO) measure of sampling adequacy and Bartlett's test of sphericity (Field, 2009). We obtain a KMO of 0.835, which shows good sample adequacy (Hutcheson & Sofroniou, 1999), and the Bartlett's test of sphericity is <0.001, which indicates sufficient relations between indicators for the EFA. Since the average communality (i.e., the proportion of the common variance present in the variables (Field, 2009)) is lower than 0.6, and the sample size is well over 200, we follow the scree plot criterion (Cattell, 1966) to decide on the number of factors (Field, 2009). This leads us to retain 5 factors in the factor analysis, which explains 44.6% of the variance.

Table 2.2: Results of the pattern matrix of the exploratory factor analysis

Factors and their indicators	Factor loading
Mobility integration factor	
It is important to use public transport to preserve the environment	0.586
I choose to travel with public transport or to share rides to reduce my trip costs	0.580
I do not mind which transport mode I use, as long as it suits my trip needs	0.491
I am willing to try new ways to travel	0.474
People like me only use their own bike and/or car (reversed)	0.473
I often compare different travel options and transport modes before choosing how to travel	0.467
I like the privacy in the car or bike (reversed)	0.423
It makes me uncomfortable to ride with strangers on public transport	
I would not mind if other travellers get in or off the FLEXI vehicle during my ride	
I think the public transport is not so clean or decent	
I like travelling always in the same way	
It is essential to be able to easily combine different transport modes (such as bus, car, bike or car-sharing) in order to improve transportation in the Netherlands	
FLEXI over Public Transport (PT) factor (shared mobility modes)	
FLEXI seems to me more reliable than current public transport	0.595
I would feel safer in FLEXI than in a regular bus	0.587
I find FLEXI's flexibility in the departure time more convenient than traditional transit.	0.565
The proximity of a driver would make me feel safe in FLEXI	0.558
FLEXI would give me the freedom to travel where I need to be when needed	0.548
I like that FLEXI does not have a fixed schedule or route	0.543
FLEXI concerns factor (shared mobility modes)	
FLEXI does not have fix schedules. That would worry me.	0.624
I would be worried that FLEXI departs without me	0.587
I think that FLEXI drivers do not drive carefully	0.414
I would find it annoying that FLEXI does not drive the fastest route (e.g., FLEXI's route is 18 minutes instead of 15 minutes)	
Mobile application factor	
I would use a (smartphone) app if it gave me access to all available travel alternatives	0.727
I like to pay for my rides via a (smartphone) app	0.562
It is easy for me to find FLEXI's pick-up point if it is displayed on a map in the (smartphone) app	0.535
Willingness to pay factor	
I would be ready to pay for precise and reliable travel information	0.605
I am willing to pay more to have a more predictable travel time for my journey	0.420
I find it difficult to find information of all available travel alternatives	

Table 2.2 shows the factors founds and the factor loadings for the rotated pattern matrix. For interpretation, we only consider loadings bigger than 0.4, as advised in (Field, 2009). The rest of the indicators belonging to a factor are depicted in Table 2.2 in grey without the loading. A subsequent EFA on the variables that loaded significantly (>0.4) on the previous factors, leads to the exact same factors and very similar indicators (KMO=0.802, Bartlett's test of sphericity <0.001, 51.1% variance explained). Only these loaded statements are considered for the posterior LCCA. The comparable loadings of the indicators belonging to the different factors indicate that they all contribute to a similar degree to the factor to which they belong. Therefore, factor scores

are calculated using the "non-weighted sum scores" method. (For the interested reader, the scree plots of both EFA are included in Appendix A).

The factors found are well in line with those from the survey design phase (Figure 2.1). The mobility integration factor shows how a positive multimodal mind-set aligns with a positive attitude towards public transport and a low car drive. In line with expectations, those three subcategories belong to an overarching factor. Interestingly, we found two factors regarding indicators pertaining (pooled) shared mobility modes, and they do not pertain to the flexibility and safety traits of these services. Instead, they refer to (i) the comprehensive preference of FLEXI (i.e., pooled on-demand services) over traditional transit (or vice versa), and (ii) concerns towards the new mobility service. The two factors being distinct suggests that even if there may be people that prefer public transport over pooled on-demand services, they may not necessarily have concerns related to using pooled on-demand services; similarly, individuals that prefer pooled on-demand services over public transport are still not necessarily very positive towards these services and may have concerns related to their usage.

2.3.3 Latent Class Cluster Identification

We perform the Latent Class Cluster Analysis (LCCA) using the Latent GOLD software (version 5.1) (Vermunt & Magidson, 2016). We include the five EFA factors as well as the intention to use pooled on-demand services (binary variable, yes/no) as model indicators. To decide on the number of classes, we analyse both the BIC and the AIC global goodness-of-fit statistics in models ranging from one to seven classes. While the lowest BIC is shown for the 3-class model, the AIC keeps decreasing with the increase in the number of classes. We also examine the classification errors for all models. Taking all these three things into account, we consider the 5-class model as the most adequate. In this model, the BVR of the pair 'FLEXI over PT' & 'FLEXI concerns' is very low. Thus, we add a direct effect between these two factors, freeing the local dependence between them. All the attitudinal statements involved in these two factors share attitudes towards (the fictitious) FLEXI. Similar wording and varying interpretation of this new service from different respondents (as a result of the service description in the survey) may have led to the association between the two factors in the LCCA. As a result, we consider adding the direct effect useful (Magidson & Vermunt, 2004). Given that the overall bootstrapped L^2 p-value of the model is adequate, we do not add additional direct effects.

As the next step, we explore the effect of covariates presented in Figure 2.3 on the latent class membership. Inclusion of covariates leads to changes in the clusters, but it helps differentiate individuals in the different clusters further, which, in turn, helps target policy recommendations. The covariate analysis is first done per type (using the types mentioned in Figure 2.3). Covariates that prove significant per type are then put together incrementally one by one, and deleted if they become insignificant when combining different covariates. We find seven covariates to improve the model: 3G bundle availability, working status, education level, urbanisation level, bike use frequency, acquaintance with bike-sharing systems and presence of children in the household. The overall bootstrapped L^2 p-value of the final model is 0.30 (values > 0.05 provide an adequate fit (Vermunt & Magidson, 2005)), and the entropy of the model amounts to 0.66.

The profile of the indicators and active covariates of our final model are depicted in Table 2.3 (for the interested reader, parameters are included in Appendix A). We name the five clusters, ordered by their share from the largest to the smallest, as follows:

– *Cluster 1 (32% of the sample): "MaaS-FLEXI-ready individuals".* This cluster, which includes roughly one third of the respondents, has the highest average on all six indicators in comparison to all other 4 clusters, indicating the highest inclination for MaaS adoption and a remarkable 99% usage intention towards pooled on-demand services (FLEXI). It has the highest willingness to pay of all clusters, albeit still lower than the neutral value (2.9) – suggesting that the urban Dutch society is not willing to pay for improvements in mobility.

– *Cluster 2 (25%): "Mobility neutrals".* With a quarter of the sample, this cluster has an average of neutral in relation to almost all factors. They can be regarded as conservative, undecided or neutral-minded. Intention to adopt pooled on-demand services is the second highest among the five clusters, which can indicate that even if they have an overall neutral approach regarding the analysed attitudes, they are still open towards adopting new mobility services.

– *Cluster 3 (22%): "Technological car-lovers".* This cluster differs from the two previous clusters in the low value of the 'mobility integration' factor, showing a stronger inclination towards privately owned modes over public transport or other shared modes. Further, adoption intention towards pooled on-demand services is lower than the average of our sample despite this group having a neutral attitude towards these services. The further analysis of the covariates shows that within the owned modes, it is the car which is most dominant in this cluster. This preference may stem from enthusiasm towards the car or due to perceived need. Despite the low value of the factor related to mobility integration, this cluster is associated with a high value in the 'mobile application' factor. This underscores the importance of differentiating mobile-application from mobility-related aspects in the study of MaaS adoption.

– *Cluster 4 (15%): "Multimodal public transport supporters".* With roughly one sixth of the sample, this is the only cluster that next to Cluster 1 has a higher than neutral average value for both 'mobility integration' and 'mobile application' factor. Notwithstanding, this cluster strongly differs from Cluster 1 in the FLEXI over PT factor: while individuals of Cluster 1 prefer pooled on-demand services over traditional public transport, this is the other way around for individuals in this cluster. This difference highlights that having a positive attitude towards mobility integration does not imply future adherence to the new shared modes. Intention to use pooled on-demand services is at a level between the one observed among respondents in Cluster 3 and Cluster 1. Also, respondents in this cluster have a lower average score in the willingness to pay factor than the previous three clusters for improvements in mobility, showing higher cost sensitivity.

– *Cluster 5 (6%): "Anti new-mobility individuals"*. The smallest cluster can be described as the contra of Cluster 1: showing negative attitude towards all presented factors and an extremely low intention to use pooled on-demand services (12%). This cluster shares with Cluster 3 the low value for the 'mobility integration' factor. However, unlike Cluster 3, respondents in this cluster also show limited technology affinity and a very negative attitude towards pooled on-demand services. Respondents in this cluster are therefore very unlikely to adopt any new mobility solution that is presented to them.

We graphically present the scores of the five EFA factors for the different clusters in Figure 2.5. We further investigate the average values of the individual attitudinal indicators for the different clusters in Figure 2.6. Indicators excluded from the LCCA (share of 'non-applicable' values >5% or EFA factor loadings <0.4) are also included in the radar graphs for a more comprehensive overview of all studied aspects. To ease the interpretation, indicators negative to MaaS and/or to their pooled on-demand services have been reversed. The radar graphs confirm that the general trends represented by the factors are also present for the individual attitudinal indicators, with 'MaaS-FLEXI-ready individuals' scoring, in general, highest and 'anti new-mobility individuals' scoring lowest. The strong positive attitude of the 'multimodal public transport supporters' towards public transport is also clear from the public transport related statements in the graphs. The graphs also provide deeper insights into the extent to which MaaS related indicators differ. Privacy stands out for its importance while willingness to pay for travel information is distinct for its low scores. Regarding the mobile application factor, the app payment acceptance indicator scores significantly lower than the other related indicators.

Table 2.3: Profile of the final LCCA model for both indicators and active covariates. For the active covariates, we highlight in bold the class with the highest share for each characteristic.

	LC1 MaaS-FLEXI-ready individuals	LC2 Mobility neutrals	LC3 Technological car-lovers	LC4 Multimodal public transport supporters	LC5 Anti-new-mobility individuals
Cluster Size	32%	25%	22%	15%	6%
Indicators					
Mobility integration factor					
Mean	3.4	3.1	2.5	3.3	2.1
FLEXI over PT factor					
Mean	3.3	3.1	3.1	2.5	2.2
FLEXI concerns factor					
Mean	2.8	3.0	2.9	2.8	3.4
Mobile application factor					
Mean	3.9	3.0	3.5	3.3	2.2
Willingness to pay factor					
Mean	2.9	2.7	2.6	2.4	2.2
Intention to use FLEXI for free-time purposes					
No	1%	25%	40%	28%	88%
Yes	99%	75%	61%	72%	12%
Active covariates					
Working (voluntary work excluded)					
No	30%	**79%**	22%	27%	31%
Yes	70%	22%	**78%**	73%	69%
Highest education					
Low	15%	**48%**	23%	13%	31%
Medium	25%	36%	**43%**	26%	38%
High	60%	17%	34%	**61%**	31%
Child under 12 years old in household					
No	88%	**98%**	77%	88%	90%
Yes	12%	2%	**23%**	12%	10%
Urbanisation level					
Highly urbanised	44%	63%	**66%**	35%	58%
Very highly urbanised	56%	37%	34%	**65%**	42%
Reported bike use frequency					
(almost) never	5%	**24%**	16%	2%	20%
less than 1 day/month	5%	6%	9%	5%	**11%**
1 to 3 days a month	10%	6%	**19%**	9%	15%
1 to 3 days a week	**27%**	22%	26%	24%	20%
4 or more days a week	52%	42%	29%	**60%**	34%
Heard about bike sharing systems (no Dutch OV-bicycle)					
No	46%	54%	60%	53%	**75%**
Yes	**54%**	46%	40%	47%	25%
3G bundle available on smartphone or tablet					
No	4%	**72%**	0%	11%	43%
Yes	96%	28%	**100%**	89%	57%

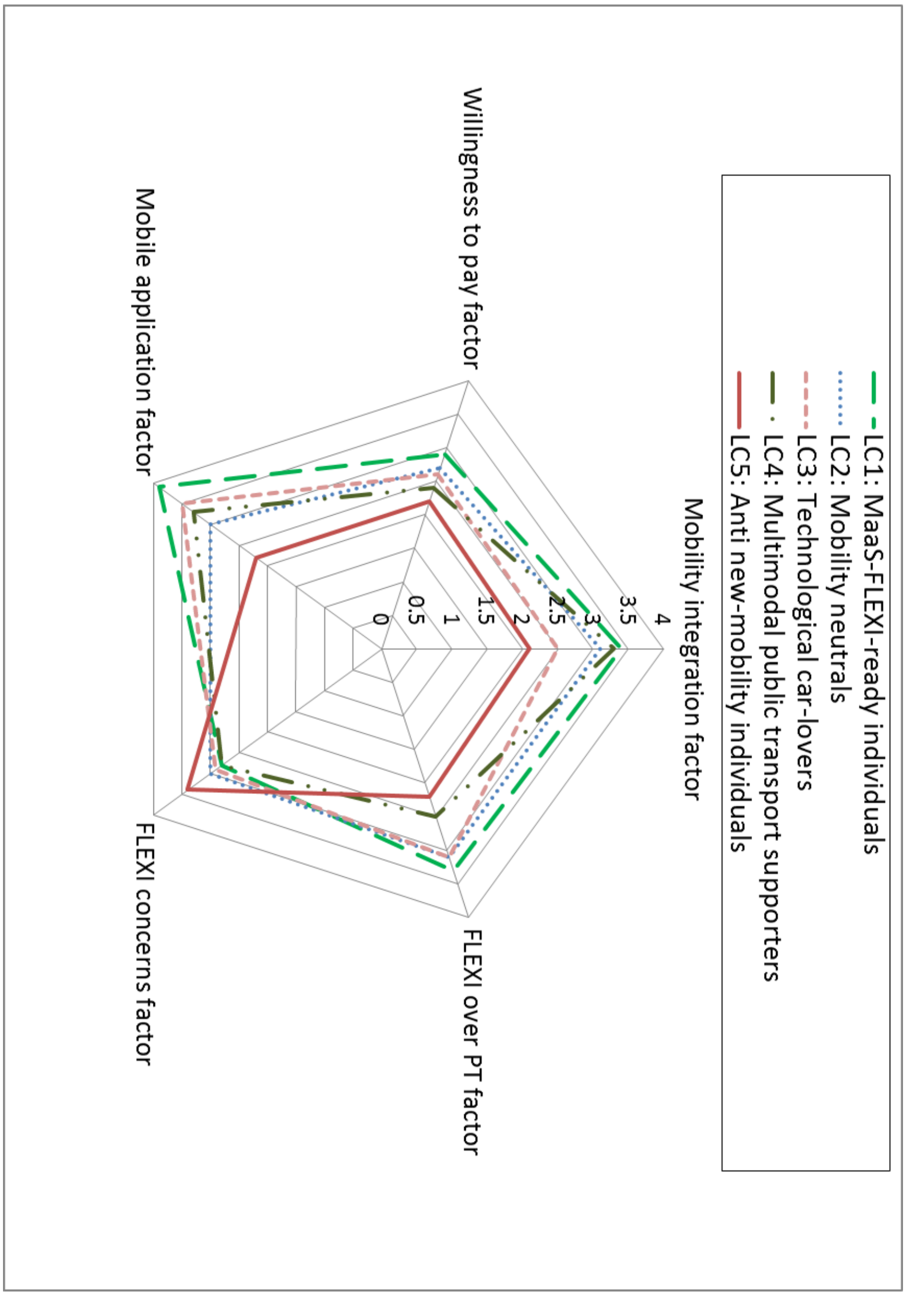

Figure 2.5: Average score of the five EFA factors for the different clusters

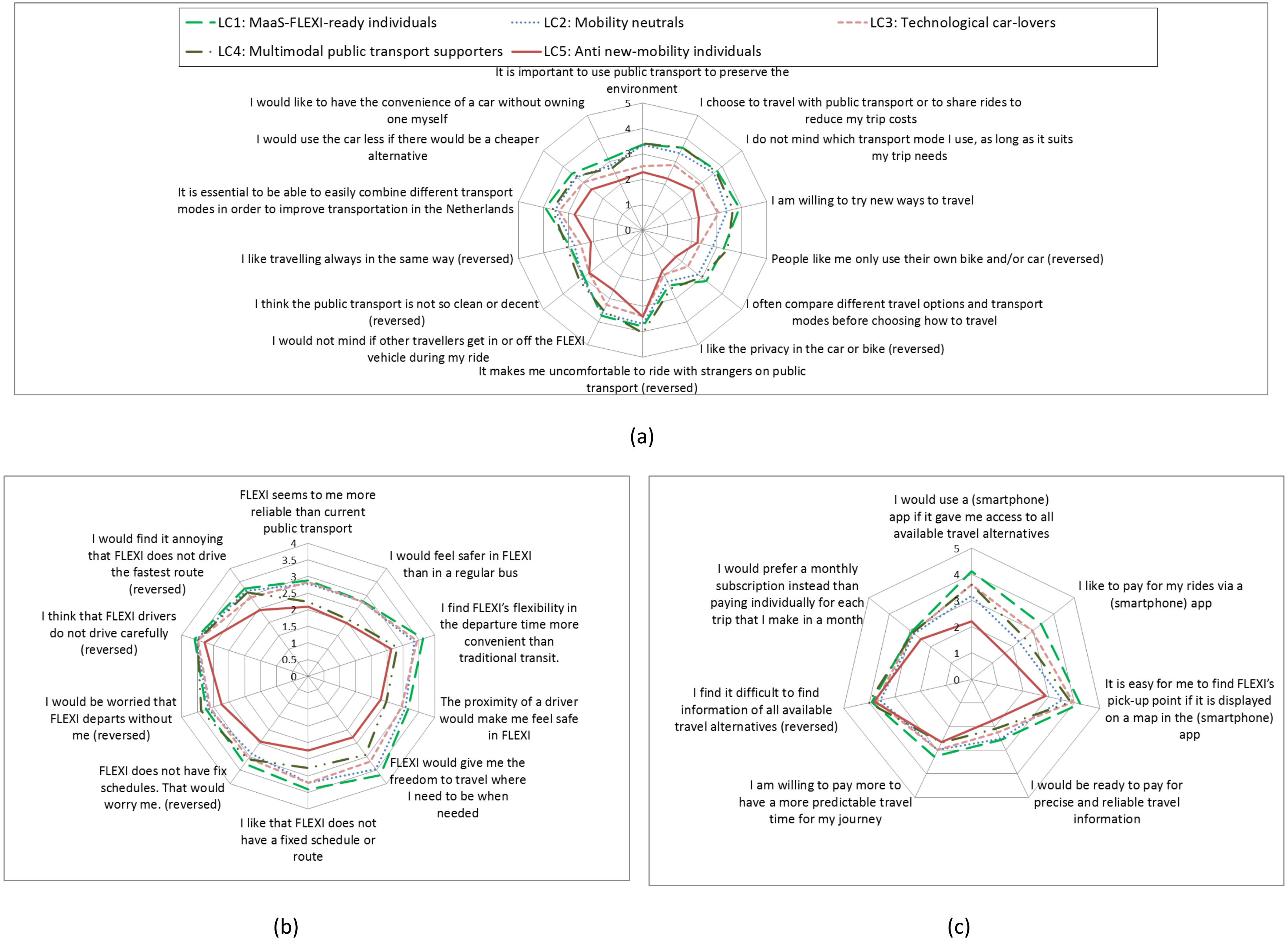

Figure 2.6: Average score for the attitudinal indicators related to: (a) mobility integration; (b) (pooled) shared mobility modes, and; (c) mobile applications and willingness to pay.

2.4 Detailed Characterisation of the Clusters

The five clusters of our final model are further profiled with the information of covariates (active and passive). We differentiate three aspects (as indicated in Figure 2.6): (a) socioeconomic characteristics, (b) mobility characteristics, and (c) technology related characteristics. They are discussed in sections 2.4.1, 2.4.2 and 2.4.3, respectively.

2.4.1 Socioeconomic Characteristics' Analysis of the Latent Clusters

Different socioeconomic covariates are included in the model to better understand the five clusters. Working status, education level, urbanisation level of the residence location, and the existence of children under 12 years old improve the membership function of the model (active covariates, depicted in Table 2.3). We also add age, gender, household composition and income as passive covariates in the model (see Table 2.4).

Table 2.4: Socioeconomic inactive covariates for individuals of the five clusters. For each cluster, we highlight in bold the class with the highest share.

	LC1 MaaS-FLEXI-ready individuals	LC2 Mobility neutrals	LC3 Technological car-lovers	LC4 Multimodal public transport supporters	LC5 Anti-new-mobility individuals
Gender					
Male	48%	44%	54%	45%	**55%**
Female	52%	**56%**	46%	55%	45%
Age					
18-34 years old	**39%**	10%	33%	38%	27%
35-49 years old	24%	7%	**29%**	27%	24%
50-64 years old	20%	25%	25%	20%	**28%**
65+ years old	17%	**57%**	13%	15%	21%
Household composition					
Single	52%	50%	38%	**60%**	42%
Couple	25%	**38%**	25%	18%	35%
Couple (or single parent) + children	23%	12%	**37%**	22%	23%
Personal net monthly income					
No personal income	8%	10%	8%	9%	**12%**
< 2000 €	34%	**48%**	35%	35%	42%
2000 - 3000 €	36%	35%	**41%**	38%	38%
>3000 €	**21%**	7%	15%	17%	8%
Missing value	1%	0%	1%	1%	0%

'MaaS-FLEXI-ready individuals' tend to be highly educated, young, have slightly higher average incomes and reside in the highest urbanised areas. These characteristics go in line with the characteristics that have been attributed to adopters of shared-mobility services (Alemi, 2018; Clewlow, 2016; Shaheen et al., 2012). 'Multimodal

PT supporters' have a similar socioeconomic profile, only differing from the first cluster in their slightly lower average income.

'Mobility neutrals' are associated with a high percentage of 65+ age old respondents (57%). Most of the individuals in this cluster (79%) do not work, arguably due to the large number of retired people in this cluster, and have a lower average income.

The 'technological car-lovers' and the 'anti new-mobility individuals', the classes less inclined towards mobility integration, share the (slight) over-representativeness of males. This may be explained by the higher modal share of car among men than women in the Netherlands (Molin et al., 2016). These two classes strongly differ in relation to other socioeconomic characteristics, though. 'Technological car-lovers' are distinct from all others for the higher percentage of households with children (37%), many of them including children aged 12 or younger (23%). In line with this result, Md Oakil et al. (2016) found a higher car dependency among those becoming parents. 'Anti new-mobility individuals' have the most balanced age composition, representing roughly even shares of all age segments, and this cluster is associated with relatively lower income individuals, higher only those of the 'mobility neutrals'.

2.4.2 Mobility Characteristics' Analysis of the Latent Clusters

This subsection presents a detailed analysis of the mobility characteristics of the five clusters. We first examine respondents' travel patterns and then their main drives when choosing a transport mode.

Travel Patterns

Reported bike frequency use and bike sharing awareness are active covariates of the model. Other variables related to mobility are also added to the model as inactive covariates (presented in Table 2.5), namely: car ownership, public transport card possession, car use (stated frequency), public transport use (stated frequency), weekly mobility patterns (stated), usage of new modes and main reasons to choose a transport mode.

'MaaS-FLEXI-ready individuals' and 'multimodal PT supporters' are the classes with the highest share of individuals in possession of a public transport smartcard (over 90%) while the 'technological car-lovers' and the 'anti new-mobility individuals' have the highest household car ownership shares (roughly 90%). The shares of the 'mobility neutrals' in these two aspects are in the middle of the five groups, in line with their intermediate position towards mobility. Usage of car and public transport resemble the trends in car ownership and smartcard possession. Interestingly, bike usage follows the same pattern as public transport, with 'MaaS-FLEXI-ready individuals' and 'multimodal PT supporters' biking the most often and 'technological car-lovers' and 'anti new-mobility individuals' the least often.

Table 2.5: Mobility inactive covariates for individuals of the five clusters. For each characteristic, we highlight in bold the class with the highest share.

	LC1 MaaS-FLEXI-ready individuals	LC2 Mobility neutrals	LC3 Technological car-lovers	LC4 Multimodal public transport supporters	LC5 Anti-new-mobility individuals
Car in household					
No	30%	27%	8%	**37%**	12%
Yes	70%	74%	**92%**	63%	88%
Public transport card					
No	8%	17%	29%	5%	**31%**
Yes	92%	83%	71%	**95%**	69%
Reported car frequency					
(almost) never	8%	**11%**	2%	**11%**	4%
Less than 1 per month	8%	7%	2%	**14%**	5%
1 to 3 days per month	**19%**	14%	8%	**19%**	7%
1 to 3 days per week	33%	**38%**	28%	32%	36%
4 or more days per week	32%	30%	**60%**	24%	48%
Reported train frequency					
(almost) never	18%	39%	45%	11%	**52%**
Less than 1 per month	41%	42%	**44%**	33%	38%
1 to 3 days per month	18%	11%	7%	**23%**	4%
1 to 3 days per week	12%	5%	2%	**17%**	4%
4 or more days per week	12%	3%	3%	**15%**	4%
Reported BTM (Bus/Tram/Metro) frequency					
(almost) never	13%	23%	47%	16%	**48%**
Less than 1 per month	34%	36%	**38%**	34%	36%
1 to 3 days per month	**31%**	22%	7%	23%	9%
1 to 3 days per week	15%	15%	3%	**20%**	4%
4 or more days per week	**8%**	4%	5%	**8%**	4%
OV-bicycle ever used (specific bike sharing scheme)					
No	75%	93%	94%	68%	**96%**
Yes	25%	7%	6%	**32%**	4%
Bike sharing ever used (different from OV-bicycle)					
No	97%	**100%**	**100%**	98%	98%
Yes	**3%**	0%	0%	2%	2%
Uber ever used					
No	81%	**98%**	94%	88%	97%
Yes	**19%**	2%	6%	12%	3%
Car sharing used (in the past 12 months, question from annual 2017 MPN wave)					
No	96%	99%	99%	94%	**100%**
Yes	**4%**	1%	1%	6%	0%

We visualise the weekly mobility patterns of the individuals in Figure 2.7 (considering car, public transport and (e-)bike). 40% of 'technological car-lovers' and 'anti new-mobility individuals' have an unimodal car behaviour, while this percentage drops to around 10% for 'MaaS-FLEXI-ready individuals' and 'multimodal PT supporters' (the two most multimodal clusters). Nonetheless, car usage is still more recurrent than public transport usage in all five clusters. Around 40% of 'multimodal PT supporters' and around 30% of 'MaaS-FLEXI-ready individuals' use some sort of public transport on a weekly basis. This percentage drops to less than 10% for 'technological car-lovers' and 'anti new-mobility individuals'. Moreover, a large share of individuals in these last two clusters report that they never use public transport. These results further show the alignment between attitudes and behaviour regarding mobility. Current unimodal car users are the least likely to be attracted by MaaS and the shared flexible transport modes offered by it.

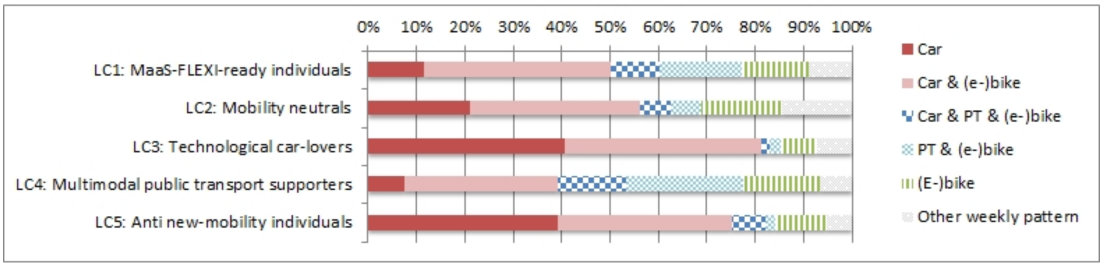

Figure 2.7: Current weekly mobility patterns of respondents of the different latent classes (train and BTM have been merged in the public transport (PT) category)

We also analyse both individuals' awareness and usage of new shared mobility modes. Uber and OV-bikes (station-based bike-sharing of the Dutch train operator NS) are familiar to the large majority of respondents. Respondents are less familiar with bike-sharing schemes other than the OV-bikes (now proliferating in the Netherlands) (Table 2.3), with the two clusters with higher multimodal mind-sets ('MaaS-FLEXI-ready individuals' and 'multimodal PT supporters') being more aware of their existence than the non-multimodal-minded clusters ('technological car-lovers' and 'anti new-mobility individuals'). When examining usage of new modes of transport, we observe that the share of people who have used these modes varies depending on the mode, but is always highest for 'MaaS-FLEXI-ready individuals' and 'multimodal PT supporters' (OV-bike 25-32%; other bike-sharing systems 4-6%; Uber 12-19%; car-sharing 4-6%) than for the other groups (for which values under 5% are the rule). 'Mobility neutrals' resemble more 'technological car-lovers' and 'anti new-mobility individuals' with respect to new mobility modes. Presumably, the higher age range of these respondents (and somewhat lower technology capabilities) may be a hindrance in the usage of new modes of transport, even if they might be more willing to be multimodal.

Main Factors behind Mode Choice

Next, we analyse the main factors behind mode choice. Among 15 different possibilities (comfort, relax, time, safety, flexibility, joy, status, reliability, price, environment, directness, ownership, health, carrying space, and other) respondents were asked to choose the three that are most relevant for them in deciding which mode of transport to use. These drives are depicted in Figure 2.8, ordered from most to least chosen. Three characteristics set the two more car-driven clusters ('technological car lovers' and 'anti new-mobility individuals') apart from the other three.

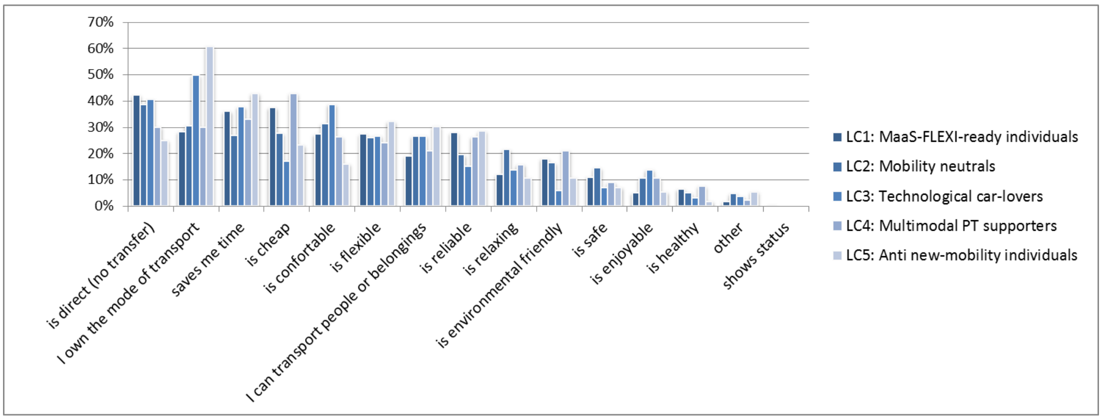

Figure 2.8: Share of respondents of the different latent clusters for whom each of the presented statements were among the three most important reasons to choose a mode of transport

The first one is ownership. Despite it not being a strict reason to choose a mode of transport but rather a precondition state, it is the most often mentioned reason among respondents from these two clusters (50-60% chose this factor in contrast to around 30% of respondents in the other three clusters). Therefore, mode ownership may indeed be one of the reasons behind their lesser interest in MaaS. The second is price relevance. There seems to be a link between multimodal-minded individuals and price consciousness, the more unimodal car individuals being less driven by economic reasons in their mobility decisions. And the third is environmental friendliness. The two more car-driven clusters are less environmentally friendly than the other three (even if this is not a major drive for any of the clusters). When asked directly whether respondents took into account the environment in their travel behaviour, less than 25% from the two more car-driven clusters did so, in contrast to around 40% of respondents in the other three clusters.

It is also worth noticing the low number of respondents that chose safety as driving force in their mode decisions. This is likely not due to them granting safety a low importance. Rather, they presumably consider safety a precondition present in all modes from which they make their mode decisions.

2.4.3 Technology-related Characteristics' Analysis of the Latent Clusters

For a user to make use of MaaS and their on-demand services, he needs to have a smartphone and internet connection. However, 29% of the 'mobility neutrals' and 22% of the 'anti new-mobility individuals' do not currently own a smartphone, and a much higher percentage (79% and 43% respectively), are not subscribed to a 3G bundle, necessary for ubiquitous internet connection. As a result, these two groups are in a disadvantageous situation to use new mobility solutions. 'Multimodal public transport supporters' also lie a bit behind the top tier technology classes ('MaaS-FLEXI-ready individuals' and 'technological car lovers'), with 11% of respondents lacking 3G bundles (see Table 2.3).

Additionally to the MaaS-related attitudinal statements included in our analysis, respondents were faced with five Likert-scale statements regarding their innovativeness attitude (see Appendix A for the statements' description). A 'general innovativeness factor' is calculated from these using the "non-weighted sum scores" method (after checking that all five statements load together satisfactorily). "MaaS-FLEXI ready individuals" are the most positive towards innovativeness (3.4), followed by "Mobility neutrals" (3.2) and "Technological car-lovers" (3.1). The somewhat lower score of "Multimodal public transport supporters" (2.8) highlights that their lower openness to innovation encompasses other aspects beyond new on-demand mobility services. Finally, as could be expected, "Anti new-mobility individuals" have the lowest average value (2.4).

We also analyse journey planner usage (see Table 2.6). Technology adoption and attitude towards integrated mobility seem to explain the encountered differences among the clusters. The vast majority of individuals in the two pro-integrated-mobility clusters ('MaaS-FLEXI-ready individuals' and 'multimodal public transport supporters') use travel information via their smartphone or tablet (over 50% of them on a weekly basis), whereas over one third of respondents in the less technological clusters ('mobility neutrals' and 'anti new-mobility individuals') never do so. Motives to look for travel information also vary widely among classes. While one third of respondents from the pro-integrated-mobility clusters use travel information to help them decide the most adequate mode for a given trip, only 7%-14% of respondents in the other three clusters do so. 'Technological car-lovers' have the highest percentage of individuals using car-related travel information, but their rates using travel information for public transport or active mode trips are half than those for the pro-integrated-mobility clusters.

Table 2.6: Journey planners' usage for individuals of the five clusters. For each characteristic, we highlight in bold the class with the highest share.

	LC1 MaaS-FLEXI-ready individuals	LC2 Mobility neutrals	LC3 Technological car-lovers	LC4 Multimodal public transport supporters	LC5 Anti-new-mobility individuals
How often do you look for travel information via your smartphone and/or tablet?					
Never	3%	34%	7%	7%	**35%**
less than once a month	19%	30%	**32%**	16%	27%
1-3 days a month	**25%**	19%	21%	**25%**	16%
1-3 days a week	**36%**	15%	23%	**36%**	15%
4 or more days a week	**17%**	1%	16%	16%	7%
I use travel or route information …					
…to decide which mode of transport I use	**34%**	14%	11%	33%	7%
[car or motorcycle]...to find information about my travel time, congestion or accidents	64%	45%	**68%**	57%	54%
[car or motorcycle]...to decide which route to take	50%	45%	**60%**	49%	58%
[public transport] … to get information about schedules, travel time and delays	80%	54%	46%	**81%**	39%
[public transport] … to decide which route to take	53%	37%	23%	**58%**	17%
[bicycle, moped or on foot] … to decide which route to take	43%	24%	25%	**44%**	14%
I do not use any online travel and route information	1%	**9%**	6%	2%	7%

2.5 Discussion

In this section, we discuss the key findings and provide some policy recommendations specific for each of the clusters.

2.5.1 Key Findings

From the mobility point of view, MaaS integrates the available mobility alternatives. Results of this study show that there is an underlying mobility integration factor, in which a positive multimodal mind-set is aligned with a favourable attitude towards public transport and a low car drive. Results also show that these attitudes are aligned with current mobility patterns. As a result, individuals with more unimodal car behaviours seem less inclined to adopt MaaS. This is in line with earlier research; e.g.Ho et al. (2018) also identified very frequent car users as less likely to adopt MaaS.

Our two clusters with a most favourable attitude towards mobility integration are also the two most multimodal clusters. Individuals in these two clusters tend to be young, highly educated people who live in more dense urban areas and have no children. These socioeconomic characteristics have also been found among early adopters of shared modes (Alemi, 2018; Clewlow, 2016; Dias et al., 2017; Shaheen et al., 2012), as well as among the more general multimodal individuals (both in Europe (Molin et al., 2016) and in the USA (Buehler & Hamre, 2015)). We also found that it is more common among individuals belonging to these two clusters to rely on travel information for their transport mode choices instead of solely considering their preferred or habitual mode of transport. Indeed, multimodal individuals are known to have more complex strategies to choose transport mode and exercise weaker travel habits (Verplanken et al., 1997). This, in turn, facilitates the introduction of new mobility solutions such as MaaS.

We found, however, a strong difference between these two more multimodal clusters. While ‘MaaS-FLEXI-ready individuals’ (32% of the sample) have a very positive attitude towards pooled on-demand services, ‘multimodal public transport supporters’ (15% of the sample) strongly prefer traditional transit over other new modes. Previous research has highlighted that public transport users are less likely to shift from fixed public transport usage to pooled on-demand services (Al-Ayyash et al., 2016) or to adopt MaaS (Ho et al., 2018), in line with our observations for the ‘multimodal public transport supporters’. This can be due to the (in general) higher usage of public transport by lower income individuals (Hensher, 1998; Ryley et al., 2014), for which the on-demand modes of transport included in MaaS may be perceived as a premium and potentially expensive service. In fact, while ‘MaaS-FLEXI-ready individuals’ show the highest average score regarding willingness to pay, ‘multimodal public transport supporters’ have the second lowest willingness to pay among the five found clusters.

In the Dutch setting, having less income inequalities (Gini coefficient of 0.28 (World Bank, 2018)) than in the two countries of the abovementioned studies (Lebanon 0.32 and Australia 0.35 (World Bank, 2018)), and relatively high fares of public transport (Eurostat, 2018), some current public transport adepts (the ‘MaaS-FLEXI-ready individuals’) are arguably more open towards accepting alternative on-demand services. This reasoning seems consistent with Hall et al. (2018), who suggest that it is current public transport users with the higher incomes that are more open to complementing their public transport usage with on-demand services, which is what makes adopting MaaS an attractive alternative. In addition, the share of public transport users in the Dutch population is currently quite low, with most individuals not using public transport on a weekly basis, even in the more public transport minded clusters. As a result, there is potential for these users to incur a modal shift from their car trips to MaaS. In contexts different than the Netherlands, we expect clusters that resemble the same characteristics as the ones found in this study. The higher the percentage of public transport users, the higher their technological capabilities and interest, and the lower their cost sensitivity; the higher the adoption potential for MaaS will be in that setting.

This research has also shown that pooled on-demand services are more appealing than transit for 'mobility neutrals' and 'technological car-lovers'. Pooled on-demand services can thus attract individuals from these clusters to more sustainable mobility patterns. Similarly, pooled on-demand services can facilitate a switch from the private car and into MaaS for areas characterised by poor public transport, as suggested by Lavieri & Bhat (2018) for the American context.

We identify two main barriers for potential MaaS adoption: (a) high (car) ownership need as a determinant of mode choice (for 'technological car-lovers' and 'anti new-mobility individuals'), and (b) low technology adoption (for 'mobility neutrals' and 'anti new-mobility individuals'). Additionally, clusters more inclined to keep their unimodal car behaviour showed lower environmental and financial sensitivity. Strong sense of ownership, as well as low environmental and financial sensitivity have also been found in literature as important variables that deter individuals from moving away from a car-centric behaviour and into adopting new mobility solutions (Burkhardt & Millard-Ball, 2006; Efthymiou et al., 2013; Lane, 2005; Paundra et al., 2017; Zheng et al., 2009). Additionally, Lavieri & Bhat (2018) also found technology adoption as a relevant barrier for MaaS adoption in the USA context. To this end, some policy recommendations tailored to each of the five latent classes found in our analysis are described in the following subsection.

2.5.2 User Cluster Specific Recommendations

Based on the results of this study, we highlight some relevant policy recommendations that can increase the adoption of (sustainable) MaaS schemes in relation to the five clusters:

1. The *"MaaS-FLEXI-ready individuals"* (32% of the sample) are most inclined to adopt MaaS schemes and use pooled on-demand services thereby. These individuals are therefore more likely to reduce their car usage in favour of other modes. Simultaneously, they can also be expected to (slightly) lower their public transport usage by switching to on-demand services such as pooled on-demand services, given their attitudinal preference towards the new mode against traditional transit. Travel awareness campaigns can support the modal shift of this cluster away from private car usage by focusing on concrete functional benefits that MaaS can bring them (time and price benefits) while avoid a major shift from traditional transit usage by appealing to their environmental sensibility.

2. The *"Mobility neutrals"* (25%) are mainly composed of individuals aged 65 and older. The analysis of technology related covariates showed how their lower technological adequacy can prevent them from profiting from new mobility trends. Providing hybrid systems that do not only rely on a mobile app but also include a smartcard ticket version can address this barrier. Allowing for SMS correspondence or having a call centre for ordering purposes (even if implemented

at a small fee for the customer) can also allow that individuals with no smartphones or internet connection can profit from on-demand services or real time information.

3. The *"Technological car-lovers"* (22%) have a car-centred attitude and behaviour, as well as a below average environmental friendliness or cost sensitivity, making it difficult to trigger a behavioural shift. Previous research suggests promoting new mobility modes to these individuals solely as an alternative for the occasions in which their car is unavailable instead of suggesting to replace it altogether (Paundra et al., 2017). This can help them experience the new system and its novelty, which may appeal to their high technological affinity. Attention should also be given to providing mobility alternatives that suit the needs of families with children, more prevalent in this cluster. Additionally, measures to avoid that young families shift towards unimodal car usage with the birth of their first child as well as measures to facilitate a mode shift away from car-based patterns once these children grow older can help reduce the size of this cluster.

4. The *"Multimodal public transport supporters"* (15%) have positive attitudes and behaviour towards public transport usage. These individuals do not exclude new shared modes yet (strongly) prefer scheduled public transport. Still, only around 40% of their individuals use public transport weekly, less than the percentage that use car on a weekly basis. The introduction of new modes can help these individuals reach destinations for which arguably they currently need the car. As a result, their multimodal mind-set with positive attitudes towards public transport and lower car drive can become more aligned with their future travel patterns. Given their above average positive attitude towards transit, they can become the most sustainable MaaS users, considering public transport as main mode and other on-demand services as mere complements to transit when necessary. Compared to 'MaaS-FLEXI-ready individuals' and 'technological car lovers', this cluster has a somewhat lower technology affinity. Easy to use MaaS apps offered by trusted public transport operators can provide a familiar and reliable environment for these individuals in their MaaS adoption process. Their public transport card/subscription could be extended to give them access to additional shared mobility services and enable them to try these for free. This measure could help them overcome their resistance to innovation and does not require them to pay via an app (which they would rather not do).

5. The cluster *"Anti new-mobility individuals"* (6%) represents the individuals least inclined to adopt MaaS, since they show both high psychological car ownership and low technology adoption. Strategies applied to 'mobility neutrals' and 'technological car lovers' can also be of relevance to individuals in this cluster. Still, these individuals are unlikely to adopt MaaS or on-demand services such as pooled on-demand services in the short term. This cluster likely represents the laggards of mobility innovations (Rogers, 1983).

2.6 Conclusions

The present study has identified five different clusters in relation to individuals' inclination to adopt MaaS based on attitudinal indicators. Special focus was given in this research to pooled on-demand services, which exemplify the flexibility characteristics of on-demand services while accounting for the collective mobility services, needed to meet the objectives of urban mobility (reduce congestion, reduce parking space, increase liveability, etc.).

To this end, we first identified relevant factors regarding MaaS and designed a series of attitudinal indicators addressing them. We presented these aspects to a representative sample of urban Dutch population, having a valid sample size of over thousand respondents. We then performed an exploratory factor analysis and latent class cluster analysis on the data as data reduction and clustering techniques so as to identify homogeneous clusters. To provide a comprehensive picture of the individuals belonging to the different clusters, we enriched our model with a series of covariates that covered socioeconomic, mobility and technology-related characteristics.

Two of the identified clusters ('MaaS-FLEXI-ready individuals' and 'multimodal public transport supporters', which represent 47% of the respondents) have positive inclinations towards two main aspects of MaaS (mobility-integration aspects and mobile-application aspects). However, the somewhat lower (despite positive) app inclination of individuals in the latter cluster, their below average willingness to pay and their strong preference of traditional public transport over (pooled) on-demand services by individuals belonging to this cluster, may prevent individuals of this cluster to adopt MaaS at a first instance. Even if these two clusters are the ones with the highest shares of public transport usage, their average car usage is still higher, indicating potential for shifts from private car. The MaaS adoption potential on settings different from the one in this study will likely also depend on the share of public transport users, with urban areas with higher shares of public transport users having more individuals that are ready to adopt MaaS.

Nonetheless, before any modal shifts are materialised, enough availability of on-demand services needs to be granted, so that these individuals can find the anticipated mobility benefits that MaaS promises them. Also, their willingness to pay showed to be average to low. This should be taken into account when designing the offered services. Individuals belonging to the other three clusters presented high (car) ownership needs and/or low technology adoption, which have been identified in this study as main barriers towards MaaS adoption and as a starting point for policy recommendations to increase MaaS adoption by these individuals. Policy makers, public transport operators, MaaS providers and companies entering the shared mobility landscape can use findings in this research to evaluate the possible changes that urban settings can undergo as a result of MaaS and provide targeted strategies to different customer segments of the population.

Even if behaviour and attitudes are closely linked, our research (pertaining to attitudes) does not allow us to conclude to what extent those attitudes will culminate in a behavioural change or if habitual behaviour will emerge. This is best tested in real life pilots or full launch MaaS schemes. Also, the obtained results are dependent on the attitudinal statements presented to respondents in the study. While we tried to cover a wide range of attitudes, some aspects such as autonomy / perceived behavioural control, which have been previously found to be predictors of PT usage (Anable, 2005; Hunecke et al., 2010), have not been included in the present study. In our study, we adopted the main MaaS aspects identified in Durand et al. (2018) in defining the indicators. Further research could consider a theoretical basis such as the Theory of Planned Behaviour (Ajzen, 1991) or the Technology Acceptance Model (Davis, 1989b) as basis for deriving the single indicators.

Future MaaS pilots could consider involving a representative sample of the population among their participants, so as to assess mobility shifts and characteristics beyond those for early adopters. This would enable the comparison between the expectations derived from attitudes and behavioural intentions to actual behaviour, and could additionally help analyse the impact of MaaS for different trip types. Given the novelty of the research topic, and to avoid overloading respondents, this research only considered pooled on-demand services explicitly. Further research could also consider other on-demand services different from pooled on-demand services.

Chapter 3

Value of Time and Value of Reliability

After having investigated individuals' attitudes towards pooled on-demand services and the broader new mobility paradigm of which these services are expected to be part, Part II of this thesis focuses on individuals' preferences regarding pooled on-demand services. What is the ideal pooled on-demand trip? Ideally, it is cheap, it takes little time (there are little or no detours and few extra stops), and the expected waiting and travel times match the experienced times. In reality, some trade-offs will have to be made among these attributes. This leads to the following research question (RQ 2): What is individuals' willingness to pay to reduce travel time (i.e., their value of time (VOT)) and to reduce travel time variability/uncertainty (i.e., their value of reliability (VOR)) for the different stages of pooled on-demand trips? And how do these values differ for different individuals and for different trip stages?

This chapter analyses these time-reliability-cost trade-offs. We differentiate between the waiting stage and the in-vehicle stage. Moreover, since, as seen in Chapter 2, pooled on-demand services are one type of service in a more complex and integrated mobility ecosystem, we also consider multi-modal trips. In particular, we analyse the transfer stage for trips between pooled on-demand services and public transport. Since pooled on-demand services have the potential to offer a portfolio of services that match different market segments, we account for preference heterogeneity in our analyses.

The chapter is structured as follows. Section 3.1 introduces the relevance of the study of the VOT and VOR; Section 3.2 explains the research methodology; Section 3.3 presents the results; Section 3.4 discusses the implications of the findings for the design of pooled on-demand services, and Section 3.5 draws the final conclusions.

This chapter is an edited version of the following article:

Alonso-González, M.J., van Oort, N., Cats, O., Hoogendoorn-Lanser, S. & Hoogendoorn, S. P. (2020) Value of Time and Reliability for Urban Pooled On-Demand Services, *Transportation Research Part C: Emerging Technologies*, Volume 115, 102621.

3.1 Introduction

Urban transport is changing. Flexible transport services are appearing in cities as transport alternatives to traditional public transport and to privately owned modes. One of these types of services are pooled on-demand services (also known as Demand Responsive Transport (DRT) services). These can be offered by transit operators or by so-called Transport Network Companies (TNCs). UberPool, UberExpressPOOL, Shared Lyft, Ola Share or ViaVan are examples of pooled on-demand services currently in operation offered by TNCs.

They are enabled in large-scale settings thanks to the emergence of new technologies and ubiquitous communication. These services combine the flexibility of taxi services (flexible route and schedule) with the collective nature of public transport (different travel requests are matched together in the same vehicle). Therefore, they can potentially yield a service that offers some of the advantages associated with the private car while attaining some of the supply-side efficiency gains made possible by bundling travel demand.

Previous research has shown that pooled on-demand services can efficiently match current individual trips in urban areas with very little extra travel time for the users (Tachet et al., 2017). Ride pooling also allows for a better performance of on-demand systems, in comparison to individual-only systems (Liang et al., 2020; Vosooghi et al., 2019). Moreover, trip matching can contribute to large decreases in the congestion, pollution and space problems of urban areas, as shown in previous simulation studies (ITF, 2016, 2017). However, these models did not include an underlying behavioural model for describing user preferences in relation to pooled on-demand services; they assigned a fixed demand to these services – either the entire urban travel demand or the existing demand for taxi services. Unreliable behavioural attributes may lead to an under- or over-estimation of the benefits and thus mislead decision making.

In this study, we aim at estimating the time-reliability-cost trade-offs of individuals regarding pooled on-demand services. We study both the value of time (VOT) (i.e., the willingness to pay to reduce travel time) and the value of reliability (VOR) (i.e., the willingness to pay to reduce travel time variability/ uncertainty). A good understanding of how individuals value reliability in pooled on-demand services is especially important given a) their flexible nature (with their lack of predefined schedules or routes, in contrast to traditional public transport); and b) their shared nature (with the related inherent reliability challenges, in contrast to the private alternative) (Li et al., 2019). We also analyse the reliability ratio (VOR/VOT).

To this end, we conduct three different stated preference (SP) experiments targeting individuals living in (sub)urban areas of the Netherlands. In them, we analyse the value of time and value of reliability of these services for the different trip stages: waiting time, in-vehicle time, and transfer time when the service feeds traditional public transport. The transfer stage for the intermodal scenario is included since research has found that integration of pooled on-demand services with public transport can complement first/last-mile transit access (Yan et al., 2019), improve overall system efficiency (Luo & Nie, 2019), and significantly enhance mobility (Stiglic et al., 2018). SP experiments provide respondents with hypothetical scenarios in order to analyse individuals' trade-offs. In settings where the studied service has not yet been implemented, this approach allows to estimate behavioural attributes; and in settings where these services are already present, this approach allows to a) estimate behavioural attributes for individuals who have not opted in, and therefore avoid selection-bias of early-adopters, and b) estimate preference towards attribute value ranges which are not yet observed and avoid the attribute collinearity often present in real situations.

Previous studies have evaluated the VOT for pooled on-demand services using SP experiments in different settings (e.g., Al-Ayyash et al. (2016) in Lebanon, Frei et al. (2017) in the USA, König et al. (2018) in Germany, and Ryley et al. (2014) in the UK). However, none of them analyse the VOR of these services, even though there is a common understanding that reliability is a fundamental determinant of travel behaviour (Carrion & Levinson, 2012; Jin et al., 2015; Prashker, 1979). One recent study, Bansal et al. (2019), did consider pick-up reliability in their on-demand SP experiment, and found that reliability plays an important role in the likelihood of passengers to choose these services. Their study, however, exclusively considers the average pick-up delay as reliability attribute portrayed to respondents (rather than a list of possible arrival values, which better represents the uncertainty/variability of the pick-up time). Also, the mentioned study does not consider cost as an attribute, and, therefore, the VOR cannot be calculated. As a result, our study contributes to literature by enabling the analysis of both VOT and VOR of pooled on-demand services and doing so for the different trip stages.

Our study also adds to previous research by including a segmentation approach regarding different time-reliability-cost sensitivities among travellers. Previous research has found that preference heterogeneity exists regarding adoption of different new mobility services (Alemi et al., 2019; Alonso-González et al., 2020b; El Zarwi et al., 2017), and pooled on-demand services in particular (Alonso-González et al., 2020a). We identify different latent classes with different values of time and values of reliability. This segmentation can then help on-demand providers develop a portfolio of pooled on-demand services, targeting different market segments (as offered in Atasoy et al. (2015)).

3.2 Methodology

The methodology section consists of three sub-sections. First, we discuss in Section 3.2.1 our research approach with regards to how to convey reliability to respondents. Second, Section 3.2.2 presents the design of our stated preference experiments given the considerations outlined in Section 3.2.1. Last, Section 3.2.3 covers the modelling approach for the analysis of the experiments.

3.2.1 Approach Used to Convey Reliability to Respondents

Due to the importance of the VOT and VOR in the assessment of travel demand studies (Carrion & Levinson, 2012), there is a large body of literature that investigates them (e.g., Bates et al. (2001); Brownstone & Small (2005); Kouwenhoven et al. (2014); Tseng (2008); Wardman (2004)). We refer the interested reader to Carrion & Levinson (2012), Li et al. (2010) and Wardman et al. (2016) for some recent literature reviews on the VOT and VOR.

In the literature, there is a common understanding of how to portray and analyse individuals' VOT. However, this differs for the analysis of the VOR. There are various conceptualisations of the notion of reliability and this has led to many discrepancies in how to convey reliability to respondents (which in turn, affect the subsequently obtained values). In the following, we highlight the three main distinctive aspects that play a role in how reliability has been operationalised in stated preferences studies in the literature, along with stating our own approach in relation to each of them:

Reliability representation – The first point of discrepancy lies in how to present reliability to respondents in SP experiments. Different representations have been used in literature, ranging from bar diagrams, histograms, circular arrangements, percentages to representing the likelihoods of certain travel times, time variability with a single time component ($\pm$ X min), and verbal description of five equally probable travel times. Tseng et al. (2009) found the latter to be the most suitable one to represent reliability to respondents and to be appropriate for people with different levels of education. This representation, which was first used in Black & Towriss (1993) and Small et al. (1999), is still considered the state-of-the-art representation for SP preference reliability studies (Carrion & Levinson, 2012) and has been adopted in several recent studies (e.g., Asensio & Matas (2008); Kouwenhoven et al. (2014); Swierstra et al. (2017)). We also adopt it in this study.

Shape of the underlying reliability distribution – Less discussed, though still important, is the shape of the underlying distribution that is considered to obtain the five equally probable travel times. While Small et al. (1999) and Asensio & Matas (2008) used lognormal distributions for percentiles' values (which are the 10th, 30th, 50th, 70th and 90th percentiles of such distributions), Kouwenhoven et al. (2014) (see full report of the study under De Jong et al. (2007)) and Swierstra et al. (2017) consider additional parameters to quantify the increase in time of the points that form the travel time distributions. The first approach (use of a lognormal distribution) has two main advantages, namely: (1) this shape best represents real travel time distributions in field tests of pooled on-demand services (Lu et al., 2017) (as well as best fits in-vehicle travel times for bus (Kieu et al., 2014) and private car (Durán Hormazábal, 2016)); and (2) the ratios between the different percentiles shown follow a certain pattern (due to their common underlying shape), which avoids that the obtained results also depend on different shapes. For consistency reasons, we use the lognormal distribution also for the distribution of waiting times (which is expected to be right skewed as shown in

Chen et al. (2017)) and waiting times during the transfer stage.

Two values are used as a starting point for the lognormal distributions: the planned time and the coefficient of variation (C_v)[1]. The μ and σ of the lognormal distribution (from which the 10th, 30th, 50th, 70th and 90th percentile values are calculated) relate to these two design attributes of the non-logarithmised distribution as follows:

$$\mu = \ln\left(\frac{\text{planned time}}{\sqrt{1+\frac{C_v}{\text{planned time}}}}\right) \tag{3.1}$$

$$\sigma = \sqrt{\ln\left(1+\frac{C_v}{\text{planned time}}\right)} \tag{3.2}$$

In our study, we do not only consider variability as a source of unreliability, but also the deviation of the real (to be experienced) waiting/in-vehicle time from the expected (announced) waiting/in-vehicle time. For this we include an additional parameter, a systematic lateness that shifts the entire distribution (what we call displacement and is similar to the departure time shift included in Small et al. (1999)). The five equally probable values shown to respondents correspond to the previously rounded percentiles plus the displacement. Any posterior calculation during the modelling stage is performed based on these final values shown to respondents and not on the original lognormal distribution from which the values originate (same as in Noland et al. (1998)).

Reliability conceptual framework – There are two main conceptual frameworks to incorporate reliability in random utility choice models: the mean-variance method (which considers unreliability as the disutility of variability), and the scheduling method (which considers unreliability as the disutility of arriving early or late). It has been shown that the two methods are equivalent under certain assumptions (Fosgerau & Karlström, 2010) and that the mean-variance method is to be preferred on practical grounds, since the scheduling method does not directly yield a valuation of reliability (Bates et al., 2001). Given that our study aims not to test the disutility of arriving late for different individuals but rather the disutility of the variability of the offered service (to help design such services), we consider the mean-variance model as most suitable framework for this research.

3.2.2 Design of the Stated Preference Experiments

Pooled on-demand services can have different characteristics. Ours offers a flexible route and schedule, and it is stop-to-stop (instead of door-to-door) with an average walking time of 1 minute to the pick-up point (in line with findings from Zheng et al.

[1]The coefficient of variation is used instead of the standard deviation as a base attribute for the variability distribution because its standardised value makes it possible to compare the relative degree of variability for distributions with different means.

(2019)). Figure 3.1 shows the explanation presented to respondents in the context of our research. This explanation was slightly modified for individuals without internet connection in their mobile phone (communication via phone call and sms). We branded our service FLEXI, which provided respondents with an easy and intuitive name. Two trip purposes are investigated: commuting trips and leisure trips. Both are framed from home towards the work/leisure activity location. Each individual is assigned one trip purpose exclusively throughout the entire questionnaire (non-working individuals being always assigned to the leisure trip purpose).

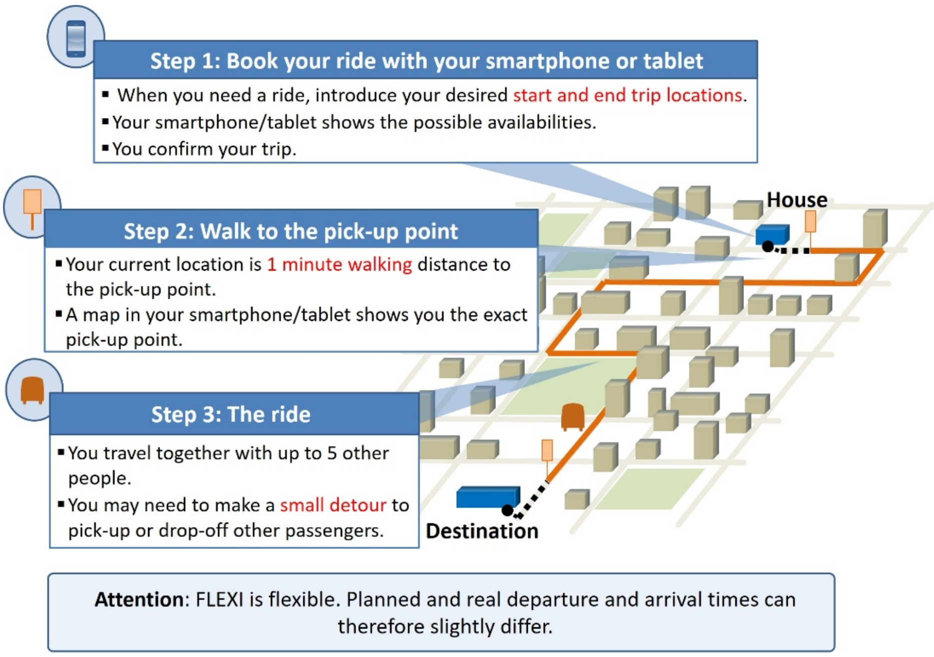

Figure 3.1: Description of pooled on-demand services shown to respondents. Layout inspired from Kim et al. (2017).

We use three different SP experiments to investigate the three trip stages of (un)reliability in pooled on-demand services: waiting stage, in-vehicle stage, and transfer stage for intermodal trips. Figure 3.2 to Figure 3.4 show an example of a scenario of each of the experiments as an illustration. The large amount of calculations that are necessary to obtain the five equally probable values of the reliability distributions makes it difficult to have pivoted experiments. To still present respondents with trip times they could relate to, we divide individuals in two segments: those with a reference trip of short distances ($<$ 12km) and those with a reference trip of medium distances ($>$12 km). We present them values accordingly (short and medium version of the experiments), similar to the approach followed inArentze & Molin (2013).

The experimental design is orthogonal fractional factorial with blocking. Each block consists of four scenarios for each of the two first experiments, and six scenarios for the third experiment. Different Likert-scale attitudinal indicators are placed between the second and third SP experiments as a break between the SP experiments. Each of the attributes has three attribute levels in order to be able to capture non-linearity. We use existing literature to get an indication of which range of values to include in

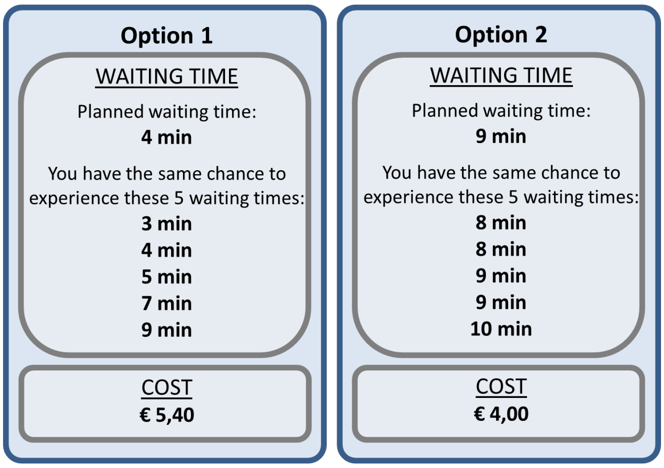

Figure 3.2: Example of a choice task of the waiting time SP experiment

Figure 3.3: Example of a choice task of the in-vehicle time SP experiment

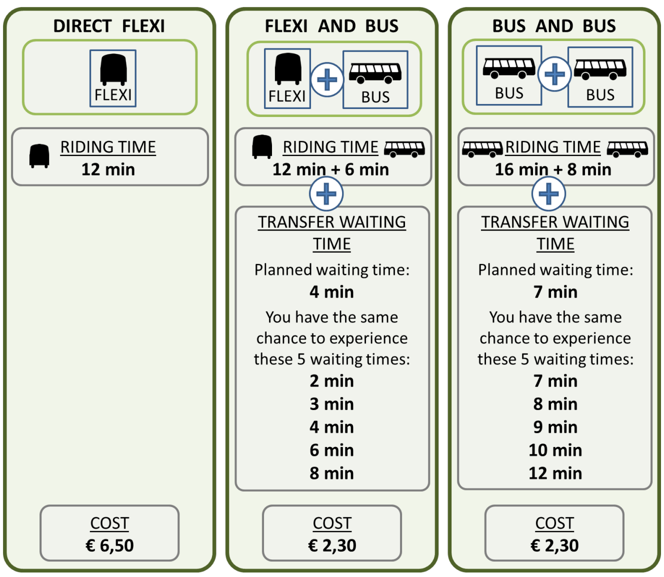

Figure 3.4: Example of a choice task of the transfer SP experiment

our attribute levels (Chen et al. (2017) and Stiglic et al. (2016) for the time values, and Black & Towriss (1993) and Turnquist & Bowman (1980) for the coefficient of variation). The attribute levels are chosen to be non-equally spaced so as to obtain a larger number of trade-offs from the scenarios and not restrict the power of the design thereof (Small et al., 1999). All attribute levels of each of the experiments can be found in Appendix B.

The two first questionnaires (waiting time and in-vehicle time) are displayed in the classical format of VOT – VOR studies, with the time, reliability distribution and cost components as unique attributes (see Figure 3.2 and Figure 3.3). However, the layout of the transfer SP experiment is more complex (see Figure 3.4). It has a larger number of attributes (given the importance of framing during the transfer stage) and it is a labelled experiment. Three alternatives are shown: a direct ride (to allow individuals opt out of transferring), a FLEXI+Bus alternative, and a Bus+Bus alternative. Garcia-Martinez et al. (2018) found that users perceive negatively transfers between different line-based public transport modes. Our design enables examining if a more tailored service (pooled on-demand services) reduces the intermodal transfer burden. Note that the FLEXI+Bus transfer may be perceived differently from the Bus+FLEXI transfer. However, in order to avoid increasing the cognitive workload too much, and given the limited/inexistent experience of respondents with pooled on-demand services, we limit our research to the FLEXI+Bus transfer type.

Reliability experiments rarely have layouts as complex as that of our transfer experiment. An exception is Swierstra et al. (2017), who also showed respondents a transfer SP experiment with the five equally probable values and additional attributes. However, in their research, finding models with significant reliability parameters proved to be difficult. Two explanations can help explain this outcome: 1) individuals are unable to correctly take reliability into account when additional parameters are added to the choice experiment, or 2) reliability attributes are considered negligible in comparison to other attributes in the final decision process (at least regarding the transfer stage). Our experiment can help identify which of the two explanations may play a larger role, given individuals' previous exposure to the other two similar (yet simpler) reliability experiments. To facilitate comparison in the obtained results, we choose to also specify a lognormal underlying reliability distribution for the transfer stage. This ensures consistency with the previous experiments.

3.2.3 Modelling Approach

In this section, we discuss the modelling approach we follow to analyse the data obtained from the SP experiments.

Utility Function Specifications

We investigate the choices of individuals regarding pooled on-demand services using Logit discrete choice models under the random utility maximisation framework. This framework assumes that, when making choices, individuals try to maximise their utility. We include two final model specifications for each trip purpose of each of the three SP experiments. Our first model is a linear Multinomial Logit (MNL) model, which we consider our base model. For the leisure trip purpose mode, we weight respondents on age and working status, so that the sample mirrors our target population. Our second model is a Mixed Logit (ML) model, estimated with 10,000 Halton draws. We use the software PythonBiogeme (Bierlaire, 2016) to perform the analysis.

The estimated ML models differ from their corresponding MNL models in three main aspects. First, they consider unobserved heterogeneity. We include a panel effect (also known as individual fixed effect), to account for the correlations between the different observations of the same individual; and we test for different nests in the transfer SP experiment, to account for correlations between some of the given alternatives. Second, we include interaction effects in the leisure trip purpose models, in order to account for taste variation between working and non-working individuals. Working status influences individuals' available time and money, both potential determinants of individuals' VOT and VOR. And third, in the ML models, we test for non-linear specifications of the different SP attributes (in particular, quadratic and squared root formulations), in order to test if the disutility associated with the unit increase of a specific attribute is different for different values of the attribute (and for the reliability attributes, to test whether individuals have risk-taking or risk-adverse attitudes instead of the risk-indifferent attitude that the linear parameter would imply (Li et al., 2012)). We compare the different formulations with the likelihood ratio test (p. 164-167 in Ben-Akiva & Lerman (1985)). If including a non-linear specification in an attribute leads to very slight increases of model fit, we keep its linear specification. Slight increases are not considered sufficient to justify the increased complexity in model interpretation.

In the utility function, we include two parameters to model the information originating from the five equally probable values. First, a parameter to account for the variability of the distribution. For this, we test three different specifications: (a) the standard deviation of the shown distribution; (b) the Reliability Buffer Time (RBT) (expressed as the difference between the 90th percentile and the scheduled time, following the results of Swierstra et al. (2017)[2], and (c) the coefficient of variation (recommended as a measure of service reliability for the passenger in Abkowitz et al. (1978) but largely disregarded in recent studies). And second, a component to account for the inherent delay of the distribution with respect to the planned time. This is expressed in the

[2]Note that Swierstra et al. (2017) refer to the RBT as the 80th percentile minus the scheduled time, but they consider the fifth value of their equally probable values as such, and this should correspond to the 90th percentile (middle point between the 80th and the 100th percentile) and not to the 80th percentile.

utility function as the difference between the mean of the new distribution and the expected time announced in the scenario.

Based on the obtained parameters of the final models, the VOT and VOR are calculated. The VOT is the ratio of the marginal utility of time and the marginal utility of money, and the VOR is the ratio of the marginal utility of the reliability attribute and the marginal utility of money. These marginal utilities equal the estimated time and cost parameters when both attributes have a linear specification in the utility function.

Latent Class Choice Models

In order to capture the potential heterogeneity in VOT and VOR of different individuals, we additionally perform a latent class choice model (LCCM) analysis. LCCMs determine the probability of each individual to belong to different classes (which correspond to different market segments). The different classes are identified statistically, rather than using predefined characteristics such as age or income, hence their name (Walker & Ben-Akiva, 2002). To decide on the most suitable number of distinct classes of the different models, we use the BIC (Bayesian Information Criterion) index. The BIC index takes into account both the model fit and the number of parameters in the model.

We adopt the ML model formulations as a starting model for our LCCM analysis, and we constrain all time and cost attribute values to be negative or zero. We weight respondents in the leisure trip purpose models on age and working status to mirror the sample population. In them, taste variation is analysed directly with the different classes. The waiting and in-vehicle stage SP experiments are modelled together in the latent class models, so as to account for the relation between the waiting and the in-vehicle preferences of the different individuals in the classes specification. Conversely, the transfer stage SP experiment needs to be modelled separately, since it is a labelled experiment. There, given the substantial weight and heterogeneity of the ASC in the utility of the alternatives, we add a random intercept coefficient in the transfer LCCM (modelled in LatentGOLD using a CFactor, see Vermunt & Magidson (2005)). This inclusion leads to final models with lower BIC and fewer classes.

In order to better assign individuals with different characteristics to the diverse classes (improve prediction of the segments), the model can be enriched with active covariates (individual characteristics such as age or income), in what is called the class membership function. However, this comes to the cost of obtaining classes that are also influenced by individual characteristics and not only by the SP attributes. Since our goal is to identify a portfolio of services that can be offered to all users (with different VOT and VOR) rather than to provide unique services to different population subgroups, we opt for not including individual characteristics actively in the membership function. Instead, we examine the characteristics of the individuals that belong to each of the obtained classes (passive covariates). In particular, we look at socioeconomic characteristics (gender, age, education level, working status, working hours, existence of children and urbanisation level), trip characteristics (trip length and trip frequency), and mobility-related characteristics (commuting transport mode, Uber usage, car availability and public transport usage). We perform the latent class analysis using the dedicated latent class software LatentGOLD (version 5.1) (Vermunt & Magidson, 2016).

3.3 Results

In this section we present the results of our analyses. Section 3.3.1 describes our data collection and sample. Section 3.3.2 presents the results of our choice model estimation for the three different SP experiments. Lastly, in section 3.3.3, we apply latent class choice models to differentiate market segments.

3.3.1 Data Collection and Sample Description

We performed an on-line pilot in April 2018 to test our questionnaire. Following the pilot, additional explanations were added to highlight the transition from the waiting stage to the in-vehicle stage SP experiments and hence to improve clarity. The final on-line questionnaire was then distributed in May 2018 (in Dutch). Survey participants were recruited from a panel designed for the longitudinal study of travel behaviour in the Netherlands, the Netherlands Mobility Panel (MobilitieitsPanel Nederland, MPN) (Hoogendoorn-Lanser et al., 2015). We target individuals aged 18 and older, owning a mobile phone and living in (sub)urban areas (known as (very) high urbanised areas according to the Dutch urbanity degree indicator (Centraal Bureau voor de Statistiek (CBS), 1992). Note that we do not restrict our target sample to individuals with specific mobility patterns or socioeconomic characteristics since there are still uncertainties regarding who will adopt pooled on-demand services in urban European contexts. Moreover, preferences of early adopters may differ from those of other potential users.

A total of 1006 individuals were considered valid respondents after data cleaning (93% of the obtained sample). Table 3.1 shows the socio-economic characteristics of the sample and the average Dutch values for (very) high urbanised areas and for the whole country. Our full sample satisfactorily represents the shares of our target population regarding urbanisation level, gender and age (middle aged adults being slightly underrepresented and the elderly population slightly overrepresented). Education level, working status and household composition can only be compared to the average of the Dutch population. Our sample has a higher proportion of highly educated individuals, working respondents and single person households than the national average. We can expect our target population to also differ from the overall Dutch context in these directions. Therefore, we consider the sample to represent our target population adequately.

Table 3.1: Comparison between the sample and Dutch population for different socio-economic variables. Sources for the population data: Centraal Bureau voor de Statistiek (CBS) (2018d,c,a,b).

Socio-economic variable	Category	Total sample (N=1006)	Commuting trip purpose sample (N=308)	Leisure trip purpose sample (N=698)	Dutch (very) high urbanised areas	Dutch 2018 shares
Gender	Male	48.2%	49.4%	47.7%	48.9%	49.6%
	Female	51.8%	50.6%	52.3%	51.1%	50.4%
Age	18* to 39	38.1%	53.2%	31.4%	38.1%	31.8%
	40 to 64	35.6%	46.5%	30.8%	42.0%	44.0%
	65 and above	26.3%	0.3%	37.8%	19.8%	24.2%
Education	Low	25.2%	16.2%	29.2%		31.5%
	Average	32.5%	35.4%	31.2%		37.8%
	High	42.0%	48.4%	39.3%		29.2%
	Unknown	0.2%	0.0%	0.3%		1.4%
Employment status	Working	59.9%	100.0%	42.3%		50.9%
	Not working	40.1%	0.0%	57.7%		49.1%
Household	1 person household	49.0%	46.8%	50.0%		38.2%
	> 1 person household	51.0%	53.2%	50.0%		61.8%
Urbanisation level	Very high urbanised (>2500 inhab./km²)	46.9%	47.7%	46.6%	48.2%	23.3%
	High urbanised (1500-2500 inhab./km²)	53.1%	52.3%	53.4%	51.8%	25.1%

* 18 to 39 for the share sample, but 20 to 39 for the Dutch population 2018 values

The large majority of the non-working individuals are retirees (62%), followed by individuals incapacitated to work (11%) and students (10%). Individuals who have a job as a secondary occupation (e.g., students with part-time jobs) are included in the working sample (since they can also relate to commuting trips). The majority of the working individuals (around 70%) were directed to the commuting trip (in order to have enough commuting entries). As a result, non-working individuals are overrepresented in the leisure trip sample. This fact is accounted in our performed models either by weighting the individuals to mirror the target sample or by including interaction effects that capture taste variation between working and non-working individuals (following the market segmentation procedure described in Ben-Akiva & Lerman (1985)).

3.3.2 Model Estimation

In this section, we present and analyse the choice models. Our results, in line with previous literature, indicate larger VOT for the commuting than for the leisure trip purpose. All our final models include the standard deviation as final variability component given that (a) neither the RBT nor the coefficient of variation perform better than the standard deviation in all models, and (b) the standard deviation allows for an easier comparison to values from other studies.

Results for the Waiting and In-Vehicle Stage SP Experiments

Table 3.2 and Table 3.3 present the results of the waiting stage and the in-vehicle stage SP experiments respectively. The ML models clearly outperform their MNL equivalents (there are significant improvements in the rho-square). In all eight models, all attributes are negative (as expected) and significant at the 0.05 level (the vast majority also at the 0.01 level).

The inclusion of an additional quadratic coefficient for the waiting time attribute of the ML models clearly improves model fit. This means that individuals associate a higher per-minute waiting disutility to longer waiting times. Interaction effects regarding working situation are added to the ML specifications of the leisure purpose when these improve the model fit. Interestingly, we find that in the waiting stage, working individuals are more sensitive than non-working individuals towards variability, while, in the in-vehicle stage, working individuals are more sensitive than non-working individuals towards absolute increases of time (both regarding the expected time and the systematic unexpected delay).

*Table 3.2: MNL and ML model estimation for the waiting stage SP experiment (p-value: ≦ 0.01 ***, ≦ 0.05 **, ≦ 0.1*)*

	Leisure trip purpose		Commuting trip purpose	
	MNL, weighted	ML, taste variation on working status	MNL	ML
	Parameter (robust t-test)	Parameter (robust t-test)	Parameter (robust t-test)	Parameter (robust t-test)
Attribute				
Waiting time	-0.294 (-18.08) ***	-0.332 (-6.57) ***	-0.369 (-12.80) ***	-0.366 (-4.42) ***
Squared waiting time	N/A	-0.00605 (-3.34) ***	N/A	-0.00824 (-2.91) ***
Standard deviation	-0.125 (-4.97) ***	-0.0950 (-2.53) ***	-0.203 (-5.56) ***	-0.319 (-6.57) ***
Additional standard deviation parameter (working indiv. only)	N/A	-0.186 (-3.03) ***	N/A	N/A
Displacement (i.e. mean minus scheduled time)	-0.184 (-5.15) ***	-0.283 (-6.79) ***	-0.0960 (-1.97) **	-0.126 (-2.61) ***
Cost	-1.61 (-18.32) ***	-2.54 (-15.34) ***	-1.51 (-10.61) ***	-2.23 (-9.69) ***
Sigma panel	N/A	-2.12 (-15.02) ***	N/A	-2.05 (-9.65) ***
Quality of fit statistics				
Initial log likelihood	-1930.609	-1935.267	-853.957	-853.957
Final log likelihood	-1684.758	-1503.961	-696.247	-622.587
Likelihood ratio test for the initial model	491.702	862.611	315.420	462.741
Rho-square	0.127	0.223	0.185	0.271

*Table 3.3: MNL and ML model estimation for the in-vehicle stage SP experiment (p-value: ≦ 0.01 ***, ≦ 0.05 **, ≦ 0.1*)*

	Leisure trip purpose		Commuting trip purpose	
	MNL, weighted	ML, taste variation on working status	MNL	ML
	Parameter (robust t-test)	Parameter (robust t-test)	Parameter (robust t-test)	Parameter (robust t-test)
Attribute				
In-vehicle time	-0.297 (-20.24) ***	-0.420 (-15.55) ***	-0.303 (-13.55) ***	-0.495 (-11.86) ***
Additional in-vehicle time parameter (working individuals only in leisure purpose)	N/A	-0.110 (-4.05) ***	N/A	N/A
Standard deviation	-0.105 (-7.10) ***	-0.168 (-7.41) ***	-0.164 (-7.18) ***	-0.264 (-6.71) ***
Displacement (i.e. mean minus scheduled time)	-0.118 (-5.42) ***	-0.110 (-3.10) ***	-0.120 (-3.57) ***	-0.202 (-4.36) ***
Additional displacement parameter (working individuals only in leisure trip purpose)	N/A	-0.125 (-2.20) **	N/A	N/A
Cost	-2.04 (-18.29) ***	-3.20 (-17.54) ***	-1.72 (-10.41) ***	-2.75 (-10.16) ***
Sigma panel	N/A	-2.03 (-14.03) ***	N/A	-2.11 (-9.29) ***
Quality of fit statistics				
Initial log likelihood	-1930.609	-1935.267	-853.957	-853.957
Final log likelihood	-1610.213	-1455.763	-681.316	-611.827
Likelihood ratio test for the initial model	640.792	959.009	345.282	484.261
Rho-square	0.166	0.248	0.202	0.284

Table 3.4 and Table 3.5present the VOT and VOR corresponding to the different models. The in-vehicle VOT values in this study for both commuting (10.80 €/h) and leisure purposes (7.88-9.94 €/h) are well in line with the Dutch car values presented in Kouwenhoven et al. (2014) (9.25 €/h commuting and 7.50 €/h other purposes, referring to the year 2010), and somewhat higher than those presented in that study for public transport (6.00 €/h commuting and 7.75 €/h other purposes, referring to the year 2010). These differences may be due to user type effects being larger than mode type effects (as found in Wardman (2004)). That is, traditional public transport is usually chosen by individuals who have a lower willingness to pay (Zamparini & Reggiani, 2007), while, in our research, we target the average Dutch population. Moreover, our sample targets Dutch individuals living in urban areas, which have arguably higher values of time than the average Dutch population.

Table 3.4: VOT and VOR of the ML specification for the waiting stage SP experiment in €/h

	Leisure trip purpose	Commuting trip purpose
VOT waiting (5 min)	9.27	12.06
VOT waiting (15 min)	12.13	16.50
VOR waiting standard deviation (non-working individuals)	2.24	N/A
VOR waiting standard deviation (working individuals)	6.64	8.58
VOR waiting displacement	6.69	3.39

Table 3.5: VOT and VOR of the ML specification for the in-vehicle stage SP experiment in €/h

	Leisure trip purpose	Commuting trip purpose
VOT in-vehicle (non-working individuals)	7.88	N/A
VOT in-vehicle (working individuals)	9.94	10.80
VOR in-vehicle standard deviation	3.15	5.76
VOR in-vehicle displacement (non-working individuals)	2.06	N/A
VOR in-vehicle displacement (working individuals)	4.41	4.41

We find the VOT for the waiting stage to be in the range of 9.27-16.50 €/h, depending on trip purpose and total waiting time (increasing with longer waiting times due to the squared component in the utility function). The ratio between waiting and in-vehicle times varies between 1 and 1.5, depending on the waiting time. Traditionally, this ratio has been known to be 2 and above (Wardman, 2004). The waiting VOT has likely decreased thanks to the more widely available and accurate real-time information. Frei et al. (2017) even found the waiting VOT to be lower than the in-vehicle time for pooled on-demand services in the US context. As found in previous research (e.g., Ehreke et al. (2015); Kouwenhoven et al. (2014); Li et al. (2010)), we find waiting and in-vehicle VOT to be somewhat higher – around 30% higher in our research – for the commuting trip purpose than for the leisure trip purpose.

The VOR values regarding the standard deviation (3.15-5.76 €/h) of the in-vehicle time are also in line with those found on Kouwenhoven et al. (2014) for car and public transport in the Dutch context (3.25-4.75 €/h in 2010 terms). In both studies, reliability ratios (RR), ratio between the VOR and the VOT, are, on average, around 0.5. This is a reassuring finding for the Dutch context, given that different studies worldwide reported a wide range of RR values, ranging from 0.1 to 2.5 (Carrion & Levinson, 2012). For the waiting stage, the range of VOR found is a bit more spread out, 2.24-8.58 €/h, with RR values ranging between 0.2-0.7 depending on the working situation and waiting time.

To measure reliability, other than measuring the traditional variability, expressed with the standard deviation, we modelled the displacement value (calculated as the difference between the expected time and the mean of the presented distribution). Interestingly, the VOR value associated with this systematic delay tends to be similar to the corresponding VOR of the variability of the distribution (ranging between 2.06 €/h and 6.69 €/h), and always lower than the corresponding VOT. This suggests that the effect of a (small) unannounced yet systematic additional time in the utility function is lesser than that of the announced times. Even though this seems counterintuitive and contrary to findings from previous research (unexpected times are more heavily penalised by individuals than expected times (Currie & Wallis, 2008)), this suggests that a small additional unannounced increase in time may not be fully accounted for by individuals.

Results for the Transfer Stage SP Experiments

Results of the MNL and ML models of both trip purposes for the transfer stage SP experiment are shown in Tables 3.6 and 3.7. A nest structure is found between the two transfer alternatives. This is included in the ML model with a common transfer random error component. Also, interaction effects are added in the leisure trip purpose ML model to address the higher sensitivity of working individuals (with respect to non-working individuals) regarding the in-vehicle time and the expected waiting time.

The signs of all time and cost parameters are negative, as expected. The two reliability related parameters for the FLEXI-Bus alternative and the standard deviation parameter for the Bus-Bus one are, however, not significantly different from zero at the 95% confident level. In line with the results of Swierstra et al. (2017), finding significant parameters for the reliability attributes in more complex reliability SP experiments proved to be difficult. Since respondents were familiar with the reliability distribution representation from the waiting and in-vehicle experiments, and reliability values were significant in those, we hypothesise that the main explanation for non-significance is that individuals consider reliability attributes proportionally less important than other attributes in more complex decision processes (at least regarding the transfer stage).

Table 3.8 shows the VOT and VOR of the different parameters of the ML transfer stage SP experiment. In-vehicle VOT values range between 5.48 €/h and 10.95 €/h, depending on trip purpose and working status. Differences in the range of VOT values among the three alternatives are not pronounced. Contrary to what may be expected, all VOT for the waiting transfer times are lower than their corresponding in-vehicle times. Waiting transfer VOT range between 4.04 €/h and 9.13 €/h. We hypothesise that this finding may be due to the fact that part of the disutility from the transfer waiting stage arises from the uncertainty of the waiting time, which is modelled separately in this study. However, further research is needed to test this hypothesis and empirically underpin it.

As previously mentioned, three of the four reliability parameters are not significant at the 95% level. For the Bus-Bus alternative, the systematic delay (displacement) incurs in a much higher VOR than the variability (standard deviation). However, these values are much similar for the FLEXI-Bus alternative. This finding may suggest that individuals associate a higher disutility towards the systematic (i.e., certain) delay in services with fixed schedules, but that unreliability stemming from variability is less desired for more flexible (and more unknown) transport services.

*Table 3.6: MNL and ML model estimation for the transfer stage SP experiment (p-value: ≦0.01 ***, ≦0.05 **, ≦0.1*)*

	Leisure trip purpose		Commuting trip purpose	
	MNL, weighted	ML, taste variation on working status	MNL	ML
	Parameter (robust t-test)	Parameter (robust t-test)	Parameter (robust t-test)	Parameter (robust t-test)
Attribute				
Direct FLEXI – ASC	0	0	0	0
FLEXI-Bus – ASC	0.709 (3.03) ***	0.644 (1.45)	1.26 (3.55) ***	0.818 (1.25)
Bus-Bus – ASC	0.899 (4.06) ***	0.647 (1.46)	1.60 (4.45) ***	1.06 (1.70)*
Direct FLEXI – In-vehicle time	-0.0957 (-13.59) ***	-0.100 (-6.19)***	-0.104 (-9.70) ***	-0.160 (-8.19)***
Additional Direct FLEXI – In-vehicle time parameter (working people only)	N/A	-0.0589 (-3.00)***	N/A	N/A
FLEXI-Bus – In-vehicle time leg 1	-0.103 (-11.19) ***	N/A	-0.119 (-8.26) ***	N/A
FLEXI-Bus – In-vehicle time leg 2	-0.106 (-11.48) ***	N/A	-0.113 (-7.98) ***	N/A
FLEXI-Bus – Total in-vehicle time	N/A	-0.129 (-10.79)***	N/A	-0.165 (-10.14)***
Additional FLEXI-Bus – Total in-vehicle time parameter (working people only)	N/A	-0.0648 (-3.85)***	N/A	N/A
Bus-Bus – In-vehicle time leg 1	-0.112 (-12.01) ***	-0.143 (-11.08)***	-0.125 (-8.73) ***	-0.184 (-10.07)***
Bus-Bus – In-vehicle time leg 2	-0.0933 (-10.26) ***	-0.106 (-8.20)***	-0.130 (-8.95) ***	-0.177 (-9.02)***
Additional Bus-Bus – Total in-vehicle time parameter (working people only)	N/A	-0.0650 (-3.89)***	N/A	N/A
FLEXI-Bus – Exp. waiting time	-0.0983 (-8.14) ***	-0.118 (-6.43)***	-0.130 (-6.88) ***	-0.176 (-8.35)***
Additional FLEXI-Bus – Exp. waiting time parameter (working people only)	N/A	-0.0503 (-2.01)**	N/A	N/A
Bus-Bus – Exp. waiting time	-0.0817 (-6.73) ***	-0.0782 (-4.53)***	-0.128 (-6.74) ***	-0.172 (-7.22)***
Additional Bus-Bus – Exp. waiting time parameter (working people only)	N/A	-0.0766 (-2.92)***	N/A	N/A
FLEXI-Bus – Standard deviation waiting time	-0.0587 (-1.69) *	-0.0555 (-1.28)	-0.0473 (-0.89)	-0.0768 (-1.15)
Bus-Bus – Standard deviation waiting time	-0.0626 (-1.87) *	-0.0113 (-0.33)	-0.0666 (-1.28)	-0.0352 (-0.62)

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*Table 3.7: MNL and ML model estimation for the transfer stage SP experiment (p-value: ≦0.01 ***, ≦0.05 **, ≦0.1*) (cont.)*

	Leisure trip purpose		Commuting trip purpose	
	MNL, weighted	ML, taste variation on working status	MNL	ML
	Parameter (robust t-test)	Parameter (robust t-test)	Parameter (robust t-test)	Parameter (robust t-test)
Attribute				
FLEXI-Bus – Displacement waiting time	-0.0612 (-1.46)	-0.0508 (-1.09)	-0.0861 (-1.37)	-0.103 (-1.39)
Bus-Bus – Displacement waiting time	-0.176 (-4.04) ***	-0.160 (-3.05)***	-0.229 (-3.29) ***	-0.211 (-2.51)***
Direct FLEXI – cost	-0.514 (-16.72) ***	-0.996 (-17.15)***	-0.498 (-10.59) ***	-0.877 (-10.79)***
FLEXI-Bus – cost	-0.797 (-16.75) ***	-1.11 (-17.56)***	-0.868 (-11.69) ***	-1.16 (-12.19)***
Bus-Bus – cost	-0.849 (-17.92) ***	-1.16 (-19.71)***	-0.841 (-11.66) ***	-1.13 (-11.92)***
Transfer error component	N/A	3.21 (17.34)***	N/A	2.73 (12.11)***
Quality of fit statistics				
Initial log likelihood	-4589.914	-4254.988	-2030.236	-1891.774
Final log likelihood	-3888.750	-3205.868	-1670.066	-1414.436
Likelihood ratio test for the initial model	1402.329	2098.241	720.340	954.675
Rho-square	0.153	0.247	0.177	0.252

Table 3.8: VOT and VOR of the ML specification for the transfer stage SP experiment in €/h

	Leisure trip purpose	Commuting trip purpose
VOT in-vehicle FLEXI (non-working individuals)	6.02	N/A
VOT in-vehicle FLEXI (working individuals)	9.57	10.95
VOT in-vehicle FLEXI-Bus (non-working individuals)	6.97	N/A
VOT in-vehicle FLEXI-Bus (working individuals)	10.48	8.53
VOT in-vehicle Bus-Bus (leg 1, non-working individuals)	7.40	N/A
VOT in-vehicle Bus-Bus (leg 2, non-working individuals)	5.48	N/A
VOT in-vehicle Bus-Bus (leg 1, working individuals)	10.76	9.77
VOT in-vehicle Bus-Bus (leg 2, working individuals)	8.84	9.40
VOT waiting transfer FLEXI-Bus (non-working individuals)	6.38	N/A
VOT waiting transfer FLEXI-Bus (working individuals)	9.10	9.10
VOT waiting transfer Bus-Bus (non-working individuals)	4.04	N/A
VOT waiting transfer Bus-Bus (working individuals)	8.01	9.13
VOR waiting transfer standard deviation FLEXI-Bus	3.00	3.97
VOR waiting transfer standard deviation Bus-Bus	0.58	1.87
VOR waiting transfer displacement FLEXI-Bus	2.75	5.33
VOR waiting transfer displacement Bus-Bus	8.28	11.20

3.3.3 Service Differentiation for Different Market Segments

Tables 3.9 – 3.12 depict the VOT and VOR of the different latent classes (model parameters of the latent class models are included in Appendix B). The latent class models strongly improve model fit of all models (rho-squared vales increase from 0.16-0.19 for the one latent class MNL models up to 0.58-0.61 for the latent class models). To get insights on our segment composition, we also describe in Tables 3.9 – 3.12 the different segments in terms of their passive covariates pertaining to socioeconomic, trip, and mobility-related characteristics.

The waiting plus in-vehicle stage LCCMs have four different classes for the leisure trip purpose and three different classes for the commuting trip purpose (Table 3.9). The two largest classes of the leisure trip purpose (40% and 36% of individuals respectively) have the most balanced VOT values. They mainly differ in the waiting versus in-vehicle disutility. While the waiting VOT and VOR values are similar to those of the in-vehicle stage for individuals in the first class, the waiting VOT and VOR values are twice as high as their in-vehicle counterparts for individuals in the second class. In this aspect, the largest class of the commuting trip purpose (60%) can be seen as a middle point of these two balanced leisure trip purpose classes. For both trip purposes, the two smallest classes represent individuals who are either very time sensitive or very cost sensitive. In all classes, the VOR values tend to be somewhat lower than the VOT related values. This suggests a harmonious perception of the reliability ratio (ratio between VOR and VOT) across different market segments. The more balanced classes are characterised by a higher percentage of young individuals. Cost sensitive classes are formed primarily by low educated individuals, and, for the leisure trip purpose, individuals aged 65 years old or older and non-working individuals. For both time sensitive classes, the main common characteristics is the higher car availability and the higher share of individuals aged 50-64.

For the transfer stage LCCMs, we find three and two classes for the leisure and commuting trip purposes respectively (Table 3.11). As was the case for the waiting and in-vehicle LCCM, classes mainly differ from each other in their overall time/cost sensitivity degree. Within each class, we tend to find similar in-vehicle times for the three alternatives. Also, the in-vehicle VOT are in line with their corresponding transfer waiting VOT. Regarding the VOR values, they tend to be lower than their respective waiting VOT (except for the displacement VOR of the Bus-Bus alternative). Still, most of these values (as was the case for the one class models) are not significant. Regarding class composition, the more cost sensitive classes have larger percentages of non-working individuals and part-time workers (¡35h a week), as expected. The opposite applies for the more time sensitive classes. As was the case for the waiting plus in-vehicle stage LCCMs, in the transfer LCCMs, the more balanced class (for the leisure trip purpose) has a larger percentage of young individuals.

Table 3.9: Results for the latent class estimation of the waiting and in-vehicle stage SP experiments. For the cluster profile identification, we highlight in bold the class with the highest share of each characteristic.

	Leisure trip purpose					Commuting trip purpose			
	1LC	4LC				1LC	3LC		
Main class characteristic		Time-cost balance. Waiting ~ In-vehicle	Time-cost balance. Waiting > In-vehicle	Time sensitive	Cost sensitive		Time-cost balance	Time sensitive	Cost sensitive
Class size	100%	40%	36%	13%	11%	100%	60%	26%	14%
VOT and VOR values (€/h)									
VOT waiting 5 min	9.75	4.37	19.49	23.65	0.99	12.71	9.86	120.84	2.87
VOT waiting 15 min	11.74	9.18	19.49	32.92	2.98	16.78	15.65	130.14	2.87
VOR sigma waiting	4.93	3.00	10.99	2.08	0.73	9.15	*9.34*	*10.93*	*5.06*
VOR displacement waiting	7.12	5.78	13.17	11.01	0.86	4.15	4.18	57.93	0.00
VOT in-vehicle	8.71	7.72	9.74	58.02	1.85	10.59	9.25	64.42	2.96
VOR sigma in-vehicle	3.08	3.00	2.83	38.19	0.55	5.72	*5.15*	*34.99*	*1.36*
VOR displacement in-vehicle	3.46	3.05	3.39	24.64	0.94	4.19	3.44	29.18	1.37
Cluster profile identification									
<u>*Socioeconomic characteristics*</u>									
Gender									
Male	49%	49%	48%	**51%**	44%	49%	47%	51%	**58%**
Female	51%	51%	52%	49%	**56%**	51%	**53%**	49%	42%
Age									
18-34	30%	**34%**	29%	23%	24%	41%	**47%**	30%	31%
35-49	21%	**23%**	21%	20%	14%	31%	29%	34%	**36%**
50-64	23%	19%	22%	**33%**	25%	28%	24%	**35%**	33%
65 or above	26%	23%	28%	24%	**36%**	0%	0%	**1%**	0%
Education level									
Low	23%	21%	22%	27%	**34%**	16%	14%	16%	**25%**
Middle	32%	32%	**35%**	25%	34%	35%	35%	**40%**	31%
High	44%	47%	43%	**48%**	32%	48%	**51%**	44%	44%
Working status									
Not working	40%	37%	41%	31%	**60%**				
Working	60%	63%	59%	**69%**	40%				
Working hours									
≤35 hours a week						47%	**49%**	44%	44%
>35 hours a week						53%	51%	**56%**	**56%**
Has children aged ≥12									
No	88%	86%	**91%**	87%	88%	83%	82%	84%	**88%**
Yes	12%	**14%**	9%	13%	12%	17%	**18%**	16%	12%
Urbanisation level									
Highly urbanised areas	53%	54%	49%	52%	**59%**	52%	**54%**	49%	51%
Very highly urbanised areas	47%	46%	**51%**	48%	41%	48%	46%	**51%**	49%

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Table 3.10: Results for the latent class estimation of the waiting and in-vehicle stage SP experiments. For the cluster profile identification, we highlight in bold the class with the highest share of each characteristic. (cont.)

	Leisure trip purpose					Commuting trip purpose			
	1LC	4LC				1LC	3LC		
Main class characteristic		Time-cost balance. Waiting ~ In-vehicle	Time-cost balance. Waiting > In-vehicle	Time sensitive	Cost sensitive		Time-cost balance	Time sensitive	Cost sensitive
Cluster profile identification									
Trip characteristics									
Trip length									
≤12 km trip	50%	48%	48%	54%	**61%**	49%	48%	49%	**55%**
>12 km trip	50%	**52%**	**52%**	46%	39%	51%	**52%**	51%	45%
Trip frequency									
1-3 times a month	71%	72%	**73%**	66%	68%				
≥4 times a month	29%	28%	27%	**34%**	32%				
Mobility-related characteristics									
Commuting transport mode									
Car						38%	35%	**49%**	32%
Public transport						19%	18%	**23%**	20%
Active modes (bike or walk)						36%	40%	25%	**41%**
Other						6%	**7%**	3%	**7%**
Uber ever used									
No	90%	91%	86%	89%	**97%**	87%	87%	84%	**95%**
Yes	10%	9%	**14%**	11%	3%	13%	13%	**16%**	5%
Car availability									
No car in household	22%	**23%**	22%	20%	22%	26%	29%	17%	**31%**
Yes, but not always available	16%	17%	15%	10%	**20%**	24%	24%	**27%**	17%
Yes, and always available	62%	61%	63%	**70%**	57%	50%	47%	**56%**	51%
Public transport (PT) usage									
No PT used previous week	46%	49%	43%	**52%**	39%	47%	47%	45%	**52%**
PT used previous week	54%	51%	57%	48%	**61%**	53%	53%	**55%**	48%

Table 3.11: Results for the latent class estimation of the transfer stage SP experiment. For the cluster profile identification, we highlight in bold the class with the highest share of each characteristic.

	Leisure trip purpose				Commuting trip purpose		
	1LC	3LC			1LC	2LC	
Main class characteristic		More time sensitive	Time-cost balance	Cost sensitive		More time sensitive	More cost sensitive
Class size	100%	52%	35%	13%	100%	55%	45%
VOT and VOR values (€/h)							
VOT direct flexi	11.18	14.45	3.30	0.00	12.54	16.78	5.49
VOT flexibus1	7.76	18.36	4.42	1.13	8.24	18.92	3.30
VOT flexibus2	8.01	14.62	8.64	0.00	7.84	15.79	4.67
VOT busbus1	7.89	16.59	6.26	2.18	8.94	24.63	5.81
VOT busbus2	6.60	12.95	6.27	1.80	9.30	29.48	5.16
VOT waiting transfer flexibus	7.40	11.21	8.67	0.00	8.99	13.32	7.00
VOT waiting transfer busbus	5.77	14.27	5.26	0.00	9.12	23.62	5.46
VOR sd flexibus	4.41	0.50	6.75	0.00	3.27	17.78	0.00
VOR sd busbus	4.42	0.00	0.00	0.00	4.75	5.80	3.01
VOR disp flexibus	4.61	3.09	3.59	7.43	5.95	11.59	2.11
VOR disp busbus	12.42	18.10	0.58	0.00	16.32	12.29	12.18
ASC monetisation (€/trip)							
ASC_FLEXI/(∂V/∂cost_FLEXI)	1.04	-0.14	-0.25	1.45	1.92	0.22	0.25
ASC_FLEXI-Bus/(∂V/∂cost_FLEXI-Bus)	-0.22	0.41	-0.07	0.48	-0.35	-0.26	0.16
ASC_Bus-Bus/(∂V/∂cost_Bus-Bus)	-0.43	-0.24	0.40	-1.32	-0.77	0.10	-0.41
Cluster profile identification							
Socioeconomic characteristics							
Gender							
Male	49%	**51%**	45%	**51%**	49%	47%	**52%**
Female	51%	49%	**55%**	49%	51%	**53%**	48%
Age							
18-34	30%	27%	**36%**	25%	41%	37%	**45%**
35-49	21%	**24%**	18%	18%	31%	**35%**	27%
50-64	23%	**24%**	22%	18%	28%	28%	28%
65 or above	26%	25%	24%	**39%**	0%	0%	**1%**
Education level							
Low	23%	22%	22%	**32%**	16%	16%	**17%**
Middle	32%	31%	**34%**	31%	35%	**39%**	32%
High	44%	**46%**	44%	37%	48%	46%	**52%**
Working status							
Not working	40%	36%	42%	**52%**			
Working	60%	**64%**	58%	48%			
Working hours							
≤35 hours a week					47%	41%	**54%**
>35 hours a week					53%	**59%**	46%

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Table 3.12: Results for the latent class estimation of the transfer stage SP experiment. For the cluster profile identification, we highlight in bold the class with the highest share of each characteristic. (cont.)

	Leisure trip purpose				Commuting trip purpose		
	1LC	3LC			1LC	2LC	
Main class characteristic		More time sensitive	Time-cost balance	Cost sensitive		More time sensitive	More cost sensitive
Cluster profile identification							
Socioeconomic characteristics (cont.)							
Has children aged ≥12							
No	88%	85%	**93%**	86%	83%	82%	**85%**
Yes	12%	**15%**	7%	14%	17%	**18%**	15%
Urbanisation level							
Highly urbanised areas	53%	53%	**56%**	44%	52%	**53%**	51%
Very highly urbanised areas	47%	47%	44%	**56%**	48%	47%	**49%**
Trip characteristics							
Trip length	50%	50%	**51%**	48%	49%	47%	**52%**
≤12 km trip	50%	50%	49%	**52%**	51%	**53%**	48%
>12 km trip							
Trip frequency	71%	71%	70%	**72%**			
1-3 times a month	29%	29%	**30%**	28%			
≥4 times a month							
Mobility-related characteristics					38%	**39%**	36%
Commuting transport mode					19%	19%	**20%**
Car					36%	35%	**38%**
Public transport					6%	**7%**	6%
Active modes (bike or walk)							
Other	90%	88%	91%	**92%**	87%	86%	**88%**
Uber ever used	10%	**12%**	9%	8%	13%	**14%**	12%
No							
Yes	22%	19%	**26%**	24%	26%	24%	**29%**
Car availability	16%	**16%**	15%	14%	24%	23%	**24%**
No car in household	62%	**65%**	59%	62%	50%	**53%**	47%
Yes, but not always available							
Yes, and always available	46%	**49%**	44%	42%	47%	**50%**	43%
Public transport (PT) usage	54%	51%	56%	**58%**	53%	50%	**57%**

3.4 Implications of the VOT and VOR Analysis for the Design of Pooled On-Demand Services and Further Reliability Considerations

The obtained parameters can be included in transport demand forecasting models such as macroscopic static assignment and agent-based simulation models to assess the possible modal shift towards new pooled on-demand services. Our findings can also help assess the impact of service provision design on users' choices, supporting service providers in developing their design strategies. For example, the ratio between the VOT for the waiting time and in-vehicle time can help service providers select the most suitable strategy to match new users and (re)route their vehicles. Also, the ratio between the VOT for commuting and leisure trips could help them set the price for different times of the day, in order to maximise profit and reduce the need to deploy a larger fleet during peak hour.

The latent class analyses presented in the previous section help identify different market segments for on-demand services. Service differentiation may offer the more cost sensitive individuals the option to book a service with higher uncertainty and larger detours for a lower fare. Simultaneously, services with lower uncertainty or shorter waiting times can be offered for the more time sensitive individuals. Offering different services to cater for heterogeneity in preferences can additionally increase patronage and is the current strategy of ride-sourcing companies such as Uber. Service portfolios have also been suggested by Al-Ayyash et al. (2016) and Atasoy et al. (2015).

For the reliability specification, we opted for the mean-variance approach instead of the scheduling approach. Even if these two specifications have been proven to be similar, one underlying difference exists. In our approach, no specific (desired) arrival time is indicated. As a result, individuals are not presented with a situation of lateness. Instead, disutility stems exclusively from the variability/uncertainty of the distribution, which would allow them to choose slack time so as to minimise arriving late (even if this comes at the cost of arriving too early). This means that, even if we believe that this approach better represents the real VOR of the individual, when presented with an unexpected situation, the VOR may be higher than found in this study to avoid lateness.

König et al. (2018) found that individuals with no ride-pooling experience attach more importance to travel time and fare and less importance to reliability related attributes than those with some ride-pooling experience. As a result, the ratio between the obtained values of reliability and values of times can be expected to somewhat increase with familiarity of these services. Note that service comfort and the sharing experience, not directly addressed in this research, may arguably partially explain this change. Having to share the vehicle with other passengers can be perceived by individuals as a source of inconvenience/discomfort that induces travel impedance. Alonso-González et al. (2020a) and Lavieri & Bhat (2019) estimate the willingness to share rides in pooled on-demand services.

Other than the discomfort associated with sharing per-se, some individuals may consider that the number of co-riders in the vehicle (with the accompanying comfort implication) is related to the level of unreliability (and in-vehicle time duration) of the alternatives shown in our scenarios[3]. In that case, the omission of the number of co-riders in the shown attributes could be linked to a certain omission variable bias, impacting the obtained parameter values. Specifically, this omission bias would have led to a negative bias in the measured related parameters (i.e., to an overestimation of the absolute values of our parameters) due to the (potentially assumed) positive correlation between the number of co-riders and the time and reliability attributes. We believe that the impact of such a potential bias, if any, is very limited and that it does not lead to an overestimation of our obtained parameters for the following two reasons: (a) Alonso-González et al. (2020a) shows that for the Dutch context the disutility associated with the number of co-riders is small, and that the decision choice is driven by the time-cost trade-offs instead (similar results were found in Lavieri & Bhat (2019) for the USA context); and (b) our obtained values and the reliability ratio obtained are in line with those found in a previous study for the Dutch context (Kouwenhoven et al., 2014).

A further aspect related to the flexibility/reliability of the offered on-demand services is uncertainty in the availability. Unguaranteed availability plays a key role in the probability of subscribing to shared mobility alternatives (Kim et al., 2017), and even a low probability of unavailability may be considered unacceptable by users that rely on using on-demand services on a daily basis (Fricker & Gast, 2016). In fact, vehicle unavailability was a decisive reason for individuals of the higher income groups to stop using the pooled on-demand service Kutsuplus (Helsinki, Finland) (Weckström et al., 2017). Additional research is needed to further understand how unavailability influences behaviour if this is a condition users may encounter.

3.5 Conclusions

We analysed the Value of Time (VOT) and Value of Reliability (VOR) of the different trip stages of pooled on-demand services, namely the waiting stage, the in-vehicle stage and the transfer stage (when combined with traditional public transport). To the best of our knowledge, this is the first study that analyses the time-reliability-cost trade-offs for all trip stages of new flexible transport modes, in particular for pooled on-demand services. This allows for VOT-VOR comparison, both within and between the different trip stages. We have differentiated between commuting and leisure trip purposes, and identified the taste variation between working and non-working individuals for the VOT and VOR values of their leisure trips. Additionally, to further classify the preference heterogeneity among different individuals, we identified different latent market segments.

[3] Note however that, in reality, no direct relation exists between these attributes. A ride with one extra co-rider may result in higher unreliability and a longer detour time than another with four additional co-riders who are picked-up before us and are dropped-off afterwards.

Our research methodology can be divided in a design phase and an analysis phase. We first designed and executed a series of stated preference (SP) experiments. Our final sample was a representative sample of individuals living in (sub)urban areas in the Netherlands (N=1006). We then analysed our data using mixed logit and latent class discrete choice models.

Results show a higher willingness to pay for (the in-vehicle stage of) pooled on-demand services than known values for traditional public transport: 7.88 – 10.80 €/h depending on trip purpose and working status. Values of time for the waiting stage (both before the trip and during the transfer stage) are lower than values reported in the literature (around 1 – 1.5 and around 0.7 – 1 times in-vehicle VOT, respectively). Two reasons can account for this: first, currently available real time information reduces uncertainty and the related disutility; and second, we separately measure (and model) the waiting uncertainty, which is otherwise masked by the waiting VOT.

Values of reliability in the waiting and in-vehicle stages are found to be lower than their respective values of time, the ratio being around 0.5. This is in line with values found by Kouwenhoven et al. (2014) for car and public transport in the Dutch context. In the transfer stage, most reliability parameters proved insignificant (at the 95% level).The larger amount of attributes in the transfer stage SP experiment may have been the reason to the non-significance of these reliability parameters in our models. Further, the subsequent latent class analysis showed that the main difference between the classes of the different models pertains to the overall price-cost trade-offs rather than in different valuations of reliability in comparison to their corresponding values of time. This suggests a harmonious perception of the reliability ratio (ratio between VOR and VOT) across different market segments.

This research has presented individuals with outcomes of different reliability distributions. In reality, individuals are not directly confronted with this information when taking their transport decisions. Future research may delve into which attributes influence the perception of reliability or on how to better align the reliability characteristics of a service to individuals' perceptions of it. It would also be interesting to investigate if reliability for individual services is perceived differently than for pooled services, given that the latter are presumingly more susceptible to travel time variations. Additional research is also necessary regarding the extent to which VOR can be reduced by providing users with related real-time information. We also recommend future research to further investigate the transfer stage among experienced users, in order to analyse if a 'public transport + pooled on-demand' trip is perceived differently from a 'pooled on-demand + public transport' trip. Finally, future research could analyse whether and how users change their VOT and VOR valuations when gaining experience with pooled on-demand services.

Understanding not only the VOT of pooled on-demand services but also their VOR is of utmost importance, given the premise of their flexibility and the lack of clear reference values such as timetables. Results of this study can be used to forecast modal shift when introducing pooled on-demand services in urban contexts. Additionally, our findings can help in the design of such services by taking users' preferences into consideration.

Chapter 4

Willingness to Share Rides

We started Part II of this thesis modelling individuals' preferred time-reliability-cost trade-offs (Chapter 3). This chapter models individuals' preferences towards another key attribute pertaining pooled on-demand services: the willingness to share a vehicle. Simulation studies suggest that pooled on-demand services can bring large traffic benefits to dense urban areas, yet, to date, the large majority of individuals who request on-demand rides choose individual rides over pooled rides. This mismatch between individuals' current behaviour and the mobility solutions needed in dense urban areas motivates our third research question (RQ 3): What are the determinants of the willingness to share rides in pooled on-demand services?

This chapter investigates the extent to which fare discounts, additional travel time (due to having to share the ride), and the (un)willingness to share the ride with (different numbers of) other passengers play a role in the decision of individuals to share rides. To this end, we perform a stated preference experiment in which individuals need to choose between an individual and a pooled on-demand alternative. While disentangling the sharing aspect from related time-cost trade-offs (e.g. detours), preference heterogeneity is analysed, and distinct market segments are identified. Additionally, the estimated parameters are incorporated in a scenario analysis (as model application), to deduce their policy implications.

This chapter is structured as follows. Section 4.1 introduces the trade-offs, impacts and current usage of individual versus pooled on-demand services. Previous research regarding individuals' willingness to share is then reviewed in Section 4.2. Section 4.3 introduces the research methodology, and Section 4.4 presents the results. In the subsequent results section (Section 4.4). Last, Section 4.5 provides further interpretation of the study findings and Section 4.6 draws the main conclusions.

This chapter is an edited version of the following article:

Alonso-González, M.J., Cats, O., van Oort, N., Hoogendoorn-Lanser, S. & Hoogendoorn, S.P. (2020) What are the Determinants of the Willingness to Share Rides in Pooled On-Demand Services? *Transportation*.

4.1 Introduction

The new on-demand mobility services appearing in cities can foster a shift from the current ownership paradigm into a service paradigm (ITF, 2017). Among these services, the uptake of on-demand rides (provided by companies such as Uber, Lyft, DiDi Chuxing or Grab and also known as ridesourcing or ride-hailing services) has been remarkable all over the world, with Uber alone serving 14 million trips a day (Uber, 2019).

On-demand rides improve their users' accessibility, given that (a) these individuals are less likely to own a car themselves (Rayle et al., 2016), and (b) these services are often used for trips that would have taken over twice as long by public transport (Rayle et al., 2016). However, recent research has shown that these services have also increased motorised vehicle miles travelled (VMT) (Erhardt et al., 2019; Henao & Marshall, 2018) due to empty vehicle miles, induced trips, and modal shifts from public transport, cycling and walking. This increase in VMT has also been acknowledged by the on-demand providers themselves (Hawkins, 2019).

On-demand ride requests can be categorised as individual or pooled, depending on whether the user is willing to share her ride with other passengers for a cheaper fare. The increase in VMT stems from the fact that, to date, the large majority of on-demand trips are individual trips. Currently, on-demand providers do not always offer pooled rides, and even in cities where pooled alternatives are available, only 20% of on-demand users request pooled rides (Gehrke et al., 2018), amounting to around 20% of the rides (Chen et al., 2018; Uber, 2018). Further, the share of rides that has been eventually pooled together in on-demand operations with at least one other ride for part of their trip has been found to be much lower (around 2% in Denver (Henao & Marshall, 2018) and 6-7% in Chengdu (Li et al., 2019)). Tachet et al. (2017) found that the potential of sharing trips in very diverse urban settings in massive, but the current density of requested pooled on-demand trips seems too low to enable that.

Pooled rides (also known as ridesharing or ridesplitting) can help achieve large benefits regarding traffic, emissions, accessibility and parking in urban settings compared to the current situation (ITF, 2016, 2017). However, benefits of pooled rides will only materialise if enough individuals are willing to adopt them. While Fagnant & Kockelman (2018) estimate that a market share of pooled services of 20-50% would be necessary to bring tangible mobility improvements, results from Rodier et al. (2016) indicate that even a higher share is likely to be necessary. In the San Francisco context, Rodier et al. show that if participation is as low as 20%, less than 1% of the trips end up being sharable, with negligible VMT reductions. They find that a participation rate of at least 50% is necessary to achieve large VMT reductions from pooled services. But, are individuals willing to share their rides?

After analysing the characteristics of over one million on-demand trips using an ensemble learning model, Chen et al. (2017) identified in-vehicle travel time and trip cost as the most important determinants of whether an individual will choose to share or not their trip with other passengers. In their model, time and cost attributes had importance weights of over twice as much as the other studied attributes (e.g., pick-up time or weather). Additional service attributes were investigated in Al-Ayyash et al. (2016), who used stated preference data. Al-Ayyash et al. (2016) found that the number of co-riders that can be assigned per vehicle is also an important factor regarding the willingness to adopt a pooled trip. The percentage of individuals willing to use the presented pooled on-demand service was 7-8% higher if the trip could be shared with a maximum of two additional passengers rather than if it could be shared with up to five additional passengers. This leads us to our central research questions: What is the value of time (VOT) (time-cost trade-off) of individuals for on-demand rides? And, what is the monetary disutility associated with sharing an on-demand ride with (different numbers of) other passengers (denominated hereby as the willingness to share (WTS))?

To answer these questions, our methodology approach comprises the design and analysis of a stated preference experiment. We include in-vehicle time, cost and the number of additional passengers as mode attributes. Given that on-demand providers can cater for different market segments by offering a variety of services, it is valuable to understand taste variation of individuals regarding the studied attributes. We account for both continuous and discrete taste heterogeneity in our model estimation. Additionally, we simulate different scenarios to better understand the impact of different time-cost trade-offs (and the impact of different numbers of passengers) on the breakdown between an individual and a shared alternative, based on the estimated parameters of our choice model analysis. We target individuals living in urban areas of the Netherlands in our research.

We summarise the aims of the current research as follows:

– Quantify the WTS in on-demand services for different numbers of passengers and the VOT, in order to disentangle the sharing aspect from related time-cost considerations (e.g. detours) in the context of choosing between individual and pooled rides.

– Analyse preference heterogeneity regarding the WTS and VOT for these on-demand services, and whether distinct market segments can be identified.

– Simulate the effect that different price-cost trade-offs and that different number of co-riders have on the breakdown between an individual and a pooled alternative based on the estimated parameters. We do so by means of a scenario analysis varying the previously mentioned attributes.

4.2 Literature Review

In this section, we review previous literature that tries to understand individuals' decision to share rides. This decision is of utmost importance in dense urban settings, given that simulation studies have shown that, had the majority of the on-demand trips been pooled, they would have reduced both the VMT and the number of required vehicles, even when taking into account the extra distance due to the involved detours (Bischoff et al., 2017; Rodier et al., 2016; Sun & Zhang, 2018; Tirachini & Gomez-Lobo, 2019). And pooling rides will become even more relevant in the age of autonomous vehicles, when riding on-demand services and not driving one's own car may become the rule.

Three main attributes play a role in the decision of individuals to choose for a pooled ride over an individual alternative: the fare discount, the additional travel time incurred, and the (un)willingness to share the ride with other passengers. Time, cost and the number of co-riders are the aspects investigated in this study, and, therefore, are the focus of this literature review. Still, it is worth mentioning that there are other motives that can impact individuals' decision to adopt on-demand services (see Tirachini (2019) for a recent overview), and that, other than the mere utilitarian motives, adoption of shared mobility in general has been linked to environmental and social aspects (Ciasullo et al., 2018; Javid et al., 2017; Mattia et al., 2019; Min et al., 2019).

The cost and time trade-offs that individuals encounter when choosing between the individual and pooled alternatives can be measured in monetary units versus minutes. Bösch et al. (2017) estimated that pooled on-demand services in urban settings can imply a cost benefit of 30-40% versus the individual alternative, whereas currently offered savings vary between 25% and 60% (Shaheen & Cohen, 2018). Regarding time loss, empirical research has found that individuals experience (on average) ten minutes of added travel time as a result of pooling rides (Li et al., 2019). But simulation studies have shown that there is potential to reduce this value substantially. Previous research has shown that an average time disutility of less than three minutes per passenger is possible if all New York (Alonso-Mora et al., 2017) or Berlin (Bischoff et al., 2017) taxi rides would be requested as pooled rides. And Sun & Zhang (2018) estimated a travel time increase of 25% as a result of pooling rides. More generally, Tachet et al. (2017) has found that less than five minutes delay per passenger can provide successful matching potential in very diverse urban settings (e.g., for the Amsterdam context, a request trip density of 2.5 trips/h/km^2 would already enable a matching rate of 92%).

The willingness to share (WTS) is more difficult to quantify. Sarriera et al. (2017) indicate that safety concerns, feelings of prejudice and the fear of having negative social interactions may deter individuals from requesting pooled rides. But the question is, to what extent? One way to measure part of this WTS aspect is to monetize how much money individuals are willing to pay to (not) share their trip with other individuals. We identify seven relevant stated preference studies that quantify the effect of sharing the ride with other individuals (see Table 4.1). The WTS is modelled in these studies either by a mode specific parameter (the alternative specific constant, ASC), which captures the difference of that alternative from all the other presented alternatives, or by an attribute of one of the included alternatives. The effect of additional passengers is measured either by a fixed number, by a range of fellow passengers (depending on vehicle capacity), or by the number of additional pick-ups (hence assuming that the pooling disutility is a function of the extra stops during the ride and not the number of extra passengers in the vehicle).

The WTS parameters' values were found significantly different from zero (i.e. the null hypothesis) in previous studies (except for Steck et al. (2018)). The magnitude of their impact remains, however, inconclusive. As indicated in Table 4.1, the studies were conducted in different geographical contexts. This can presumably partly explain the differences observed. Next to cultural differences, differences can stem from differences in the familiarity with on-demand services or in public transport usage (i.e., familiarity with collective transport modes). Finally, the survey design can also play a role in the outcome. For example, while Lavieri & Bhat (2019) found that cost-time trade-offs are much more relevant than the sharing disutility itself, Krueger et al. (2016) found that the relevance that individuals attach to sharing, makes them perceive individual and pooled services as two distinct mobility options rather than an extra disutility resulting from sharing the ride. Individuals in the first study are familiar with on-demand services thanks to the current popularity of Uber and Lyft in the USA, and these operators offer similar services for both individual and pooled alternatives (other than the differences in time and cost). On the other hand, Krueger's respondents may have been less familiar with pooled services (data collection took place earlier on and on-demand alternatives were not as prevalent in the Australian context). This may lead their respondents to consider both services as different alternatives altogether. Other than whether the trip is shared or not, the number of additional passengers with whom the ride is shared also has an influence on individuals' preference. Alternatives with fewer passengers (or pick-ups) are preferred.

Some of the mentioned studies have also identified certain socioeconomic characteristics, mobility patterns and trip purposes that impact the willingness of individuals to shift towards pooled on-demand rides from their current mode and/or to prefer pooled on-demand rides over individual on-demand rides. For example, Lavieri & Bhat (2019) found that young individuals are more likely to adopt both individual and pooled services than older individuals, and Chavis & Gayah (2017) found that individuals younger than 25 years old seem to prefer pooled rides over individual rides. Pertaining to other socioeconomic characteristics, Lavieri & Bhat (2019) also found that the likelihood to adopt pooled services is lower for non-Hispanic whites, full time and self-employed workers, high income individuals and among those living alone.

Regarding mobility habits, more multimodal individuals (Krueger et al., 2016) and those who do not commute by car (Lavieri & Bhat, 2019) are more likely to adopt on-demand rides (both individual and pooled). And those individuals that have the car as main transport mode tend to prefer individual rides over shared alternatives (Chavis & Gayah, 2017). In order to increase the likelihood of car users to shift towards pooled

Table 4.1: Characteristics of SP studies with the willingness to share attributes

Study	Target population and setting	Mode alternatives *	Attributes considered				Mobility patterns and socioeconomics that play a role in the likelihood of individuals to…		Scenario analysis included?
			Time	Cost	Willingness to share	Number of extra pass.	…shift towards pooled on-demand rides from current used mode	…prefer pooled on-demand rides over individual on-demand rides	
Al-Ayyash et al. (2016)	University students commuting by car or PT (Beirut, Lebanon)	Shared taxi, current mode (car or PT)	X	X	-	X (1-2 or 3-5)	Commuting mode (car or PT), gender.	-	Yes, adoption rate of the new shared taxi service (versus current PT and car shares) with varying waiting time, in-vehicle time, trip cost and maximum number of additional passengers.
Chavis and Gayah (2017)	Commuters (commuting trip) (Baltimore, US)	Bus, microtransit, individual taxi	X	X	X (ASC)	-	-	Car is primary mode, age.	No
Krueger et al. (2016)	Residents (major Australian metropolitan areas)	Individual SAV, pooled SAV, current mode	X	X	X (ASC)	-	Car usage (as passenger or driver), multimodality degree, car-sharing usage, trip purpose.	-	No
Lavieri and Bhat (2019)	Commuters (commuting and leisure trips) (DFW Metropolitan Area, US)	Individual SAV, pooled SAV	X	X	X (ASC)	X (1, 2, or 3)	Commuting mode, age, urbanity degree, ethnicity, working situation, income, household composition.	Gender, ethnicity, education, income, vehicle availability.	No

(continued on next page)

Table 4.2: Characteristics of SP studies with the willingness to share attributes (cont.)

Study	Target population and setting	Mode alternatives *	Attributes considered				Mobility patterns and socioeconomics that play a role in the likelihood of individuals to…		Scenario analysis included?
			Time	Cost	Willingness to share	Number of extra pass.	…shift towards pooled on-demand rides from current used mode	…prefer pooled on-demand rides over individual on-demand rides	
Liu et al. (2018)	Residents (New York, US)	Uber, UberPool, current mode	X	X	X (ASC)	-	-	-	Yes, impact of varying fleet sizes and impact of a per-ride tax.
Steck et al. (2018)	Commuters (commuting trips) (Germany)	Walk, bicycle, AV, SAV (individual or pooled), PT	X	X	X (Add. pass.: yes/no)	-	-	-	No
Yan et al. (2018)	University students and staff (Michigan, US)	Car, flexible pooled transit, bicycle, walk	X	-	-	(X) Add. pick-ups (0, 1, or 2)	-	-	Yes, forecast of the modal share of the new flexible pooled transit (which replaces current bus service) under different deployment scenarios.

* PT: public transport; AV: (privately owned) autonomous vehicle; SAV: shared autonomous vehicle

on-demand services, a good level of service should be provided. Al-Ayyash et al. (2016) identified level of service as the main factor for this group of individuals, while cost was the most important determinant for public transport users. Also, having used car-sharing schemes seems to increase the likelihood to adopt pooled services (Krueger et al., 2016).

Finally, trip purpose was also found to be an important determinant. Krueger et al. (2016) found that pooled rides were preferred over individual rides for shopping trips. Also, Lavieri & Bhat (2019) found differences in the characteristics of individuals interested in pooled rides depending on their trip purpose. They found that females, young individuals and those who had a car in the household were less likely to prefer the pooled alternative for commuting trip purpose, while highly educated individuals were less likely to prefer the pooled alternative for leisure trip purposes.

Leveraging on the estimated behavioural models, three of the stated preference studies included in Table 4.1 also include a scenario analysis. Al-Ayyash et al. (2016) and Yan et al. (2019) show how the predicted shares of their pooled on-demand alternative would decrease in scenarios where more additional passengers/pick-ups are expected. These studies, however, do not include an individual alternative. Thus, a comparison between potential individual and pooled shares is not possible. Liu et al. (2018), on the other hand, does consider both individual and pooled on-demand services in their model. They show different forecasted modal shares for these services with varying fleet sizes and the impact of a per-ride tax. They study these scenarios from a service design perspective, with the objective of optimising the supply-side parameters.

Our research adds to the aforementioned studies in two ways. First, it delves further into the characteristics that underlie the heterogeneity in individuals' WTS and identifies different market segments. Previous studies account for taste variation related to different characteristics rather than identifying different groups. Second, it provides a scenario analysis of the impact of different time-cost trade-offs taking into account both individuals' WTS and the disutility associated with having different numbers of additional passengers. Previously, these two attributes had only been modelled together in Lavieri & Bhat (2019), without offering a scenario analysis. Contrary to Liu et al. (2018), our scenarios aim to provide insight into the time-cost trade-offs of individuals and the effect of varying numbers of passengers, instead of the effect that different fleet sizes have on the overall modal share of the on-demand system or the effect that additional external costs have on system profitability.

4.3 Methodology

The methodology section consists of four parts: survey design (Section 4.3.1), data collection (Section 4.3.2), discrete choice modelling methodology (Section 4.3.3) and scenario design (Section 4.3.4).

4.3.1 Survey Design

To quantify the willingness to share rides in on-demand services, we design a Stated Preference (SP) experiment. SP experiments present respondents with hypothetical situations and have been widely used in the transport literature to obtain behavioural information in scenarios that differ from the status-quo. Unlike in the USA or China, there are, at the time of writing, no large scale pooled on-demand services in the Netherlands. Thus, obtaining revealed preference data for our research purpose is not possible. We opt for a labelled experiment with two alternatives (individual ride or shared ride). We include in-vehicle time, trip cost, and the number of additional passengers of the pooled alternative as SP attributes. Figure 4.1 shows an example of a choice task. The SP setting is either a commuting trip (shown to 70% of the working respondents who do not require their own private car for their commute and have commutes of at least 2 km) or a leisure trip (shown to the remaining respondents).

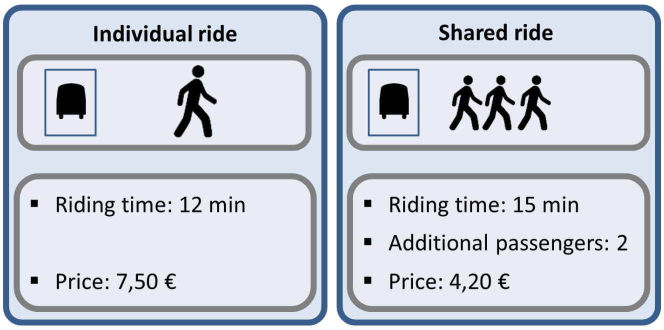


Figure 4.1: Example of a scenario of the stated preference experiment

This SP experiment is the last part of a more extensive survey focused on pooled on-demand services (which also includes a value of reliability study and attitudinal statements). The individual alternative is introduced to respondents for the first time during this SP experiment. Pooled on-demand services are presented to respondents at the beginning of the survey as depicted in Figure 4.2. To increase realism, the individual alternative is constrained to be always quicker (non-existent high occupancy vehicle lanes in our context) and more expensive than the pooled option.

The experimental design of the SP experiment is an orthogonal fractional factorial design with blocking. Orthogonal designs offer robust parameters and do not require reliable priors (in contrast to efficient designs) (Walker et al., 2018). We also add its foldover design. The foldover design is the mirrored original design. It doubles the number of scenarios with the aim of obtaining uncorrelated two-way interactions of the attributes. We decide to add the foldover design given that the disutility to have extra additional passengers may be correlated with the time and/or cost attributes (see ChoiceMetrics (2012) for more information regarding experimental SP designs). Our complete SP design results in six blocks with four scenarios each. For the attribute levels, we consider two set of values, depending on the length of the respondent's reference trip ($\leqslant$12km or $>$12km), following the approach used in Arentze & Molin

(2013). Attribute levels for time and cost for both versions are chosen such that similar values of time could be obtained in the model estimation. Attribute levels are depicted in Table 4.3.

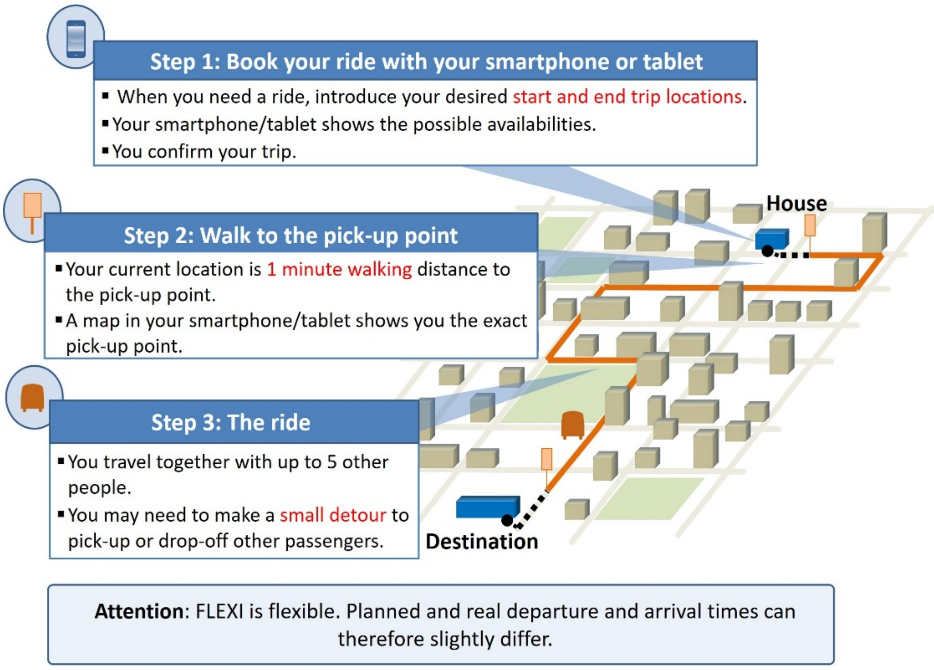


Figure 4.2: Included description of pooled on-demand services. Small adjustments were made to this representation for individuals with no 3G connection and to individuals with traditional mobile phones (as opposed to smartphones). Individuals with a smartphone but no 3G/4G data bundles were additionally offered trip updates via sms, whereas individuals with a mobile phone but no smartphone were offered to make their bookings by means of a phone call and received the exact pick-up address via sms. Layout inspired by Kim et al. (2017).

Table 4.3: Attribute levels of the SP experiment depending on the length of the respondents' reference trip

	Short trip SP version			Medium trip SP version		
	Level 1	Level 2	Level 3	Level 1	Level 2	Level 3
Expected time (Individual ride) [min]	10	15	18	20	25	28
Extra expected time (Shared ride) [min]	3	6	9	4	7	12
Cost (Shared ride) [€]	2	4	6	3	5	7
Extra cost (Individual ride) [€]	0.5	2.2	3	0.6	2.2	3
Number of other additional passengers (Shared ride) [add. passenger]	1	2	4	1	2	4

Travel choices can be influenced by attitudes (Domarchi et al., 2008). Therefore, in addition to the SP experiment, we include a series of 5-point Likert scale attitudinal indicators. They cover attitudes towards the three attributes included in the SP experiment (privacy, cost, and time) and serve two aims in our study:(1) understand if respondents' differences in preferences towards individual and pooled services stem from different time-cost attitudes and/or differences in privacy attitudes, and (2) understand the main cause underlying non-trading behaviour, which could stem from either strong preferences for a particular alternative (for which the offered trade-offs are insufficient to result with a modal switch) or non-utility maximising behaviours (e.g., fatigue or boredom). We refer the interested reader to Hess et al. (2010) for more information on non-trading behaviour.

4.3.2 Data Collection

The survey was distributed on-line on May 2018 (in Dutch). Prior, initial modelling of an on-line pilot performed on April 2018 validated that the chosen SP attribute levels were adequate for our modelling purposes. Target respondents were individuals aged 18 years and older with a mobile phone living in highly urbanised areas in the Netherlands (defined as areas with more than 1,500 inhabitants/km^2 (Centraal Bureau voor de Statistiek (CBS), 1992)). Survey respondents were recruited from a household panel designed for the longitudinal study of travel behaviour in the Netherlands: the Netherlands Mobility Panel (MPN) (Hoogendoorn-Lanser et al., 2015). This provided access to information on socioeconomic and mobility characteristics of respondents. All individuals invited to fill in the survey of this study belonged to different households.

4.3.3 Discrete Choice Modelling Methodology

We analyse the SP experiment using discrete choice analysis, under the Random Utility Maximisation (RUM) framework (Train, 2009). We test different model specifications in our analysis, including interactions of the sharing attribute with the cost and time attributes (i.e., we test whether the disutility of sharing the ride with other passengers is a per ride disutility or it increases with increases in trip duration or trip costs). We also test whether different socioeconomic characteristics help explaining individual preferences for either of the two alternatives (and, if significant, quantify what their impact is), as well as whether both trip purposes are best modelled separately or jointly.

Our first model is a multinomial logit model with an added panel component to account for the correlations among the different observations of the same individual (making it a mixed logit (ML) model). A shortcoming of this model is its inability to account for unobserved heterogeneity, which is exclusively incorporated into the error term. Two main approaches exist to improve the specification in this respect: accommodate heterogeneity in certain continuous distributions of the modelled parameters (using more complex mixed logit (ML) models) or account for heterogeneity by identifying a discrete number of distinct classes, each having different (discrete) values for the modelled parameters (using latent class choice models (LCCM)). In other words, the first approach considers that the unknown parameters are randomly distributed over the population following a certain distribution instead of having a unique value. Alternatively, the second approach considers individuals' heterogeneity by allocating them to different classes in a probabilistic fashion.

Both ML and LCCM have strengths and weaknesses (Greene & Hensher, 2003; Hess, 2014). To make the most of the strengths of both modelling approaches, we include a ML model with random coefficients and a LCCM in our analysis. The first one is able to encompass the overall heterogeneity of the data with a reduced number of parameters. The second one provides flexibility to define different attribute specifications for different classes, as well as is able to link taste heterogeneity to sociodemographic indicators. We use this second model to identify different market segments regarding pooled on-demand services. We refer the reader to Hess (2014) and Walker & Ben-Akiva (2002) for more information on these model structures and their mathematical specification.

In our analyses, we use 80% of our sample for modelling, and keep the remaining 20% for validation (as was done in Atasoy et al. (2010)). We use the software PythonBiogeme (Bierlaire, 2016) for modelling the ML models, and make use of the dedicated latent class software LatentGOLD (version 5.1) (Vermunt & Magidson, 2016) for the LCCM analysis.

4.3.4 Scenario Design

To better understand the impacts of the time-cost trade-offs involved in the WTS rides in on-demand services, we used the estimated discrete choice models to perform a scenario analysis. We are interested in studying a wide range of trade-offs, and we use the widest trade-offs allowed given the design of the experiment, since the validity of the estimated parameters cannot be extrapolated beyond the range of values used for their estimation. This allows us to estimate scenarios with an excess of 3-12 minutes in in-vehicle time for the pooled alternative (compared to the individual option). This range covers both the minimum mean added time that simulation studies have reported (3 minutes (Alonso-Mora et al., 2017; Bischoff et al., 2017)) as well as the average added time found in empirical studies (10 minutes (Li et al., 2019)). Regarding price difference between both services, Bösch et al. (2017) estimated that pooled services can reduce individual prices on 30-40% in urban settings. Currently, savings of 25-60% for the pooled alternative can be expected (Shaheen & Cohen, 2018), with prices for Dutch pooled options ranging between €3.50 (BrengFlex in the Arnhem-Nijmegen area) and €5.00 (ViaVan in Amsterdam). We cover a larger range of values in our scenarios (within the range of values included in the survey).

To ease the scenario comparison, we design a base scenario with the following characteristics: 20 minutes (mean time for single rides (Li et al., 2019)) and €6.00 for the individual ride, and +7 minutes and €-2.00 (-33%) for the pooled ride. Scenarios are computed using Monte Carlo simulation (100,000 draws used). The full sample (and not just the 80% used for estimation of the parameters) is used.

4.4 Results

We divide the results section into three sections. First, in Section 4.4.1, we depict the descriptive analysis, including the description of the data collection and sample and an evaluation of the non-trading behaviour; then, in Section 4.4.2, we cover the choice modelling analysis; and in Section 4.4.3, we report the scenario analysis as final model application.

4.4.1 Sample Description and Descriptive Analysis

A total of 1077 respondents finished the questionnaire, of which 1006 (93%) were considered valid after data cleaning (based on survey completion time and straight lining checks throughout the whole survey). Table 4.4 shows the socioeconomic characteristics of the sample, the target population (highly urbanised areas in the Netherlands), and the overall Dutch values. Gender and the two urbanisation levels are well represented in our sample. Sample age distribution is overall representative of the respective population, although middle aged adults are a bit underrepresented and the elderly population slightly overrepresented. Shares for education, working status and household composition can only be compared to the national values. As expected, our (sub)urban sample has a higher percentage of higher educated individuals, working respondents and single households. Given the similitudes between the analysed sample shares and their Dutch counterparts, we consider that our sample adequately mirrors the socioeconomic characteristics of the target population.

Out of the 1006 respondents, 308 were directed to the commuting trip purpose and 698 answered the survey for the leisure trip. The leisure trip purpose subsample had 42% of working individuals. Differences in working status between both subsamples led to differences in age and education levels (higher proportion of older and lower-education level individuals in the leisure subsample).

A significant share of respondents (around 30%) exhibited a non-trading behaviour in the SP experiment, despite that all blocks contained scenarios with values of time that ranged from less than 5 €/hour to over 30 €/h (initial choice modelling analysis showed an average value of time of around 15 €/h). 50% of non-traders chose the individual alternative in all of the shown scenarios (we refer to these respondents as "individual-only" respondents), and the other 50% chose exclusively the pooled alternative ("pooled-only" respondents). Given the link between attitudes and behaviour (Molin et al., 2016), we perform an exploratory factor analysis (EFA) on the included privacy, cost and time related attitudinal indicators to shed light on the main reason behind the exhibited non-trading behaviour. We use principal axis factoring with direct oblimin rotation, and extract factors with eigenvalues greater than one (Kaiser-Meyer-Olkin measure KMO=0.797 and Bartlett's test of sphericity p¡0.001, indicating sampling adequacy and adequate correlation between the EFA items). The included statements and the related performed analysis is included in Appendix C .

Table 4.4: Comparison between the survey sample and the Dutch population. Sources for the population data: Centraal Bureau voor de Statistiek (CBS) (2018d,c,a,b).

Socio-economic variable	Category	Total sample (N=1006)	Dutch (very) high urbanised areas	Dutch 2018 shares
Gender	Male	48.2%	48.9%	49.6%
	Female	51.8%	51.1%	50.4%
Age	18* to 39	38.1%	38.1%	31.8%
	40 to 64	35.6%	42.0%	44.0%
	65 and above	26.3%	19.8%	24.2%
Education**	Low	25.2%		31.5%
	Medium	32.5%		37.8%
	High	42.0%		29.2%
	Unknown	0.2%		1.4%
Employment status	Working	59.9%		50.9%
	Not working	40.1%		49.1%
Household	1 person household	49.0%		38.2%
	> 1 person household	51.0%		61.8%
Urbanisation level	>2500 inhab./km²	46.9%	48.2%	23.3%
	1500-2500 inhab./km²	53.1%	51.8%	25.1%

* 18 to 39 for the share sample, but 20 to 39 for the Dutch population 2018 values
** Low: no education, basic education or uncompleted general secondary education; Medium: completed general secondary education (diploma to be admitted to higher education attained); High: bachelor candidate or above at a university or university of applied sciences

We extract three factors from the EFA (privacy, cost and time factors), as expected. We measure the reliability of the factors with the Cronbach's alpha coefficient, and obtain (for the Cronbach's Alpha based on the standardized items) 0.61 (privacy factor), 0.70 (cost factor) and 0.57 (time factor). Values over 0.60 are considered acceptable in exploratory research (Nunnally & Bernstein, 1994). Cronbach's Alpha value, however, is dependent on the number of items that belong to a factor (Tavakol & Dennick, 2011), which explains the somewhat lower value for the time factor (which consists of two items). Following Schmitt (1996) and Taber (2017), which argue that factors with lower alphas can also prove both acceptable and useful, and after checking that the two attitudinal time items are highly correlated (their Pearson correlation is 0.40), we decide to not discard the time factor due to the exploratory (and not confirmatory) nature of our factor analysis.

The means of all attitudinal indicators display the same trend: "individual-only" respondents (15% of the sample) are the most privacy and time sensitive, and the least cost sensitive; the opposite holds for the "pooled-only" respondents (15%). The mean values of "traders" (70%) always lie always in between both groups. ANOVA tests confirm that these differences are significant for all indicators at the 95% confidence level or beyond. This difference is largest between the "individual-only" and the "pooled-only" groups, significant at the 99% level (independent t-test). Therefore, we consider the existence of strong preferences as the main underlying cause for the non-trading behaviour, and accept non-traders as valid respondents in the posterior choice modelling analysis.

Further, pair-wise comparison between "individual-only" and "traders" shows statistically different means in all indicators (in all but one at the 99% level) while differences between "pooled-only" and "traders" are insignificant for some of the privacy indicators. This suggests that differences in preferences between "individual-only" and "traders" stem from both different values of time and willingness to share, while differences between "pooled-only" and "traders" stem mainly from differences in the values of time of the two groups.

4.4.2 Discrete Choice Model Estimation

We estimate three model structures (see Table 4.5), as indicated in the Discrete Choice Modelling Methodology subsection. The first model is a mixed logit model with a random component to account for the panel structure of the data. All included parameters in this first model are significant and have the expected signs. Time and cost are modelled linearly as generic parameters (i.e., they have the same parameters for both alternatives). We find that working individuals have a larger time disutility, and include this taste heterogeneity in the model with an additional time disutility parameter for this segment of the population. The models tested show that the effect of the number of additional passengers is best modelled as a trip specific disutility for the case of one or two extra passengers (same disutility for both situations). However, the WTS disutility for the four extra passengers scenario is higher (starting at 20% higher for 13 minute rides, the shortest trip included in the experiment) and increases per minute of in-vehicle time. We speculate that individuals consider that a similar level of privacy and enough personal space is granted in both the single and the two co-rider scenarios, which may explain why the same disutility is attributed to both scenarios. This threshold is however surpassed for the four co-rider situation, leading not only to a higher value but to a per-minute value. We find that having a high income, never using bus/tram/metro (BTM) and having a low usage of cycling increases the preference towards the individual ride alternative. These effects are also included in the model specification. We also find, that, unlike in Lavieri & Bhat (2019), commuting and leisure trip purposes are best modelled together (tested using a likelihood ratio test (Ben-Akiva & Lerman, 1985)).

Our second model adds random components to the time and cost attributes, to account for unobserved heterogeneity. Adding a random component to the WTS-related attributes did not improve the model. We tried different distributions for these random components: a normal distribution, a lognormal distribution, and a doubly-truncated (i.e., bounded) normal distribution. The two latter distributions allow to not associate individuals with positive parameter values (which would be counterintuitive for the time and cost attributes). From the three distributions, the doubly-truncated distribution provides the best model fit (truncation is done by normalising the remaining surface). The time-related random component only affects the common time parameter and not the additional time-related parameter concerning working individuals. Unlike in the previous model, not using BTM (bus/tram/metro) did not prove to be significant, and is removed from the final model specification. The final adjusted rho-squared of the two ML models are 0.281 and 0.291 respectively, indicating a better model fit of the second model specification. Both models are estimated using 10,000 Halton draws.

*Table 4.5: Parameter values (and robust t-tests) of the mixed logit (ML) models and parameter values (and z-value) of the latent class choice model (LCCM) (p-value: ⩽0.01 ***, ⩽0.05 **, ⩽0.1*). N/A: not applicable/no parameter was estimated.*

	Mixed logit model with panel effect	Mixed logit model with panel effect and random coefficients for time and cost	Latent class choice model			
			LC1 “It's my ride”	LC2 “Sharing is saving”	LC3 “Time is gold”	LC4 “Cheap and half empty, please”
Class size	100%	100%	29%	28%	24%	19%
Stated preference attributes						
Time	-0.318 (-11.05) ***	-0.389 (-10.28) ***	-0.1936 (-3.14) ***	-0.2685 (-5.56) ***	-1.3185 (-3.01) ***	-2.0418 (-2.23) **
Additional time working individuals	-0.0662 (-2.68) ***	-0.0916 (-2.90) ***	N/A	N/A	N/A	N/A
Cost	-1.59 (-17.17) ***	-1.83 (-14.98) ***	-0.6843 (-4.24) ***	-1.1492 (-5.95) ***	-3.0138 (-2.50) **	-15.7452 (-2.03) **
ASC pooled alternative (i.e., pooled and cheaper)	N/A	N/A	-1.7265 (-2.84) ***	2.1580 (4.57) ***	3.0540 (2.99) ***	N/A
1 or 2 extra passengers	-0.693 (-2.46) ***	-0.745 (-2.32) **	N/A	N/A	N/A	N/A
2 extra passengers (dummy)	N/A	N/A	-0.3762 (-2.06) **	-0.3762 (-2.06) **	-0.3762 (-2.06) **	N/A
4 extra passengers (dummy)	N/A	N/A	N/A	-0.6818 (-2.37) **	-1.9873 (-1.65) *	N/A
4 extra passengers (per minute in-vehicle time)	-0.0636 (-5.68) ***	-0.0681 (-5.08) ***	-0.0555 (-3.47) ***	N/A	N/A	N/A
Number of passengers (exponential)	N/A	N/A	N/A	N/A	N/A	-0.4661 (-1.89) *
<u>*Random parameters*</u>						
Sigma panel	2.37 (15.19) ***	1.79 (8.01) ***	N/A	N/A	N/A	N/A
Std. dev. in-vehicle time (normally distributed, doubly-truncated z=1.28)	N/A	0.310 (6.00) ***	N/A	N/A	N/A	N/A
Std. dev. cost (normally distributed, doubly-truncated z=1.28)	N/A	1.45 (8.84) ***	N/A	N/A	N/A	N/A

(continued on next page)

*Table 4.6: Parameter values (and robust t-tests) of the mixed logit (ML) models and parameter values (and z-value) of the latent class choice model (LCCM) (p-value: ⩽0.01 ***, ⩽0.05 **, ⩽0.1*). N/A: not applicable/no parameter was estimated. (cont.)*

	Mixed logit model with panel effect	Mixed logit model with panel effect and random coefficients for time and cost	Latent class choice model			
			LC1 "It's my ride"	LC2 "Sharing is saving"	LC3 "Time is gold"	LC4 "Cheap and half empty, please"
Personal attributes (included in the utility function of the individual alternative)						
High income	0.880 (2.97) ***	0.840 (2.41) **	N/A	N/A	N/A	N/A
BTM never used	0.522 (2.09) **	N/A	N/A	N/A	N/A	N/A
Frequency bicycle	-0.171 (-2.74) ***	-0.229 (-3.11) ***	N/A	N/A	N/A	N/A
Model for classes						
Intercept	N/A	N/A	0.3599 (2.31) **	0.1457 (0.81)	0.0391 (0.19)	-0.5447 (-2.44) **
Covariates						
Working individual	N/A	N/A	0.0681 (0.89)	-0.2531 (-2.84) ***	0.1211 (1.20)	0.0640 (0.56)
BTM never used	N/A	N/A	0.2218 (2.93) ***	-0.0363 (-0.38)	-0.0287 (-0.28)	-0.1567 (-1.30)
High personal income	N/A	N/A	0.2625 (2.83) ***	-0.0640 (-0.51)	0.0424 (0.33)	-0.2409 (-1.53)
Young individual (18-34 years old)	N/A	N/A	-0.1920 (-2.24) **	0.0722 (0.74)	0.2244 (2.43) **	-0.1046 (-0.85)
Model fit statistics						
Final log-likelihood	-1594.91	-1572.75	-1533.66			
Adjusted rho-squared	0.281	0.291				
BIC	3262.51	3226.27	3274.73			

We additionally calculate the values of time (VOT) of the estimated models, which help us further compare their results. The basic VOT calculation (as direct division between the β_{time} and β_{cost} coefficients), does not apply in the case of random coefficients. In this case, a second order approximation can be used (Seltman, 2012). Given that the covariance of both parameters can be assumed to be zero (as a result of the choice model formulation), Frei et al. (2017) approximate the VoT in this case as follows:

$$VoT = E\left[\frac{\beta_{time}}{\beta_{cost}}\right] \approx \frac{E\left[\beta_{time}\right]}{E\left[\beta_{cost}\right]} - \frac{Cov(\beta_{time}, \beta_{cost})}{E^2\left[\beta_{cost}\right]} + \frac{Var\left[\beta_{cost}\right] \times E\left[\beta_{time}\right]}{E^3\left[\beta_{cost}\right]}$$

$$\approx \frac{E\left[\beta_{time}\right]}{E\left[\beta_{cost}\right]} + \frac{Var\left[\beta_{cost}\right] \times E\left[\beta_{time}\right]}{E^3\left[\beta_{cost}\right]} \tag{4.1}$$

Unlike the model reported in Frei et al. (2017), our time and cost distributions do not follow a normal distribution but rather a doubly truncated normal distribution (z_1=-1.28, z_2=1.28). Therefore, the mean remains the same as the non-truncated distribution, but the truncation shrinks the variance of the distribution relative to the non-truncated case. Therefore, the $Var\left[\beta_{cost}\right]$ introduced in 4.1 has to be adjusted. For our symmetrical case, the corresponding formulation is as follows (we refer the reader to Burkardt (2014) and Johnson et al. (1994) for the general mathematical formulation):

$$Var\left[\beta_{cost}\right] = \sigma^2\left[1 + \frac{z_1 \times \phi(z_1) - z_2 \times \phi(z_2)}{\Phi(z_2) - \Phi(z_1)}\right] \tag{4.2}$$

where σ is the variance of the non-truncated normal distribution, and z_1 and z_2 are the lower and upper truncation bounds of the equivalent standard normal distribution. The functions ϕ and Φ are:

$$\phi(z) = \frac{1}{\sqrt{2\pi}} exp\left(-\frac{1}{2}z^2\right) \tag{4.3}$$

$$\Phi(z) = \frac{1}{2}\left(1 + erf\left(\frac{z}{\sqrt{2}}\right)\right) \tag{4.4}$$

The WTS calculations are analogous to the VOT ones (including $\beta_{\text{add passenger}}$ instead of β_{time}). Values of these VOT and WTS values are depicted in Table 4.7. As can be observed, values for the ML model with random components are a bit higher. Not capturing the unobserved heterogeneity in the model formulation can thus lead to an underestimation of the VOT and WTS.

For the ML model with random components, we obtain a VOT of 16.25 €/h for non-working individuals and 20.08 €/h for working individuals. WTS values are much lower. They amount to 0.52 €/trip when the ride is shared with one or two additional passengers, and 2.85 €/h when the ride is shared with four additional passengers (remember that the ML model included the four co-rider disutility as a time-dependent variable).

Next, we compare the obtained VOT and WTS values with previous studies, in particular those reported in Al-Ayyash et al. (2016) and Lavieri & Bhat (2019). These studies, similarly to this study, include the time, cost and the number of additional passengers as explanatory variables. Al-Ayyash et al. (2016) is set in Beirut, Lebanon, and addresses university students and university employees. It estimates different parameters

Table 4.7: Value of Time (VOT) and Willingness to Share (WTS) values for the estimated models

VOT and WTS values	ML (panel effect)	ML (panel effect and random coefficients)	Latent Class Choice Model			
			LC1 "It's my ride"	LC2 "Sharing is saving"	LC3 "Time is gold"	LC4 "Cheap and half empty, please"
VOT (€/h)	N/A	N/A	16.98	14.02	26.25	7.78
VOT (non-working individuals) (€/h)	12.00	16.25	N/A	N/A	N/A	N/A
VOT (working individuals) (€/h)	14.50	20.08	N/A	N/A	N/A	N/A
ASC_pooled_alternative/beta_cost	N/A	N/A	2.52	-1.88	-1.01	N/A
WTS 1 additional pass. (€/trip)	0.44	0.52	N/A	N/A	N/A	0.08
WTS 2 additional pass. (€/trip)	0.44	0.52	0.55	0.33	0.12	0.44
WTS 4 additional pass. (€/trip)	N/A	N/A	N/A	0.59	0.66	6.47
WTS 4 additional pass. (€/h)	2.40	2.85	4.87	N/A	N/A	N/A

depending on how often individuals would be willing to adopt the pooled on-demand service for their university commuting habits, and it differentiates between car and public transport commuters. Their obtained VOTs (converted to Euros) range between 3 €/h and 13 €/h. These are lower than our obtained values, which may be arguably attributed to the lower purchasing power of individuals in Lebanon in comparison to those in the Netherlands. Lavieri & Bhat (2019), in turn, is set in the Dallas-Fort Worth Metropolitan Area, USA, and studies commuters. Its obtained VOTs are around 26 €/h for working trip purposes, and 21 €/h for leisure trip purposes, slightly higher values than those found in our study ($\sim$20 €/h for working individuals).

Regarding the WTS, results from Al-Ayyash et al. (2016) indicate that respondents are willing to pay between 0.5 €and 2 €to perform their ride in a vehicle that allows for a maximum of two extra passengers instead of riding a vehicle that allows for up to five extra passengers. This result resonates well with our findings. In Lavieri & Bhat (2019), the ratio between the parameter of additional passengers and cost yields a disutility of around 0.4 – 0.8 €/trip per additional passenger. Again, these values are in line with our findings.

We conclude the comparison between the studies comparing the ratio between the WTS and the VOT values in the three studies. The ratios that can be obtained from the different traveller categories analysed in Al-Ayyash et al. (2016) lead to values around 0.1. To match their approach and obtain a comparable ratio from our study, we need to consider as WTS value the difference between the four co-rider scenario and the 1-2 co-rider scenario. We obtain ratios of 0.05-0.1 for trips lasting 30-60 minutes. WTS-VOT ratios in Lavieri & Bhat (2019) amount to 0.02-0.07 for the 1-2 co-rider scenario. In this case, our ratios are also in the same range, amounting to around 0.03. This comparison shows that the VOT and WTS values obtained in our study are well aligned with results reported in previous SP experiments.

Finally, we perform the LCCM analysis. We do so with the first ML specification as a starting point. We determine the number of classes to be included in the model based on the BIC (Bayesian Information Criterion) index. The four class model minimises the BIC index and yields a meaningful segmentation, and is therefore adopted. The final model, shown in Table 4.5, includes different pooling parameters for different classes. This indicates that the sharing attribute is best modelled using different specifications for different individuals. All time and cost parameters are significant at the 95% level and have the expected negative signs. Parameters related to the number of additional passengers are also negative, with a higher disutility the more extra passengers are in the vehicle, as expected. The majority of the passenger related attributes are also significant at the 95% level. Three of the classes include an alternative specific constant (ASC) in their model specification. The positive sign of two of them implies a preference towards the pooled alternative over the individual one when time and cost parameters are zero and there is one extra passenger in the pooled option. A first explanation could be that the two classes prefer sharing their vehicle (e.g., environmental or social considerations). However, individuals in this classes do experience a higher disutility when sharing the vehicle with two individuals than with one, and this is again higher with four individuals than with two (negative related dummy coded parameters, largest for the four extra passenger specification). Therefore, we conclude that the positive ASC is not due to a preference towards sharing the vehicle, but it is linked to the cost-saving characteristic of the pooled alternative. The LCCM also includes four active covariates, which help define the classes and forecast class membership: being a working individual, having a high personal income, never using bus/tram/metro and being aged 18-34. Three of them also played a role in the ML specification, underscoring their relevance in explaining preference heterogeneity in our SP experiment.

To better understand the main differences between the classes, we calculate the VOT and WTS values for the different classes (Table 4.7) and depict percentage differences between classes regarding socioeconomic and mode use characteristics (Figure 4.3). We also attach a motto to each class, as follows:

– *LC 1 (29% of the sample*[1]*): "It's my ride"*. Individuals in this class experience the highest disutility related to sharing their ride. This preference is confirmed with the attitudinal indicators: this class has the strongest attitude towards privacy, the highest sharing-related time sensitive attitude, and the lowest price sensitive attitude of all classes. "Individual-only" respondents are to be found in this class, amounting to over half of this class' respondents. Sharing disutility for rides shared with four other passengers is proportional to the in-vehicle time (as specified for the ML model) for individuals in this class. Individuals in the

[1]Note that latent class models allocate individuals to classes in a probabilistic and not in a deterministic manner. An individual could, for example, belong to classes one to four with weights 0.5, 0.3, 0.1 and 0.1, respectively (the sum always amounts to one and an individual can have the same probability to belonging to different classes). All percentages regarding class size or class profile mentioned here refer to the sum of these probabilistic distributions of individuals.

other three classes (less adverse to sharing) perceive it as a per-ride fix disutility. Individuals in this class tend to be male, middle aged (35-64), and have high personal incomes. Regarding current mobility, they differ from the other classes in their higher car usage, and lower bicycle and public transport usage.

– *LC 2 (28%): "Sharing is saving"*. They are the most positive towards the pooled alternative, which can be explained by their price sensitivity (the pooled option offers them always cheaper rides) and low sharing reluctance. These two characteristics explain why "pooled-only" respondents are to be found (almost exclusively) in this class. Individuals aged 65 and older, females and not working respondents are more predominantly in this class.

– *LC 3 (24%): "Time is gold"*. These individuals display the highest value of time. They differ from "It's my ride" individuals in their higher acceptance towards pooling. This higher acceptance explains why despite having a somewhat lower value of time, "it's my ride" individuals have a more time sensitive attitude towards increases in time caused by sharing their ride. Their strong time sensitivity, together with the little disutility they attach to pooling per se cause the ASC of this class to have a positive sign. Note, however, that the lowest added time for the pooled alternative is three minutes, and "Time is gold" individuals already associate a larger disutility towards pooling for the three minutes extra time than the positive utility stemming from the ASC, implying that if no cost differences would exist, the individual alternative is preferred for the scenarios included in the SP. Respondents also seem to be more time sensitive for shorter trips (i.e., for the $\leqslant$ 12km version of the SP experiment), with 55% of individuals in this class having had the short version, versus 45-50% in the other three classes. Young (18-34), female, highly educated individuals characterise this class. Frequent car usage in this class is also higher than the average, second to "It's my ride" individuals.

– *LC 4 (19%): "Cheap and half empty, please"*. This is a very cost sensitive class, with a value of time even lower than the "Sharing is caring" class. The main difference compared to the second class is the more negative preference of "Cheap and half empty, please" individuals towards the pooled alternative, especially when four extra passengers are in the vehicle (the disutility regarding pooling with an increasing number of passengers increases exponentially). This explains why, despite their lower value of time, "Cheap and half empty, please" did trade between the individual and the pooled alternative in the SP experiment. This fourth class has a higher share of male and middle educated respondents than the average sample. The likelihood to belonging to this class is similar for individuals with different age groups or working situation.

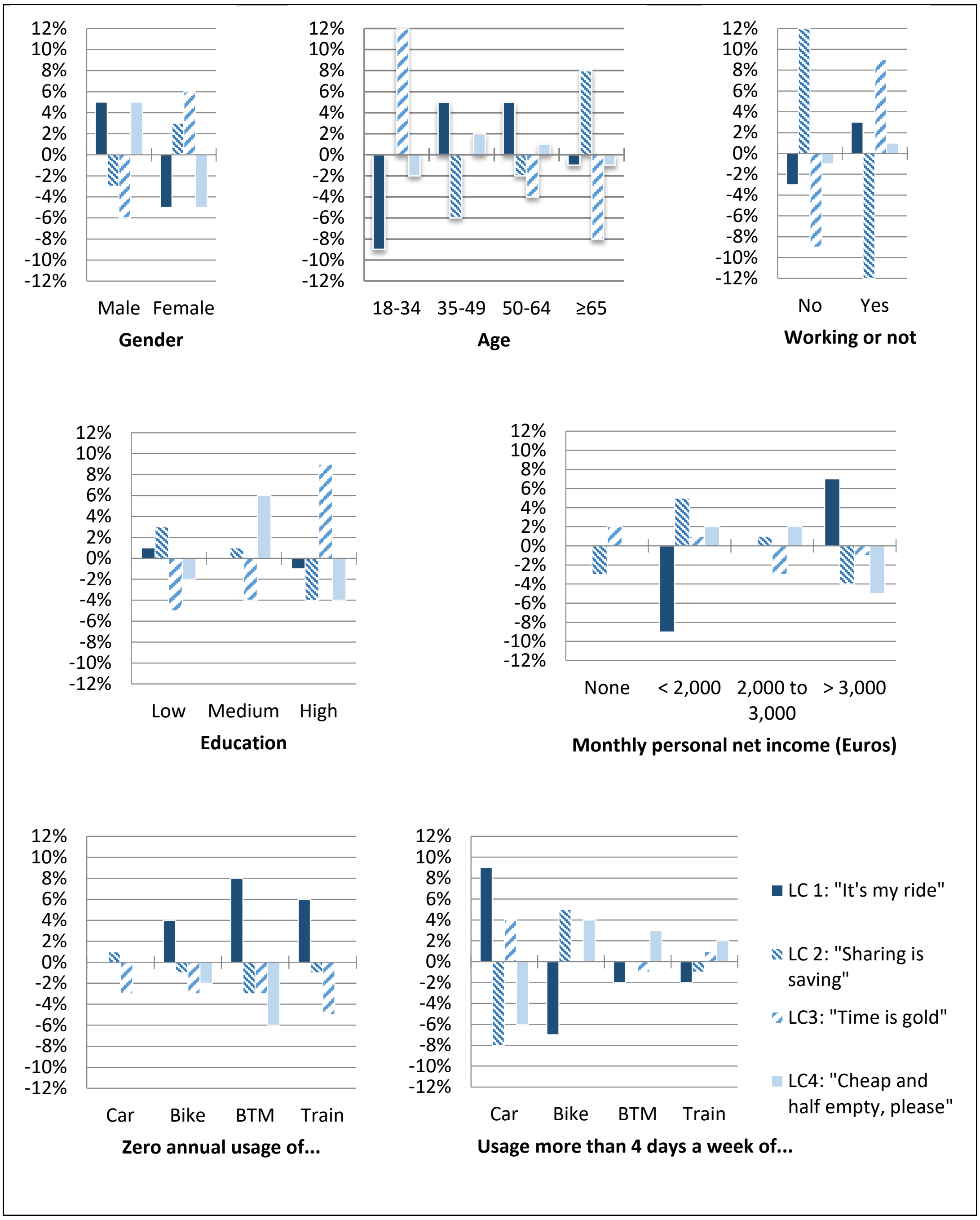


Figure 4.3: Class profiles regarding different socioeconomic characteristics and mode use frequency (percentage deviations from the estimation sample mean values)

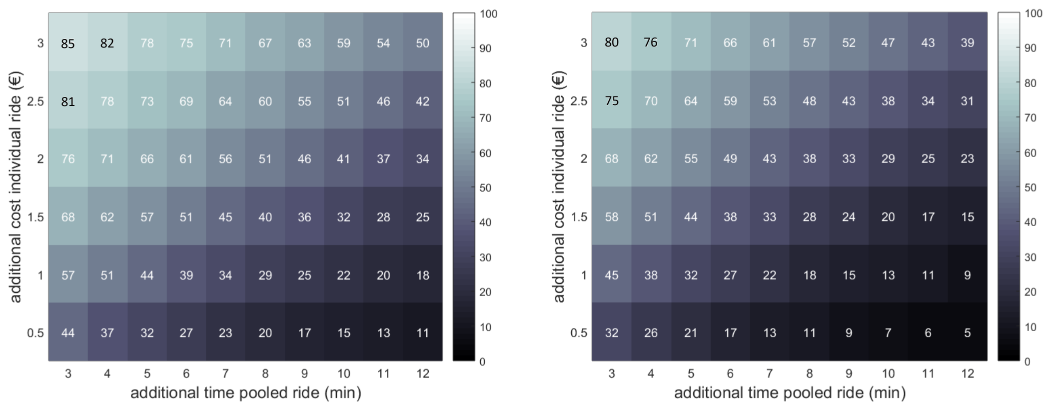
We now turn to validating the obtained models by comparing the prediction rate of both the estimation and the validation subsamples (all models were estimated on 80% of the sample and the remaining 20% was kept for validations purposes). We obtain respectively 71% and 71% for the in-sample data and 73% and 72% for the out-of-sample data for the two ML models. Both offer adequate and similar prediction performance. We obtain similar prediction rates (72% and 75% for the estimation and validation samples respectively) for the LCCM using prior membership probabilities (i.e., using only information regarding the active covariates to infer the membership probabilistic distribution to each of the classes). Moreover, when using the individual's posterior membership probabilities of the LCCM (i.e., statistical inference using an empirical Bayes method which includes information from the observed choices and not exclusively the active covariates to determine the individual's probabilistic distribution to each of the classes), a 93% correct prediction rate for both estimation and validation samples is achieved. This, in turn, suggests that the presented classes succeed in describing the existent heterogeneity of different individuals regarding preferences towards time, cost and pooling attributes when choosing between individual and pooled on-demand services.

4.4.3 Scenario Analysis

We subsequently perform a scenario analysis as model application. These scenarios seek to quantify the impact of time, cost and the number of passengers on the willingness to request pooled rides (over individual ones). The scenarios are designed to demonstrate the impact of the modelling results and, thus, understand their policy implications. Consequently, scenario analyses can help prioritise effective policies triggered by the behavioural change caused by new mobility services (Tarabay & Abou-Zeid, 2019). The ML model with random components has the lowest BIC value out of the three previously estimated models (3226.27 versus 3262.51 and 3274.73), showing the best model fit, and is therefore the one used for the scenario analysis. The discrete choice model is based on disaggregate demand, but the aggregate demand is necessary to derive indicators at the population level, i.e. we need to weight individuals such that they mirror the real distribution of the population. Even if the socioeconomic characteristics of our sample are already quite representative, we weight our sample to mirror the age and gender shares of the target (urban) population for the scenario analysis.

Figure 4.4 shows the effect of varying time-cost trade-offs in the expected percentage of requested pooled rides for the one or two extra passenger scenario and the four extra passenger scenario (versus the individual shares). As expected, the pooled share increases with increasing price difference and decreasing time difference. For the same time-cost trade-off, the achieved pooled share with one or two additional passengers is 5-13% higher than with four additional passengers (mean 10.5%, median 11.1%). Pooled shares vary in our scenarios from 5% to 85%, showing the great impact that the studied range of additional times and fees has on the outcomes. In our experiment, the pooled alternative is preferred by 85% of the individuals when this entails a €3.00 price reduction and only 3 minutes of extra time with either one or two additional passengers.

For the base scenario (20 min and €6.00 for the individual ride; +7 min and - €2.00 for the pooled ride), we obtain the following shares: 56% for the pooled alternative if sharing with one or two extra passengers and 43% in case of sharing with four extra passengers. These shares are well above current shares for pooled rides reported from



(a) (b)

Figure 4.4: Shares for the pooled alternative for different time-cost trade-offs for the (a) 1 or 2 extra passenger scenario, and (b) 4 extra passenger scenario. Duration individual trip: 20 minutes.

deployed commercial on-demand services (reported in the Introduction). We highlight three main reasons for that. First, it can be that real time-cost trade-offs presented to on-demand users are more negative for the pooled alternative than those represented in our base scenario. Second, our results are inevitably influenced by the attribute levels used in our SP design. And third, while some segments of the population are over-represented among users of on-demand services, our scenarios make the breakdown between individual and pooled services for a representative sample of the overall population. For example, currently a higher percentage of higher income individuals tend to use on-demand services. Their preference towards the individual alternative (confirmed by our estimated model), explains the lower pooled share in reality compared to the one found in our scenario. Still, these results suggest that there is potential for the share of pooled requests to increase once on-demand services as a whole become more common place.

In our model formulation, only absolute differences in time and cost between the two alternatives matter (given that an additional minute or Euro are associated with the same linear disutility in the individual and pooled alternatives). For the four passenger scenario, however, sharing disutility varies as a function of the total time of the pooled ride. Figure 4.5 and Figure 4.6 show the influence of time and cost, respectively, on the share of pooled trips (while keeping the other variable constant). For any 10 minutes of added individual ride, we see a drop of around 7% in the share of individuals who opt for the pooled alternative when the trip is shared with four additional passengers. This does not affect the shares when sharing rides with just one or two extra passengers, given that, in the ML model, the one and two co-rider disutility (unlike the four co-rider disutility) is a per trip and not a per minute value.

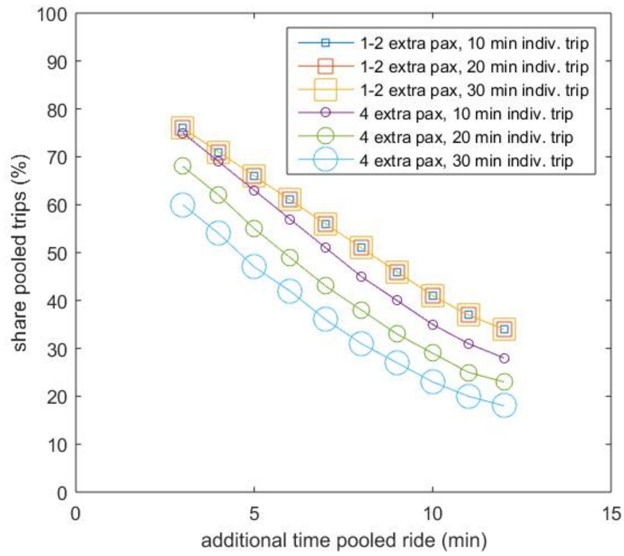


Figure 4.5: Influence of varying time loss (in the pooled alterative) with varying individual trip time durations on the shares for the pooled alternative. Extra cost of individual trip in the shown scenarios: + €2.00.

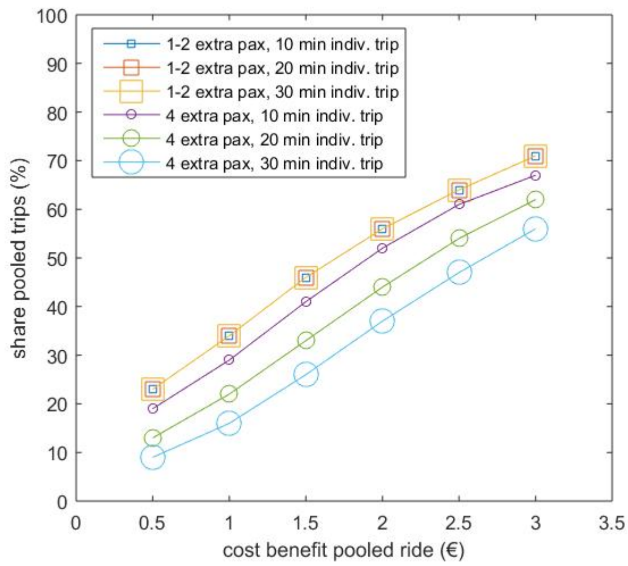


Figure 4.6: Influence of varying cost gains (in the pooled alterative) with varying individual trip time durations on the shares for the pooled alternative. Extra time of pooled trip in shown scenarios: +7 min.

4.5 Discussion

In this section, we further discuss the study results. We divide it in two parts. First, we elaborate on implications and recommendations that stem directly from the study results (Section 4.5.1); and then, we further discuss modal shifts that can be offset by pooled on-demand services, as well as the importance of framing in the uptake of these services (Section 4.5.2).

4.5.1 Implications and Recommendations

The model estimation results (more tangible thanks to the scenario analysis) underpin that the percentage of pooled rides greatly depends on the time-cost trade-off. They also show that the disutility stemming from sharing per se is less of a deterrent than the time-cost trade-off in determining the likelihood to choose pooled rides, in line with previous research (Lavieri & Bhat, 2019; Sarriera et al., 2017; Stoiber et al., 2019). When pooling rides, the disutility of having one or two extra passengers is constant, regardless of the trip length. This disutility further increases in the event that one shares the ride with four additional passengers, in which case it increases the longer the pooled trip. Our study suggests that this may constitute a tipping point in the way that the sharing disutility is perceived. This finding can also be due to the respondents' perception that a vehicle larger than a normal car is needed in the four co-rider situation. Further research is needed to delve into the source of the difference in disutility. Regardless of the underlying cause, most of the pooled requests (for which a matching trip is found) are in reality currently shared with just one additional passenger (Chen et al., 2018), and simulation studies suggest that at most two or three requests in a vehicle (i.e., one or two additional passengers) would be the rule for the majority of the pooled on-demand rides (Bischoff et al., 2017; ITF, 2016). Offering rides with the upfront information that only one or two additional passengers will be in the vehicle can increase the share of pooled requests. Moreover, this would not imply high losses in terms of fleet utilisation efficiency given that having four passengers in the same vehicle would have been a rare occurrence anyhow.

The latent class analysis identifies four distinct classes that explain taste variation. These classes have different specifications to represent WTS, indicating that the disutility attributed to sharing is perceived differently among individuals. Individuals in "It's my ride" class (29% of the sample), attribute a high penalty to sharing (high WTS value) and have high a high value of time (VOT). As a result, they strongly prefer individual rides. Individuals in this class have different travel patterns than those in the other classes, with a higher car usage, and a lower bicycle and public transport usage. Previous studies also found that adopters of new shared mobility alternatives tend to cycle more and perform fewer private car trips (Kopp et al., 2015). Individuals in the "Cheap and half empty, please" class (19%), also experience a high WTS penalty, but only when the ride is shared with four additional passengers. The remaining two classes show a low WTS penalty, and have either time ("Time is gold", 24%) or cost ("Sharing is saving", 28%) as the main determinant of their choices. The somewhat higher shares of females in these two classes suggests a lower WTP penalty for this population segment.

Policymakers may be interested in avoiding scenarios with high individual on-demand shares, and make riders internalise the externalities associated with the increase in VMT associated with these rides. Introducing a per-ride tax on individual requests (or a per-passenger subsidy for pooled rides) could be a policy measure to do so. In fact, different cities in the US have already implemented a tax on on-demand rides

(Hu, 2018). In the case of one or two extra passengers in our base scenario, an extra €1.00 individual tax (or alternatively, pooled subsidy), would raise the percentage of individuals who prefer the pooled alternative from 56% to 71% (i.e., +15%).

Regarding the additional incurred time, simulation studies suggest that a time disutility in pooled rides of just 3 minutes per passenger are possible (Alonso-Mora et al., 2017; Bischoff et al., 2017), yet real data indicates that currently the mean lies around 10 additional minutes per passenger (Li et al., 2019). A reduction from 10 minutes to 3 minutes in incurred additional time would imply, in our simulated scenarios, an increase from 41% of individuals preferring pooled rides to 76% (+35%) (assuming €2.00 price difference and one or two extra passengers). A higher demand density of such rides may be necessary to reduce the extra time. Allocating curb space for pooled on-demand rides can both speed the pick-up/drop-off process and ensure that there is clarity regarding the exact pick-up point, reducing the additional incurred time.

4.5.2 Further Considerations

The positive benefits of pooled rides may be, to some extent, offset by modal shifts from transit and active modes. Our modelling results indicate that it is individuals with a higher usage of cycling and transit that are more attracted to the pooled alternative. Indeed, previous research indicates modal shifts of 34-54% from transit and (to a lesser extent) active modes to on-demand services (Gehrke et al., 2018; Henao & Marshall, 2018; Rayle et al., 2016; Tirachini & Gomez-Lobo, 2019), while higher percentages 48-63% have been found in a study considering pooled services exclusively (Chen et al., 2018). Competition with cycling stems from the short distance of many of the on-demand trips. For example, average distance of the on-demand rides in the city of Chengdu are eight kilometres (Li et al., 2019), the distribution being right-skewed (i.e., the median is lower than the mean). This suggests that there is a significant share of trips within cycling distance. The competition between transit and pooled on-demand services in particular can be best explained by the fact that these pooled services present a cost-effective option for some otherwise underserved origin-destination pairs (Alonso-González et al., 2018; Schwieterman, 2019), or provide a premium service for certain segments of transit trips. Cooperation between transit authorities and on-demand companies can help improve the overall provided urban mobility (e.g., by improving the level of service of traditional transit for the more dense corridors and facilitating the usage of pooled on-demand services for the first-last mile leg).

An additional remark should be made explicit regarding this research. Our SP experiment was the last part of a longer survey in which only pooled on-demand services were considered. The individual option was introduced to respondents only at the end of the survey. Individuals can therefore see the individual option as a "service upgrade", while major on-demand providers offer the individual ride as their base product and the pooled option as their cost-saving one. Framing influences individuals to choose the default option, and previous research has found that framing can influence travel-related choices (e.g., Avineri & Owen (2013); Garcia-Sierra et al. (2015); Mattauch et al. (2014)). We speculate that the estimated pooled shares would have been somewhat lower if respondents had considered the individual service as the base and the pooled option as a "service downgrade".

4.6 Conclusions

This chapter has analysed individuals' willingness to share rides by comparing individuals' preferences towards individual versus pooled alternatives. Previous studies have shown the potential of pooled services to tackle current urban challenges, yet currently the large majority of on-demand trips are requested as individual trips. To help explain the low pooled shares, we first designed a stated preference (SP) experiment targeting individuals living in (sub)urban areas of the Netherlands. We performed a choice modelling analysis that accounted for the unobserved heterogeneity of individuals, including mixed logit and latent class choice models in our analysis. Additionally, this research applied the estimated behavioural modelling results in a scenario analysis. These scenarios simulated the impact of different time-cost trade-offs, as well as the impact of individuals' disutility associated with sharing the rides with different numbers of extra passengers.

Results show that the share of individuals who prefer to share rides lies primarily on the time-cost trade-off they encounter, rather than on the on-board discomfort associated with ride-pooling. There are large differences between the extra time that individuals pooling rides currently experience and the extra time that simulation studies believe to be possible. Also, price discounts associated with pooled rides are often insufficient due to the low probability of matching rides. This may explain the low shares of shared rides currently observed in practice, and suggest a potential vicious cycle unless targeted efforts to generate a positive spiral are made. In that case, our results suggest potential to achieve an increase in the share of rides that are booked as shared. Given the expected large gains in VMT from pooled rides reported in literature, policy makers could consider imposing a tax on individual rides in order to internalise the related externalities and steer demand towards pooled alternatives instead.

Our obtained behavioural model also indicates that current travel patterns and personal income influence individuals' preferences to share rides. Less than one third of individuals ("It's my ride" individuals) have strong preferences towards individual rides, and these individuals are characterised by a more unimodal car behaviour. This suggests that: (1) the uptake of pooled rides can still increase considerably and (2) current car-centred individuals are less likely to shift to more collective modes of transport. Our findings also indicate that the willingness to share of individuals depends on the number of additional passengers. Therefore, a beforehand specification of the number of people that are expected in the pooled ride (or a prediction thereof) can encourage individuals to use the pooled alternative. In the absence of such a prediction, users may refrain from opting for the pooled service in order to avoid the most adverse case in which they share their ride with four or more co-riders.

Finally, we need to acknowledge the limitations associated with the present study. Other than those related to the stated preference nature of the data, we pinpoint two main limitations. First, our research considers the choice between an individual and a pooled on-demand alternative. In reality, individuals have the option to opt out and perform the trip using a different transport mode. Individuals who opt in may not mirror a representative sample of the population, and, thus, the split between both alternatives may differ from the obtained values in this study. Future research could include the parameters estimated in this research to calculate market shares, calibrating the model with the breakdown that they observe in their specific setting. Second, previous studies have identified trust as an important aspect when pooling rides (Amirkiaee & Evangelopoulos, 2018). This suggest that individuals' willingness to pool rides may depend on their previous experience with the service (as well as of those around them), which is not contemplated in this study. Future research could study the willingness to share and the time-cost trade-offs manifested by users of platforms that already offer both individual and pooled services, and investigate how (or if) these aspects change with individuals' experience. Future research could also delve into how vehicle size or uncertainties in the number of passengers affects the obtained willingness to share for pooled on-demand trips.

Chapter 5

Usage Assessment Framework

The previous chapters have shed light into attitudes and preferences regarding pooled on-demand services. But, what are the (temporal and spatial) characteristics of the actual performed pooled on-demand trips? This is the research question we pose in this chapter (RQ 4). Its answer also provides insights regarding the implications that the usage of pooled on-demand services has for other modes. For example, the combination of pooled on-demand services with traditional fixed public transport holds the promise of improved mobility and increased service coverage. However, Chapter 2 identified some clusters that have more positive attitudes towards pooled on-demand services than towards public transport, which could suggest that pooled on-demand services may be being used as a substitute for public transport due to their higher comfort instead of as a complement of public transport for cases of inconvenient poor public transport alternatives or as feeder services.

This study presents an assessment framework to evaluate the usage and performance of pooled on-demand services. It analyses the accessibility and mobility improvements that pooled on-demand services have granted to their users, and can help identify whether pooled on-demand services are being used as a complement or a substitute of public transport.The proposed framework is also applied to BrengFlex, an urban pooled on-demand system in the city of Nijmegen, the Netherlands.

The chapter is organised as follows. Section 5.1 provides an introduction; Section 5.2 describes the methodology; Section 5.3 applies the proposed framework to the BrengFlex case study, and Section 5.4 discusses the results. Finally, Section 5.5 draws the chapter conclusions.

This chapter is an edited version of the following article:

Alonso-González, M.J., Liu, T., Cats, O., van Oort, N. & Hoogendoorn, S. P. (2018) The Potential of Demand-Responsive Transport as a Complement to Public Transport: An Assessment Framework and an Empirical Evaluation. *Transportation Research Record*, 2672(8), 879–889.

5.1 Introduction

Reducing car use is high on the agenda for transport planners, yet the flexibility and convenience that the car provides often makes it a more attractive alternative than traditional fixed (i.e., fixed route and schedule) public transport (for convenience, in the remaining of the chapter, we refer to fixed public transport solely as public transport). To compete with private car use, public transport could benefit from embracing the new flexible services that have appeared in urban areas so as to improve and complement its services. Specially, pooled on-demand services could potentially complement public transport in urban areas.

Even though pooled on-demand services are not a new innovation (they were already recommended for future urban transport in the sixties (Cole, 1968)), only recent technological advancements have enabled their real-time large scale operation. As a result, new urban pooled on-demand services have appeared, both in the USA (e.g., Bridj, Lyftline, UberPOOL, Via) and in Europe (such as Abel in Amsterdam, Kutsuplus in Helsinki, Padam in Paris or Radiobus di Quartiere in Milan). To better understand the utilisation of these services and the role they play in relation to public transport, a systematic assessment framework is proposed in this study.

Several studies have aimed at helping planners design pooled on-demand systems. These studies help estimate the required capacity for a given level of service and the resulting operating costs (Markovic et al., 2016), or assess whether they should substitute public transport for a given scenario (Kalpakci & Unverdi, 2016; Li & Quadrifoglio, 2010). Research has also evaluated via simulation the impact that these services would have in real urban networks, such as in Hino (Japan) (Atasoy et al., 2015), Lisbon (Portugal) (Martinez et al., 2015) or New York City (USA) (Alonso-Mora et al., 2017). However, little is known about how these services perform in real settings. A notable exception is Kutsuplus, "apparently the world's first fully automated, real-time demand-responsive public transport service" (Helsinki Regional Transport Authority, 2016), which operated between 2012 and 2015 in Helsinki, and for which a final project report is available. However, despite Kutsuplus being implemented as part of the public transport system, its final report does not include an analysis on the extent to which the new service improved the mobility in comparison to the already existent alternatives.

This study fills this gap by introducing an assessment framework that analyses the improvement in mobility that pooled on-demand services add to the transport network based on empirically observed usage patterns. Current assessment frameworks regarding pooled on-demand services are high level frameworks without including concrete indicators (Ferreira et al., 2007) or focus on Key Performance Indicators (KPI) that consider them in isolation from other modes (Morse et al., 2017). In this study, the accessibility gains (i.e., the increased easiness to reach the required or desired activities (Yigitcanlar et al., 2007)) that pooled on-demand services granted for the performed trips are examined. The main objective of this study is to help transport authorities in assessing the improvement in mobility that users of the pooled on-demand service have experienced in relation to the co-existing public transport alternatives.

5.2 Methodology

The proposed assessment framework covers three aspects. First, it analyses the characteristics of the pooled on-demand service. Second, it examines its operation, involving both usage and performance. Finally, based on the operational characteristics of the system, a series of accessibility indicators are examined. This framework is depicted in Figure 5.1 and its components are detailed in the subsequent sub-sections.

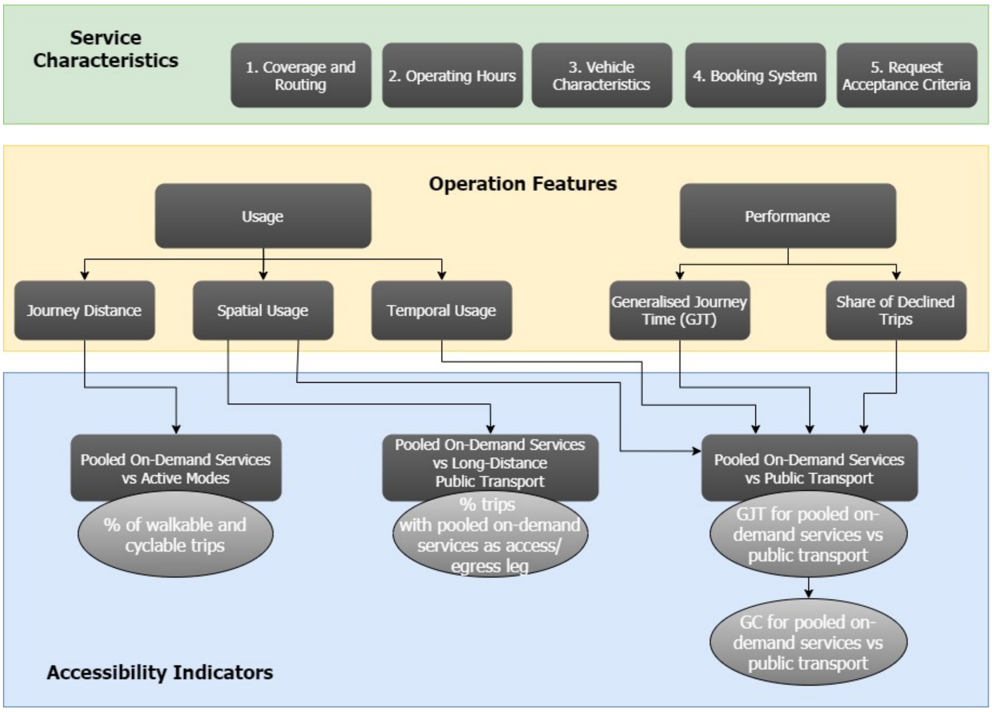


Figure 5.1: Assessment Framework of the pooled on-demand service

5.2.1 Service Characteristics

Before analysing the operation of the pooled on-demand service, it is necessary to understand the intrinsic characteristics of the system under consideration (upper box of Figure 5.1). We highlight five aspects:

1. Coverage and routing. Defined by the operating area and the degree of flexibility in the operation. The latter can range from a fully flexible door-to-door service, to more rigid configurations in which only partial deviations from a planned route are possible.

2. Operating hours. Equivalent to the service span considered in public transport.

3. Vehicle characteristics. Vehicles fleets of pooled on-demand services often consist of minibus vehicles, with previous research suggesting that a vehicle capacity of eight is the preferred vehicle size (Khattak & Yim, 2004). Fleet size is also a key design variable of these services as it will determine the different routes that can be covered simultaneously by the system.

4. Booking system. The system can allow for instant bookings in real-time, require advanced bookings or allow for both options. Traditionally, dial-a-ride schemes relied on telephone reservations, but large-scale real-time pooled on-demand services require Internet connection to perform the bookings in an efficient manner.

5. Request acceptance criteria. Time required to the pick-up point or vehicle availability are the often-used criteria in deciding whether a request is accepted or rejected.

5.2.2 Operation Features

Because of its inherently dynamic interaction with demand, performance of pooled on-demand services is directly tied to its usage (Lerman et al., 1980). As such, both aspects are an integral part in the operation evaluation (see middle box of Figure 5.1).

Usage

Usage is analysed in terms of demand patterns. Three important aspects are highlighted: journey distance, spatial usage patterns and temporal usage patterns. Journey distance can provide insights into the modes that would compete with pooled on-demand services. For instance, short trips might substitute walking and cycling. The analysis of spatial usage reveals which origins, destinations and routes are most frequently used. This can shed light on areas with high demand that may not be conveniently served by public transport. Lastly, the temporal usage identifies peaks in the operation, both by time of the day and by day of the week. Traditionally, transport demand in general, and public transport services in particular, tends to exhibit two daily peaks following commuting patterns. Since shopping and social trips have been identified as the most recurrent trip purposes for pooled on-demand trips (Jain et al., 2017), different temporal usage patterns might be expected for these trips.

Performance

Regarding performance, the presented framework considers two aspects: the Generalised Journey Time (GJT) and the share of declined trips. The GJT represents the perceived passenger journey time. It is calculated by multiplying the time of the different segments of the door-to-door journey by different weighting factors so as to transform them into equivalent in-vehicle time (Balcombe et al., 2004). The different segments to take into account are the walking time ($\mathbf{t^f}$), the waiting time ($\mathbf{t^w}$), the in-vehicle time ($\mathbf{t^v}$), and the number of transfers ($\mathbf{n^t}$). The GJT can be expressed as

$$GJT = \alpha_f \cdot t^f + \alpha_w \cdot t^w + t^v + \alpha_t \cdot n^t \tag{5.1}$$

where α represent the different weighting factors. The estimation of these α has been the subject of a large number of public transport studies (e.g., Booz Allen & Hamilton (NZ) Ltd (2000); Wardman (2004)). It is important to note that the waiting time can be expected or unexpected, with unexpected waiting time being valued by passengers as 2 to 3 times longer than expected waiting times (Currie & Wallis, 2008). As such, an accurate and up-to-date forecast of the pick-up times in pooled on-demand services is of outmost importance to lower GJT.

This study also includes the share of declined trips by the operator as a separate element in this assessment since it is an important reliability indicator of the pooled on-demand service. A systematic analysis of the declined trips can also help improve the offered service and search for inequalities in operation (e.g., some zones may have a higher share of declined or less profitable trips and may thus suffer from more recurrent cancellations). For example, pooled on-demand operators could be penalised when declining trips for which no adequate public transport alternative is available.

5.2.3 Accessibility Indicators

Following the analysis of pooled on-demand operation, this chapter proposes a series of indicators that measure the change in accessibility attributed to the pooled on-demand service. These are depicted in the ovals in Figure 5.1.

Pooled On-Demand Services vs. Active Modes

Pooled on-demand services can be seen as a competitor of walking and cycling for admissible walking and biking distances. The threshold for admissible walking and cycling distances needs to be adjusted based on the setting, as these values differ by region (International Transport Forum, 2012), as well as by trip purpose and population subgroup (Yang & Diez-Roux, 2012). The first accessibility indicator expresses the share of walkable and cyclable trips as follows:

$$\%\text{ walkable trips} = \frac{\text{number of trips shorter than the walking threshold}}{\text{total number of trips}} \tag{5.2}$$

$$\%\text{ cyclable trips} = \frac{\text{number of trips shorter than the cycling threshold}}{\text{total number of trips}} \tag{5.3}$$

The smaller these shares are, the less the actual usage of the pooled on-demand service is competing with active modes. Note that although the former is a subset of the latter, biking is not always a feasible alternative (e.g., lack of a bicycle or cycling knowledge). Including both indicators serves to, depending on the setting, better assess the actual competition of the pooled on-demand service with active modes.

Pooled On-Demand Services vs. Long-Distance Public Transport

Pooled on-demand services are often restricted to a certain area. For trips that extend beyond these boundaries, these services can be used as a complementary mode and connect passengers with long-distance public transport modes such as train, long-distance bus, or regular bus (i.e., be used as a feeder mode). The second accessibility indicator is thus expressed as:

$$\begin{gathered}\%\text{ trips with pooled on-demand services as access or egress leg} = \\ \frac{\text{transit trips with pooled on-demand services as access or egress leg}}{\text{total number of trips}}\end{gathered} \tag{5.4}$$

The larger this share is, the more the pooled on-demand system constitutes a connecting service to long-distance public transport.

Pooled On-Demand Services vs. Public Transport

Pooled on-demand services can also be used as the main mode of transport, competing with public transport. This is the more general scenario due to the similitudes that both transport modes exercise. In order to address this key aspect, the assessment framework provides a more complex benchmark against public transport, in which two KPIs – the GJT and the Generalised Costs (GC) – are calculated and compared for the pooled on-demand service and public transport.

Following the workflow described in Figure 5.2, the GJT is calculated for the pooled on-demand trips and, if available, for the declined trips. The GJTs of the pooled on-demand trips are compared with the GJTs that the passengers would have experienced if they had travelled using public transport. Three parameters are used to calculate the GJT of the public transport alternatives: booking time (as the desired start time), and origin and destination locations. Automatic Vehicle Location (AVL) data can be used for this purpose. If this information is unavailable, scheduled information from public transport journey planners can be used. The GJT Ratio (GJTR) of each trip is expressed as:

$$GJTR = \frac{GJT^{\text{pooled on-demand trip}}}{GJT^{\text{public transport trip}}} \tag{5.5}$$

The GJTR indicator is analysed by considering its distribution, and performed and declined trips are to be assessed separately. It is important to note that the median (or the quartiles for a more detailed representation) should be used to assess the distribution rather than rely on the mean due to the asymmetry caused by the ratio calculation.

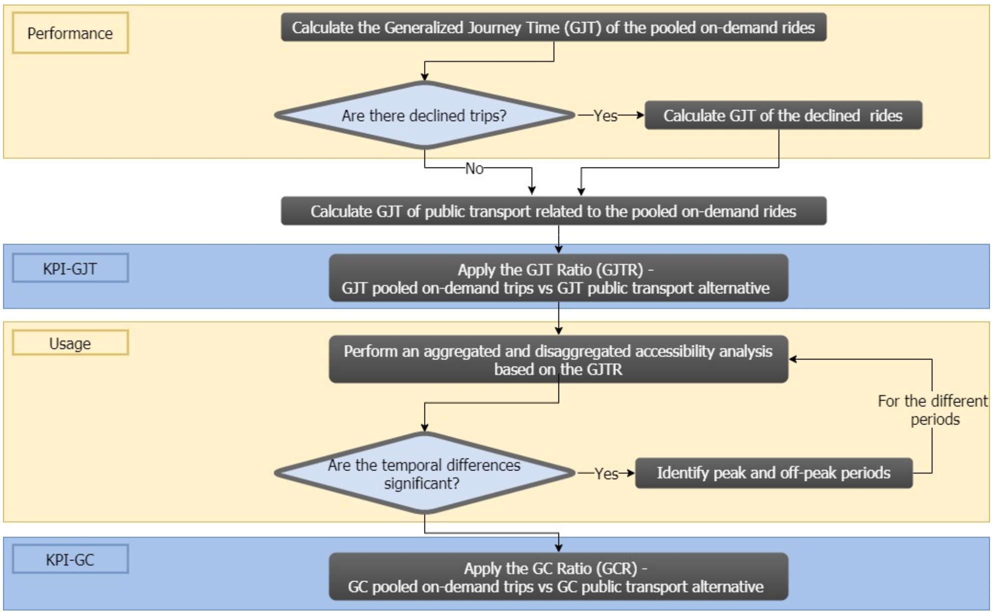


Figure 5.2: Pooled on-demand service accessibility performance benchmarks against public transport

The GJTR can be further evaluated both spatially and temporally. An aggregated representation of this KPI can identify origin-destination (O-D) connections for which the pooled on-demand service has mostly improved the public transport provision. A comparison between the number of performed and declined trips for the different O-D pairs can identify whether rejections are more prevalent in certain areas. Moreover, a disaggregated representation can identify connections that are underserved by conventional public transport. If significant temporal differences exist (either daily or weekly), the spatial analysis can be performed for different time intervals.

The last step of the comparison between pooled on-demand trips and their public transport alternative is based on the GC in which the GJT values are multiplied by the corresponding value of time (VoT). The monetarised value of the GC Ratio (GCR) indicator is expressed, similarly to the GJTR as:

$$GCR = \frac{GC^{\text{pooled on-demand trip}}}{GC^{\text{public transport trip}}} \tag{5.6}$$

Whenever the focus is set on the total monetary cost of the passenger instead on the temporal convenience of both modes, this GC indicator can be used.

5.3 Application: BrengFlex

We divide this section in two: case study description and results analysis.

5.3.1 Case Study Description

The assessment framework described in the previous section was applied to the pooled on-demand pilot ‘BrengFlex’ which operates in the Arnhem-Nijmegen region in the east of the Netherlands. In the following, the BrengFlex service in Nijmegen is analyzed. The pilot started in December 2016 and it offers stop-to-stop connection with a total of 255 stops. The service area includes the city of Nijmegen and the neighbouring municipalities of Wijchen, Berg en Dal and Oosterhout, with a total of approximately 200,000 inhabitants. BrengFlex is run by Breng, the incumbent local bus operator. With its introduction, two bus lines that linked the municipality of Wijchen, traversed the central parts of Nijmegen and terminated at the northern part of Nijmegen, were simultaneously cancelled. The BrengFlex service has a fixed price of €3.50 per person and operates from 6:30 to 24:00 during the weekdays, 8:00 to 24:00 on Saturdays and 9:00 to 24:00 on Sundays. The fleet comprises five minibuses (maximum of five seats for passengers and two wheelchairs) and four electric cars (maximum of three seats for passengers). Rides can be booked in real-time via a mobile app or a telephone number, and no advance booking option is available. Maximum waiting time is set to 20 minutes, rides that cannot be served within this time window will not be accepted.

The analysed data includes the pick-up and drop-off locations for all registered ride requests – both performed and declined trips – between the 16th December 2016 and 18th May 2017. Booking times and expected in-vehicle times are available for the declined trips. Data for the performed trips also include actual in-vehicle time and waiting time. Rides with unrealistic average travel speed – lower than 10km/h (6.21 mph) or higher than 70km/h (43.48 mph) – are not considered in the analysis. For declined trips, requests with the same spatial characteristics that differed by less than 5 minutes are included only once in the analysis to prevent multiple counts. A total of 4,719 performed trips and 130 declined trips (2.7% of all requests) are considered valid for the analysis.

5.3.2 Results

The average distance of the served pooled on-demand trips is 7.05 km (4.38 mi). Since no sociodemographic data of the pooled on-demand service users is available, the average walking and cycling distances in the Netherlands are used as thresholds for these modes – i.e., 1.2 km (0.75 mi) for walking trips (International Transport Forum, 2012) and 3.6 km (2.24 mi) for cycling trips (KiM Netherlands Institute for Transport Policy Analysis, 2016). In total, 0.1% and 16.5% of the pooled on-demand trips could have been performed on foot and by bike respectively, with the large majority of the rides covering a longer distance than the average active mode trips.

The obtained data does not allow identification of pooled on-demand trips that constitute a part of a longer public transport trip. In order to have an approximation of the number of trips that could have used BrengFlex as access or egress leg, we identify the number of pooled on-demand trips that have one of the six train stations within the case study area as pick-up point (12.3% of the rides) or drop-off point (8.3%). These numbers are upper bounds and suggest that up to 20% of the rides could have been used to access or egress one of the train stations.

The other indicators compare the pooled on-demand rides to public transport rides. The characteristics of the public transport rides that could have substituted the performed and declined pooled on-demand rides are obtained introducing the booking time and the start location and end locations of the pooled on-demand rides in the public transport Google Maps Directions API (Google Developers, 2017). The Google Maps Directions API provides scheduled rather than actual public transport data, hence possible deviations from plans in public transport operations are not accounted for. As retrieval criterion, we select the public transport trip with 'the earliest time at the destination'. However, using this criterion, the option shown for 5% of the performed trips and for 13% of the declined trips (242 and 17 respectively) does not involve any public transport, only walking. This is arguably an indication that the existing public transport connection for these origins and destination is inadequate, or that the distance covered is rather short. To allow for a fair comparison where public transport values can be attained, these trips are not included in the subsequent comparison of the pooled on-demand service and public transport.

For the previous trips, the GJT for the performed and declined trips are calculated (the factors used being $\alpha_f = \alpha_w = 2$ and $\alpha_t = 10$ (Booz Allen & Hamilton (NZ) Ltd, 2000)). The average waiting time of the performed trips (9.4 min) is taken as the estimated waiting time for the declined trips. The distribution of the GJTR is illustrated in Figure 5.3 for both served trips (a) and declined trips (b). The median for the performed trips is 0.50 (0.38 for the 25th percentile and 0.68 for the 75th percentile). In other words, for 50% of the performed trips, the public transport alternative is perceived by the passengers over twice as long as the pooled on-demand service alternative. For the declined trips, the median is 0.54 (0.45 for the 25th percentile and 0.71 for the 75th percentile). These results attest to how the pooled on-demand alternative considerably improves the accessibility of the performed trips in comparison to the public transport alternative.

The distribution of the GJTR is now analysed spatially, both in an aggregated and in a disaggregated manner. Figure 5.4 presents the aggregated spatial analysis of the performed trips, with (a) the zonal delimitations used (in which Nijmegen has been divided into three parts by following natural water barriers), (b) the O-D matrix in hundreds, and (c) the median of the GJTR corresponding to each of the O-D pairs. The difference in the number of rides for each of the O-D pairs is partly due to the difference in the population size of the different areas. Moreover, part of the demand between Wijchen and the different areas of Nijmegen may be attributed to users of the two bus lines that were eliminated with the introduction of BrengFlex. This fact could also explain why trips from Nijmegen North to Wijchen have the lowest median for the GJTR indicator (the median GJT of the pooled on-demand trips is 22% of the public

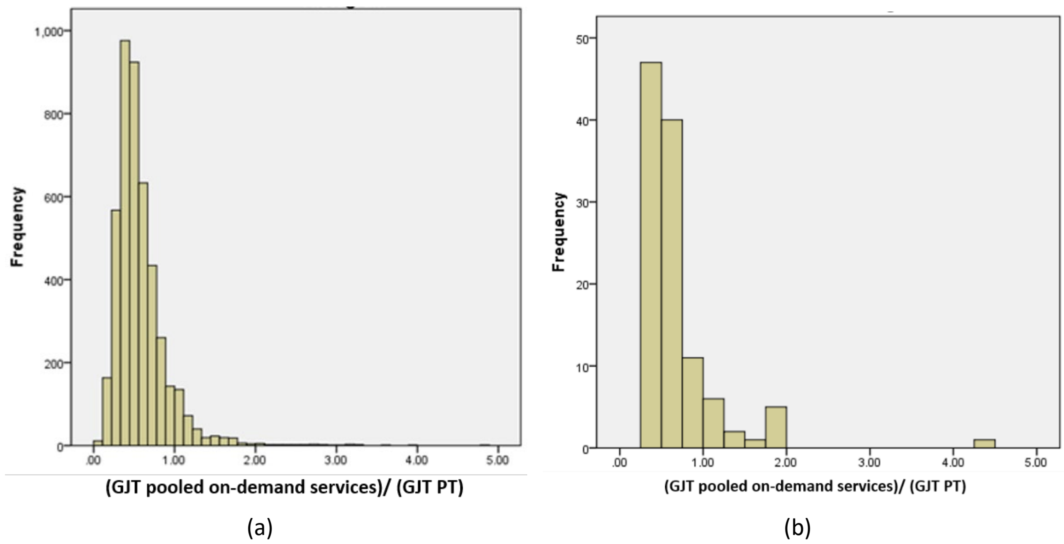


Figure 5.3: Distribution of the GJTR for pooled on-demand trips in comparison to public transport (PT): (a) for the performed trips (N = 4477) and (b) for the declined trips (N = 113).

transport GJT value). Conversely, the O-D pair for which the increases of accessibility provided by the pooled on-demand service in comparison to public transport are the lowest is Oosterhout-Oosterhout (GJTR = 0.69). Regarding the declined trips, the low number of occurrences (with no occurrence at all for many of the O-D pairs) does not provide a representative sample to analyse if there are statistical differences between both trip groups and is therefore not included in the shown figures. Importantly, the number of declined trips for each O-D pair correlates with the number of served trips. Thus, there are no spatial disparities in the pooled on-demand service availability.

The disaggregated spatial analysis is presented geocoded in Figure 5.5. The performed rides have been distributed in three graphs (a), (b), (c), according to their GJTR, whereas declined rides are illustrated in (d). Node size is consistent with the use frequency, as well as link size and link colour intensity. The direction of the trips is represented clockwise. The large majority of the trips for which public transport outperformed the pooled on-demand service (GJTR>1) were radial trips with an end in the centre of Nijmegen, whereas recurrent links with a distinctive benefit for the pooled on-demand service have a more tangential nature. No distinctive pattern can be observed between performed and declined trips. The large majority of the 255 stops of the pooled on-demand service are utilised during the study period, and the stop at the 'Nijmegen central railway station' is one of the two most recurrently used stops.

The analysis of the evolution of the demand for BrengFlex services shows a constant increase in the number of rides since the implementation of the pooled on-demand service. The number of trips in the last week quadruple the trips in the first weeks to its introduction. Due to this large variation in demand volumes, only the data from the last 10 weeks is considered in the search for daily and weekly variations in the demand levels. No statistically significant differences are found in the demand on

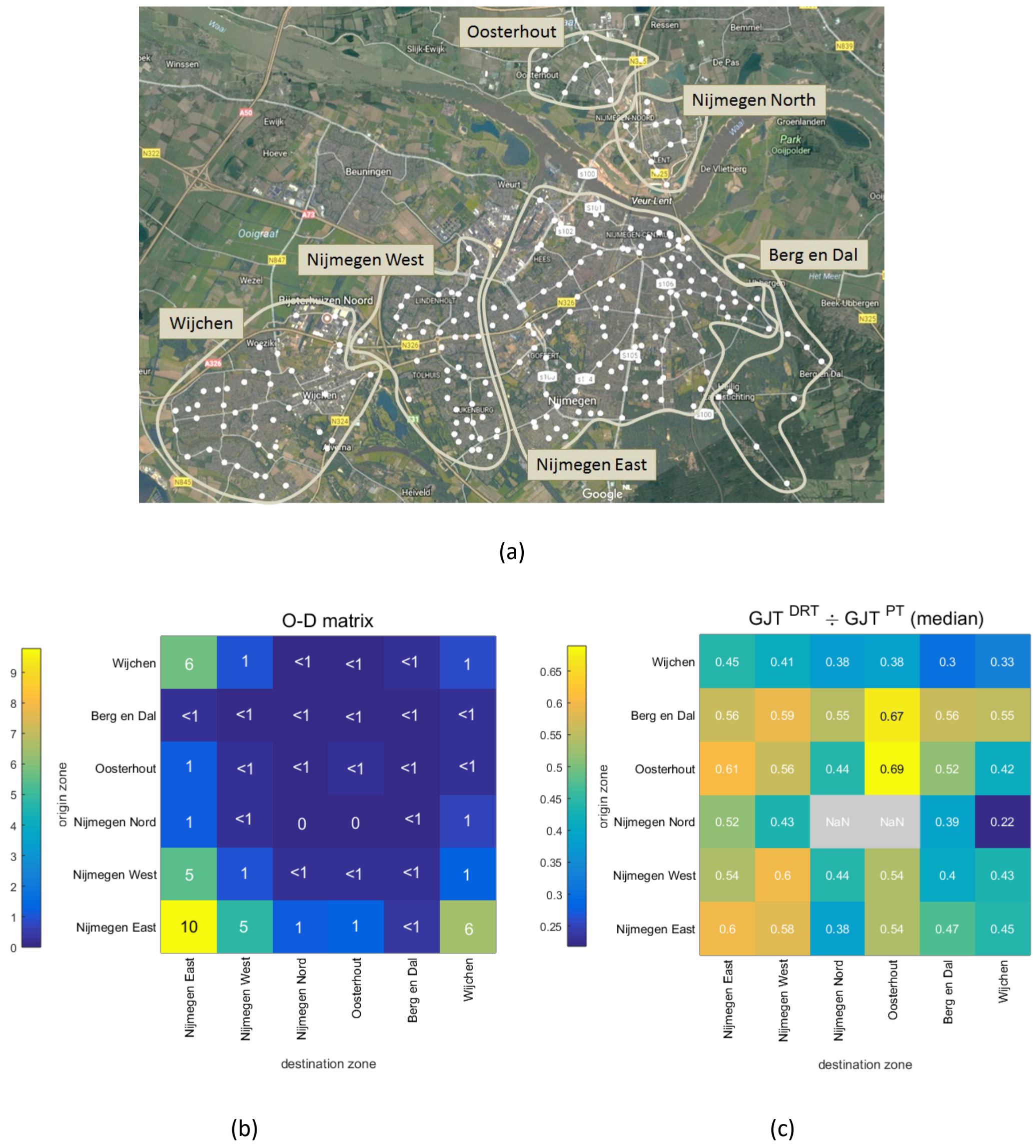


Figure 5.4: Aggregated spatial analysis of pooled on-demand trips: (a) Zonal delimitation, (b) O-D matrix (in hundreds) and (c) median of the GJTR for each O-D pair.

different days of the week (p=0.113 for one-way ANOVA) but differences in demand levels at different hours of the day are statistically significant (p=0.001 for one-way ANOVA studying the hourly demand between 9:00 and 21:00). The hourly demand of the pooled on-demand service does not show strong commuting peaks as in the case for public transport, but smaller peaks still do exist, with the highest demand observed in the afternoon (around 15:00). A spatial representation of the peak period could further identify the highest demand areas during this timeslot.

The last step described in the assessment framework involves the calculation of the GC of both performed and declined trips. A future modal shift from public transport to the pooled on-demand service can arguably be expected if the GCR distribution favours pooled on-demand trips to a large extent. The VoT used for this study (both for pooled on-demand trips and public transport trips) is the VoT calculated in Kouwenhoven et al. (2014) for bus/tram/metro for all trip purposes in the Netherlands, which is 7.39€per hour per person in 2016 terms. The distribution of the GCR is represented in Figure 5.6. The median for the performed trips is 0.75 (0.60 for the 25th percentile and 0.97 for the 75th percentile). For the declined trips, the median is 0.80 (0.63 for the 25th percentile and 0.99 for the 75th percentile). These results show that while the pooled on-demand service outperforms public transport for the trips for which passengers opted for the former, the distributions of the GC are closer to 1 than those of the GJT (Figure 5.3). This shift is caused by the higher fixed price for pooled on-demand trips than the distance-based public transport fare, resulting in a smaller discrepancy in passenger disutility between the services when accounting for the price difference.

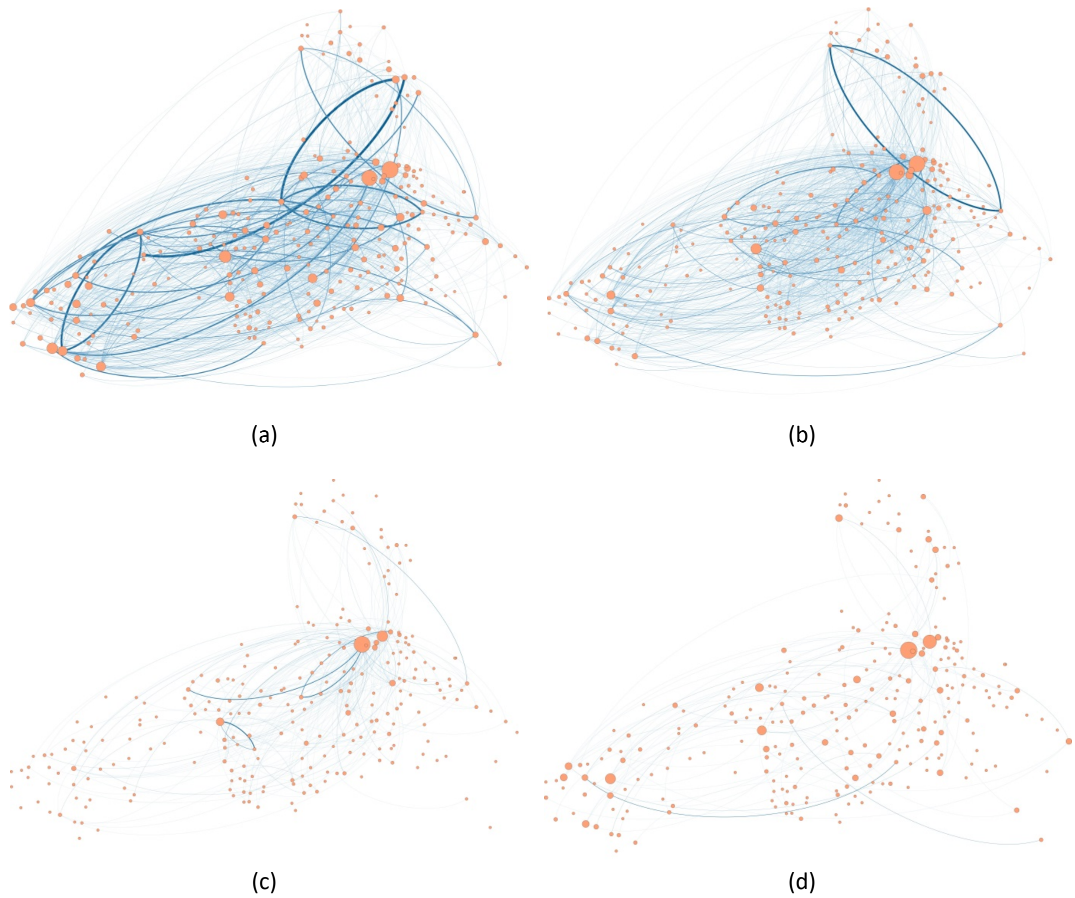


Figure 5.5: Disaggregated spatial analysis of pooled on-demand trips: (a) performed rides with GJTR<0.5 (2206 rides), (b) performed rides with 0.5<GJTR<1 (1905 rides), (c) performed rides with GJTR>1 (366 rides), and (d) declined rides (113 rides). Plotted in Gephi (Bastian et al., 2009).

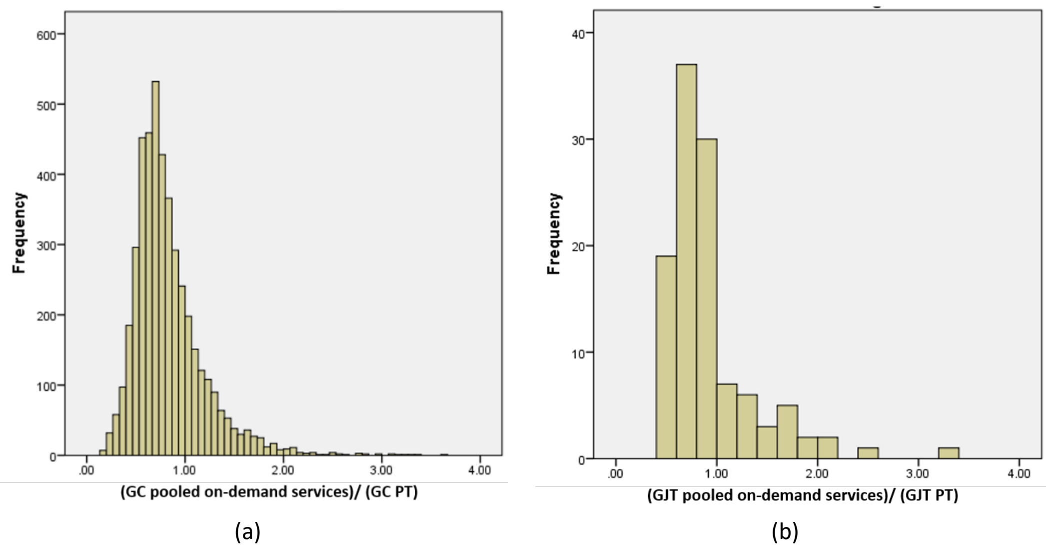


Figure 5.6: Distribution of the GC for pooled on-demand trips in comparison to public transport (PT): (a) for the performed trips (N = 4477) and (b) for the declined trips (N = 113).

5.4 Discussion

Until recently, the main reasons for introducing pooled on-demand services were to substitute public transport in low demand areas or to fulfil the needs of specific sectors of the population (mainly the elderly and the disabled). The case study service was also partly introduced based on these grounds (it offers a barrier-free service and two fix bus lines were eliminated in conjunction with its introduction). Notwithstanding, it also offers a complementary service to public transport, with the objective of improving the mobility offered in the area and to better address passengers' needs. This additional role of pooled on-demand services is in line with the Mobility-as-a-Service paradigm, in which "mobility services [are bought] as packages based on consumers' needs instead of buying the means of transport" (Kamargianni et al., 2016), and for which different mobility services complement public transport.

Results of the case study show that for half of the performed rides, the GJTs offered by the pooled on-demand service are half or less than the GJTs offered by the available public transport alternative, showing that large improvements in mobility can be attributed to the pooled on-demand service. Rayle et al. (2016) compared the times that performed ridesourcing trips (i.e. trips provided by Transportation Network Companies (TNCs) such as Uber and Lyft) would have taken with public transport. In line with the results of this study, they found that "the majority of ridesourcing trips would have taken more than twice as long if made by public transport". Both results show that, even though these services may be competitors of public transport, they improve the offered mobility, with the subsequent economic and social benefits.

Despite the opportunities that pooled on-demand services provide as complement to public transport, its implementation also brings a series of risks that should not be overlooked. Three main risks are identified. Firstly, for a pooled on-demand system to achieve a high degree of efficiency, a relative large fleet is necessary, as stressed in Kutsuplus' final report (Helsinki Regional Transport Authority, 2016). As a result, the offered pooled on-demand service can become a (possibly heavily subsidised) individual taxi service. Secondly, if pooled on-demand services provide a lower GC than public transport, more users may shift from public transport to the pooled on-demand service, with the public transport revenue seeing a decrease and, in extreme cases, a possible increase in road congestion. An analysis of the incurred GC of both the pooled on-demand service and public transport (as performed in this study) can help identify large differences in the costs that passengers incur with both services. Furthermore, public transport revenue decrease can lead to the deterioration (or elimination) of the offered public transport service, even though the pooled on-demand alternative may not be capable of absorbing the entire passenger demand. This second risk is elevated by recent research, which has found that public transport users are more prone to use pooled on-demand services than non-public-transport users (Alonso-González et al., 2017). Finally, pooled on-demand services in their current regulatory framework do not guarantee a certain level of service. As a result, the risk of not obtaining the desired ride exists, the importance of which increases if no other alternative service (such as public transport) is available. The share of declined trips could vary for different O-D pairs, with rides for less convenient/profitable locations being more likely to be declined. Thus, a spatial analysis of the declined rides should be performed together with the spatial analysis of the performed rides, as described in the suggested framework of this chapter.

The above-mentioned risks can be reduced with an integrated public transport – pooled on-demand service approach. In an integrated public transport – pooled on-demand service network, the ride fee for the pooled on-demand service can be modified so as to obtain the desired modal split between both services. This price adjustment can be regulated based on different attributes. When striving for an equal urban accessibility, the price for the pooled on-demand ride can be calculated as a function of public transport accessibility. This would imply that price for the pooled on-demand ride would be higher when a competitive public transport alternative exists, and lower otherwise. The accessibility indicators proposed in this study can be used to adjust the price function for the pooled on-demand rides if this approach is adopted. An alternative price adjustment approach can be based on comfort considerations since more exclusive (and less collective) mobility services provide a higher utility to the passenger. This approach, which is used in the Flexible Mobility on Demand system presented in Atasoy et al. (2015), implies that passengers should pay a higher fee for using a premium service which is less capacity-efficient. Whatever the adjusting function is, an integrated public transport – pooled on-demand service approach can increase the opportunities that the pooled on-demand service can bring as a complement to public transport and decrease the collateral risks.

5.5 Conclusions

There are a wide range of innovative transport services that have recently appeared in urban areas. However, they are often considered in isolation, and the impacts of their interactions and implications for other modes are largely ignored (Ciari & Becker, 2017). This chapter presents an assessment framework for evaluating the usage of pooled on-demand services. A generalised travel cost comparison is proposed as an indicator of changes in accessibility related to the introduction of pooled on-demand services in relation to the public transport alternatives. Moreover, the usage of pooled on-demand services as a first or last leg in longer public transport journeys, and the suitability of the performed rides for walking and cycling are also considered in this assessment. To the authors' knowledge, this is the first study that measures the increase in accessibility that the implementation of these services has granted its passengers, in comparison to the public transport alternative. An empirical analysis is performed by applying the proposed framework to a case study in the Netherlands. Results indicate a reduction of over half of the generalised journey times (GJTs) for half of the rides that were performed using the pooled on-demand service, in comparison to the public transport alternatives. Results also identified areas for which this reduction is the highest, highlighting connections for which public transport offers a poor alternative.

Public transport authorities can use the proposed framework for one or more of the following purposes: 1) evaluating real performance of pooled on-demand services for the different areas, including the distribution of declined rides; 2) identifying whether these services are used as a complement of public transport, due to poor public transport connections, or as a substitute of public transport, due to the higher comfort they provide, and 3) assessing their impacts on improving mobility.

Other than pooled on-demand services, recent studies have shown that other flexible modes, such as ridesourcing and car-sharing, may also complement public transport (Feigon & Murphy, 2016). However, even if a series of partnerships between them and public transport are already in place, data concerning their usage is necessary to enhance public transport planning (New York Public Transit Association, 2017). The assessment framework provided in this study can be extended to analyse the usage of other flexible modes and better identify opportunities for synergies as opposed to symbiotic relations where new services gain the most lucrative markets.

In the absence of information on individual characteristics, the shortcomings of this study pertain to the unobserved drivers of user behaviour. The analysis of travel behaviour under different conditions would allow estimating demand elasticities, the socioeconomic characteristics of its riders or differences in perceived times for pooled on-demand services with respect to public transport values. Future studies could include these aspects in their evaluation by incorporating travel survey data. Also, further research is needed to analyse how urban development characteristics and public-transport-related factors influence the usage of pooled on-demand services, as already researched for taxi ridership (Nam et al., 2016).

Chapter 6

Conclusions, Implications and Future Research

In this thesis, we have studied the demand for urban pooled on-demand services. In particular, we have identified individuals' attitudes, preferences and usage regarding these services while accounting for the heterogeneity among individuals. This final chapter summarises and reflects on the main findings of the thesis (Section 6.1), discusses implications for practice (Section 6.2), and provides recommendations for future research (Section 6.3).

6.1 Main Findings, Conclusions and Recommendations

In this section, we provide answers to the research questions raised in Section 1.3 and summarise the main findings of our work.

RQ1: What are the drivers and barriers for adopting Mobility as a Service (MaaS) for different (groups of) individuals? (Chapter 2)

To answer this research question, we identified relevant factors regarding MaaS and designed a series of attitudinal indicators that address them. We identified homogeneous clusters by means of a latent class cluster analysis and we characterised each cluster regarding its socioeconomic, mobility and technology-related characteristics.

We find five different clusters, with varying inclination to adopt MaaS. The largest cluster (32% of the sample) is the cluster with the highest inclination for future MaaS adoption. Results show that the attitudes towards the mobility-related aspects of MaaS are aligned with current mobility patterns: while individuals in the previous mentioned cluster have multimodal weekly mobility patterns, individuals with more unimodal car behaviours appear to be less inclined to adopt MaaS. Results also show that pooled on-demand services are more attractive than public transport for some clusters. These services can thus help facilitate shifts stemming from individuals in these clusters to more sustainable travel patterns. We identify two main barriers for future MaaS adoption: (1) high (car) ownership need as a determinant of mode choice, and (2) low technology adoption.

The research was conducted in urban areas in the Netherlands. In other urban contexts, we expect to find clusters with similar characteristics, yet with different share distributions. We expect that individuals' public transport usage, their technological capabilities and interest and their cost sensitivity influence the adoption potential for MaaS; the two first aspects affecting positively and the last one negatively. MaaS adoption among the more car-centred individuals can be stimulated by promoting MaaS services to them for occasions in which their personal car is unavailable. In order to overcome the technology barrier of the less tech-savvy individuals, MaaS services could offer hybrid systems that do not only rely on a mobility app but which also include a smartcard alternative.

RQ2: What are (the differences in) individuals' values of time (VOT) and values of reliability (VOR) for the different stages of pooled on-demand trips? (Chapter 3)

In order to analyse the VOT and VOR of pooled on-demand services, we designed and executed a series of stated preference experiments. We investigated three trip stages: the waiting stage, the in-vehicle stage, and the transfer stage (when combined with traditional public transport). This allowed for VOT-VOR comparison, both within and between the different trip stages.

We find in-vehicle values of time for pooled on-demand services which are somewhat higher than known values for traditional public transport. These values range from

7.88 to 10.80 €/h, depending on trip purpose and working status (while previous research identified the VOT for public transport to be 6.00 – 7.75 €/h for the Dutch context). Values of time for the waiting stage before the trip and during the transfer stage are around 1 – 1.5 and around 0.7 – 1 times the in-vehicle VOT, respectively. These values are lower than values reported in the literature. This can be due to (i) reduced uncertainty thanks to current real-time information and (ii) the explicit (independent) measurement of uncertainty. Values of reliability for both the waiting and the in-vehicle stages are found to be lower than their respective values of time, their ratio being around 0.5. This ratio is in line with previous Dutch literature (Kouwenhoven et al., 2014), yet it strongly differs in other contexts. These differences may stem from cultural preferences or from the reliability values that they currently experience in their daily mobility. The reliability parameters, however, are found to be insignificant for the more complex transfer experiment. This suggests that when individuals are faced with a larger number of attributes, reliability parameters play a secondary role in the decision process. Finally, we analysed differences in the preferred time-reliability-cost trade-offs of individuals and identified distinct (latent) classes. We find a uniform perception of the reliability ratio (ratio between VOT and VOR) among the classes. In contrast, the main difference across market segments pertains to the overall time-cost and reliability-cost trade-offs.

In pooled on-demand services, supply and demand strongly influence each other. Therefore, the performed analysis of VOT and VOR can support service providers in their supply strategy. For example, the differentiation between commuting and leisure trip purposes in our analysis can help service providers set different prices for different times of the day, so as to maximise profit and reduce the need to deploy a larger fleet during peak hour. Also, the flexibility of pooled on-demand services allows on-demand transport providers to offer a range of services in order to cater for preference heterogeneity. The found classes can be set as basis for the design of a portfolio of services that addresses the preferences of different market segments simultaneously, and, thus, help increase patronage.

RQ3:What are the determinants of the willingness to share rides in pooled on-demand services? (Chapter 4)

In order to analyse individuals' willingness to share rides in pooled on-demand services, we carried out a stated preference experiment. This allowed us to investigate the extent to which fare discounts, additional incurred travel time (e.g. due to detours and additional pick-ups), and the (un)willingness to share the ride with (different numbers of) other passengers play a role in individuals' decision to choose a pooled ride over an individual ride.

The estimated parameters indicate that the share of individuals that prefers the pooled alternative over the individual one depends primarily on the time-cost trade-offs individuals encounter, rather than on the disutility they associate to pooling rides per se (with different number of co-riders). The number of co-riders also plays a role in individuals' preferences to pool rides. While individuals associate a constant per ride disutility with sharing the ride with one or two extra passengers (amounting to 0.52 €/trip for the mixed logit model with random coefficients), this disutility further increases the longer the pooled trip when sharing the ride with four additional passengers (amounting to 2.85 €/h for the previous mentioned model). Further differences in the perceptions of the willingness to share are identified among the market segments stemming from the performed latent class analysis. Four different latent classes are identified. It is only individuals in one of these classes, accounting for less than one third of respondents, that have strong preferences for not sharing their rides. Individuals in this class show a higher car usage, and a lower bicycle and public transport usage. This suggests that the more car-centred individuals are less likely to shift to more collective modes of transport. Finally, we applied the estimated behavioural modelling results to simulate the breakdown between individual and pooled services under different scenarios. This scenario analysis helps visualise the results and understand their policy implications.

Overall, our results suggest that the share of individuals who opt for pooled services (versus the individual alternative) is likely to increase when on-demand services as a whole become a more common place. Given the importance of the time-cost trade-offs in individuals' decision to share their rides, two recommendations are given for policymakers interested in avoiding scenarios with high individual on-demand shares: (1) introduce a per-ride tax on individual requests (or a per-passenger subsidy for pooled rides) to increase the fare difference between the two alternatives, and (2) allocate strategically located curb space for pooled on-demand services to speed the pick-up/drop-off process and, thus, reduce their additional incurred time. Additionally, on-demand providers could offer pooled services with only one or two additional passengers: our results indicate that this measure would reduce the related pooling disutility, and simulation studies in literature have shown that having four passengers in the same vehicle would be a rare occurrence anyhow.

RQ4: What are the temporal and spatial characteristics of the pooled on-demand trips? (Chapter 5)

We developed an assessment framework to evaluate the characteristics of pooled on-demand trips. The framework measures the mobility improvements that the pooled on-demand service has granted their passengers and can help identify whether pooled on-demand services are used as a complement or a substitute of public transport. In particular, the framework proposes indicators to (i) quantify the increases in accessibility that pooled on-demand services have offered their users when compared to the existent fixed-line public transport alternatives, (ii) analyse the usage of pooled on-demand services as first or last leg mode in longer public transport journeys, and (iii) evaluate the suitability of the performed rides for walking and cycling. The framework covers the spatial and temporal dimensions, and it considers rejected trips explicitly as an integral part of the evaluation.

We applied the proposed framework to BrengFlex, an urban pooled on-demand system in the Netherlands. Results suggest large accessibility improvements for users of the pooled on-demand service: for half of the performed rides, the pooled on-demand alternative provides their users a reduction of over half of the generalised journey times, in comparison to the fixed public transport alternatives. Note that the generalised journey time, and not the standard journey time is used in the analysis. Generalised journey times account for the disutility that individuals associate to the different trip stages, and can, therefore, better explain individuals' perceived accessibility regarding the different travel alternatives. Results identify areas for which the pooled on-demand service has increased accessibility the most, highlighting connections for which public transport offers a poor alternative. When also accounting for price differences between the pooled on-demand trip and the public transport alternative (by means of the generalised costs), results show a smaller discrepancy in passenger disutility between both services. This is the case given that the more premium pooled on-demand alternative has a higher price than the corresponding public transport alternative.

On the whole, results show that, despite its competition with traditional public transport, pooled on-demand services improve the offered mobility, with the subsequent economic and societal benefits. An integrated public transport – pooled on-demand service approach could help strive for a more equal urban accessibility, and decrease any collateral risks that may stem from reduced revenue of well performing fixed public transport routes. A possible mechanism (inspired by the proposed framework) would be to price the on-demand service as a function of the improvements in accessibility it offers in relation to the one offered by the public transport alternative.

6.2 Implications for Practice

This thesis supports forecasting the demand for urban pooled on-demand services. It also supports the evaluation of how these services are being – or will be – used. In this section, we highlight several practical implications of our research findings, which are relevant to policy makers, on-demand transport providers and public transport providers.

Improved understanding of future mobility changes stemming from the new mobility ecosystem (Chapter 2)

We clustered urban individuals according to their attitudes towards MaaS. In the absence of large-scale well-stablished MaaS schemes, our insights can help policy makers, public transport operators, MaaS providers and companies entering the shared mobility landscape evaluate the possible mobility changes that MaaS may trigger and adjust their strategy accordingly. Our findings indicate that current car-centred individuals are less likely to adopt MaaS than individuals with more multimodal mobility patterns. In fact, we identify high (car) ownership need as one of the main barriers that hinder MaaS adoption (the other main barrier being low technology adoption). Policy makers interested in overcoming these barriers can find in our work a series of policy recommendations tailored to the MaaS-related market segments identified in this research.

Behavioural models to forecast the demand for urban pooled on-demand services (Chapters 3 and 4)

The choice models presented in this thesis provide the different stakeholders with individuals' preferred time-reliability-cost trade-offs for the different trip stages. Our work also quantifies individuals' disutility arising from sharing their on-demand trips with different numbers of additional passengers. The obtained parameters can be introduced in transport assignment models to better asses the possible modal shifts towards new pooled on-demand services. The different stakeholders can thus use the gained information to adjust their strategy. We highlight two concrete practical implications:

- Our findings support on-demand providers in developing their strategy in designing such services. For example, individuals in the Netherlands value a reduction in travel time more than a reduction in travel time variability/uncertainty (their value of time is higher than their value of reliability). As a result, service providers may be more interested in trying to reduce the expected times than travel time variability, provided that both can be achieved at the same costs.
- Our findings show that the share of individuals who are willing to share on-demand rides depends primarily on the time-cost trade-offs they encounter, rather than on the disutility stemming from pooling rides per se. As a result, policy makers may consider the introduction of policies aimed at reducing the additional time incurred in pooled trips (e.g., by allocating designated curb space for these pooled trips), or an increase in the cost benefits of the pooled trips (e.g., by introducing a per-ride tax in individual rides or a per-passenger subsidy for pooled rides).

Identification of market segments (Chapters 2, 3 and 4)

Our findings stress that "one size does not fit all". The latent class analyses performed in this thesis help the different stakeholders identify (latent) market segments. Tailored solutions are a unique selling point of both MaaS ecosystems and pooled on-demand services. MaaS providers and on-demand operators can directly benefit from our segmentation insights. The MaaS-related clusters can help the different stakeholders understand the mobility attitudes of different individuals and provide differentiated solutions or transport policies. The parameters from the latent class choice models can help on-demand providers develop a portfolio of services to address the preferences of different segments, increasing patronage. Furthermore, the direct consideration of preference heterogeneity results in choice models that better explain choice, increasing their predictive power.

Usage assessment framework to evaluate accessibility impacts of operating on-demand services (Chapter 5)

The proposed assessment framework provides concrete quantitative metrics that can help transport authorities and operators (1) evaluate the real performance of pooled on-demand services; (2) identify whether pooled on-demand services are rather used as a complement of public transport due to poor public transport connections or as a substitute of public transport due to the higher comfort pooled on-demand services provide, and (3) assess the impacts of pooled on-demand services on improving mobility. Results for the investigated case study indicate that pooled on-demand services provide large accessibility gains to their users compared to the available public transport alternatives. Transport authorities can use the developed framework to develop a subsidy-tax scheme for pooled on-demand rides aiming at increasing equitability from an accessibility standpoint. Public transport operators can use the framework to understand which high-demand origin-destination pairs are underserved by fixed public transport services. The scheme can also be adjusted for other on-demand modes, such as individual on-demand services or car-sharing. The bottom line of this practical implication is that on-demand services should not be evaluated individually, but integrated with the other existing alternatives.

Vision for pooled on-demand services from a demand perspective (Chapters 2, 3, 4 and 5)

Despite the potential shown in simulation studies, operating pooled on-demand services often come to a stop due to their low revenue. Our findings (Chapter 4) indicate that the disutility of sharing the ride with a reduced number of co-riders is quite low for most individuals. This, together with the rapid uptake of on-demand services worldwide, suggest that there is potential for an increase in the demand for pooled on-demand services (at least in settings with no major safety concerns). The challenge, however, is to get the critical mass of users necessary in order to match different individuals in one single trip. Not obtaining that critical mass results in either not being able to offer trip discounts (versus an individual ride) or becoming financially unstable, leading in both cases to the disappearance of the pooled service. In order to increase patronage, pooled on-demand providers may offer a portfolio of services with different time-cost trade-offs, catering for the needs of different market segments simultaneously (Chapter 3). The flexible nature of on-demand services allows to pool together rides of the more time sensitive segments together with rides of the more cost sensitive segments. Therefore, it is not necessary to keep the services separate (e.g., the more cost sensitive co-rider gets a longer detour that better fits the needs of the time sensitive co-rider, and is benefited with a cheaper ride). Both the passengers and the on-demand system can benefit from the preference heterogeneity existent in the population.

One of the main expected benefits of pooled on-demand services and of the more broader MaaS ecosystem is their potential to reduce the vehicle miles travelled (VMT) in urban areas. Our results show, however, that car-centred individuals are less attracted towards pooled on-demand services (Chapter 4) or MaaS (Chapter 2) than more multimodal users. As a result, the effective VMT reduction may be less than expected, and modal shifts from walking, cycling and public transport trips can also be expected. Ideally, the usage of pooled on-demand services would be highest for trips for which public transport offers a poor connection and that span larger distances than what is considered acceptable for walking and cycling. An evaluation framework as the one proposed in Chapter 5 provides insights into the mobility benefits incurred by the usage of operating pooled on-demand services. If pooled on-demand services are mainly used due to the higher comfort they provide, even if adequate public transport alternatives are available, an integrated network including public transport and pooled on-demand services might be needed.

6.3 Future Research Directions

Several recommendations for future research directly linked to the different articles comprising this thesis have already been presented at the end of each chapter. In this section, we sketch a research agenda and elaborate on future research directions. These arise from the overall consideration of the thesis' findings. The highlighted research directions pertain to the link between attitudes, preferences and usage regarding the demand for pooled on-demand services (the three parts of this thesis), and/or the customisation of these services (addressed thorough the thesis with different latent class analyses).

Progression from attitudes and preferences to behavioural change

Ultimately, we are interested in the behaviour that will eventually emerge, i.e., in the modal shifts that will take place. However, real settings only allow for the study of a limited number of situations (collinearity exists between the attributes), and, often enough, only early adopters can be monitored (being the ones using new services at an early stage). Therefore, and given the link between attitudes, preferences and behaviour, we made use of attitudes (Chapter 2) and stated preference experiments (Chapters 3 and 4) to answer some of our research questions in this thesis. Future research could add to this work by monitoring the evolution from attitudes to adoption of new mobility services and overarching MaaS ecosystems. This could be done through a longitudinal study targeting a representative sample of the population living in a setting where MaaS schemes and pooled on-demand services are expected to be operating in the near future.

Influence of experience on individuals' preferred mobility-related trade-offs

Chapters 3 and 4 of this thesis investigate individuals' preferred trade-offs in on-demand services. The obtained parameters can be included in macroscopic static assignment and agent-based simulation models to forecast the modal shifts. In our research, we acknowledge that socioeconomic characteristics and travel patterns influence individuals' preferences, and include these aspects in our models. In their research, König et al. (2018) also found that experience can influence the relative importance that individuals give to the different attributes. This is not a factor that we could take into account, given that the vast majority of the individuals in our sample had no previous experience with pooled on-demand services. Also, this factor can be heavily influenced by the characteristics of the service that individuals are making use of. We recommend the use of controlled experiments to study the extent to which experience influences individuals' behavioural parameters and the number and nature of experiences that trigger this change in preferences and contribute to the formation of new habits. Also we recommend studying whether individual characteristics influence this change. We believe that reliability attributes and the willingness to share are the two aspects that may be most dependent on experience and, therefore, most suitable for this additional study.

Design of service portfolios

On-demand providers can offer a portfolio of services to their users. Results from the latent class choice models from Chapters 3 and 4 can be introduced in their supply models so as to find the optimal range of services to offer to their users, and, thus, take into account both individuals' preferences and supply needs. Findings from Chapters 2 and 5 (providing insights into the bigger mobility picture and current usage of pooled on-demand services respectively) can also be considered in a qualitative manner while designing the service portfolio. Two additional things need to be taken into account while designing these service portfolios. First, our parameters stem from stated preference experiments. As such, results are inevitably influenced by the design of the experiments. We took great care in the design of the experiments. Still, values of time are heavily influenced by the tails of the distributions present in the design. This needs to be taken into account when introducing the parameters in the supply models and adjusting the portfolios. Second, as highlighted in the previous research direction, experience may influence the attribute parameters. Our parameters offer a good starting point for the initial portfolio design. Later, further parameters can be modelled from the acquired revealed preference data stemming from individuals' real choices among the offered alternatives. Revealed preference data will also allow operators to better focus on the preferences of the real users of the service.

Study of similarities and differences in urban settings outside of the Netherlands

Throughout the thesis, we stress the importance of having a good understanding of the different market segments regarding usage of pooled on-demand services and MaaS adoption, and we performed different latent class analyses in Chapters 2, 3 and 4. Our findings, however, are based exclusively on samples from the urban Dutch setting. We expect culture, income, safety, technology adoption, current modal split, and public transport quality to be important factors that play a role in our findings. Therefore, we finally suggest that further research investigates similarities and differences among countries regarding the studied aspects.

Appendices

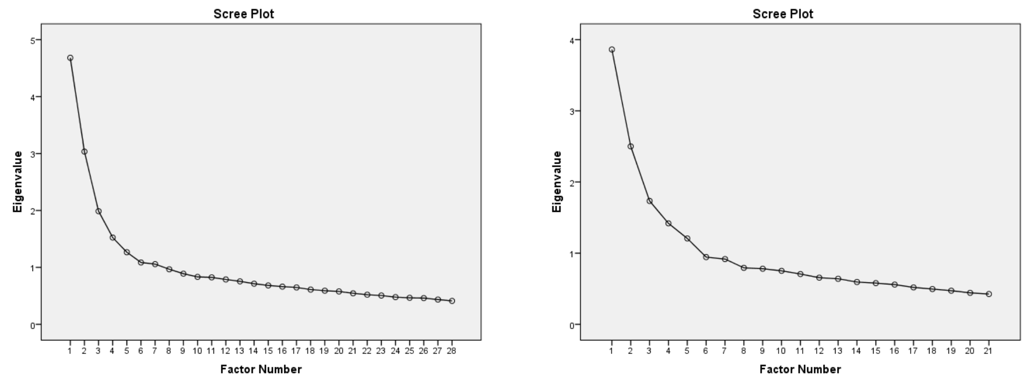
A Appendix Chapter 2

Attitudinal indicators

Tables A.1 and A.2 show the attitudinal indicators and their relation to the keywords used in Figure 2.1. All statements have been modified from their sources, indicated in the Table by [Mod.].These sources are the following: Atasoy et al. (2010); Rubin (2011); Kamargianni et al. (2018); Spears et al. (2013); Khattak & Yim (2004); Al-Ayyash et al. (2016); Shiftan et al. (2008); Roehrich (2004); Jensen et al. (2014); Caiati (2018); Ewing & Sarigöllü (2000).

Scree plot of the exploratory factor analyses

See Figure A.1.



(a) (b)

Figure A.1: Scree plot of the EFA with (a) all mentioned indicators, and (b) only indicators loading significantly (>0.4) in the first EFA.

Parameters of the final LCCA model

See Tables A.3 – A.5.

Table A.1: Attitudinal indicators used. [Mod.] = Modified from. (Table continued on next page)

CATEGORY	Keywords	Full statement in English	Source (where applicable)
MOBILITY INTEGRATION			
Multimodal mind-set			
	Mode agnosticism	I do not mind which transport mode I use, as long as it suits my trip needs	
	Multimodal considerations	I often compare different travel options and transport modes before choosing how to travel	[Mod.] Atasoy et al. (2010)
	Mode integration wish	It is essential to be able to easily combine different transport modes (such as bus, car, bike or car-sharing) in order to improve transportation in the Netherlands	
	Way of travel innovation	I am willing to try new ways to travel	
	Habits' importance	I like travelling always in the same way	
Public transport attitude			
	Uneasiness of sharing	It makes me uncomfortable to ride with strangers on public transport	[Mod.] Rubin (2011)
	PT cleanliness concerns	I think the public transport is not so clean or decent	
	Environmental importance	It is important to use public transport to preserve the environment	
	Cost saving importance	I choose to travel with public transport or to share rides to reduce my trip costs	
Private car attitude			
	Ownership need	I would like to have the convenience of a car without owning one myself	[Mod.] Kamargianni et al. (2017)
	Privacy need	I like the privacy in the car or bike	[Mod.] Spears et al. (2013)
	Reputation aspects	People like me only use their own bike and/or car	
	Car usage vs cost	I would use the car less if there would be a cheaper alternative	
SHARED MOBILITY MODES			
Flexibility trait FLEXI			
	Approval	I like that FLEXI does not have a fixed schedule or route	
	Freedom	FLEXI would give me the freedom to travel where I need to be when needed	
	Reliability (FLEXI vs PT)	FLEXI seems to me more reliable than current public transport	
	Convenience (FLEXI vs PT)	I find FLEXI's flexibility in the departure time more convenient than traditional transit.	
	Concerns	FLEXI does not have fix schedules. That would worry me.	
	Missed pick-up	I would be worried that FLEXI departs without me	[Mod.] Khattak and Yim, (2004)
	In-vehicle time	I would find it annoying that FLEXI does not drive the fastest route (e.g., FLEXI's route is 18 minutes instead of 15 minutes)	[Mod.] Al-Ayyash et al. (2016)
	Number of stops	I would not mind if other travellers get in or off the FLEXI vehicle during my ride	[Mod.] Al-Ayyash et al. (2016)

Table A.2: Attitudinal indicators used. [Mod.] = Modified from. (Cont.)

CATEGORY	**Keywords**	**Full statement in English**	**Source (where applicable)**
MOBILITY INTEGRATION (cont.)			
Safety trait FLEXI			
	Safety (FLEXI vs PT)	I would feel safer in FLEXI than in a regular bus	
	Driving skills	I think that FLEXI drivers do not drive carefully	
	In-vehicle safety	The proximity of a driver would make me feel safe in FLEXI	
MOBILE APPLICATIONS			
	App adoption	I would use a (smartphone) app if it gave me access to all available travel alternatives	
	App literacy	It is easy for me to find FLEXI's pick-up point if it is displayed on a map in the (smartphone) app	
	In-app payments	I like to pay for my rides via a (smartphone) app	
WILLINGNESS TO PAY			
	Willingness to pay for information	I would be ready to pay for precise and reliable travel information	
	Willingness to pay for reliable services	I am willing to pay more to have a more predictable travel time for my journey	[Mod.] Shiftan et al. (2008)
	Information need	I find it difficult to find information of all available travel alternatives	
	Price bundling preference	I would prefer a monthly subscription instead than paying individually for each trip that I make in a month	
INNOVATIVENESS (exclusively used for the technology related characteristics)			
		I try new services, such as Netflix or Uber, before my friends and family	[Mod.] Roehrich (2004)
		I try new products, such as a fitbit or the newest smartphone, before my friends and family	[Mod.]Roehrich (2004)
		I often purchase new products, even though they are expensive	[Mod.] Jensen et al. (2014)
		My family and friends usually come to me for advice about new products and services	[Mod.] Caiati (2018)
		I am enthusiastic about the possibilities offered by new technologies	[Mod.] Ewing and Sarigöllü (2000)

Table A.3: Parameters of the model indicators

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Wald	p-value	R^2
Mobility integration factor	2.115	0.8158	-1.7815	1.9748	-3.1241	73.3311	4.5e-15	0.415
Mobile application factor	2.0171	-0.6830	0.7071	0.1711	-2.2123	106.5489	4.0e-22	0.377
FLEXI over PT factor	1.6592	1.0520	0.8745	-1.4864	-2.0993	46.6031	1.8e-9	0.2803
FLEXI intention to use	3.4818	0.0861	-0.5709	-0.0431	-2.9538	47.3265	1.3e-9	0.2556
Willingness to pay factor	0.7480	0.3775	0.1191	-0.4270	-0.8177	41.2514	2.4e-8	0.0929
FLEXI concerns factor	-0.0816	0.1854	0.0710	-0.5231	0.3483	15.2871	0.0041	0.0402

Table A.4: Parameters of direct effects

FLEXI over PT & FLEXI concerns		Wald	p-value
	-0.6323	32.6183	1.1e-8

Table A.5: Parameters of the active covariates

Intercept	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Wald	p-value
	-0.1999	1.0566	-0.6576	-1.0304	0.8313	5.0817	0.28
Covariates	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Wald	p-value
Working (voluntary work excluded)							
No	-0.1265	0.943	-0.4215	-0.1867	-0.2084	24.3239	6.9e-5
Yes	0.1265	-0.943	0.4215	0.1867	0.2084		
Highest education							
Low	-0.3906	0.4872	0.0442	-0.4359	0.2952	25.5977	0.0012
Medium	-0.3644	0.6375	-0.0171	-0.2721	0.0161		
High	0.7550	-1.1247	-0.027	0.7079	-0.3113		
Exists child under 12 years							
No	-0.2798	1.1592	-0.7493	-0.2971	0.1670	13.2564	0.010
Yes	0.2798	-1.1592	0.7493	0.2971	-0.1670		
Urbanisation level							
Highly urbanised	-0.3050	0.5747	0.1248	-0.5047	0.1102	20.9191	0.00033
Very highly urbanised	0.3050	-0.5747	-0.1248	0.5047	-0.1102		
Bike usage frequency							
	0.2473	-0.2608	-0.1026	0.3586	-0.2425	26.1517	2.9e-5
Bike sharing systems heard of							
No	-0.2668	-0.1167	0.1157	-0.1056	0.3735	13.3494	0.0097
Yes	0.2668	0.1167	-0.1157	0.1056	-0.3735		
3G bundle available							
No	-0.7581	2.1628	-2.3895	-0.2051	1.1898	31.8151	2.1e-6
Yes	0.7581	-2.1628	2.3895	0.2051	-1.1898		

B Appendix Chapter 3

Attribute levels of the stated preference experiments

See Tables B.1 – B.3.

Table B.1: Attribute levels of the waiting time SP experiment

	Short version			Medium version		
	Level 1	Level 2	Level 3	Level 1	Level 2	Level 3
Expected waiting time (Option 1 only) [min]	4	7	11	4	7	11
Extra expected waiting time (Option 2 only) [min]	3	5	8	3	5	8
Coefficient of variation (Cv) [-]	0.1	0.6	2	0.1	0.6	2
Displacement [min]	0	1	2	0	1	2
Cost (Option 2 only) [€]	2	4	6	3	5	7
Extra cost (Option 1 only) [€]	0.5	1.0	1.4	0.5	1.0	1.4

Table B.2: Attribute levels of the in-vehicle time SP experiment

	Short version			Medium version		
	Level 1	Level 2	Level 3	Level 1	Level 2	Level 3
Expected in-vehicle time (Option 1 only) [min]	12	16	21	25	29	34
Extra expected in-vehicle time (Option 2 only) [min]	3	5	8	4	7	11
Coefficient of variation (Cv) [-]	0.1	0.6	2	0.1	0.6	2
Displacement [min]	0	1	3	0	2	4
Cost (Option 2 only) [€]	2	4	6	3	5	7
Extra cost (Option 1 only) [€]	0.3	0.7	1	0.5	0.9	1.3

Table B.3: Attribute levels of the transfer SP experiment

	Short version			Medium version		
	Level 1	Level 2	Level 3	Level 1	Level 2	Level 3
Total in-vehicle time (transfer alternatives) [min]	14	18	24	24	28	34
Share of the total in-vehicle time for the first vehicle (transfer alternatives) [-]	35%	50%	65%	35%	50%	65%
In-vehicle time (direct alternative) [min]	12	17	22	22	27	32
Expected waiting time transfer [min]	4	7	12	4	7	12
Coefficient of variation transfer (Cv) [-]	0.1	0.6	2	0.1	0.6	2
Displacement transfer [min]	0	1	2	0	1	2
Cost (transfer alternatives) [€]	1.5	2.3	3.3	2.5	3.3	4.3
Cost (direct alternative) [€]	3.5	5	6.5	4.5	6	7.5

Parameter values of the latent class choice models

See Tables B.4 – B.7.

Table B.4: Parameters of the leisure trip purpose LCCM for the waiting and in-vehicle stage SP experiments

Attribute	*Class 1* parameter (z-value)	*Class 2* parameter (z-value)	*Class 3* parameter (z-value)	*Class 4* parameter (z-value)	Wald	p-value	Mean	*Std. Dev.*
Waiting time	-0.1544 (-2.10)	-0.3908 (-7.91)	-1.5715 (-3.09)	0.0000 (-)	83.56	5.3e-18	-0.41	0.47
Squared waiting time	-0.0189 (-4.29)	0.0000 (-)	-0.0383 (-0.38)	-0.0055 (-1.43)	20.65	0.00012	-0.01	0.01
Standard deviation waiting	-0.2357 (-3.77)	-0.2204 (-3.99)	-0.1717 (-0.63)	-0.0405 (-0.46)	36.8	2.0e-7	-0.2	0.06
Mean minus scheduled waiting	-0.4539 (-4.32)	-0.2641 (-3.76)	-0.9095 (-1.42)	-0.0474 (-0.31)	40.69	3.1e-8	-0.4	0.23
Cost waiting time	-4.7149 (-7.24)	-1.2029 (-4.71)	-4.9577 (-0.90)	-3.3199 (-4.29)	87.3	4.9e-18	-3.34	1.66
Riding time	-0.5276 (-11.80)	-0.3564 (-11.08)	-2.3758 (-0.97)	-0.5533 (-1.51)	319.93	5.4e-68	-0.71	0.65
Standard deviation in-vehicle	-0.2047 (-5.12)	-0.1036 (-3.60)	-1.5638 (-0.66)	-0.1634 (-0.52)	58.5	6.0e-12	-0.34	0.48
Mean minus scheduled in-vehicle	-0.2085 (-4.04)	-0.1241 (-3.19)	-1.009 (-0.50)	-0.2809 (-0.61)	36.19	2.6e-7	-0.29	0.28
Cost in-vehicle time	-4.1 (-10.73)	-2.1948 (-9.12)	-2.4568 (-0.46)	-17.9007 (-1.97)	236.13	6.3e-50	-4.66	4.64
Model for Classes								
Intercept	0.6468 (-5.36)	0.5238 (-3.83)	-0.477 (-4.54)	-0.6936 (-6.26)	116.5	4.4e-25		

Table B.5: Parameters of the commuting purpose LCCM for the waiting and in-vehicle stage SP experiments

Attribute	*Class 1* parameter (z-value)	*Class 2* parameter (z-value)	*Class 3* parameter (z-value)	Wald	p-value	Mean	*Std. Dev.*
Waiting time	-0.2604 (-2.46)	-0.6749 (-1.64)	-0.1585 (-1.68)	13.93	0.003	-0.36	0.19
Squared waiting time	-0.0108 (-2.87)	-0.0027 (-0.17)	0.0000 (-)	8.76	0.013	-0.01	0.00
Standard deviation waiting	-0.3487 (-5.71)	-0.0635 (-0.22)	-0.2793 (-2.22)	41.05	6.4E-09	-0.26	0.12
Mean minus scheduled waiting	-0.1562 (-2.13)	-0.3365 (-1.00)	0.0000 (-)	6.06	0.048	-0.18	0.11
Cost waiting time	-2.241 (-8.08)	-0.3485 (-0.44)	-3.3123 (-4.66)	92.21	7.3E-20	-1.90	0.98
Riding time	-0.4304 (-10.82)	-0.6176 (-2.97)	-0.2435 (-3.01)	157.03	8E-34	-0.45	0.12
Standard deviation in-vehicle	-0.2397 (-6.82)	-0.3354 (-2.33)	-0.1118 (-1.34)	59.61	7.1E-13	-0.25	0.07
Mean minus scheduled in-vehicle	-0.1603 (-3.27)	-0.2797 (-1.50)	-0.1122 (-0.93)	16.55	0.00087	-0.18	0.06
Cost in-vehicle time	-2.7928 (-8.44)	-0.5752 (-0.66)	-4.9279 (-4.43)	94.57	2.3E-20	-2.51	1.35
Model for Classes							
Intercept	0.7743 (-6.65)	-0.064 (-0.38)	-0.7103 (-4.14)	47.58	4.7E-11		

Table B.6: Parameters of the leisure trip purpose LCCM for the transfer stage SP experiment

Attribute	*Class 1* parameter (z-value)	*Class 2* parameter (z-value)	*Class 3* parameter (z-value)	Wald	p-value	Mean	*Std. Dev.*
Direct FLEXI - ASC	0.1023 (0.23)	0.8821 (0.72)	-1.1708 (-1.33)	14.31	0.026	0.21	0.64
FLEXI-BUS - ASC	-0.3178 (-1.05)	0.1865 (0.28)	-0.6660 (-1.08)	-	-	-0.19	0.30
Bus-Bus - ASC	0.2155 (0.63)	-1.0685 (-1.33)	1.8368 (3.01)	-	-	-0.02	0.93
Direct FLEXI - In-vehicle time	-0.1793 (-9.40)	-0.1930 (-4.65)	0.0000 (-)	126.26	3.8e-28	-0.16	0.06
Direct FLEXI - cost	-0.7446 (-8.94)	-3.5108 (-5.04)	-0.8078 (-3.87)	116.88	3.6e-25	-1.72	1.31
FLEXI-Bus - In-vehicle time leg 1	-0.2385 (-10.59)	-0.1907 (-4.67)	-0.0263 (-0.57)	163.55	3.1e-35	-0.19	0.07
FLEXI-Bus - In-vehicle time leg 2	-0.1899 (-8.18)	-0.3730 (-8.16)	0.0000 (-)	122.69	2.3e-27	-0.23	0.12
FLEXI-Bus - Expected waiting time	-0.1456 (-5.40)	-0.3743 (-6.46)	0.0000 (-)	62.41	2.8e-14	-0.21	0.13
FLEXI-Bus - standard deviation waiting time	-0.0065 (-0.09)	-0.2916 (-1.87)	0.0000 (-)	3.91	0.14	-0.11	0.14
FLEXI-Bus - displacement waiting time	-0.0402 (-0.50)	-0.1550 (-0.99)	-0.1730 (-0.76)	2.46	0.48	-0.10	0.06
FLEXI-Bus - cost	-0.7796 (-7.24)	-2.5910 (-7.37)	-1.3978 (-4.48)	120.50	6.0e-26	-1.49	0.83
Bus-Bus - In-vehicle time leg 1	-0.2494 (-9.27)	-0.2776 (-6.40)	-0.0507 (-1.24)	166.88	6.0e-36	-0.23	0.07
Bus-Bus - In-vehicle time leg 2	-0.1947 (-7.06)	-0.2784 (-7.28)	-0.0418 (-1.12)	130.45	4.3e-28	-0.20	0.07
Bus-Bus - Expected waiting time	-0.2145 (-7.27)	-0.2336 (-5.38)	0.0000 (-)	94.97	2.4e-21	-0.19	0.08
Bus-Bus - standard deviation waiting time	0.0000 (-)	0.0000 (-)	0.0000 (-)	0.00	-	0.00	0.00
Bus-Bus - displacement waiting time	-0.2720 (-2.47)	-0.0257 (-0.16)	0.0000 (-)	6.68	0.04	-0.15	0.13
Bus-Bus - cost	-0.9018 (-7.18)	-2.6628 (-7.95)	-1.3961 (-6.53)	149.98	2.7e-32	-1.58	0.81
CFactor1 Direct FLEXI	1.7804 (14.21)	1.7804 (14.21)	1.7804 (14.21)	230.86	7.4e-51	1.78	0.00
CFactor1 FLEXI-Bus	-0.8908 (-12.44)	-0.8908 (-12.44)	-0.8908 (-12.44)	-	-	-0.89	0.00
CFactor1 Bus-Bus	-0.8895 (-8.59)	-0.8895 (-8.59)	-0.8895 (-8.59)	-	-	-0.89	0.00
Model for Classes							
Intercept	0.5880 (4.99)	0.1924 (1.39)	-0.7804 (-5.34)	36.43	1.2e-8	-	-

Table B.7: Parameters of the commuting trip purpose LCCM for the transfer stage SP experiment

Attribute	*Class 1* parameter (z-value)	*Class 2* parameter (z-value)	Wald	p-value	Mean	*Std. Dev.*
Direct FLEXI - ASC	-0.1408 (-0.26)	-0.4465 (-0.50)	2.63	0.62	-0.28	0.15
FLEXI-BUS - ASC	0.1970 (0.36)	-0.3247 (-0.50)	-	-	-0.04	0.26
Bus-Bus - ASC	-0.0562 (-0.11)	0.7712 (1.45)	-	-	0.32	0.41
Direct FLEXI - In-vehicle time	-0.1825 (-7.61)	-0.1618 (-3.39)	93.21	5.8e-21	-0.17	0.01
Direct FLEXI - cost	-0.6524 (-6.45)	-1.7699 (-4.52)	94.54	3.0e-21	-1.16	0.56
FLEXI-Bus - In-vehicle time leg 1	-0.2353 (-7.38)	-0.1101 (-3.12)	76.31	2.7e-17	-0.18	0.06
FLEXI-Bus - In-vehicle time leg 2	-0.1964 (-6.47)	-0.1559 (-4.49)	77.49	1.5e-17	-0.18	0.02
FLEXI-Bus - Expected waiting time	-0.1657 (4.62)	-0.2339 (-6.03)	64.45	1.0e-14	-0.20	0.03
FLEXI-Bus - standard deviation waiting time	-0.2211 (-1.96)	0.0000 (-)	3.83	0.05	-0.12	0.11
FLEXI-Bus - displacement waiting time	-0.1441 (-1.00)	-0.0706 (-0.43)	1.66	0.44	-0.11	0.04
FLEXI-Bus - cost	-0.7463 (-5.01)	-2.0047 (-9.14)	113.51	2.2e-25	-1.32	0.63
Bus-Bus - In-vehicle time leg 1	-0.2238 (-6.55)	-0.1803 (-4.97)	94.83	2.6e-21	-0.20	0.02
Bus-Bus - In-vehicle time leg 2	-0.2679 (-7.53)	-0.1599 (-4.88)	88.95	4.8e-20	-0.22	0.05
Bus-Bus - Expected waiting time	-0.2146 (-4.82)	-0.1693 (-4.00)	51.45	6.7e-12	-0.19	0.02
Bus-Bus - standard deviation waiting time	-0.0527 (-0.43)	-0.0933 (-0.88)	1.16	0.56	-0.07	0.02
Bus-Bus - displacement waiting time	-0.1117 (-0.74)	-0.3777 (-2.59)	8.35	0.01	-0.23	0.13
Bus-Bus - cost	-0.5452 (-3.40)	-1.8609 (-9.31)	98.88	3.4e-22	-1.14	0.66
CFactor1 Direct FLEXI	1.3290 (9.29)	1.3290 (9.29)	94.74	2.7e-21	1.33	0.00
CFactor1 FLEXI-Bus	-0.9833 (-8.20)	-0.9833 (-8.20)	-	-	-0.98	0.00
CFactor1 Bus-Bus	-0.3457 (-3.06)	-0.3457 (-3.06)	-	-	-0.35	0.00
Model for Classes						
Intercept	0.0907 (0.88)	-0.0907 (-0.88)	0.78	0.38	-	-

C Appendix Chapter 4

Exploratory Factor Analysis of the attitudinal indicators

See Table C.1.

Table C.1: EFA loadings, mean and standard deviation of the attitudinal indicators and significance of independent t-tests between traders and each of the non-trading groups (equal variance not assumed.)

Attitudinal statement (and source, where applicable)	EFA loadings (pattern matrix)	Mean (sd) of total sample	Mean (sd) of "individual-only"/ "trading"/ "pooled-only" respondents	t-test signific. (2-tailed) ##
Privacy attitude				
It makes me uncomfortable to ride with strangers on public transport (modified from Rubin (2011))	0.622	2.31 (0.90)	2.67/2.26/2.13 (0.98/0.88/0.84)	** ( )
I think the public transport is not so clean or decent	0.571	3.06 (0.93)	3.31/3.06/2.86 (0.96/0.91/0.94)	** (+)
I like the privacy in the car or bike (modified from Spears et al. (2013))	0.438	3.76 (0.87)	4.07/3.74/3.53 (0.79/0.85/0.97)	** (+)
People like me only use their own bike and/or car	0.407	3.08 (1.13)	3.41/3.03/3.01 (1.12/1.12/1.13)	** ( )
Cost sensitivity and multimodal mind-set #				
I would use the car less if there would be a cheaper alternative	0.602	3.29 (1.05)	2.95/3.31/3.53 (1.06/1.03/1.00)	** (+)
I choose to travel with public transport or to share rides to reduce my trip costs	0.583	3.30 (0.98)	2.64/3.37/3.61 (1.03/0.91/0.93)	** (++)
I am willing to try new ways to travel	0.534	3.46 (0.83)	3.14/3.51/3.55 (0.99/0.79/0.83)	** ( )
I often compare different travel options and transport modes before choosing how to travel (modified from Atasoy et al. (2010))	0.500	2.78 (1.04)	2.56/2.81/2.88 (1.12/1.03/0.99)	* ( )
I do not mind which transport mode I use, as long as it suits my trip needs	0.401	3.44 (1.01)	3.14/3.48/3.53 (1.15/0.98/0.94)	** ( )
In-vehicle time flexibility attitude				
I would not mind if other travellers get in or off the FLEXI vehicle during my ride (reversed) (modified from Al-Ayyash et al. (2016))	0.674	2.50 (0.96)	3.13/2.43/2.23 (1.07/0.89/0.89)	** (+)
I would find it annoying that FLEXI does not drive the fastest route (e.g., FLEXI's route is 18 minutes instead of 15 minutes) (modified from (Al-Ayyash et al. (2016))	0.578	2.91 (0.96)	3.27/2.88/2.66 (1.08/0.91/0.98)	** (++)

\# We cover multimodality together with cost sensitivity since previous research found that cost sensitive individuals tend to also be more interested in shared modes (Burkhardt and Millard-Ball, 2006)

\## Legend:
"individuals-only" vs "traders" p-value ≤0.01 **, ≤0.05 *
"pooled-only" vs "traders" p-value ≤0.01 (++),≤0.05 (+)

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Summary

A wide range of new tailored on-demand mobility alternatives are emerging in urban regions worldwide. One of these alternatives are pooled on-demand services (shared taxi-like services such as UberPOOL, LyftLine, OlaShare or ViaVan). Their flexibility can fit the mobility needs of different individuals, and, at the same time, their collective nature suits the needs of dense urban areas. Simulation studies have already shown that adoption of pooled on-demand services can help reduce congestion, pollution and parking space problems, while bringing accessibility gains. However, individuals' uptake of operating pooled on-demand services is still very limited. Understanding the traveller demand for pooled on-demand services is, therefore, essential in order to capitalise on all the potential benefits that the usage of these services can evoke.

To gain this knowledge, this research aims to *identify individuals' attitudes, preferences and usage regarding urban pooled on-demand services while accounting for the (hypothesised) heterogeneity among individuals*. The thesis is divided in three main parts (see Figure I.1), corresponding to the three perspectives investigated: attitudes, preferences and usage. While the two latter perspectives have pooled on-demand services in the spotlight, the attitudinal study considers these services as a component of Mobility as a Service (MaaS). MaaS stands for the integration of all available mobility alternatives and is envisaged to become the future mobility ecosystem in which a private car will potentially be no longer desired.

In order to achieve our main research objective, we formulate the following four research questions, each of them answered in one of the four core chapters of the thesis (Chapters 2-5):

- RQ 1: What are the drivers and barriers for adopting Mobility as a Service (MaaS) for different (groups of) individuals? (Chapter 2)
- RQ 2: What are (the differences in) individuals' values of time (VOT) and values of reliability (VOR) for the different stages of pooled on-demand trips? (Chapter 3)
- RQ 3: What are the determinants of the willingness to share rides in pooled on-demand services? (Chapter 4)
- RQ 4: What are the temporal and spatial characteristics of the pooled on-demand trips? (Chapter 5)

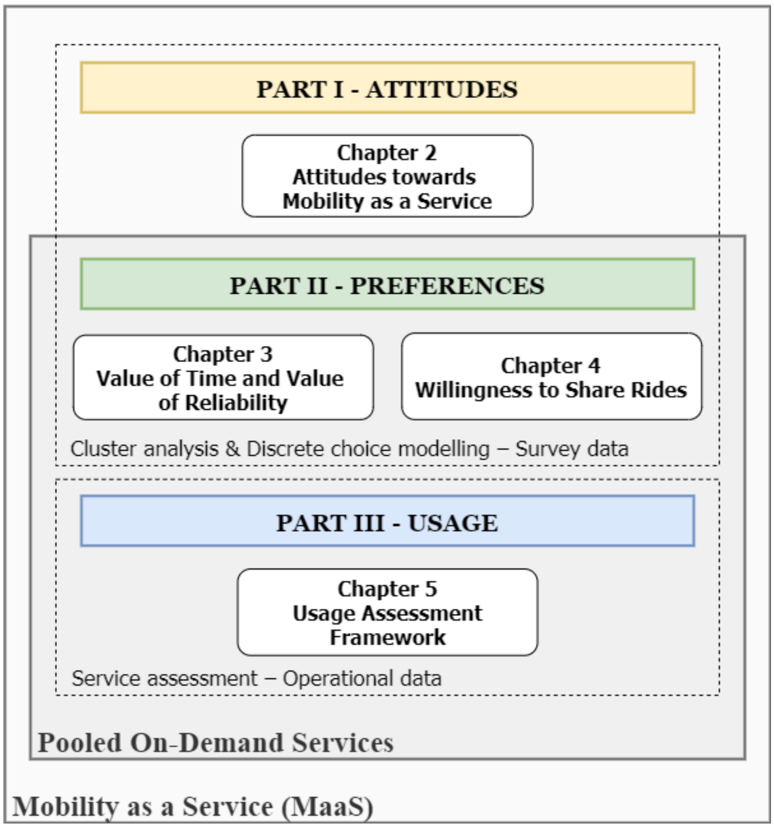

Figure I.1: Thesis scheme

We use three main methods in order to answer our research questions, each of them related to one of the three studied perspectives. Attitudes and preferences are analysed using cluster analysis and discrete choice modelling (with a market segmentation approach), respectively, while usage is evaluated with a service assessment framework. As for the data, for the attitudinal and preference analyses these stem from a dedicated survey designed for the purpose of this thesis, while the data for the usage analysis stem from field observations of an operational pooled on-demand service. In all three cases, data come from urban Dutch settings, yet findings can be applicable to different urban settings in developed countries. In the following, we highlight the main research contributions of the thesis together with a summary of the related research findings.

Identification of the drivers and barriers playing a role in adopting Mobility as a Service (MaaS) for different individuals (Chapter 2, addressing RQ1)

We identify relevant factors regarding MaaS and design a series of attitudinal indicators that address them. By means of a latent class clusters analysis, we find five different clusters that relate to individuals' inclination to adopt MaaS. We characterise each cluster regarding its socioeconomic, mobility and technology-related characteristics. The largest cluster (32% of the sample) is the cluster with the highest inclination for future MaaS adoption. These individuals tend to be young, high educated and have higher than average incomes. Results show that the attitudes towards the mobility-related aspects of MaaS are aligned with current mobility patterns: individuals with multimodal mobility patterns tend to be in the clusters that are more inclined to adopt MaaS, while the contrary happens for individuals with car-centred mobility patterns. Based on the outcomes of our analyses, we identify two main barriers for future MaaS adoption: (1) high (car) ownership need as a determinant of mode choice, and (2) low technology adoption.

Quantification of individuals' values of time (VOT) and values of reliability (VOR) for the different stages of pooled on-demand trips (Chapter 3, addressing RQ2)

We design and execute a series of stated preference experiments in order to analyse individuals' time-reliability-cost trade-offs in pooled on-demand trips. We investigate three trip stages: the waiting stage, the in-vehicle stage, and the transfer stage (when combined with traditional public transport). This allows for VOT-VOR comparison, both within and between the different trip stages. We find in-vehicle VOT for pooled on-demand services which are somewhat higher than known values for traditional public transport, ranging from 7.88 to 10.80 €/h, depending on trip purpose and employment status. VOTs for the waiting stage before the trip and during the transfer stage are around 1 – 1.5 and around 0.7 – 1 times the in-vehicle VOT, respectively. In line with previous Dutch literature, VORs are found to be lower than the corresponding VOT (their ratio being around 0.5 for the waiting and the in-vehicle stages). Finally, we analyse preference heterogeneity regarding individuals' time-reliability-cost trade-offs. The main difference across market segments pertains to the overall time-cost and reliability-cost trade-offs and not to the time-reliability trade-offs. The latter remains quite uniform across classes.

Analysis of the determinants of the willingness to share rides in pooled on-demand services (Chapter 4, addressing RQ3)

We investigate the extent to which fare discounts, extra travel time, and the (un)willingness to share the ride with (different numbers of) other passengers play a role in individuals' decisions to choose a pooled ride over an individual ride. We do so by means of a stated preference survey. Results indicate that the share of individuals that prefer the pooled alternative over the individual one depends primarily on the time-cost trade-offs individuals encounter, rather than on the disutility they associate to pooling rides per se (with different number of co-riders). The pooling disutility also depends on the number of co-riders (one or two additional passengers being preferred over four additional passengers). While individuals associate a constant per ride disutility with sharing the ride with one or two extra passengers (around fifty euro cents per trip), this disutility further increases with increasing time of the pooled trip when sharing the ride with four additional passengers (amounting to almost three euros per hour). We further apply the estimated behavioural modelling results to a scenario analysis. This helps visualise the results and understand their policy implications. Additionally, we perform a latent class analysis to delve into preference heterogeneity and identify four latent classes. Individuals in one of these classes (amounting to less than one third of respondents) have strong preferences for not sharing their rides. Individuals in this class have more car-centred mobility patterns than individuals in the other classes.

Development of a usage assessment framework to evaluate the characteristics of pooled on-demand trips (Chapter 5, addressing RQ4)

The proposed framework includes indicators to (i) quantify the increases in accessibility that pooled on-demand services have offered their users when compared to the existent fixed (i.e., fixed route and schedule) public transport alternatives, (ii) analyse the usage of pooled on-demand services as a first or last leg mode in longer public transport journeys, and (iii) evaluate the suitability of performing the ride by bike or on foot. The framework covers the spatial and temporal dimensions, and it considers rejected trips explicitly as an integral part of the evaluation. We apply the framework to BrengFlex, an urban pooled on-demand system in the Netherlands. The large majority of the performed trips span longer distances than the average cycling distance in the Netherlands (83.5% of the trips are longer than 3.6 km). Moreover, BrengFlex may have been used as the access or egress leg of a longer public transport journey for up to 20% of the trips (they started or ended at a train station). Results also suggest large accessibility improvements for users of the pooled on-demand service versus the public transport alternatives: for half of the performed rides, the pooled on-demand alternative provides their users a reduction of over half of the generalised journey times in comparison to the fixed public transport alternatives. A smaller discrepancy is found when also accounting for price differences between the two alternatives.

Conclusions, practical implications, recommendations and outlook

This thesis supports forecasting the demand for urban pooled on-demand services. It also supports the evaluation of how these services are being -or will be- used. The findings of this thesis have practical implications especially relevant to policy makers, on-demand transport providers and public transport providers. We highlight the following practical contributions linked to the main research conclusions:

- Better understanding of the future mobility changes stemming from MaaS. Individuals' public transport usage, their technological capabilities and interest and their cost sensitivity influence the adoption potential for MaaS; the two first aspects affecting positively and the last one negatively. MaaS adoption among the more car-centred individuals can be stimulated by promoting MaaS services to them for occasions in which their personal car is unavailable. In order to overcome the technology barrier of the less tech-savvy individuals, MaaS services could offer hybrid systems that do not only rely on a mobility app but which also include a smartcard alternative.

- Behavioural models that can be used to forecast the demand for urban pooled on-demand services. As could be expected, time and cost are identified as the most important attributes in explaining demand for pooled on-demand services; more than reliability with respect to the expected trip times or the number of co-riders. To stimulate adoption, policy makers could allocate strategically located curb space for pooled on-demand services to speed the pick-up/drop-off process. Also, policy makers could increase the fare difference between pooled on-demand services and their individual counterparts by introducing a per-ride tax on individual requests (or a per-passenger subsidy for pooled rides). The obtained behavioural parameters quantify the extent of the disutility that individuals associate to each of the studied attributes. These parameters can be introduced in transport assignment models to better assess the possible modal shifts towards pooled on-demand services.

– Market segmentation analyses regarding MaaS and pooled on-demand services that can be used to design tailored mobility policy strategies and service portfolios. As is often the case in the service industry, "one size does not fit all". The identified classes can help develop a portfolio of services which address the preferences and needs of different individuals, increasing patronage.

– A usage assessment framework to evaluate accessibility impacts of operating on-demand services which takes into consideration the available alternatives. The case study analysis suggests that an integrated public transport – pooled on-demand service framework approach could help strive for increases in urban accessibility and decreases in any collateral risks stemming from reduced revenue of well performing public transport routes.

This thesis investigates attitudes, preferences and usage regarding pooled on-demand services. Future research could study the link between the three, and investigate how attitudes and preferences could result in behavioural change. Similarly, future research could investigate how experience contributes to changes in individuals' attitudes and preferences. Throughout the thesis, we also address the need to offer a portfolio of pooled on-demand services in order to tailor to different market segments simultaneously. Future research could use the obtained behavioural parameters in supply models to help decide on the optimal portfolio of services to offer, taking into account operational constraints. Finally, and regarding the highlighted customer perspective, future research could perform similar research in other settings, in order to investigate the behavioural similarities and differences across contexts.

Samenvatting

In stedelijke gebieden wereldwijd zijn er nieuwe, op maat en op vraag gestuurde, mobiliteitsalternatieven aan het opkomen. Een van deze alternatieven zijn de vraaggestuurde deelmobiliteitsdiensten (deeltaxi-achtige diensten, zoals UberPOOL, LyftLine, OlaShare of ViaVan). De flexibiliteit van deze diensten sluit beter aan bij de mobiliteitsbehoeften van verschillende reizigers en tegelijkertijd zorgt het collectieve karakter voor efficiënt ruimtegebruik, wat goed aansluit bij de uitdagingen van dichtbevolkte, stedelijke gebieden. Simulatiestudies hebben al aangetoond dat het gebruik van deze diensten kan helpen om congestie, vervuiling en parkeerproblemen te verminderen en tegelijkertijd de bereikbaarheid te verbeteren. Het gebruik van deze diensten is echter nog steeds zeer beperkt. Inzicht in de vraag van reizigers naar en voorkeuren voor vraaggestuurde deelmobiliteitsdiensten is daarom essentieel om alle potentiële voordelen te kunnen benutten.

Om deze inzichten te krijgen is dit onderzoek *gericht op het identificeren van individuele attitudes en voorkeuren met betrekking tot, en individueel gebruik van, vraaggestuurde deelmobiliteitsdiensten in een stedelijke omgeving, waarbij de (veronderstelde) heterogeniteit onder individuen expliciet wordt geadresseerd.* Dit proefschrift is onderverdeeld in drie hoofdonderdelen (zie Figuur II.1) die overeenkomen met de drie onderzochte perspectieven: attitudes, voorkeuren en gebruik. Voor deze twee laatste perspectieven ligt de nadruk op vraaggestuurde deelmobiliteitsdiensten, terwijl het onderzoek naar attitudes (deel I) deze diensten ruimer beschouwd, namelijk als een onderdeel van Mobility as a Service (MaaS). MaaS staat voor de integratie van alle beschikbare (deel)mobiliteitsalternatieven en is ontworpen om het toekomstige mobiliteitsecosysteem te worden waarin een eigen auto mogelijk niet meer nodig is.

Om de genoemde inzichten te krijgen hebben we de volgende vier onderzoeksvragen geformuleerd die we elk in één van de vier kernhoofdstukken van het proefschrift (Hoofdstuk 2-5) beantwoorden:

- Onderzoeksvraag 1: Wat zijn de drijfveren en barrières voor het gebruik van Mobility as a Service (MaaS) voor verschillende (groepen van) individuen? (Hoofdstuk 2)
- Onderzoeksvraag 2: Wat zijn (de verschillen in) de individuele tijdswaarderingen van reizigers (Value of Time (VoT)) én betrouwbaarheidswaarderingen (Va-

lue of Reliability (VoR)) voor de verschillende fasen van gedeelde, vraaggestuurde reizen? (Hoofdstuk 3)

- Onderzoeksvraag 3: Wat zijn de belangrijkste factoren voor reizigers om ritten (niet) te delen bij vraaggestuurde mobiliteitsdiensten? (Hoofdstuk 4)

- Onderzoeksvraag 4: Wat zijn kenmerken van de gedeelde, vraaggestuurde reizen, in tijd en ruimte? (Hoofdstuk 5)

We gebruiken drie methodes om de onderzoeksvragen te beantwoorden die elk betrekking hebben op één van de drie bestudeerde perspectieven. De attitudes en voorkeuren (deel I en II) worden geanalyseerd met behulp van respectievelijk clusteranalyse en discrete keuzemodellering (inclusief een marktsegmentatiebenadering), terwijl het gebruik (deel III) wordt geëvalueerd met behulp van een beoordelingskader. De gegevens voor de analyse van de attitudes en voorkeuren zijn het resultaat van een voor dit onderzoek ontworpen enquête, terwijl de gegevens van het gebruik voortkomen uit gebruiksdata van een vraaggestuurde deelmobiliteitsdienst, te weten BrengFlex in de regio Arnhem-Nijmegen. In alle drie de gevallen hebben de gegevens betrekking op de Nederlandse (stedelijke) situatie, maar de bevindingen zijn grotendeels ook toepasbaar op stedelijke omgevingen in andere, vergelijkbare landen. Hieronder worden de onderzoeksbijdragen van het proefschrift belicht samen met de belangrijkste resultaten.

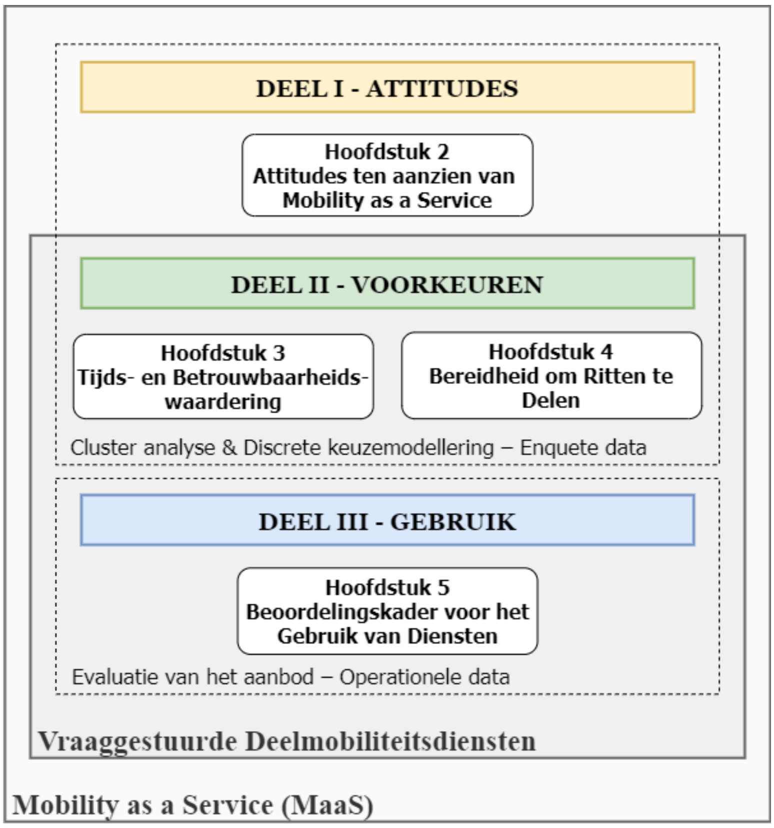

Figure II.1: Proefschrift schema

Identificatie van de drijfveren en barrières die een rol spelen bij het aannemen van Mobility as a Service (MaaS) voor verschillende individuen (Hoofdstuk 2, onderzoeksvraag 1)

In dit hoofdstuk identificeren we relevante factoren met betrekking tot MaaS. Door middel van een latente clusteranalyse hebben we vijf verschillende clusters gevonden die betrekking hebben op de bereidheid van individuen om MaaS te gebruiken. We hebben elk cluster gekarakteriseerd met betrekking tot de sociaaleconomische, mobiliteits- en technologie-gerelateerde kenmerken. Het grootste cluster (32% van de steekproef) is het cluster met de hoogste bereidheid tot toekomstig MaaS gebruik. Deze individuen zijn over het algemeen jong, hoogopgeleid en hebben een hoger dan gemiddeld inkomen. De resultaten tonen aan dat de attitudes ten aanzien van de mobiliteitsgerelateerde aspecten van MaaS in lijn zijn met de huidige mobiliteitspatronen van deze groep: Individuen met multimodale mobiliteitspatronen zijn eerder geneigd om MaaS te adopteren, terwijl het tegenovergestelde te zien is voor individuen met auto-georiënteerde mobiliteitspatronen. Op basis van de resultaten, identificeren we twee belangrijke barrières voor toekomstige MaaS gebruik: (1) een hoge (auto)eigendomsbehoefte, en (2) een lage technologie-adaptatie.

Kwantificering van individuele tijdswaarderingen (VoT) en betrouwbaarheidswaarderingen (VoR) voor de verschillende fasen van de gedeelde, vraaggestuurde reis (Hoofdstuk 3, onderzoeksvraag 2)

We voeren een reeks van stated preference experimenten uit in dit hoofdstuk om de tijd-betrouwbaarheid-kostenafwegingen van individuen te analyseren in gedeelde, vraaggestuurde reizen. We onderzoeken drie fasen van de reis: het wachten, de daadwerkelijke tijd in het voertuig en de overstapfase (van/naar het traditionele openbaar vervoer). Dit maakt een VoT-VoR vergelijking mogelijk, zowel van de verschillende momenten zelf als tussen de momenten. We vonden dat de VoT voor de in-voertuigtijd van vraaggestuurde deelmobiliteitsdiensten iets hoger is dan die waarden voor het traditionele openbaar vervoer, variërend van €7,88 tot €10,80 per uur, afhankelijk van het doel van de reis. De tijdwaarderingen voor de wachtfase voorafgaand aan de rit en die tijdens de transferfase zijn respectievelijk ca. 1 - 1,5 en 0,7 - 1 keer de VoT van de in-voertuigtijd. In lijn met de (Nederlandse) literatuur zijn de VoR's lager dan de corresponderende VoT's (de verhouding is ongeveer 0,5 voor de wacht- en de in-voertuig fase). Tot slot analyseren we in dit hoofdstuk de heterogeniteit van de voorkeuren van het individu met betrekking tot de afweging tussen tijd en kosten. Het belangrijkste verschil tussen de marktsegmenten betreft de totale afweging van tijd, kosten en betrouwbaarheid en niet de afweging van tijd en betrouwbaarheid. Deze laatste blijft vrij uniform over de segmenten heen.

Analyse van de factoren van de bereidheid om ritten te delen in vraaggestuurde deelmobiliteitsdiensten (Hoofdstuk 4, onderzoeksvraag 3)

In dit hoofdstuk onderzoeken we in hoeverre kortingen, extra reistijd en de (on)bereidheid om de rit te delen met (verschillende aantallen) andere passagiers een rol spelen in de beslissing van reizigers om te kiezen voor een gedeelde rit boven een individuele rit. Dit doen we door middel van een stated preference onderzoek. De resultaten laten zien dat voor het deel van de reizigers dat de voorkeur geeft aan het gedeelde alternatief boven het individuele, de (extra) tijd die ze ervaren doorslaggevend is, en niet zozeer het nadeel dat ze associëren met gedeelde ritten op zich. Dit nadeel hangt wel af van het aantal medepassagiers (één of twee extra passagiers krijgen de voorkeur boven vier extra passagiers bijvoorbeeld). Terwijl reizigers een constant nadeel per rit associëren als ze de rit met één of twee extra passagiers delen (ongeveer €0,50 per rit), hangt dit bij het delen met vier extra passagiers af van de duur van rit (wat neerkomt op bijna €3,- per uur). Om de resultaten te visualiseren en de beleidsimplicaties ervan te begrijpen, hebben we de resultaten van de gedragsmodellering toegepast in een scenario-analyse. Daarnaast hebben we een latente clusteranalyse uitgevoerd om de heterogeniteit van de voorkeuren te onderzoeken en vier latente clusters te identificeren. Individuen in één van deze clusters, die minder dan een derde van de totale hoeveelheid respondenten uitmaakt, hebben een sterke voorkeur om hun ritten niet te delen. Deze groep heeft een meer autogerichte mobiliteitspatroon dan individuen in de andere clusters.

Ontwikkeling van een beoordelingskader om de kenmerken van gedeelde, vraaggestuurde ritten te evalueren (Hoofdstuk 5, onderzoeksvraag 4)

Het voorgestelde kader omvat indicatoren om (i) de verandering in bereikbaarheid te kwantificeren door de introductie van vraaggestuurde deelmobiliteitsdiensten in vergelijking met de bestaande openbaarvervoeralternatieven (met vaste route en dienstregeling), (ii) het gebruik van vraaggestuurde deelmobiliteitsdiensten te analyseren als voor- of natransport naar traditioneel openbaar vervoer, en (iii) te evalueren of de gemaakte ritten ook te voet of per fiets gemaakt hadden kunnen worden. Het beoordelingskader neemt zowel de tijd- als ruimtelijke dimensies mee en ook afgewezen ritten zijn onderdeel van de evaluatie. We hebben het kader toegepast op BrengFlex, een vraaggestuurde deelmobiliteitsdienst in de regio Arnhem-Nijmegen. Het overgrote deel van de uitgevoerde ritten beslaan langere afstanden dan de gemiddelde fietsafstand in Nederland (83,5% van de ritten zijn langer dan 3,6 km). Bovendien wordt BrengFlex voor maximaal 20% van de ritten (ze begonnen of eindigden op een treinstation) gebruikt als voor-of natransport van een langere ov-reis. De resultaten suggereren ook grote bereikbaarheidsverbeteringen: voor de helft van de gemaakte ritten biedt BrengFlex een reductie van meer dan de helft van de reistijd die het gekost zou hebben met traditioneel ov. Een kleiner verschil wordt gevonden als de (hogere) ritprijs ook wordt verdisconteerd in de vergelijking.

Conclusies, (praktische) aanbevelingen en vooruitzichten

In dit proefschrift hebben we methoden geïntroduceerd die het voorspellen van de vraag naar vraaggestuurde deelmobiliteitsdiensten mogelijk maken. Deze methoden faciliteren ook de evaluatie van de manier waarop deze diensten worden - of zullen worden - gebruikt. De bevindingen van dit proefschrift hebben praktische implicaties, die met name relevant zijn voor beleidsmakers, aanbieders van vraaggestuurd vervoer en aanbieders van traditioneel openbaar vervoer. We benadrukken de volgende praktische bijdragen:

- Beter inzicht in de toekomstige mobiliteitsveranderingen als gevolg van MaaS. De mate van ov-gebruik, de technologische vaardigheden en -interesse van reizigers en hun kostengevoeligheid beïnvloeden het adoptiepotentieel voor MaaS; de eerste twee aspecten hebben een positieve en de laatste een negatieve invloed. MaaS-adoptie onder de meer autogerichte individuen kan worden gestimuleerd door MaaS-diensten bij hen te promoten voor gelegenheden waarbij hun persoonlijke auto niet beschikbaar is. Om de technologische barrière van de minder technisch onderlegde personen te overwinnen, zouden MaaS-diensten hybride systemen kunnen aanbieden die niet alleen op een app zijn gebaseerd, maar ook een chipkaart-alternatief hebben.

- Gedragsmodellen die kunnen worden gebruikt om de vraag naar vraaggestuurde deelmobiliteitsdiensten in de stad te voorspellen. Zoals te verwachten valt, worden tijd en kosten geïdentificeerd als de belangrijkste factoren om de vraag te verklaren. Deze zijn van groter belang dan de betrouwbaarheid van de reistijd of het aantal medereizigers. Om de adoptie te stimuleren, zouden beleidsmakers ruimte kunnen toewijzen in het openbare domein voor gedeelde, vraaggestuurde diensten om het in- en uitstapproces te versnellen. Ook zouden de beleidsmakers het tariefverschil tussen de gedeelde diensten en hun individuele tegenhangers kunnen vergroten door de invoering van een belasting per rit op individuele aanvragen (of een subsidie per passagier voor gedeelde ritten). De verkregen gedragsparameters uit dit onderzoek kwantificeren het nadeel dat reizigers associëren met elk van de bestudeerde factoren. Deze parameters kunnen worden ingevoerd in vervoersmodellen om de mogelijke modal shift beter te kunnen beoordelen.

- Marktsegmentatieanalyses met betrekking tot MaaS en vraaggestuurde deelmobiliteitsdiensten die kunnen worden gebruikt om op maat gemaakte beleidsstrategieën te ontwerpen. Zoals vaak het geval is in de dienstensector, is ”one size does not fit all” van toepassing. De geïdentificeerde reizigersgroepen kunnen helpen bij het ontwikkelen van een dienstenportfolio dat is afgestemd op de voorkeuren en behoeften van verschillende individuen, waardoor het gebruik kan toenemen.

- Een beoordelingskader om de gebruiks- en bereikbaarheidseffecten van vraaggestuurde deelmobiliteitsdiensten te evalueren, waarbij rekening wordt gehouden met de beschikbare alternatieven. Uit de analyse van de casestudy blijkt dat een geïntegreerde aanpak van het kader voor zowel ov als vraaggestuurde diensten, kan bijdragen aan een betere bereikbaarheid van de stad en eventuele bijkomende risico’s zoals lagere inkomsten uit goed presterende ov-routes kan verminderen.

In dit proefschrift onderzoeken we de attitudes, de voorkeuren en het gebruik van vraaggestuurde deelmobiliteitsdiensten. Toekomstig onderzoek zou het verband tussen de drie kunnen bestuderen en kunnen onderzoeken hoe attitudes en voorkeuren kunnen leiden tot gedragsverandering. Ook kan in toekomstig onderzoek worden onderzocht hoe ervaringen van reizigers bijdragen aan veranderingen in de attitudes en voorkeuren. In dit proefschrift wordt ook aandacht besteed aan de noodzaak om een portfolio van vraaggestuurde deelmobiliteitsdiensten aan te bieden, zodat deze op verschillende marktsegmenten kunnen worden afgestemd. Toekomstig onderzoek zou gebruik kunnen maken van onze verkregen gedragsparameters in vervoersmodellen om te helpen beslissen over het optimale portfolio van aan te bieden diensten. Ten slotte, en met betrekking tot het benadrukte reizigersperspectief, zou toekomstig onderzoek uitgevoerd kunnen worden in andere settings, om gedragsmatige overeenkomsten en verschillen tussen de verschillende contexten te vinden.

About the Author

María J. Alonso González was born in Guadalajara, Spain, on October 21st 1990. In 2014, she obtained a double Master's degree in Civil Engineering from the Universidad Politécnica de Madrid (graduated with Matrícula de Honor) and the Technische Universität München (graduated with distinction). For her engineering studies, María was awarded a second University Graduate National Prize in Engineering (Premio Nacional Fin de Carrera) by the Spanish Ministry of Education.

As part of her master theses and for a couple of months thereafter, she worked at the German transportation consultancy TRANSVER. Then, curious to understand the more practical side of civil engineering, María joined the construction company STRABAG, where she worked in various international projects.

In June 2016, María moved to Delft to start her PhD studies at the Transport & Planning department at Delft University of Technology. Her research focused on the demand for new mobility services, matching her interests in travel behaviour and the future of urban mobility. In 2019, María was awarded the Michael Beesley Award for the best young researcher paper at the Thredbo 16 international conference in Singapore. Later, in 2020, she won a second prize in the European TRA VISIONS Young Researcher Competition. Her research was also shortlisted among the top 12 submissions for the 2020 ITF (International Transport Forum) Young Researcher of the Year Award. After handing in her PhD thesis in March 2020, María used her specialised knowledge to work as a consultant for the World Bank.

During her PhD studies, María presented her research at a number of national and international scientific and professional conferences. She supervised several bachelor and master theses, organized workshops, and served as a reviewer for various international conferences and journals. Additionally, she was part of the TU Delft Civil Engineering and Geosciences PhD council.

Mobility is not only what drives María's research interests, but also what links her different hobbies. In her leisure time, she enjoys travelling, exploring different cultures, walking and cycling. Captivated by languages, she is fluent in Spanish, English, German and Italian, and she has attained intermediate Dutch level.

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