# Potential of on-demand services for urban travel

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# Abstract

On-demand mobility services are promising to revolutionise urban travel, but preliminary studies are showing that they may actually increase the total vehicle miles travelled, thereby worsening road congestion in cities. In this study, we assess the demand for on-demand mobility services in urban areas, using a stated preference survey, to understand the potential impact of introducing on-demand services on the current modal split. The survey was carried out in the Netherlands and offered respondents a choice between bike, car, public transport and on-demand services. 1,063 valid responses are analysed with a multinomial logit and a latent class choice model. By means of the latter, we uncover four distinctive groups of travellers based on the observed choice behaviour. The majority of the sample (55%) are avid cyclists and do not see on-demand mobility as an alternative for making urban trips. Two classes (27% and 9% of the sample) would potentially use on-demand services: the former is fairly time-sensitive and would thus use on-demand service if they were sufficiently fast. The latter class however is highly cost-sensitive, and would therefore use on-demand mobility primarily if it is cheap. The fourth class (9%) shows very limited potential for using on-demand services.

**Keywords:** Mobility-on-demand, Ride-hailing, Urban mobility, Stated preference, Choice modelling, Latent class

# 1 Introduction

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

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

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They conclude that, were it not for TNCs, these travellers would have generated almost 50-times fewer VMT.

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

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

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

The rest of the paper is structured as follows. The current literature covering on-demand services, their role in the current mobility environment and analyses related to adoption and use of on-demand services are presented in Chapter 2. Chapter 3 describes the methodology used to address the identified gaps in literature. The first subchapter elaborates on the survey design method and the data gathering, and the second subchapter presents the modelling framework used to analyse the gathered data and the third then describes the obtained sample. Chapter 0 then showcases the results of the model estimation, the identified user groups and the potential of the different classes to use Flex services. Finally, the results and policy implications of the emergence of on-demand services are discussed in Chapter 6.

### 2 Literature review

The impact of on-demand services on the use of public transportation has already been the topic of several studies. Ride-hailing services can complement public transport by offering first/last mile access/egress service, making PT more attractive (Mohamed, Rye, & Fonzone, 2019). Additionally, on-demand services can be used for making trips that are not served well by public transport, like tangential trips carried out by Kutsuplus in Helsinki (Haglund, Mladenović, Kujala, Weckström, & Saramäki, 2019). The Bridj service in Sydney offers both feeder service to train stations during peak times and stop-to-stop services during off-peak times (Perera, Ho, Hensher, & Studies, 2019). Another way on-demand services can complement public transport is to provide services in late evenings and early mornings. Many ride-hailing trips are already made at these times (Fridays and weekends in the late evening),

mostly for leisure purposes (King, Conway, & Salon, 2020; Mohamed et al., 2019; Tirachini & del Río, 2019). Given that these trips happen at times when public transport services are mostly limited or nonexistent, some studies suggest that car and taxi trips are the most likely to be affected. On the other hand Young, Allen, & Farber (2020) found that a large part of ride-hailing trips substitute public transport. They analysed ride-hailing trips in Toronto and found that a third of all trips were only up to 15 minutes faster than public transport and only around 25% were more than half an hour quicker.

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

To better understand the behavioural trade-off travellers make when faced with an option to choose for on-demand services, several studies employed stated preference (SP) experiments. Most of these studies applied either a multinomial logit (MNL) a mixed logit (ML) model formulation (Table 1). They mostly introduce pooled on-demand next to the car and/or public transportation. Liu, Bansal, Daziano, & Samaranayake (2018) carried out a study in New York, comparing pooled and private ride-hailing with car and public transport and found the highest preference for car, followed by PT, with on-demand services at the bottom (private being preferred over pooled). The same preference order amongst modes was also found in studies in Chicago (Frei, Hyland, & Mahmassani, 2017), Ann Arbor, Michigan (Yan, Levine, & Zhao, 2019) and in North England (Ryley, Stanley, Enoch, Zanni, & Quddus, 2014), while Choudhury et al. (2018), who carried out the survey in Lisbon, found a higher preference for public transport compared to car, while on-demand services were still less preferred. They hypothesize that the former can be attributed to the high quality public transport and congested roads in the city centre. They compared a much larger number of alternatives and trip contexts by employing novel four-step multi-dimensional pivot SP experiment. Alongside the previously mentioned modes, they also considered car rental, bus, express bus, train/metro, bus + train/metro and a park-and-ride alternative. Their findings show a higher willingness-to-pay for car-based modes (including on-demand mobility) and lower for public transport modes. A similar Willingness to Pay (WtP) pattern was observed by Frei et al. (2017), who also modelled the impact of weather on the attractiveness of ride-hailing and found that colder and rainy weather makes it more attractive for respondents, compared to using the car or public transport.

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

Another avenue of exploring the attractiveness and adoption potential of on-demand services is through different latent class clustering methods. Applying a latent class adoption model (Alemi, Circella, Mokhtarian, & Handy, 2019) on the California Millennials dataset (Circella, Tiedeman, Handy, Alemi, & Mokhtarian, 2016), to analyse the potential of the respondents to adopt ride-hailing revealed that among the three uncovered classes, the most likely to adopt ride-hailing are those who are highly

educated and independent Millennials, living in urban areas and are without children, whereas the least likely to adopt it are those living in rural areas.

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

This study adds to the existing literature by analysing respondents' mode choice in a setting where both private and pooled on-demand services exist alongside cycling, cars and public transport (Table 1). In contrast to most literature undertaking such research, heterogeneity among decision-makers is accounted for by employing a latent class choice model (LCCM), instead of a mixed logit model specification. Using an LCCM enables the identification of market segments and through performing a posterior analysis, we obtain detailed insights into the different classes' socio-demographic characteristics, their attitudes and current travel behaviour.

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

Table 1. Overview of studies using stated preference data collection for analysing on-demand mobility

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

# 3 Methodology

To analyse the role of on-demand mobility services and the perceptions and preferences related to them, we employ a stated preference approach. On-demand services are not yet widespread in the Netherlands, and while many people have heard of such services before, very few have ever used such a services before. Given this circumstance, we opt for a SP choice experiment.

#### Survey design 3.1

To elicit respondents decision-making behaviour with respect to on-demand mobility, a stated preference survey is constructed and conducted. In the survey, on-demand mobility is labelled as "Flex" to ease communication (Alonso-González, van Oort, et al., 2020), as such services typically have the "Flex" suffix (Brenaflex (Arnhem-Nijmegen), TwentsFlex (Rijssen-Holten), Mokumflex (Amsterdam) etc.). Flex is positioned next to the most commonly used modes for urban trips in the Netherlands, namely the bike, car and public transport. Walking was excluded due to the longer trip distance and also to reduce the number of alternatives shown. Modes are compared based on in-vehicle time, walking time, waiting time, trip cost and whether or not the ride is shared. In the Netherlands more than half of all the trips are up to five kilometres long and another 20% are between 5 and 15 kilometres (de Graaf, 2015). To determine the attribute levels, a trip that is approximately five kilometres long is selected and a range of values for a trip of such distance is obtained from Google (n.d.). All but one attribute ("Type of ride") are described with three levels, to allow the analysis of non-linear attribute evaluation. The four modes along with their respective attributes and levels can be seen in Table 2. This design is used to asses preferences for two different trip purposes: a commute trip (travelling to work or education) and a leisure trip (travelling for recreation, visiting friends / family). Each choice set contains five alternatives, with two "Flex" alternatives alongside the three existing modes. This, together with the "Type of ride" attribute allows a direct comparison between two "Flex" alternatives, be it two shared options, two private options or one shared and one private (as seen in Figure 1).

Table 2. Modes, altributes and	able 2. Modes, altribules and altribule levels used in the Orban survey					
Attributes	Bike	Public transport	Car	Flex		
Walking time [min]	-	1, 5, 9	0, 5, 10	0, 3, 6		
Waiting time [min]	-	1, 5, 9	-	1, 5, 9		
In-vehicle time [min]	12, 16, 20	8, 12, 16	8, 12, 16	8, 12, 16		
Type of ride	-	-	-	shared, private		
Cost [€]	-	0.5, 2, 3.5	1, 5, 9	2, 5, 8		

Table 2. Modes, attributes and a	attribute levels used	l in the Urban s	urvey
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To avoid making a-priori assumptions on parameter values and willingness-to-pay (WtP), an orthogonal design is selected for this survey (Walker, Wang, Thorhauge, & Ben-Akiva, 2018). Findings from studies on the perceptions of on-demand mobility are not fully in agreement, and if the actual preferences among the respondents do not align with those of the priors, a D-efficient design might become highly inefficient (Walker et al., 2018). An orthogonal design is generated in the software tool Ngene (ChoiceMetrics, 2018). The design is made up of 72 choice sets, which are blocked over 12 blocks of six choice sets. Each respondents is randomly allocated to two different blocks, one for a commute and one for a leisure trip purpose. Each of the 12 blocks is allocated to a roughly equal number of respondents for both trip purpose. One example choice set (originally in Dutch) can be seen in Figure 1. Respondents who do not have access to a car in their household are presented with choice sets without the car alternative. It should be noted that the "Waiting time" attribute for public transport and "Flex" are not presented to respondents in the same way for the two modes. For public transport, waiting is said to be endured at a stop, while for the on-demand service, respondents are given a summary of their trip, indicating how many minutes they need to leave their origin (home) in and then possibly walk to a pickup point. With that in mind, the two different waiting times are shown to respondents in distinctly different ways. For transit, the word "waiting" (wachten in Dutch) is used and positioned between "walking" and "in-vehicle time" (lopen and OV tijd in Dutch respectively), whereas for "Flex", the attribute is shown first as "depart in" (translated from the Dutch vertrek over).

Bike	Public transport	Car	FLEX 1	FLEX 2
	×alking 9 min waiting 1 min	k walking C min	depart in 1 min walking 6 min	depart in 9 min \$ 0 min
<sup>cycling</sup>	in-vehicle time	driving	in-vehicle time 16 min type of ride Shared	in-vehicle time 16 min type or ride Private
	travel cost € 2,00	travel cost € 1,00	travel cost € 2,00	travel cost €2,00

Figure 1. Example of the choice set shown to respondents (translated to English)

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

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

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

Category		Statement
Use of (travel	1	I find it difficult to use travel planning apps. <sup>1</sup>
planning) apps	2	Using travel planning apps makes my travel more efficient. <sup>1</sup>
	3	I am willing to pay for transport related services within apps.

	4	I do not like using GPS services in apps because I am concerned for my privacy.
Mobility	5	I am confident when travelling with multiple modes and multiple transfers.
integration	6	I do not mind infrequent public transport, if it is reliable.
	7	I do not mind having a longer travel time if I can use my travel time
		productively. <sup>2</sup>
	8	Not having to drive allows me to do other things in my travel time. <sup>2</sup>
Sharing a ride	9	I am willing to share a ride with strangers ONLY if I can pay a lower price. <sup>2</sup>
	10	I feel uncomfortable sitting close to strangers. <sup>2</sup>
	11	I see reserving a ride as negative, because I cannot travel spontaneously.
Sharing	12	I believe the sharing economy is beneficial for me.
economy	13	I believe the sharing economy is beneficial for society.
	14	Because of the sharing economy, I use traditional alternatives (taxis, public
		transport, hotels,) less often.
	15	Because of the sharing economy, I think more carefully when buying items
		that can be rented through online platforms.
	16	I think the sharing economy involves controversial business practices (AirBnB
		renting, Uber drivers' rights,).
<sup>1</sup> adapted from (Lu	Mao	Wang & Hu 2015)

<sup>1</sup> adapted from (Lu, Mao, Wang, & Hu, 2015) <sup>2</sup> adapted from (Lavieri & Bhat, 2019)

the remaining statements were formulated for the purpose of this study

Familiarity with six different shared mobility and sharing economy services is also inquired, with the services and the examples given, shown in Table 4. Respondents are asked to indicate their familiarity with the service on a 5-point scale:

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

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

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

#### 3.2 Model estimation

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

A generic-parameter model (Equation 1) is estimated as a benchmark for the more detailed models that follow. All attributes ( $\beta_{at}$ ) are coded by a single generic parameter for the four different modes, with the exception of waiting time, which is modelled separately for public transport and Flex (see the Survey design section above for the argumentation). The ASP model (Equation 2) then expands on the GP model by splitting the parameters for each individual mode ( $\beta_{mode,at}$ ), allowing a comparison of how the same attribute is perceived across different modes. Finally, the DCP model (Equation 3) is estimated to uncover and analyse potential non-linarites in the perceptions of attributes. This is done by modelling the utility contribution of each attribute level ( $X_{mode,at}$ ) by means of its own parameter ( $\beta_{Xmode,at}$ ), with one of the levels being fixed to 0.

Leisure trip purpose and sharing.

Equation 1. GP model formulation

$$V_{mode} = ASC_{mode} + \sum_{at} \beta_{at} \cdot X_{mode,at}$$

Equation 2. ASP model formulation

$$V_{mode} = ASC_{mode} + \sum_{at} \beta_{mode,at} \cdot X_{mode,at}$$

Equation 3. DCP model formulation

$$V_{mode} = ASC_{mode} + \sum_{at} \beta_{X_{mode,at}} \cdot X_{mode,at}$$

To analyse respondent heterogeneity, a latent class choice model is chosen (Greene & Hensher, 2003). Unlike a mixed logit model, a latent class model enables for the estimation of individual parameters for each obtained class, resulting in a straightforward interpretation of the classes and a clear distinction between them. The added value of a latent class model is also the possibility of making a posterior analysis of the attitudinal and socio-demographic characteristics for each of the classes. The model formulation of the LC model is presented in Equation 4. The probability of respondent *n* to select alternative *i* is obtained by summing the probability of this alternative being selected, given the different parameter estimates ( $\beta$ ) in the different latent classes (*s*). The class specific choice probabilities ( $P_n(i|\beta)$ ) are multiplied with the class allocation probability ( $\pi_{ns}$ ). In its simplest form, the class membership function is static (Hess, Ben-Akiva, Gopinath, & Walker, 2008), meaning that only a constant ( $\delta_s$ ) is used. By using only a constant, respondents are allocated to classes solely based on how well the estimated parameters capture their choice behaviour. This approach is chosen, as a distinction purely based on choice behaviour is desired. Alternatively, socio-demographic information could have been added to the class allocation function so that also influences the classes and reduced the influence of the parameter estimates on class membership.

Equation 4. Formulation of the LC model

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

Equation 5. Formulation of the class allocation probability

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

For the individual class formulations, a model based on the GP model specification is used rather than an ASP-like model, to allow for faster estimation, ease of interpretation and to guarantee that sufficient parameters of interest can be identified. One additional parameter is introduced compared to the GP model. The in-vehicle time parameter is split between bicycle (in-)vehicle time (cycling time) and motorised-modes in-vehicle time (including the remaining modes: PT, car, Flex). This is done because (1) the perception of in-vehicle time was found to significantly differ between the bicycle on one hand and the other three modes on the other hand, and because (2) the cycling alternative is described solely by its in-vehicle time, whereas the other modes have between three and five attributes characterising them. A single in-vehicle travel time could have been used as well, which would most likely have impacted the mode-specific constants.

To obtain socio-demographic information for the different latent classes, a posterior probability of being allocated to each of the classes is calculated for each respondent. This is based on the size of the latent classes and how well each of the class-specific parameters predict the individual's observed choices. Using these probabilities, socio-demographic, attitudinal and travel behaviour characteristics for each of the classes are obtained.

#### 3.3 Data collection

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

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

The socio-demographics of the sample and the Dutch population are shown in Table 5 (Centraal Bureau voor de Statistiek, 2020). The sample is largely representative of the Dutch population. We do note a slight overrepresentation of older individuals in the survey compared to the population. Household income differs as well, which can partly be explained by respondents having the option to not disclose their income in the survey, while the census data has a complete overview of everyone's incomes.

Variable	Level	Sample	Population
Gender	Female	52%	50%
	Male	48%	50%
Age	18-34	21%	27%
	35-49	20%	23%
	50-64	30%	26%
	65+	29%	24%
Education <sup>2</sup>	Low	30%	32%
	Middle	41%	37%
	High	29%	31%
Urbanisation level	Very highly urban	23%	24%
	Highly urban	32%	25%
	Moderately urban	17%	17%
	Low urban	20%	17%
	Not urban	8%	17%
Household income <sup>3</sup>	Below average	24%	26%

Table 5. Comparison of socio-demographic variables for the survey sample and the Dutch population.	Source for the
population data: (Centraal Bureau voor de Statistiek, 2020)	

<sup>2</sup> Low: no education, elementary education or incomplete secondary education Middle: complete secondary education and vocational education High: bachelor's or master's degree from a research university or university of applied sciences

<sup>&</sup>lt;sup>3</sup> Below average: below modal income (< €29,500) Average: 1-2x modal income (€29,500 – €73,000)

	Average	50%	47%
	Above average	12%	27%
	Unknown	14%	0%
Employment status	Working	50%	51%
	Not working	50%	49%
Household size	One person	22%	17%
	2 or more	78%	83%

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

#### 4 Results

Outcomes of the three different MNL model specifications, as well as the latent class model, are shown in Table 6. The 4-class latent class model significantly outperformed the other three models. Of the MNL models, the DCP model achieves the highest model fit and adjusted rho-squared value. Surprisingly, the ASP model performs relatively well compared to the DCP model, with a final log-likelihood only 13 points lower and essentially no difference in the value of the adjusted rho-squared. Performing a likelihood ratio test, the DCP model is found to be superior to the ASP model. Considering the BIC value on the other hand, the ASP model is superior, as it achieves a similarly high model fit with fewer parameters.

Table 6. Outcomes of models with different parameter specifications

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

#### 4.1 Results of discrete choice model

The parameter estimates of the alternative-specific model are presented in Table 7, and the estimates of the dummy coded parameter in Table 11 in the Appendix. Exploring the parameter estimates, most attributes seem to have a mostly linear impact on the utility of an alternative, which the alternativespecific model can capture just as well as the dummy-coded model. The impact of cost, in-vehicle time, walking and waiting time on utility in both models is shown in Figure 2. Adjusting the ASP model parameters to the reference level of the DCP model parameters, the estimated dummy parameters follow a linear pattern with only minor deviations from the alternative-specific parameters. With respect to cost, a slight reduction of marginal utility contribution can be seen (each additional euro has a lower impact on utility than the previous one), whereas with all three time-related parameters, a slightly increasing marginal utility contribution (each additional minute of travel/walking/waiting contributes more disutility than the previous one) can be observed. A notable exception here is the waiting time for Flex. As explained in Section 2, Flex waiting time and PT waiting time are expected to be perceived and experienced differently (and were therefore presented differently in the survey), and this is indeed confirmed by the model estimation results. What is most striking about the Flex waiting time is that a 5min waiting time seems to have a more negative impact than a 9-min waiting time. The latter of which is also insignificantly different from zero, meaning no direct impact (negative nor positive) on the overall utility of the alternative can be assumed. One possible explanation for this is in the way Flex waiting time was specified in the survey: waiting at home, which can be seen as hidden waiting time. A 5-minute duration can be seen as period of time that cannot really be spent on doing anything - just waiting while nine minutes could already be enough time to accomplish a quick errand at home, meaning the 'waiting' time is well spent and therefore does not have such a high disutility. A 1-min waiting time is still most preferred, meaning that respondents still preferred the shortest possible waiting time.

Looking at the parameter estimates in Table 7, most parameter estimates are highly significant, at the 0.05 or even 0.01 level. Three of the four in-vehicle time parameters however turned out insignificant, with the dummy parameter estimates showing a similar picture. These are the car, Flex and PT in-vehicle time parameters. This is somewhat contradictory to most research (Choudhury et al., 2018; Frei et al., 2017; Liu et al., 2018), but given the relatively small variation in the in-vehicle time attributes (8, 12 or 16 min), it could mean that respondents do not care about the travel time when the differences are relatively small and only the mode which is used appears to be important. Those preferences are then captured in the mode-specific constants, rather than the in-vehicle time parameters. Other parameters (cost, walking and waiting time) may also play a more important role in the decision-making process. This could also explain, why the parameter estimate for bicycle in-vehicle time is highly significant, as the in-vehicle time is the only attribute describing the bicycle alternative, whereas the other modes have three or more attributes characterising them.

A model with a combined in-vehicle time parameter for the three motorised modes is also estimated, in which this parameter is found significant. In this model, cycling time is perceived six times more negatively than in-vehicle time in motorised modes. This hybrid model is not investigated further here, but is the base model used in the latent class choice model estimation, described in the following section.

The mode specific constants capture all other factors not included in the modelled attributes, which are associated with a specific mode. Table 7 reveals that the ASC for bike (fixed to 0) is the highest, followed by car, with the PT and Flex constants having a similar value. This is mostly in-line with findings reported in the literature (Frei et al., 2017; Liu et al., 2018), although most did not include cycling and the one that did (Yan et al., 2019) found cycling to have the lowest ASC. This likely has to do with the survey being set in Michigan, USA, where the cycling conditions and culture are very different from those in the Netherlands. Choudhury et al. (2018) found car to have a lower ASC than the PT alternatives, but they also state that this is due to the survey being conducted in Lisbon.

Comparing the cost and walking time perception across different modes, parameters related to the car are perceived as least negative, whereas Flex-related parameters are perceived most negative. The explanation for Flex walking time could be that in some alternatives a door-to-door service was offered, so walking a few minutes is experienced comparatively more negatively. For PT on the other hand, travellers expect to walk to and from the station. The even lower penalty for walking time in a car-based trip could be because it refers to walking at the end of the trip, giving respondents more certainty as to what happens afterwards, unlike walking to access a ride/PT stop, which is associated with some inherent uncertainty. With respect to cost, the perception of car-related costs is often lower. The difference in perception between Flex and PT can again be described by their perceived service similarity (especially if the Flex ride is shared), yet Flex often being more expensive.

Table 7. Model estimation results of the ASP model

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

Waiting time [Flex]	-0.022	-1.73	*	
Waiting time [PT]	-0.040	-4.27	***	
Sharing [Flex]	-0.198	-2.56	**	
** $p \le 0,01$ , ** $p \le 0,05$ , * $p$	$0 \le 0, 1$			

Of prime interest for this research is the willingness-to-share on-demand services. Sharing is explored

both as a dummy variable (as seen here) and by interacting it with in-vehicle time, as a perceived invehicle time multiplier. A superior model fit is achieved when the former model specification is used. In the case of the alternative-specific model, respondents are willing to pay up to 0.48 more for a private trip, which is very similar to the 0.41 reported by Alonso-González, Cats, et al. (2020) that respondents are willing to pay to avoid sharing with one or two other people, but much less than over \$6 reported by Liu et al. (2018). This could be due to the cultural context, with the latter study being performed in the USA, while the former and this study are based in the Netherlands. Respondents are also willing to walk almost 2 min farther for a private ride. A trade-off comparison with Flex in-vehicle time cannot be made, as the in-vehicle time parameter is insignificant.

Several different model specifications are explored with respect to trip purpose (commute and leisure). The trip purpose is interacted with all estimated parameters separately. The best model fit and a highly significant parameter estimate is obtained when the trip purpose is interacted with trip cost. In line with other findings (Alonso-González, van Oort, et al., 2020; Choudhury et al., 2018), respondents are more cost-sensitive in leisure trips than in their commute trips. For both public transport and car trips, the respondents' value of time is approximately 25% lower for leisure trip, meaning they are willing to spend a lower amount of money on a leisure trip, compared to a commute trip. Cost sensitivity for mobility-on-demand however does not seem to change based on trip purpose, presumably because at the moment, it is more often used for leisure trips, especially in late evening hours (King et al., 2020; Mohamed et al., 2019). The overall cost sensitivity of Flex is also much higher than for car or public transport.





Figure 2. Utility contributions of the linear alternative-specific parameters and the dummy parameters for the attributes of cost, travel time, walking time and waiting time

#### 4.1.1 Flex-related attitudes and service familiarity

As shown in Figure 3, respondents are mostly familiar with sharing economy and shared transport services. Flexible public transport services on the other hand are much less well known than any of the other services, with 51% of the respondents never having heard of it and only 2% using it at least once. Ride-hailing and bike sharing services are most familiar to respondents, although still only around 10% of them have ever used it.



Figure 3. Familiarity and frequency of use w.r.t. different shared transport and sharing economy services

Food delivery is the most used sharing economy service, with over 40% having used it at least once before. The 16 attitudinal statements (Figure 4) are used to elicit respondents' readiness to use shared on-demand services. In general, respondent agree that apps are easy to use and make travel more efficient, they prefer not making in-app purchases. Participants overall agree that not having to drive gives opportunities to better spend one's travel time and are also willing to travel longer, if that means they can better use their travel time. Respondents are largely in agreement that they are willing to use a shared service only if they receive a discount (statement 9). There is also a clear indication that they feel uncomfortable sitting close to strangers (statement 10).

Attitudes towards the sharing economy reveal that respondents are quite optimistic for what the sharing economy has to offer to society, but for the most part, do not see many direct benefits for themselves. They do however, believe that in some cases, the sharing economy can lead to controversial business practices.



Figure 4. Responses to the attitudinal statements, including the average score for each of the statements

#### 4.2 Results of the latent class model

The model outcomes of a 4-class latent class model are shown alongside the different MNL models in Table 6. In total, models with between two and six classes are estimated. A 6-class latent class model is rejected because two of the classes are too small to serve as a meaningful representation of a market segment (both accounting for only 4% of the population). A 5-class model is rejected because of the very limited interpretability of the classes' characteristics. Models with 2 and 3 classes produced valid and interpretable results, but a model with 4-classes provides insights into a larger number of user groups, while maintaining the interpretability of the results. A latent class model with four classes is therefore chosen for both numerical and interpretation reasons.

The MNL model used in the estimation is a hybrid model of the GP and ASP models, with two in-vehicle time parameters, one for the bicycle alternative and one for the three motorised modes. The waiting time is also modelled separately for the FLEX and public transport alternatives. Cost and walking time are assumed to be generic across all four modes.

The parameter estimates of the four latent classes, along with the class sizes, are presented in Table 8. Based on their choice behaviour characteristics and their Flex-readiness, obtained from the attitudinal statements, they were given the following names:

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

The classes are compared on their parameter estimates and the corresponding willingness-to-pay (WTP) in the following paragraph. Each of the four classes is then presented in more detail in the following subchapters. Their attitudinal, travel behaviour and socio-demographic information is discussed and presented in Figure 5, Figure 6 and Table 10 respectively. These were obtained using the posterior probability analysis.

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

Table 8. Model estimation results of a 4-class latent class model

\*\*\*  $p \le 0,01, ** p \le 0,05, * p \le 0,1$ 

For more detailed information on the trade-offs within each of the four latent classes and to better distinguish between them, their willingness-to-pay for different travel time components and the ratio for cost and time sensitivity are presented in Table 9. The WTP and ratios are shown only if both parameters are significant at the 90% level.

The 'Sharing-ready cyclists' seem to be the most sensitive to out-of-vehicle time components, but at the same time the in-vehicle time for motorised modes is found insignificant for them. They also have a fairly strong preference for the bicycle over other modes, with all ASCs being highly significant. The highest WTP for in-vehicle time can be observed for the 'Flex-sceptic individuals', aligning with the high value of the ASC for car. They do however show the most difference in cost sensitivity for leisure trips, with the WTP for the latter being almost twice as high as for commute trips, whereas it is either insignificant or up to 30% higher for the other three classes. Interestingly, the 'Flex-sceptic individuals' have the lowest ratio of cycling time to in-vehicle time, meaning that they perceive cycling time relatively less negatively than the other classes. In combination with other parameter estimates however

(particularly the ASCs), this lower ratio of travel time does not contribute to a higher likelihood of the *'Flex-sceptic individuals'* to choose the bicycle.

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

Table 9. Willingness-to-pay for travel time components and ratio of cost sensitivity for different trip purposes

#### 4.2.1 Sharing-ready cyclists

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

This class looks mostly ready to use Flex services, although being somewhat reserved or cautious in many aspects (Figure 5). Use of technology and Flex-related travel aspects do not seem to pose a barrier. While they are less concerned about sitting close to strangers, they are prepared to share a ride only if they get a discount for it. Relating to the sharing economy, they are slightly pessimistic about the benefits it can offer them, but are quite strongly optimistic about its potential benefits for society. They do however share the view that it can lead to controversial business practices, possibility due to having a lot of experience with shared services.

'*Sharing-ready cyclists*' are by far the most frequent bike and E-bike users, using them almost twice as often as any of the other classes, whereas their car use is the lowest among the classes (Figure 6). They have the highest bike ownership, with 67% owning a bicycle and 34% an E-bike.

This class tends to be slightly younger, is the highest educated and most affluent. They are slightly more often found in highly urbanised areas, living without children (Table 10).



16

I do not like using GPS services in apps because I am concerned for my privacy.

I am confident when travelling with multiple modes and multiple transfers.

6 I do not mind infrequent public transport, if it is reliable.

Δ

5

- 7 I do not mind having a longer travel time if I can use my travel time productively.
- 8 Not having to drive allows me to do other things in my travel time.
- 9 I am willing to share a ride with strangers ONLY if I can pay a lower price.
- 10 I feel uncomfortable sitting close to strangers.
- 11 I see reserving a ride as negative, because I cannot travel spontaneously.
- 12 I believe the sharing economy is beneficial for me.
- 13 I believe the sharing economy is beneficial for society.
- 14 Because of the sharing economy, I use traditional alternatives (taxis, public transport, hotels,...) less often.
- 15 Because of the sharing economy, I think more carefully when buying items that can be rented through online platforms.
- 16 I think the sharing economy involves controversial business practices (AirBnB renting, Uber drivers' rights,...).

Figure 5. Responses to the attitudinal statements from the four different classes

### 4.2.2 Tech-ready individuals

For this class, the bicycle is also the most preferred mode, but less pronounced. '*Tech-ready individuals*' are more time-sensitive for both cycling time and the in-vehicle time of the motorised modes, and are therefore prepared to pay more for a shorter travel time. For motorised modes, they have a willingness-to-pay ratio of  $11.15 \notin$ /h. The ratio of cycling time to motorised mode in-vehicle time is also the highest of any class, meaning they perceive cycling time most negatively, making motorised modes comparatively more attractive. They are not as time-sensitive when it comes to walking time and PT waiting time, meaning they are willing to walk a few minutes further, if it yields a shorter in-vehicle time for example. '*Tech-ready individuals*' do not like sharing and are willing to pay  $\notin$ 1.08 more to avoid it. They are also more cost-sensitive when making leisure trips, compared to commute trips, with a WtP of 8.49  $\notin$ /h.

This class is considered tech-ready, as they score highly on technology-related statements, but poorly on travel-related and sharing-related statements. They are also slightly more negative in their perception of the sharing economy. Interestingly, they have an above average familiarity with sharing economy services, being either most or second most familiar on all six examples. They stand out most in their frequency of using food delivery services and are also fairly familiar and experienced with ride-hailing and flexible public transport services.

'*Tech-ready individuals*' are frequent car users, with 53% of the class members using it on a daily basis and another 30% at least once per week. They also have the highest household car ownership, at 1.27 vehicles per household and only 11.5% of households have no car (compared to the 17% average). They also have an above average bike ownership and are the second most frequent cyclists.

Members of this class have a middle-to-high level of education (slightly above average) and have an above average household income. They are the youngest class, live more often in suburban areas and have the largest average household size, mostly living as a couple with children or a single parent with children.



*Figure 6. Weekly travel pattern of modes being used at least once per day, for the four latent classes* 

#### 4.2.3 Flex-sceptic individuals

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

'*Flex-sceptic individuals*' have the most distinctive profile of the classes. They are strongly opinionated and quite strongly negative about travel-related and technology-related statements, as well as the sharing economy. Interestingly though, while they find sitting close to strangers quite negative, they do not demand a discount for using a shared Flex service, which is in exact contrast to the other classes. This seems to suggest that a discount is not seen as compensation for 'having to share'.

Similar to their preferences in the survey, '*Flex-sceptic individuals*' are frequent car users, but with an average car ownership rate. With respect to bike use, they are less enthusiastic cyclists in the sample and have the lowest bike ownership rate, with only 43% having a bike (low for the Dutch context), compared to the average of 62%.

This class is on average the lowest educated and has the lowest income. They also live in less urbanised areas. The latter likely contributes to their above average preference for car, as other modes are comparatively less attractive in such a context. Although a below average income and high car preference may be counterintuitive, their car ownership rate is actually average for the sample, meaning they seem to be pragmatic in their car ownership. *'Flex-sceptic individuals'* are more likely to live alone, rather than with a partner (both with or without a child) and are above average living in an atypical household (not falling into any of the 7 main household compositions). The members of this class have an above average likelihood to be pensioners: 30%, compared to the sample average of 26%.

#### 4.2.4 Flex-ready individuals

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

'*Flex-ready individuals*' are the most positive of the classes regarding the four attitudinal topics. They are ready to use technology and are confident multimodal travellers. They don't mind sitting close to strangers, but would like to receive a discount for sharing. Interestingly, they are also the least concerned about reserving a ride impeding their ability to travel spontaneously. This could be because they are the most familiar / frequent users of both flexible PT and ride-hailing services, so they already know best how it works and do not mind it.

'*Flex-ready individuals*', like the '*Flex-sceptic individuals*', have an above average use of the car and below average use of bike. They have the lowest bike ownership of any class, at only 39%. Interestingly, they are also the most likely to not travel regularly on a weekly basis by car, bike or public transport.

This class has a both a slightly below average income and a slightly below average level of education. Given that many class members are young however, this may be because they have not yet completed their education. While the average age of this class is above the sample average, it has an above average share of both younger people (below 25) and older people (above 60). They live in more urbanised areas in small households and more often live either alone or as a couple, either way without children.

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

Table 10.	Socio-demogr	aphic charac	teristics of th	he sample	e and the j	four distinct	latent classes
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# 5 Discussion

Sharing an on-demand trip is often associated with two main differences compared to taking a private trip: physically sharing the vehicle with other passengers (close presence of strangers) and potential additional travel time. To compensate for this, a discount (financial incentive) is offered for sharing, but the discount necessary to attract different user groups varies based on their preferences. In Figure 7, we show the discount needed for shared and private trips to be equally attractive (have the same utility) for the four user groups, given additional travel time. While we did not analyse the variation of travel time, only the in-vehicle time, preliminary research in the field reports that additional travel time has an equal or lower VOT than the promised travel time at the start of the trip (Alonso-González, van Oort, et al., 2020), meaning that our outcomes (Figure 7) are more likely overestimating the necessary discount rather than underestimating it.

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



Figure 7. Discount required for a shared Flex ride to be equally attractive as a private ride

From Figure 7, we would assume that 'Sharing-ready cyclists' and 'Flex-ready individuals' should be the target of Flex services, but that only compares shared and private Flex services, without yet positioning them in the wider mobility context. Considering a typical urban trip (Figure 8), the market share of a private or shared Flex service is presented in Figure 9.

Bike	Public transport	Car	FLEX	
			depart in 5 min	
	k <sup>(</sup> <sup>walking</sup> ★ 5 min	k <sup>™alking</sup> K 5 min	k walking	
	waiting 5 min			
20 min	in-vehicle time	driving 12 min	in-vehicle time	
			type of ride varied	
	travel cost € 1,50	travel cost € 5,00	travel cost varied	

Figure 8. Example choice situation

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



Figure 9. Market share of Flex (private or shared, compared to a bicycle, car and PT alternative) among different classes when Flex trip cost is varied ceteris paribus

# 6 Conclusion

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

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

To better understand market segmentation and how perceptions vary with respect to on-demand mobility, a latent class choice model is used in which four distinct market segments are uncovered. While being the smallest class (at 9% of the sample), the "*Flex-ready individuals*" have by far the highest propensity to choose a Flex service for an urban trip. With a relatively high cost-sensitivity and refraining from cycling, they are well positioned to adopt on-demand services if / when they become more

commonplace. They are quite open to sharing a Flex ride and would only use a private service if it cost only a fraction more. The largest class of the sample (55%), the "**Sharing ready cyclists**" are also very open to sharing, exhibiting similar attitudes and behaviour with respect to sharing, but do not present a high potential for using Flex. As their name implies, they are avid cyclists, and for short urban trips there is virtually no alternative for them. A higher adoption potential can be observed among the "**Techready individuals**" (27%), for whom time is of the essence. If Flex can provide them with a comparatively fast service, they are more than happy to use it. They are more averse to sharing, but if they do not lose much time, they would still consider it they receive a significant discount for sharing. For the final class, the "**Flex-sceptic individuals**" (9%), on-demand services do not seem like a viable alternative. They display a dislike towards sharing, technology and use of public transport, while at the same time highly prioritising their car. Given these results, public transport – and to a lesser degree cars – will likely suffer the biggest impact of an increased presence of Flex in cities. Cycling will likely not be impacted greatly, as the most frequent cyclists do not perceive Flex as a viable alternative for them.

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

A limitation of this study is the hypothetical bias that comes with using stated preference methods. Although some studies found limited bias, most conclude that respondents display a higher willingness-to-pay in the hypothetical setting of an SP survey (Loomis, 2011; Murphy, Allen, Stevens, & Weatherhead, 2005) and that actual behaviour may differ. The transferability of the results to other contexts is also limited. While cycling plays a dominant role for most short trips in the Netherlands, the attitude towards public transport may be lower in rural areas due to its lower quality and the perception of car more positive. While the former could make Flex comparatively more attractive to users, the latter could have a negative impact. The Dutch (north-west European) environment, with its high quality public transport and extensive cycling infrastructure also means that the results cannot be directly translated to other geographic areas with minimal cycling and/or public transport use. With respect to the market segmentation, the "sharing-ready cyclist" group is likely (much) smaller and the three remaining classes larger, the extent to which varying depending on local cycling, traffic and public transport conditions.

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

To fully understand how on-demand services can and will impact our travel behaviour, future research should evaluate the potential of Flex for other trip types. An often cited case for (autonomous) on-demand services is for access/egress to/from train stations or other high capacity public transport (Chen & Nie, 2017; Clements & Kockelman, 2017; Hall, Palsson, & Price, 2018; Ma, 2017; OECD, 2015; Tirachini

& del Río, 2019) and how such a service can impact access mode and station choice – potentially increasing the catchment area of stations. Another potential use of shared Flex services could be on medium-distance (up to 100 km) inter-city trips. Research should also consider how Flex services can aid the attractiveness of MaaS bundles, to complement public transport services by offering first/last mile access and accessibility at times of the day when public transport service are limited or non-existent, offering MaaS users a greater variety of alternatives. Finally, if / when Flex becomes more commonplace, its impact on road congestion, public transport ridership, vehicle ownership etc. needs to be evaluated, along with potential policies on how to increase its level-of-service while securing its affordability and financial viability and minimizing the negative externalities of transportation.

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# Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

# Author's contribution

The authors confirm contribution to the paper as follows:

- Study conception and design:
- Survey design and data gathering:
- Analysis and interpretation of results: 0
- Draft manuscript preparation:
- Supervision and reviewing:
- Funding acquisition:
- All authors reviewed the results and approved the final version of the manuscript

Cats

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# Appendix

Mode	Attribute	Level	Value	Robust t-stat	Significance
Bike	Constant		0 (fixed)	-	-
	In-vehicle time	12 min	0 (fixed)	-	-
		16 min	-0.2139	-4.19	***
		20 min	-0.5556	-11.21	***
Public transport	Constant		-1.5765	-18.27	***
•	Travel cost	€ 0.5	0 (fixed)	-	-
		€2	-0.4356	-4.84	***
		€ 3.5	-0.6308	-6.56	***
	Leisure trip (additional impact)	€2	-0.0974	-0.87	
		€ 3.5	-0.2097	-1.68	*
	In-vehicle time	8 min	0.0437	0.59	
		12 min	0 (fixed)	-	-
		16 min	-0.0591	-0.77	
	Walking time	1 min	0 (fixed)	-	-
	3.0	5 min	-0.2075	-2.85	***
		9 min	-0.4361	-5.67	***
	Waiting time	1 min	0 (fixed)	-	-
		5 min	-0.1207	-1.64	
		9 min	-0.3201	-4.19	***
Car	Constant		-0.8482	-12.32	***
	Travel cost	€ 1	0 (fixed)	_	-
		€5	-0.4960	-6.90	***
		€9	-0.7328	-9.59	***
	Leisure trip (additional impact)	€5	-0.1636	-1.83	*
		€9	-0.1754	-1.83	*
	In-vehicle time	8 min	0.0698	1.17	
		12 min	0 (fixed)	-	-
		16 min	-0.0175	-0.29	
	Walking time	0 min	0 (fixed)	-	-
		5 min	-0.1657	-2.81	***
		10 min	-0.3488	-5.74	***
Mobility-on-demand	Constant		-2 1523	-17.87	***
	Travel cost	€2	0 (fixed)	-	-
		€5	-1.5182	-10.79	***
		€8	-2 2061	-11 96	***
	Leisure trip (additional impact)	€5	0.2414	1.38	
		€8	-0.2404	-0.89	
	In-vehicle time	8 min	0.1691	1.81	*
		12 min	0 (fixed)	-	-
		16 min	-0.0061	-0.06	
	Walking time	0 min	0 (fixed)	-	-
	5	3 min	-0.3282	-3.35	***
		6 min	-0.7155	-6.61	***
	Waiting time	1 min	0 (fixed)	-	-
		5 min	-0.3095	-3.02	***
		9 min	-0.1991	-1.95	*
	Sharing the ride		-0.1549	-1.82	*

Table 11. Estimation results of the DCP model