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Preferences for first and last mile shared mobility between stops and activity locations: A case study of local public transport users in Utrecht, the Netherlands

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A B S T R A C T

Shared transport modes can potentially contribute to first and last mile connections of public transport (PT) trips but this remains quite underexplored in the literature. Our study explores the user preferences for shared modes as first and last mile option to connect activity locations. We have focussed on local public transport in the Utrecht province, The Netherlands, which includes bus and tram lines. Its diversity in land use and PT network density, the overall high bicycle usage, as well as the increased proliferation of shared mobility concepts yield promising information which can be a harbinger for future PT integration worldwide. For both the urban and suburban areas of the province, we have designed and conducted a stated choice experiment. Respondents were able to choose from shared bicycles, e-bikes, e-scooters, and e-mopeds to reach their urban destination from a PT stop. For suburban destinations, we also included light-electric vehicles (LEVs), e-cars, and demand-responsive taxi services. Such a complete list of possibilities to travel by shared modes allows comparing the different options and producing trade-offs not available yet in the literature. A sample of 499 respondents (285 urban and 214 suburban PT travellers) considered their first and last mile mode choice of a recent PT trip in light of the new options. Results show that shared (electric-)bicycles and e-scooters are generally preferred over other shared mobility options. The latter specifically targets younger people (<26 years) and travellers towards suburban destinations. Still, a majority of PT users prefers not to use shared modes in the first and last mile. We found that age, current cycling behaviour and weekday/weekend travelling are the most important factors which determine these preferences. We argue that shared bicycles and e-bikes are the most capable modes in providing benefits to PT travellers in this context and, given the relatively low travel time sensitivity, can best be distributed around the most important PT stops.

1. Introduction

This chapter introduces our study of preferences for shared modes as first and last mile connection in local public transport. First, we provide the context of our study topic. Second, we provide an overview of related literature on this topic. In the end, we elaborate

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on the scientific contributions of this specific study.

1.1. Context

Public transport (PT) systems bring travellers from one stop to another. To access PT, a traveller needs to bridge the distance between his/her origin and the stop. After alighting at the destination stop, again, travellers need to bridge the distance to reach their destination. These trip stages are commonly known as the first and last mile of PT trips.

From a livability and sustainability perspective, there is an ongoing challenge to improve PT systems and, therefore, to enhance the last mile of PT trips (Currie, 2021). Satisfaction with PT trips is strongly related to the travel experience in the first and last mile (Susilo & Cats, 2014). This implies that focusing on the complete door-to-door travel experience, rather than the quality of individual PT modes, can attract more PT travellers. Consequently, this can impact the effectiveness and equity of transport systems (Boarnet et al., 2017). On the other hand, negative experiences with the first and last mile could bound the willingness for people to use PT. Elongated last mile travel times limit the possibility of PT travellers reaching certain destinations. Hence, the improvement of the first and last mile will contribute to a sustainable and livable environment by increasing the general attractiveness of PT systems and door-to-door accessibility by PT.

Considering a trip from home to work: the first mile is home-connected and the last mile activity-connected. For the return trip back home this is vice versa. The work of Hoogendoorn-lanser et al. (2006) shows that mode choice differs between home- and activity-connected trip stages. The main reason for this is that the availability of transport alternatives generally differs. For the home-connected legs, instead of walking, many people can use privately-owned means such as bicycles (especially in the Netherlands) or cars. These enable faster, and perhaps more comfortable, access to PT. As a consequence, the activity-connected trip part is still problematic as it cannot be easily covered by private vehicles. Here, shared alternatives could provide an improved travel experience for PT users.

Shaheen & Chan (2016) define shared modes as "transport means that can be accessed by people to enable transport on a short-term as-needed basis". Shared micro modes can be considered as an important sub-category of shared modes that have been experiencing a significant demand growth over the recent years. These micro modes are characterized by their small size and limited weight. More and more, these are equipped with electric (support) powertrains (Liao & Correia, 2020).

Yet, the integration of PT with shared mobility is still subject to many questions. It is unclear how PT travellers perceive these shared options and how they will respond to them. Also, it is not self-evident which shared modes need to be provided by transport operators and/or authorities complementary to current PT services. As there are many shared options to consider, it is important to determine which of these align best with their transport planning goals. Shaheen & Cohen (2020) mention that it is specifically important to understand how spatial and temporal dimensions impact the integration of shared modes with PT.

Our paper is motivated by identifying which shared alternatives are most promising for PT integration. Before getting there, this first requires an exploration of the travel preferences in the first and last mile. Generally, the following aspects determine mode choice: level of service, trip characteristics, individual and household characteristics, weather and season, and built environment (e.g. Buehler, 2011). In this study, we directly include the first three determinant categories (service level of the first and last mile alternatives, characteristics of the main part of the trip, and individual characteristics) as they can explain the general trade-offs independent of spatial and temporal scale. To add, we incorporate the spatial dimension and the built environment given its importance for first and last mile mode choice, as mentioned by e.g. Mo et al. (2018). We decided to leave out temporal factors such as weather and season as we argue that general trade-offs and built environment are more relevant to address for transport planning practices.

Our study incorporates the built environment by considering PT trips toward both urban and suburban destinations. Typically, the spatial context of the activity-connected leg differs between these two area types. Most noticeable are the differences in PT density (i.e. stop and line density), population density, land-use patterns, and socio-demographic composition of PT travellers. Lower stop and population densities result in longer average last mile distances in suburban areas. The *meta*-analysis of Aston et al. (2021) shows that density, design, access and diversity are important built environment aspects having an impact on public transport demand.

In this paper, we analyse the first and last mile of PT trips that are activity-connected. This could either be the trip from a local (bus or tram) stop to the activity at the destination or, vice versa, meaning from the activity location to a local PT stop. We visualize this activity-connected leg in Fig. 1. Here, PT travellers could benefit from the introduction of shared modes given the low availability of private modes of transport. Especially in situations where the first and last mile distance is higher such that walking is not an attractive alternative. Our study includes the following options to study a large range of potential shared first and last mile options: bicycles, e-bikes, e-scooters, and e-mopeds. Their small size and limited local environmental impacts (i.e. noise and pollutants) create the

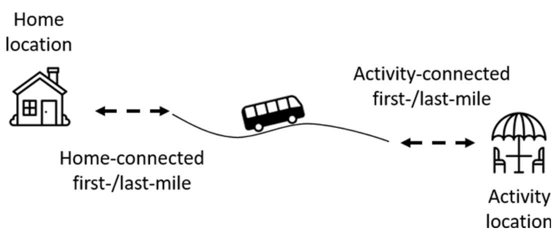

Fig. 1. Visualization of the home-connected and activity-connected first and last mile.

Table 1
Overview of consulted studies regarding user preferences for shared mobility options, including the positioning of this study.

Paper	Considers PT integration	Considers shared mobility	Shared options	Spatial context	Country	Data	Methodology
Baek et al. (2021)	Yes (metro)	Single option	E-scooter	Urban	South-Korea	Closed online survey (stated preference)	Mixed logit modelling
Yan et al. (2020)	Yes (metro)	Single option	Bicycle	Urban	China	Individual trip records	Agglomerative hierarchical clustering
Adnan et al. (2019)	Yes (train)	Single option	Bicycle	Urban	Belgium	Online survey (stated preference)	Binary logit and hybrid choice modelling
Yan et al. (2019)	Yes (bus)	Single option	DRT	Urban	United States	Closed online survey (revealed and stated preference)	MNL and mixed logit modelling
Fan et al. (2019)	Yes (bus)	Single option	Bicycle	Urban	China	Physical and closed online surveys	MNL modelling
Yap et al. (2016)	Yes (train)	Multiple options	Autonomous vehicles, bicycles, local PT	Urban	The Netherlands	Closed online survey (stated preference)	Nested mixed logit modelling
Fishman et al. (2015)	No	Single option	Bicycle	Urban	Australia	Probabilistic sampling (non–)users	MNL modelling
Bachand-Marleau et al. (2012)	No	Single option	Bicycle	Urban	Canada	Open online survey	Binary logistic and linear regression
Fishman (2016)	No	Single option	Bicycle	Urban	Multiple	Previous studies	Literature review
Transport for London (2015)	No	Single option	Bicycle	Urban	United Kingdom	Open user survey	Descriptive analysis
Goodman & Cheshire (2014)	No	Single option	Bicycle	Urban	United Kingdom	Operational registration and usage data	Comparative analysis
Guo et al. (2017)	No	Single option	Bicycle	Urban	China	Random user survey	Bivariate ordered probit modelling
Fitt & Curl (2019)	No	Single option	E-scooter	Urban	New Zealand	Open survey	Descriptive analysis
Bai & Jiao (2020)	No	Single option	E-scooter	Urban	United States	Individual trip records	Hotspot spatial analysis
McKenzie (2019)	No	Single option	E-scooter	Urban	United States	Individual trip records	Descriptive analysis
Hardt & Bogenberger (2019)	No	Single option	E-scooter	Urban	Germany	Trip diaries, before-after surveys	Descriptive analysis
Jiao & Bai (2020)	No	Single option	E-scooter	Urban	United States	Individual trip records	Binomial regression
Degele et al. (2018)	No	Single option	E-scooter	Urban	Germany	Individual trip records	Cluster analysis
Our study	**Yes (bus/tram)**	**Multiple options**	**Bicycles, e-bikes, e-scooters, e-mopeds, e-cars, LEVs, demand-responsive taxi services**	**Urban and suburban**	**The Netherlands**	**Open user survey and stated preference experiment**	**Discrete choice modelling**

potential for large-scale urban use. Also, we include other shared modes which are more suitable within car-enabling suburban areas: shared vehicles (e-cars and light electric vehicles (LEVs)) and demand-responsive taxi services.

1.2. Overview of literature

Scientific literature only limitedly covers the preferences of PT users for shared modes used as first and last mile option. Baek et al. (2021) studied the trade-off between shared e-scooters, local bus and walking as a last mile solution for people using the metro. Their main results were that previous experience with shared e-scooters and income are significant factors for shared e-scooter use. The median value of travel time (VTT) for e-scooter and local buses were found nearly identical. Yan et al. (2020) found a correlation between age and acceptance of shared bicycles in the last mile of metro trips; younger people show a higher propensity to use them. Adnan et al. (2019) considered shared bicycles for train travellers in Belgium. They found that weather, distance, rental cost, and gender are significant factors in choosing these shared bicycles. Additionally, they found a negative effect of only having a single docking station available. Yan et al. (2019) focused on ride-sourcing for urban PT travellers in Michigan, United States. They found that ridership could slightly improve by replacing low-ridership bus services with ride-sourcing services, while operational costs would lower. Fan et al. (2019) studied the shift in first and last mile mode choice after introducing shared bicycles in Beijing, China. They found that gender and distance are significant factors for using shared bicycles by 31–50 year old PT users. The study of Yap et al. (2016) included automated vehicles as a last mile alternative for train travellers in the Netherlands. A surprising result, at the time of the study, was that, on average, respondents valued in-vehicle time more negatively in an automated vehicle than in a conventional vehicle. This could be linked to distrust with vehicle automation and the short travel time.

Fortunately, more results are available regarding shared mobility preferences beyond the first and last mile context, leaving out PT integration. Most of those studies focus on the user preferences for shared bicycles and e-scooters. With regards to service requirements, shared bicycle users view convenience, availability, and saving money as important attributes for participating in shared bicycle schemes (Fishman et al., 2015). The study by Bachand-Marleau et al. (2012) shows that shared bicycles mainly replace trips made on foot or by private bicycles, and also act as a substitute for PT trips. Fitt & Curl (2019) report that shared e-scooters replace walking trips (58 %) and only limitedly replace cycle trips (6 %). Bai & Jiao (2020) produced e-scooter trip statistics (average distance, travel time, and speed) from two US cities and found that those range between the typical walking and cycling patterns.

Related to trip characteristics, Fishman (2016) found shared bicycle use to peak during weekday rush hours and around midday at the weekends. Most bike-sharing scheme members use shared bicycles for commuting (Buehler & Pucher, 2012; Transport for London, 2015). McKenzie (2019) had not found a shared e-scooter demand pattern with commute peaks and concludes that e-scooters are used for other trip purposes. In contrast, a German field test showed that e-scooters are most likely to be used for commute, business and leisure trips (Hardt & Bogenberger, 2019). Fitt & Curl (2019) seem to confirm both these findings. They found that most first time users use e-scooters for fun or out of curiosity; subsequent users are more likely to conduct commuting or shopping trips or use e-scooters for visiting family and friends.

Concerning individual characteristics, many researchers found gender to affect using shared bicycles. Less than 20 % of the trips in the London bike-sharing scheme are made by women (Goodman & Cheshire, 2014). The percentage of women in bike-sharing schemes in Melbourne and Brisbane are, respectively, 23 % and 40 % (Fishman et al., 2015). This limited use of shared bicycles by women is likely related to a lower propensity for cycling in general. In the UK, the USA and Australia, typically low-cycling countries, most cycling trips (65–90 %) are conducted by men (Buehler & Pucher, 2012). This differs from the situation in the Netherlands where many people cycle and, in fact, in this country, women cycle more than men (Harms, Bertolini, & Brömmelstroet, 2014).

The literature review of Fishman (2016) shows that shared bicycle users tend to have a higher average income, a higher education status, and a paid occupation. Guo et al. (2017) had deployed a survey in Ningbo, China which shows that gender, current cycling level, familiarity with shared bicycles and positive attitudes towards cycling as well as being environmental friendly have the largest impact on using shared bicycles. Montreal (Canada) bike-sharing data shows that PT use, combined PT-bicycle use and driver's license possession are important determinants for using shared bicycles (Bachand-Marleau et al., 2012). Regarding shared e-scooters, Jiao & Bai (2020) found that these are mainly used by young, male and highly educated people. In contrast, they found a negative relationship with household income. Degele et al. (2018) studied the individual characteristics of shared e-scooter users in Stuttgart, Germany. They found most e-scooter users to be male and between the ages of 25 and 35 years.

Table 1 sets out all consulted studies regarding user preferences for shared mobility options. Our overview shows that research attention to travel preferences of PT users in the first and last mile is limited. We found that studies typically leave out the first and last mile context of local PT trips which do not involve trains. In addition, most studies do not cover the trade-offs of PT travellers between multiple shared options. Therefore, they only limitedly help to identify which shared modes will contribute to improving first and last mile connections.

Fortunately, the body of knowledge concerning adjacent research topics is larger. These studies, related to cycling in the first and last mile, also contribute to a better understanding of the travel behaviour of PT travellers in the first and last mile. Venter (2020) found that personal safety, waiting comfort and the ease of finding information are more important first and last mile attributes than travel cost, time and distance. Typically, cyclists travel longer distances to and from PT stops compared to people who walk (Rijsman et al., 2019; Brand et al., 2017; Meng et al., 2016). Moreover, an increase in speed and service frequency for buses and trams is related to larger catchment areas in the Netherlands (Rijsman et al., 2019; Brand et al., 2017). Rijsman et al. (2019) also found that cycling in the first and last mile is less likely when this trip stage is activity-connected and with low levels of cycling frequency. Higher age, male gender, lower income, and non-availability of private vehicles increase the likelihood to cycle towards metro stations in Singapore (Meng et al., 2016). Márquez et al. (2021) indicate the importance of a safe cycling environment to stimulate cycling by PT users. They found that physical cycling safety features increases both the safety perceptions and potential demand for cycling to bus rapid transit services. Puello and Geurs (2015) found that perception of connectivity, perceived quality of bicycle facilities, and attitude towards station environment are important for cycling towards train stations. Givoni and Rietveld (2007) found that trip purpose, peak hour travelling, fare type and weather are important factors for using cycling in combination with train travelling. In the next section, we elaborate on how our study contributes to this existing body of knowledge.

1.3. Contributions of this study

To summarise, we found that the preferences of PT users for shared modes in the first and last mile are only limitedly covered in scientific literature. More specifically, we identified two knowledge gaps. First, most researchers tend to focus on interregional and urban rail-bound PT trips when studying the integration of PT with shared mobility. Thus, they leave out the first and last mile challenges related to local public transport which involves other modes such as buses and trams. The study of this specific first and last mile context is important as many residential, commercial and industrial areas depend on local public transport accessibility in the absence of nearby train services. Second, existing user preferences studies towards shared mobility are typically scoped to a single specific shared mobility option. Consequently, these do not have a wider perspective on the trade-offs between multiple shared modes. This perspective is becoming increasingly important given the emergence of novel modes of transport.

Such a holistic approach is valuable from a PT network and service planning perspective. It will help transport planning practitioners in their decisions to integrate certain shared modes with PT services. It could also steer further scientific research in integrated transport network design, simulation and optimization when promising multi-modal combinations in the local PT context are revealed.

This paper contributes to these knowledge gaps by addressing the preferences of local bus and tram users toward shared modes in the urban and suburban first and last mile. Multiple types of shared modes are included. Within the urban setting, these are bicycles, e-bikes, e-scooters, and e-mopeds. In the suburban environment, this mode set is extended with light electric vehicles (LEVs), e-cars, and two types of demand-responsive taxi services (driven by volunteer or professional drivers). We aim to identify the factors related to the use of shared first and last mile modes and which of these modes are most likely to be used by local PT travellers.

In our paper, we quantitatively explore travellers' trade-offs between shared alternatives within both urban and suburban trip contexts by building a stated choice (SC) survey. By including information regarding the level of service level of the first and last mile

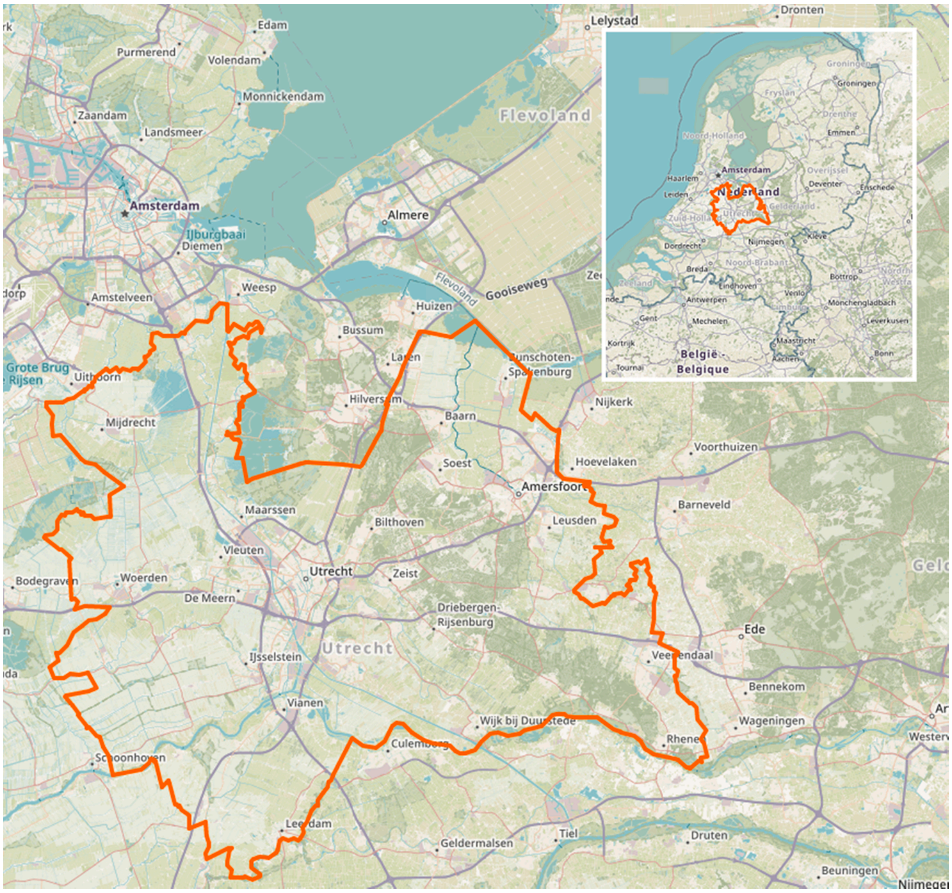

Fig. 2. position of the Utrecht province within The Netherlands (source: Google Maps).

alternatives, characteristics of the main part of the trip, and individual characteristics in the estimation of discrete choice models it is possible to determine the importance of these factors.

The SC survey is conducted within the Utrecht province, The Netherlands. This specific context is relevant for scientific research for two main reasons. First, we argue that the Dutch (Utrecht) context is a harbinger for future mobility developments. It is known for its large and widespread public acceptance of cycling. Moreover, shared mobility options are eminently present in urban areas, and Mobility as a Service platforms are currently being tested. Therefore, respondents are likely to be more acquainted with the provided options in the survey. Ideally, it would be less difficult to establish statistically significant results and would provide first indications for more generic behavioural trends in the light of multi-modal travelling and shared mobility. Second, the availability of an extensive network of bus and tram services and the spatial diversity in population density enable the smooth collection of data and the possibility to distinguish the effects between urban and suburban areas.

We structured this paper as follows. First, we describe the research methodology in section 2. Then, in section 3, we set out the model specifications and provide the results of our study. Next, we provide a discussion and reflection on our main findings and set out the implications for transport policy in section 4. We end this paper with providing conclusionsand setting out recommendations for future research in section 5.

2. Methodology

This section starts unorthodoxly with the case study description; that is because this sets out the framework for the study. Second, we present the aggregated statistics from the data sample that was collected in the Utrecht province. Next, we elaborate extensively on the hypothetical choice context for the SC experiment. Thereafter, we describe how the experiment was designed and how we established and varied the attribute levels. Finally, we describe how tested some additional hypotheses and which explanatory variables we included in the survey.

2.1. Case study: Utrecht province, the Netherlands

Our case-study region entails the complete territory of the Utrecht province, the Netherlands (depicted in Fig. 2). This province is densely populated (904 inhabitants/km2) and is located in the centre of the Netherlands. Many of the 1.34 million inhabitants live in cities such as Utrecht, Amersfoort and Veenendaal. The region is part of the so-called Randstad area which comprises the cities of Amsterdam, Rotterdam and The Hague among other cities with a total population of 8.7 million inhabitants in 2020.

The Utrecht province has a large local public transport network. As such, it complements the extensive network of train services which provides direct connections to many Dutch regions. Local PT is provided mainly through bus services, yet there are also a few tram services available in the city of Utrecht, which is the largest city in the like-named province. Many of the urban PT services are

Table 2
Sample statistics of the respondents compared to the average in-vehicle population.

	Utrecht reference	Urban sample	Suburban sample		Utrecht reference	Urban sample	Suburban sample
Gender				**Private car access**			
Male	43 %	48 %	49 %	(Almost) always	35 %	52 %	54 %
Female	57 %	52 %	51 %	Sometimes	27 %	22 %	22 %
Age				(Almost) never	38 %	26 %	24 %
<18 years	17 %	4 %	7 %	**Trip purpose**			
18–25 years	42 %	27 %	29 %	Commute	34 %	39 %	44 %
26–45 years	23 %	31 %	26 %	Education	33 %	18 %	21 %
46–65 years	14 %	29 %	31 %	Visit family /friends	11 %	11 %	9 %
>65 years	4 %	9 %	7 %	Leisure	7 %	5 %	6 %
Gross monthly income				Shopping	5 %	5 %	6 %
< 2000 euro	64 %	47 %	48 %		6 %	10 %	5 %
				Business			
2000–4000 euro	10 %	33 %	38 %	Medical reasons	2 %	10 %	6 %
> 4000 euro	26 %	20 %	14 %		1 %	2 %	3 %
				Other			
Driver's license possession				**Home-connected first/ last mile**			
Yes	56 %	70 %	63 %	Walking	NA	89 %	84 %
No	44 %	30 %	37 %	(Electric) bicycle	NA	7 %	9 %
HH composition				Other	NA	4 %	7 %
Single-adult, children	8 %	4 %	2 %	**Activity-connected first/ last mile**			
Single-adult, no children	29 %	34 %	36 %	Walking	NA	92 %	89 %
Multi-adult, children	33 %	21 %	34 %	(Electric) bicycle	NA	4 %	5 %
Multi-adult, no children	29 %	41 %	28 %	Other	NA	4 %	6 %

provided on high-frequency schedules during peak hours (>6 vehicles/hour).

We distributed a discrete choice experiment from January 20 until February 17, 2020, which was before the covid-19 health crisis began. In our experiment, only people who conducted a local PT trip in Utrecht over the last three months were included given our focus on the first and last mile of this local network. We used two different methods to approach these PT users. One was the launch of a website for direct access to the experiment, promoted by digital ads shown on the in-vehicle displays. Since this method is prone to self-selection bias of the respondents we used a complementary approach. We used the contact information (provided voluntarily) from respondents of an in-vehicle survey (N = 2363) held in the second half of January 2020 for inviting them to our experiment. The in-vehicle survey was distributed physically by surveyors to establish the composition of the local PT user population.

The Qualtrics tool (2020) was used for the development and distribution of the online survey. Through the Google Maps API we were able to obtain the postal code of the destination. We cross-referenced this information with a database from the Dutch census consisting of postal codes and a 5-level urbanization classification (Centraal Bureau voor de Statistiek, 2019). We considered PT trips to class 4 and 5 (urbanized and strongly urbanized) destinations to be urban. This matches a density of at least 1500 post addresses per km^2. PT trips to destinations with a lower urbanization classification had been considered to be suburban. Such areas vary from smaller-sized settlements around urban cores to farmlands with low population numbers. Based on this classification we provided either the urban or suburban experiment to the respondents.

2.2. Sample statistics

As we wanted to ensure valid responses and limit potential respondents' bias, we controlled for "non-trading" behaviour and too fast responses in our choice experiment. Therefore, we excluded all respondents who chose the same alternative in all 12 choice scenarios or conducted the choice experiments within 40 seconds. After excluding these respondents, the final sample consisted of 499 respondents of which 285 urban and 214 suburban respondents. We have compared these sample statistics with the composition of the population of PT users in Utrecht, which was found using the previously mentioned short in-vehicle survey (N = 2363). The survey method included all PT routes in the area for every day and hour during the two-week surveying period. Therefore, we considered this sample as the reference composition of local PT travellers in the province of Utrecht. Table 2 provides an overview of the sample composition.

The sample statistics show that the participants tend to be older than the average traveller population. Our samples underrepresent travellers below the age of 25. This is also reflected in household composition and income, as many older people have already experienced life events such as starting to live together or getting a first job. Moreover, this likely explains the higher numbers in driver's license possession and private car access. It also causes the trip purposes in our sample to be different from those of the general population; oursample consists of fewer education trips. Instead, the travellers in the sample make more commute, business, and medical trips.

Our sample is also characterized by a more equal gender distribution; this is contrary to the reference in-vehicle survey where more women were found to use PT. The number of travellers with a high income is underrepresented in our sample. We consider the deviation between population and sample as self-selection bias. We argue that travellers who are more interested in local PT (e.g. frequent PT users, dependency on local PT) are more likely to participate in our survey.

Unfortunately, we do not have statistics available for the current first and last mile mode choice for the reference population in the region. However, the survey sample statistics confirm our expectation that most people walk in the first and last mile of their PT trip and a few people cycle. As expected the share of (electric) bicycles is higher in suburban environments, especially in the home-connected first and last mile. Most of the other current first and last mile modes are car driver, car passenger, and moped.

2.3. Choice context

In our choice experiment, participants were asked to reconsider their activity-connected first or last mile mode choice of a recent PT trip which included a bus or a tram. The experimental set-up was slightly different depending on the activity location being either urban or suburban. The shared modes shown to the respondents with an urban destination were: bicycle, e-bike, e-scooter, and e-moped. For suburban destinations, we extended the choice set to e-cars, light electric vehicles (LEVs), and two types of demand-responsive taxi services: one with a volunteer driver – which could be someone living in the service area – and another with a professional driver which is contracted and paid by the transport operator. We referred to the latter two alternatives as Flex Company and Flex Volunteer in our experiment.

Another difference related to the variation of attributes concerning the main part of the trip made by PT. We varied PT frequency and PT in-vehicle time as binary attributes. Yet, the suburban PT in-vehicle travel time remained similar as we assumed that such travel time savings would not be realistic as suburban operational speeds are relatively high and the number of stops relatively low compared to the urban context.

We also limited the number of alternatives provided for each choice task to 4 shared mobility alternatives, a walking/private transport alternative and an opt-out alternative. Because of this, the 8 shared mobility alternatives in the suburban context were grouped pairwise: bicycle & e-bike, e-scooter & e-moped, LEV & e-car, Flex Company & Flex Volunteer.

We expected that several participants might not be acquainted with all shared mobility alternatives (see e.g.: Bronsvoort et al., 2020). They might also have issues understanding novel modes of transport, in particular e-scooters and e-mopeds. For that reason, we provided an extensive textual and graphical introduction to all shared mobility options included in the experiment. For each option, the maximum speed and network type (e.g. footpath or bicycle lane) were mentioned. Besides, information was provided about the

Fig. 3. The shared modes presented to the respondents in the first and last mile mode choice experiment: the upper four were provided to all respondents, the lower four only to respondents travelling to or from an suburban activity-location. (source: Utrecht province, 2020).

presence of an electric (support) engine and the need, or not, for human effort. The introduction also listed the applicable driver requirements, traffic regulations and propulsion system. Our aim was to provide a representation of all options as close to realism as possible. Fig. 3 depicts this introduction of all shared mobility options as shown to the respondents.

In addition, we provided more detailed information about the set-up of the SC experiment, and the varied attributes, to help respondents with their understanding and choosing any of the options provided. Fig. 4 shows the provided information to the respondents. Here, we also restated the information about the reference trip to emphasize the specific choice context to the respondent. Respondents were also informed that they are not obliged to use shared mobility. Alternatively, they could choose to use a private mode (including walking) or cancel the trip. We consciously chose to refer to private transport rather than walking. This was done as walking in the activity-side last mile is currently used by 84 % (urban) and 89 % (suburban) in their reference trips. With (electric) bicycles having the second largest modal share in the Utrecht context, we could not neglect other private alternatives. Cancelling the complete PT trip could be chosen when none of the alternatives, and their attributes, would satisfy their travel needs.

We varied the alternative attributes in such a way that they represent different first and last mile and PT (main trip stage) combinations for the participant's reference trip. PT attributes were included to explore the impact of the main part of the trip on mode choice behaviour in the first and last mile. Therefore, we explicitly mentioned that the choice experiment also requires the participant to consider the stop location where they alighted the PT vehicle and started their last mile. The alternatives represent stop locations that can be situated closer or further from their destination with respect to the current stop location.

Before the experiment started, respondents were also shown some detailed information about the (un)locking procedure of shared vehicles. This information is provided in Fig. 5. It is important to mention that the sharing regime was conceptualized differently for the urban and suburban contexts. We described a free-floating regime to urban travellers and a station-based regime with return obligation for suburban travellers. We made this difference as free-floating regimes would be less realistic in suburban areas given the disperse of potential demand and the related financial consequences. In the suburban context, we doubled the pricing levels due to the return obligation. Here, the choice for shared mobility from stop to activity location implies the same mode choice as the other way around. In addition, we set a time and distance constraint to avoid the use of shared options for excessive use outside the first and last mile context. Nevertheless, the possibility remained to use suburban shared modes beyond the first and last mile connection.

In part 2 you shared this recent public transport (PT) trip with us:

- Date: **<< travel day of reference trip >>**
- Departure time: **<< departure time of reference trip >>**
- Trip purpose: **<< purpose of reference trip >>**

In a few moments, we will show you a number of hypothetical situations based on your recent public transport trip where you need to replace your **<< first or final >>** public transport stop and the mode of transport **<< before access / after egress >>** at this stop by one of the given combinations of stops + modes of transport. For each situation the alternatives for the **<< first or last >>** part of your public transport trip are different. The following characteristics will change:

- Travel time = travel time **<< before access / after egress >>** at the **<< first or final >>** stop
- Travel cost * = additional (single trip) costs for your public transport trip **(only urban)**
- Travel cost * = additional costs for your public transport trip, this includes shared vehicle use for a period of 24 hour **(only sub-urban)**
- Request time (only flex services) = the minimal period before a flex service can pick you up **(only sub-urban)**

* If your employer fully pays your public transport costs you can assume this also holds for shared vehicles / flex-services

Also, the characteristics of buses and trams are changed. Values are in comparison to your recent PT trip.

PT frequency = raise of the number of buses/trams per hour. An empty field means that the PT frequency remains unchanged.
PT travel time = decrease of the travel time spent in bus/tram. An empty field means that the in-vehicle time remains unchanged. **(only urban)**

For each alternative the public transport stop is different. This means that there will be alternatives located close by or further away.

For the **<< first or last >>** part of your public transport trip you can choose one of the introduced modes of transport. You can also choose to travel by your own means of transport (e.g. walking or using your own bicycle); In that case choose the option "I arrange my own alternative". When you do not prefer any alternative please choose "I cancel this trip".

Fig. 4. Detailed description of the set-up of the SC experiment. The bold parts of the description were specified based on the individual inputs of the respondent.

Fig. 5. Visual example of the (un)locking procedure of the shared modes.

2.4. Experiment design and attribute levels

We constructed this experiment design using the NGENE software package (Choice Metrics, 2012). We adopted an orthogonal fractional factorial design for the choice experiment. This design consisted of 36 choice tasks. Therefore, we separated three different blocks of this design to limit each participant's cognitive load.

In the initial stage, we drafted a pilot survey and experiment which was shared among academic peers and transport policy makers at the Utrecht province. They provided us feedback about their understanding of the survey and experiment. This led to a limited number of comments which had been addressed in the design of the final survey and experiment.

We limited the number of alternatives provided for each choice task to 4 shared mobility alternatives, a walking/private transport alternative and an opt-out alternative. Because of this, the 8 shared modes in the suburban context were combined into 4 shared alternative groups: shared cycling modes (bicycle & e-bike), shared micromodes (e-scooter & e-moped), shared vehicles (LEV & e-car), DRT services (flex company & flex volunteer). The suburban experiment design allowed for this by including a binary variable as identifier. Consequently, this resulted in a slightly different specification of the suburban models. In these models, we used this identifier to estimate the alternative-specific constant for each of the shared options. The other parameters were estimated for both options combined. We justify this decision as these alternative pairs have many attributes in common. We also deemed it less likely that both options from the same pair would be provided at the same local PT network. The suburban experiment design also ensured orthogonality between each of the shared options shown.

We provided 12 choice situations to each respondent. Fig. 6depicts what was presented to respondents within the urban and suburban context respectively. Alternatives that require a valid driver's license were not shown to respondents who did not possess a driver's license.

Table 3 and Table 4 provide an overview of the included attributes and their levels. In the initial stage of our study, we consulted transport policymakers in the Utrecht province for defining the attribute ranges. For the first and last mile, we varied the costs (pricing) and the travel time of the shared modes. We also varied the request time using a binary variable for the DRT services as this would likely be an important factor for this specific alternative.

We defined the return trip travel costs of suburban alternatives based on the pricing of existing sharing schemes in the Netherlands using the highest travel time attributes in our experiment. Urban shared mobility options had been priced 50 % of the suburban counterparts since we provided single trip pricing for urban travellers. The suburban 24-hour rental constraint is not reflected in the travel cost ranges as we only introduced this constraint to avoid any dominance of using shared options beyond the context of the first and last mile. We assumed that pricing levels for first and last mile sharing would solely be based on the actual first and last mile travel. We were also interested in how PT travellers would respond to shared modes without any additional charge. Therefore, we decided to

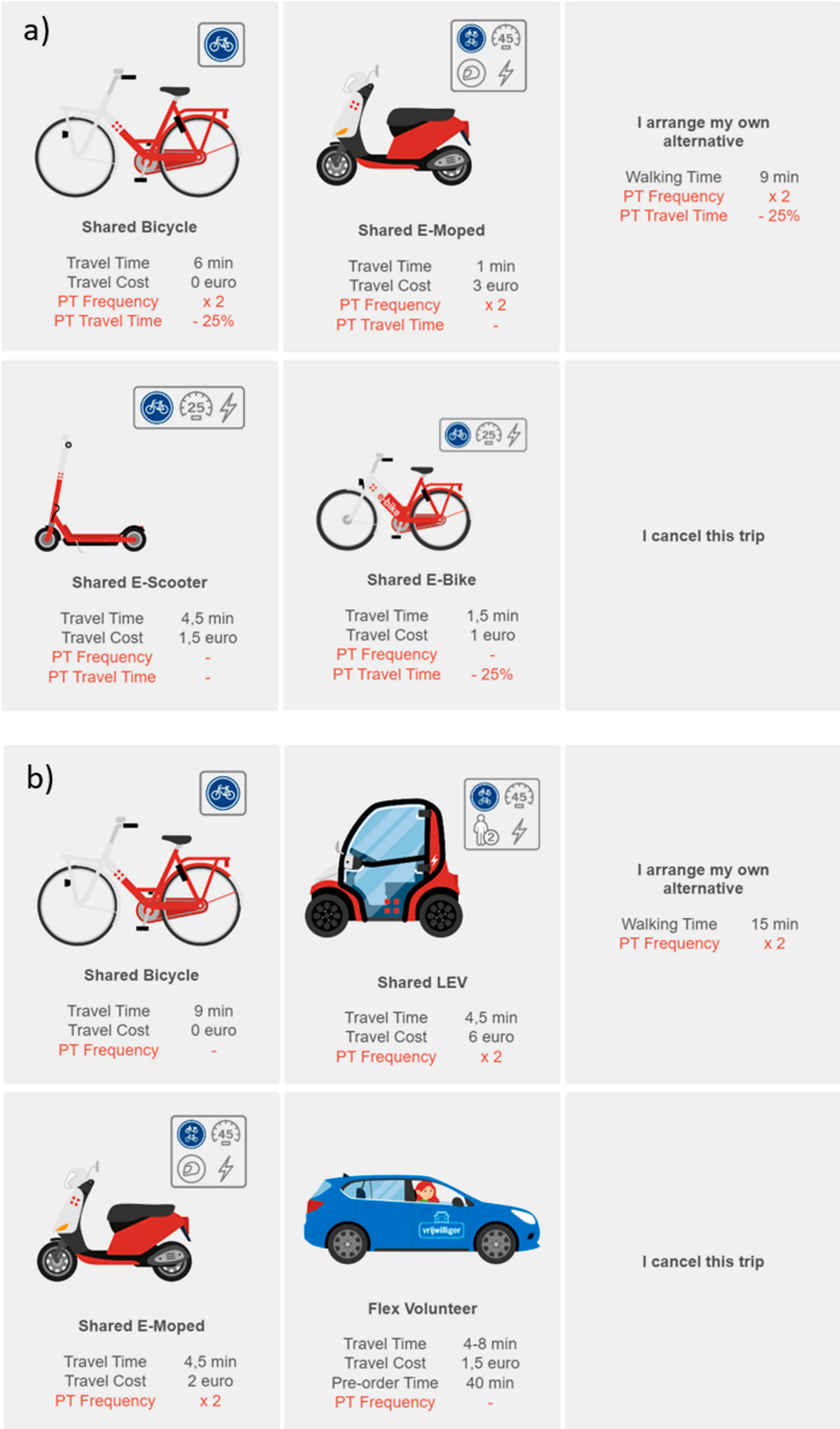

Fig. 6. Example of the experiment choice tasks in the urban context (a) and the suburban context (b).

set one of the pricing levels for shared bicycles and e-bikes to zero.

The travel times were varied such that they represent last mile distances between 300 and 1500 m for urban trips and 500–2500 m for suburban trips. We chose to present travel times to the respondents rather than travel distances since we expected that respondents relate travel impedance more to travel time rather than distance.

Table 3
Attributes and attribute levels varied in the stated choice experiment for urban destinations.

Attributes of first/last mile alternative	Shared Bicycle	Shared E-bike	Shared E-scooter	Shared E-Moped	Not Sharing
Travel time (minute)	[2;6;10]	[1.5;4.5;7.5]	[1.5;4.5;7.5]	[1;3;5]	[3;9;15]*
Travel costs (euro)	[0;0.75;1.5]	[0;1;2]	[0.5;1;1.5]	[1;2;3]	NA
PT frequency**	[1x; 2x]	[1x; 2x]	[1x; 2x]	[1x; 2x]	[1x; 2x]
PT in-vehicle travel time**	[0 %; −25 %]	[0 %; −25 %]	[0 %; −25 %]	[0 %; −25 %]	[0 %; −25 %]

* Travel time for not sharing was provided with walking time as a reference
** In relation to main mode frequency and travel time of the respondent's reference trip

Table 4
Attributes and attribute levels varied in the stated choice experiment for suburban destinations.

Attributes of first/last mile alternative	Shared bicycle	Shared E-scooter	Shared LEV	DRT driven by volunteer	Not Sharing
Travel time (minute)	[3;9;15]	[2;6;10]	[1.5;4.5;7.5]	[6;9;12]	[5;15;25]*
Travel costs (euro)	[0;1.5;3]	[1;2;3]	[4;6;8]	[1.5;3;4.5]	NA
Request time (minute)	NA	NA	NA	[20;40]	NA
PT frequency**	[100;200]	[100;200]	[100;200]	[100;200]	[100;200]
Attributes of first/last mile alternative (continuation)	Shared E-bike	Shared E-moped	Shared E-car	DRT driven by a professional driver	
Travel time (minute)	[2;6;10]	[1.5;4.5;7.5]	[1.5;4.5;7.5]	[6;9;12]	
Travel costs (euro)	[0;2;4]	[2;4;6]	[8;12;16]	[1.5;3;4.5]	
Request time (minute)	NA	NA	NA	[20;40]	
PT frequency**	[1x; 2x]	[1x; 2x]	[1x; 2x]	[1x; 2x]	

* Travel time for not sharing was provided with walking time as a reference
** In relation to main mode frequency of the respondent's reference trip

We had been chosen the travel times such that they realistically represent vehicle operational speeds in the Netherlands. It is important to keep in mind the current presence of extensive cycling infrastructure in the Netherlands which is most often segregated from other modes of transport. We have set the following operational speeds which led to the respective travel time attributes:

- Urban bicycle: 9 km/h
- Urban e-bike / e-scooter: 12 km/h
- Urban e-moped: 18 km/h
- Suburban bicycle: 10 km/h
- Suburban e-bike / e-scooter: 15 km/h
- Suburban e-moped / LEV / e-car: 20 km/h
- Suburban DRT: 20 km/h and assumed 2.5–6.5 min. additional travel time due to detours for additional travellers.

For the main part of the trip, we varied the PT frequency and PT in-vehicle time as binary attributes. The PT frequency was either equal or double relative to the main mode frequency in their reference trip. Only for the urban experiment, the PT in-vehicle travel

Table 5
Included individual and trip characteristics.

Individual characteristics	Main part trip characteristics
• Age: $\leq$ 25y., 26–45, $\geq$ 46 y. • Gender: male, female • Children < 18y. in the household: yes, no • Gross monthly income: < 2 K€, 2–4 K€, $\geq$ 4 K€ • Possession of driver's license: yes, no • Weekly car use: $\leq$ 3 days/week, > 3 days/week • Weekly bicycle use: $\leq$ 3 days/week, > 3 days/week • Weekly public transport use: $\leq$ 3 days/week, > 3 days/week • Experience of difficulty in walking, climbing stairs in local PT (often or (almost) always): yes, no • Experience of difficulties in understanding local PT system (often or (almost) always): yes, no	• Day-of-travel: week, weekend • Peak-hour-travel (departure time: 7–9 AM, 4.30–6.30 PM): yes, no • Fare covered by subscription: yes, no • Fare reimbursement by the employer: yes, no • Trip purpose: commute, education, other Transfer in local PT: yes, no Local PT combined with train: yes, no Cycling during reference trip: home-connected part, activity-connected part, both parts, not cycling.

time was set either equal to or 25 % lower than the original in-vehicle time.

2.5. Hypotheses testing and explanatory variables

The SC experiment was constructed to identify the relevance of multiple levels of service indicators. The experiment was embedded within a larger survey to include contextual factors; i.e. individual and trip characteristics. We selected many of the characteristics which had previously been included in other last mile mode choice studies and surveyed these directly from the respondent. Table 5 provides an overview of the variables which initially have been included in the model specification phase.

We did not include individual attitudes, perceptions or familiarity with shared mobility given our focus on directly measurable factors. Albeit our literature overview shows that educational level, occupational status, and private vehicle ownership can be significant factors, we decided not to include these in our behavioural models. These factors likely have a strong correlation with the included factors of income, age, and driver's license possession. We specifically included existing cycling in the home-connected or activity-connected part of public transport trips as we had found cycling behavior to be important for shared mobility in the first and last mile. We included fare type by disentangling this factor into fare covered by PT subscription, and fare reimbursement by the employer.

Our study is closely linked to policy and practice given the collaboration with the administrative body of the Utrecht province. Therefore, we designed our experiment and estimated models in order to test additional hypotheses. These hypotheses are motivated by the need for addressing challenges in inclusive mobility.

The first hypothesis is that an increase in the PT frequency during the main part of the trip increases the propensity of local PT users to use shared mobility in the first and last mile. We argued that perceived burden of using shared mobility might be traded off with additional benefits during the main trip leg. With a comparable rationale, we also tested this for a decrease in the in-vehicle time during the main part of the trip. Therefore our second hypothesis is: a decrease of the in-vehicle time in local PT faced by the respondent increases the propensity to use shared mobility in the first and last mile. This hypothesis was only tested for the urban context as we deemed such travel time savings not to be realistic in the suburban environment. Here, current operational speeds are relatively high with only a limited number of stops compared to the urban context.

The third hypothesis is that local PT users who also have children in their household would be more likely to use shared mobility in the first and last mile. This hypothesis was motivated by the idea that shared mobility could lead to an overall decrease in the door-to-door travel time. Such a decrease would better fit within the theoretically expected rigid time budgets of parents (Hamre & Buehler, 2014).

The fourth hypothesis is that people who perceive major challenges regarding physical accessibility in local PT would be more likely not to use shared modes in the first and last mile. This hypothesis originates from the idea that many people with disabilities would not be physically able to use shared modes.

Similarly, the fifth hypotheses is that people who perceive major challenges regarding understanding the current local PT system would be more likely not to use shared modes in the first and last mile. We argued that shared mobility might introduce more cognitive complexity for travelling.

In order to include the perceived challenges in physical accessibility and understanding local PT systems we had included additional statements in our survey. We surveyed the experience of problems when using local PT with regards to walking and climbing stairs by using a 5-level Likert-scale statement (varying from (almost) always to (almost) never). We did the same for problems regarding the understanding of the bus and tram system using the same Likert-scale. Respondents who answered often (level 4) or (almost) always (level 5) were considered to face major challenges. Our model compares the behaviour of this group in comparison to those respondents who did not (regularly) face such challenges.

3. Model specification, and results

First, we introduce the models used to analyse the data by describing the model specification and the estimation procedure. This also includes a performance comparison of the different models estimated. Next, we provide the model estimation results from the best performing models in the urban and suburban contexts consequetively.

3.1. Model specification and estimation

We specified and estimated multiple types of discrete choice models: multinomial logit (MNL), nested logit (NL), panel-effect, and mixed logit (ML) models. Background information on these discrete choice model specification can be found in e.g. Train (2009) and Hensher et al. (2005). Each of the estimated models is based on the random utility maximization framework. This assumes that every respondent *n* of each choice task *t* would only choose alternative *i* with utility U_{int}, when $U_{int} > U_{jnt}$, $j \neq i$.

We estimated all models using the Python Biogeme software package (Bierlaire, 2016). In all estimated models, "not sharing" was defined as the reference alternative with its alternative-specific constant fixed to zero. This alternative consisted of both non-sharing options: using own means of transport and cancelling the trip. We started with the estimation of less complex MNL models to explore the impact of the included individual and trip characteristics and experiment attributes. Equation (1) describes how utility function U_{int} is defined for the MNL model. The utility function U_{int} consists of the systematic utility V_{int} and the error term ε_{int}. The systematic utility consists of β_{int} being a vector of attribute-specific parameters and x_{int} being a vector of the attribute values. The MNL model assumes that the error terms are independently and identically (IID) Gumbel distributed.

$$U_{int} = V_{int} + \varepsilon_{int} = \beta_{int}{}^{*}x_{int} + \varepsilon_{int}, \in C_n \quad (1)$$

Given the large number of variables, we used an absolute sample *t*-statistic threshold of 1.44 ($p = 0.15$) to exclude less relevant variables other than travel time, travel costs and perceived difficulties with walking or understanding public transport.

Then, we continued with the estimation of an NL model. This type of model specification can be suitable in case choice probabilities between pairs of alternatives are correlated. We estimated multiple NL models and did not find grounds to continue the estimation of NL models; i.e. we were not able to estimate a statistically significant nest parameter. Therefore, we decided to focus on alternative model specifications.

We introduced the more relevant variables from the MNL model in the panel-effect and ML model specification. Panel-effect models mix MNL specifications with a panel-effect error term. This panel-effect error term accounts for the correlation between error terms over multiple choice tasks for the same respondent. This enables the random error term ε_{int} to be Gumbel IID for each respondent and choice task. In our model specification, we consider the panel-effect term α_{in} to be N(0,sigma) distributed for each alternative *i* and respondent *n*. Equation (2) describes the utility function within the panel-effect model specification.

$$U_{int} = V_{int} + \alpha_{in} + \varepsilon_{int}, \in C_{nt} \quad (2)$$

ML models allow for the estimation of distributions of parameters which are the result of heterogeneity of preferences between respondents. This distribution is represented by the function of ξ_{int} which provides values independent of each respondent and choice task. In our model, we consider ξ_{int} to be distributed $N(0,\sigma_{int})$. Equation (3) describes the utility function in the ML model specification.

$$U_{int} = V_{int} + \alpha_{in} + \xi_{int} + \varepsilon_{int}, \in C_{nt} \quad (3)$$

The increased complexity of these models resulted in more parameters that did not meet our initial *t*-statistic threshold. Therefore, iteratively, we left these parameters out and specified both the panel-effect and ML model such that the respective parameters met the aforementioned threshold. In the end, we aim to identify the model which provides the most statistically significant representation of the choice behaviour. We, therefore, defined several performance measures: the log-likelihood ratio, (adjusted) Rho-squared, and the Bayesian and Akaike information criteria. All provide information about the model's statistical fitness to the data.

The comparison of the model performances is set out in Table 6. For both contexts we found that the panel-effect models outperform the ML models. Therefore, we consider both the urban and suburban panel-effect models to provide the best representation of the choice behaviour.

3.2. Urban results

The results of the estimated urban panel-effect model are provided in Table 7.

To start with, we elaborate on the impact of the shared mode attributes on the first and last mile mode choices. Alternative-specific constants, $\beta_{Constant}$, describe the average part of the utility of each alternative which is not explained by any of the included variables. These constants are influenced by factors such as attitudes or social and emotional influences. We found all constants, except for e-mopeds, to be negative and significant. All other shared modes have a certain variance in utility that cannot be explained by the explanatory variables with residual utilities being negative. Despite its statistical insignificance, the large (negative) value for the alternative-specific constant of shared e-mopeds indicates that other factors than those included in the survey are important for the preference for this alternative. To add, the panel effect σ_{Panel} is large and only statistically significant for shared e-bikes.

We found that travel time only significantly affects the use of shared bicycles and not using a shared mode. It could be that the first and last mile itself causes most disutility, with the time covered therefore being less important in an urban context since distances - and thus travel times - are smaller. We were able to estimate statistically significant generic travel cost parameters. Based on travel time and travel cost parameters we calculated the value of travel time (VTT) for each alternative. The VTT for shared e-bikes and e-scooters is found to be lowest, which suggests that users of these options are less willing to pay for travel time savings. On the contrary, the VTT of shared e-moped is found much higher which suggests that shared e-mopeds specifically target the sub-group of PT travellers who are most willing to pay for shorter travel times.

Table 6
Overview on the performance measures of the considered model specifications.

	Urban Panel-effect	Urban Mixed Logit	Suburban Panel-effect	Suburban Mixed Logit
Sample size	3420	3420	2568	2568
Included parameters	51	50	61	62
Initial log-likelihood	−5020.15	−5020.15	−3649.55	−3649.55
Final log-likelihood	−3130.303	−3145.773	−2540.908	−2544.401
Likelihood ratio test	3779.423	3748.773	2217.280	2210.294
Rho-squared	0.376	0.373	0.304	0.303
Adjusted Rho-squared	0.366	0.363	0.287	0.286
BIC	6362.606	6391.546	5203.816	5212.802
AIC	6675.613	6698.416	5560.720	5575.557

Table 7
Urban results from the panel-effect model specification.

	Shared bicycle		*Shared e-bike*		*Shared e-scooter*		*Shared e-moped*		*No sharing*[1]	
	coef.	*t-test*	*coef.*	*t-test*	*coef.*	*t-test*	*coef.*	*t-test*	*coef.*	*t-test*
β_{ASC}	−1.16	−3.70**	−1.99	−5.60**	−1.14	−2.00**	−13.90	−1.60		
σ_{Panel}	−1.19	−1.88*	−1.87	−3.26**	−0.99	−1.19	−6.68	−1.65*		
Mode characteristics										
β_{Time} (minute)	−0.08	−4.43**	−0.05	−1.93*	−0.03	−0.99	−0.26	−1.22	−0.08	−5.68**
β_{Costs} (€)[3]	−0.67	−9.37**	−0.67	−9.37**	−0.67	−9.37**	−0.67	−9.37**		
VTT (€/hour)	7.35	–	4.62	–	2.97	–	23.45	–		
Individual characteristics[2]										
$\beta_{Cycling > 3 \text{ days/week}}$	0.69	3.87**	0.81	4.34**	0.37	1.76*	−2.88	−1.53		
$\beta_{PT > 3 \text{ days/week}}$	−0.28	−2.13**			−1.24	−5.69**				
$\beta_{< 2K€ \text{ gross monthly income}}$	0.53	3.20**	0.44	2.36**	−1.11	−4.08**				
$\beta_{\text{Having children}}$	0.82	3.93**	0.96	4.32**	0.57	2.09**	1.18	1.65*		
$\beta_{\leq 25 \text{ years}}$					1.01	3.44**	6.21	1.81*		
$\beta_{\geq 46 \text{ years}}$	−1.83	−6.47**	−1.60	−5.30**	−1.61	−5.69**				
Trip characteristics[2]										
$\beta_{\text{Commute trip}}$	−0.31	−1.96**	−0.35	−2.01**	−0.82	−3.47**	3.70	1.57		
$\beta_{\text{Education trip}}$	−0.69	−3.47**	−0.69	−3.07**						
$\beta_{\text{PT fare covered by PT subscription}}$	0.53	3.48**	0.51	2.89**	1.38	4.58**	2.23	1.80*		
$\beta_{\text{Weekend trip}}$	−0.86	−3.79**	−0.83	−3.09**	−2.12	−4.85**				
$\beta_{\text{Current cycling home-connected leg}}$	−0.95	−3.16**	−0.59	−1.85*						
$\beta_{\text{Current cycling activity-connected leg}}$			1.06	3.17**			5.42	1.83*		
$\beta_{\text{Experiences difficulties with walking}}$									−0.19	−0.81
$\beta_{\text{Experiences difficulties with understanding PT system}}$									0.383	1.88*

[1] reference alternative, [2] modelled as binary variables, [3] generic cost parameter
** - significant on a 95 % confidence level. * = significant on a 90 % confidence level

In models estimated previous to our final models, we were not able to find any significant parameters for an increase of the PT frequency and the in-vehicle travel time during the main part in local public transport. Based on this, we do not confirm our hypothesis that either PT frequency or the in-vehicle travel time would increase the propensity of local PT users to use shared mobility in the urban first and last mile.

Regarding the individual characteristics, the final model results show that age is a strong determinant for choosing a shared mode in the first and last mile. We found that younger people (<26 years) are generally more likely to use a shared mode as opposed to older people (>45 years). We were not able to establish a gender effect based on the collected data. Furthermore, we found that having a relatively low gross income (<2000 €/month) relates positively with the preference for shared (electric) bicycles. In contrast, this income group is less likely to use shared e-scooters.

We also found current mobility behaviour to be an important choice determinant. Generally, we found that the frequent use of public transport and cycling as current modes has a positive effect on the preference for using certain shared modes. This effect is the strongest for frequent (minimum 4 days/week) cycling. It exists for each sharing alternative except shared e-mopeds. However, we found a negative relationship with the choice of shared bicycles and e-scooters by frequent PT users.

In our modelling work we also tested the hypothesis of having children in the household increasing the likelihood to use shared mobility in the first and last mile. Our final model results provide statistically significant parameters for each shared mode, except e-mopeds. These parameters all indicate a positive contribution of having children on the propensity of using shared modes. Therefore, we accept this hypothesis for shared bicycles, shared e-bikes and shared e-scooter in the urban context.

We also tested for a relationship between perceived individual challenges in local PT (physical accessibility, understanding PT system) and the preference for not using shared modes. We did not find any statistically significant effect, yet we nearly established significance for a positive link between major perceived challenges in understanding PT systems and not using shared modes. Consequently, we reject both hypotheses related to perceived individual challenges in the urban context.

In regards to the current trip characteristics, we found that trip purpose affects the likelihood of choosing shared modes. People travelling to work show a lower preference to use shared (electric) bicycles and e-scooters compared to travellers with other trip purposes. For the education trip purpose travellers show a slightly lower preference for shared bicycles and e-bikes. Model results also show that having a local PT subscription increases the likelihood of using shared mode, although the respective parameter for e-mopeds is just outside the 95% confidence interval. To add, we found the willingness to share to be lower during the weekends compared to weekdays.

We found that current cycling in either the home-connected or activity-connected first/last mile impacts the preference of using a shared mode. People who currently cycle in the home-connected leg are less likely to use shared bicycles. We argue that travellers do not want to cycle on both trip ends, as this might require a greater amount of physical effort. On the contrary, current cyclists in the activity-connected leg are more likely to replace this cycling with shared e-bikes.

3.3. Suburban results

Table 8 provides the results of the estimated suburban panel-effect model. Here, we found all alternative-specific constants to be negative and significant. We found that the constants for shared LEVs and e-cars are the most negative. To add, the panel effect σ_{Panel} is large and statistically significant for all shared alternatives. This shows that choices made by an individual respondent are correlated for each of the shared options. The specification of alternative groups in the suburban choice models allows for comparing ASCs between these associated modes. This comparison provides the unexplained relative preference between these modes. We found no significant difference (Z-test = 0.10) between the constants of shared bicycles and e-bikes. This suggests that there is no specific special preference for either one of these modes. Contrary, we found a large difference between the ASC of e-scooters and e-mopeds indicating that e-mopeds are generally less preferred over e-scooters as far as the unexplained part of utility is concerned. The larger physical weight of e-mopeds could be an explanation for this. We also found a larger (negative) ASC for shared LEVs compared to e-cars, and for demand-responsive taxis driven by volunteers over the company-driven counterpart. All other things being equal, this suggests PT users prefer shared e-cars over LEVs and prefer DRT services with a professional driver over DRT with voluntary drivers. Familiarity and trust might explain these differences, given the preferences for more common and professional services. Still, future research needs to provide more evidence for these statements.

We found travel time to be statistically significant for each alternative except shared vehicles and demand-responsive taxi services. It seems that people who choose the latter services prefer being brought to their destination over having any physical effort of getting there, independently of the travel time involved. We also estimated a significant generic cost parameter. Based on these travel time and travel cost parameters we calculated the value of travel time (VTT) for each shared option. Users of demand-responsive taxi services show the lowest VTT which is also an indication for valuating other attributes of these services more than their travel time. For shared

Table 8
Suburban results from the panel-effect model specification.

	Shared cycling modes		*Shared micromodes*		*Shared vehicles*		*DRT services*		*No sharing*[1]	
	coef.	*t-test*	*coef.*	*t-test*	*coef.*	*t-test*	*coef.*	*t-test*	*coef.*	*t-test*
	Shared bicycle		*Shared e-scooter*		*Shared LEV*		*DRT driven by volunteer*			
β_{ASC}	−3.47	−2.71**	−2.97	−3.06**	−16.50	−1.99**	−8.79	−4.09**		
σ_{Panel}	4.01	2.78**	2.60	2.57**	12.40	2.23**	6.13	3.01**		
	Shared e-bike		*Shared e-moped*		*Shared e-car*		*DRT professional driver*			
β_{ASC}	−3.62	−2.96**	−11.70	−2.04**	−13.40	−2.02**	−5.38	−4.16**		
σ_{Panel}	3.76	2.97**	−7.01	−2.06**	10.60	2.62**	3.04	2.33**		
Mode characteristics										
β_{Costs} (€)[3]	−0.32	−6.79**	−0.32	−6.79**	−0.32	−6.79**	−0.32	−6.79**		
β_{Time} (minute)	−0.08	−3.48**	−0.09	−2.49**	−0.40	−1.44	−0.04	−0.88	−0.10	−3.51**
VTT *(€/hour)*	14.37	–	17.66	–	73.79	–	6.61	–		
Individual characteristics[2]										
$\beta_{Cycling > 3 days/week}$	2.08	3.50**	2.54	4.11**	4.20	2.79**	1.29	2.20**		
$\beta_{PT > 3 days/week}$	0.76	2.26**	2.54	4.11**			2.35	4.83**		
$\beta_{Car > 3 days/week}$	0.90	2.36**	1.07	2.06**			1.28	2.73**		
$\beta_{< 2K€ gross monthly income}$	0.56	2.31**					0.79	2.86**		
$\beta_{\leq 25 years}$	1.27	3.02**	1.52	3.39**			1.49	2.84**		
$\beta_{\geq 46 years}$	−0.53	−1.86*	−1.28	−3.44**			1.56	4.74**		
$\beta_{Having children}$							0.37	1.81*		
β_{Female}			−0.79	−3.04**						
Trip characteristics[2]										
$\beta_{Commute trip}$			−0.78	−2.20**			−1.62	−5.23**		
$\beta_{Education trip}$			−0.65	−1.47*			−1.14	−3.56**		
$\beta_{PT fare covered by PT subscription}$	−0.55	−2.05**					−0.66	−2.07**		
$\beta_{PT fare reimbursed by employer}$	1.64	3.64**	1.67	3.15**			1.25	2.49**		
$\beta_{Weekend trip}$					7.39	2.10**	0.67	2.10**		
$\beta_{Trip includes PT trans f er}$	−0.38	−1.93*								
$\beta_{Trip includes train leg}$	1.28	1.56			13.3	2.12**				
$\beta_{Current cycling home-connected leg}$			−0.94	−2.09**						
$\beta_{Current cycling activity-connected leg}$	−1.54	−2.74**					1.14	1.63		
$\beta_{Experiences difficulties with walking}$									−0.43	−1.07
$\beta_{Experiences difficulties with understanding PT system}$									0.20	0.54

[1] reference alternative, [2] modelled as binary variables, [3] generic cost parameter

** - significant on a 95 % confidence level. * = significant on a 90 % confidence level vehicles we calculated a VTT of 73.79 euro/hour. This is a very high VTT and is likely also the result of the limited number of respondents choosing this option. Yet, its VTT is not completely implausible as it indicates that shared vehicles are most likely to be used by the highest market segment which is more willing to pay for travel time savings. The large deviation from conventional public transport VTTs suggests that it is not likely that shared e-cars and LEVs will be used in the specific first and last mile context of local PT.

We were not able to find significant parameters for an increase of the PT frequency in local public transport. Based on this, we reject the hypothesis that raising the PT frequency would increase the propensity of local PT users to use shared mobility in the suburban first and last mile.

Regarding individual characteristics, we found that age is a strong determinant for choosing a shared mode in the first and last mile. We found that younger people (<26 years) are generally more likely to use a shared mode as opposed to older people (>45 years). Demand-responsive taxi services seem to be the main exception for this age effect. These services appeal specifically to older people, yet these are not very attractive to the middle age group (26–45 years). We only found a small gender effect towards the use of non-cycling shared micro modes indicating that women have a slight lower preference for these. A high level of mobility, defined as frequently (minimum 4 days/week) cycling using cars, bicycles or public transport has generally a positive effect on the preference for using certain shared modes. This effect is the strongest for frequent cycling. Also frequent public transport usage is positively correlated with choosing a shared mode.

Our modelling also tested the hypothesis of having children in the household increasing the likelihood to use shared mobility in the first and last mile. We did not find any statistically significant parameters for each shared alternative groups. Therefore, we reject this hypothesis for all shared mobility options in the suburban context.

Lastly, we tested for relationships between experiencing difficulties in PT and the preference for not using shared modes. We did not find any statistically significant effect for challenges in physical accessibility or understanding local PT systems on the preferences for shared mobility in the first and last mile.

With regards to current trip characteristics, we found that trip purpose affects the likelihood of choosing shared modes. We found a decreased preference for shared (non-cycling) micro modes among commuters. To add, demand-responsive taxi services are less preferred among both commuters and students. Having a local PT subscription decreases the likelihood of using shared cycling modes or demand-responsive taxi services. The use of shared cycling modes and micro modes is not influenced by week or weekend travelling. For shared vehicles and demand-responsive taxi services we found an increased preference during the weekends. This effect was specifically large for shared vehicles.

Furthermore, we did not find a significant effect of transfer-making between local PT services (bus-to-bus for example) on the preferences for shared modes. Some travellers in our experiment reported using a train, instead of using local PT services, in direct connection to the surveyed first and last mile. We controlled for these transfers and found that these positively relate to the use of shared vehicles. This reflects that most users of shared vehicles in our study are weekend train travellers.

Lastly, current cycling in either the home-connected or activity-connected first/last mile impacts the preference of using a shared mode. People who currently cycle in the home-connected leg are less likely to use non-cycling micro modes in the activity-connected leg. We found that current activity-connected cycling is less likely to be replaced by shared bicycles.

4. Discussion, policy implications and study limitations

This section starts with the discussion on our modelling results. Thereafter, we draft implications for transport policy based on the findings of this study. We finalise this section by reflecting on our study and lining out the limitations of this study.

4.1. Discussion

As mentioned above we were not able to estimate statistically significant travel time parameters. Nevertheless, the analysis of the calculated value of travel time (VTT) indicates that our results are valid for the Dutch context. The most recent Dutch VTT study (Kouwenhoven et al., 2014) found an average value of 6.75 euro/hour for bus, tram and metro services. The VTT found in our study for urban shared bicycles is comparable with the Dutch PT average. The lower VTT for urban shared e-bikes and e-scooters suggests that users of these options are less willing to pay for travel time savings. This might be explained by their valuation of other aspects of these novel modes such as the fun and excitement related to its use (Fitt & Curl, 2019; Hardt & Bogenberger, 2019). On the contrary, the VTT of urban shared e-moped is significantly higher and is comparable with the Dutch VTT for bus, tram and metro by business travellers (19.00 euro/hour). This suggests that shared e-mopeds specifically target the sub-group of PT travellers who are most willing to pay for shorter travel times. We also found these elevated VTTs for shared cycling options and other micro modes in the suburban context. This provides a first indication that on longer first and last mile distances PT users are more willing to limit their travel times.

It seems that the extent of the unexplained variance in utility relates to the novelty of shared mobility. This can related to the novelty of shared transport in general, and, more specifically to the recent emergence certain transport modes. It seems the more unknown the mode, the larger (more negative) the alternative-specific constant.

The age effect found in our models is in line with other studies on shared mobility (Degele et al., 2018; Jiao & Bai, 2020; Yan et al., 2020). Attitudes and capabilities which are more prevalent among young people could explain this age effect. The study of Alonso-González et al. (2020) found that young people over-represent user groups with positive attitudes towards sharing and multi-modal lifestyles. These groups are characterized by their flexibility, as they do not feel committed to a single mode of transport, and their tech-savviness.

Our finding that people with lower incomes have a higher preference for shared bicycles than other people could be explained by the nature of the Dutch cycling context. Cycling is common for many people and is not limited to higher-income groups. In addition, shared bicycles enable PT travellers to have a relatively cheap shared alternative in the first and last mile. The specific context of our study seems to play an important role in these findings as previous studies provide contrasting results for the uni-modal use of shared mobility options. Fishman (2016) found a positive relationship between income and the use of shared bicycles, while Jiao & Bai (2020) and Aguilera-García et al. (2020) found a negative correlation between income and the propensity to use e-scooters and e-mopeds. In this uni-modal context, it is suggested that higher-income groups will replace shared e-mopeds with privately-owned vehicles as soon as they can afford these (Aguilera-García et al., 2020). This substitution behaviour will likely not be present in the context of the first and last mile since PT travellers already chose to use public transport in the first place.

The general absence of a gender effect is in contrast to other studies on shared mode preferences (Buehler & Pucher, 2012; Fishman et al., 2015; Goodman & Cheshire, 2014). Also here, we expect that the Dutch cycling culture plays an important role. The findings of Ton et al. (2019) seem to underpin this statement. In their elaborate study on Dutch active mode choice behaviour also no gender effect was found.

The preferences of frequent PT users are different for urban and suburban destinations. In the suburban context PT users are more likely to choose shared mobility. We expect habits and the commitment towards PT to play an important role for urban PT travellers. These habits are also likely to be present for suburban travellers. However, the habitual effect is likely offset by the elongated first and last mile as shared modes have more potential to shorten travel times. In addition, many studies show that uni-modal trips by shared bicycles often are a replacement for PT trips (Fishman, 2016; Fishman et al., 2015; Transport for London, 2015). This indicates that many PT travellers prefer substituting PT completely by using a bicycle rather than combining these two modes.

With regards to trip characteristics, urban commuters are found to have a lower preference to use shared e-scooters which seems to be in contrast with previous studies; most of them emphasize that many trips by e-scooter are made for commuting purposes (Fitt & Curl, 2019; Hardt & Bogenberger, 2019; Transport for London, 2015). We think that attitudes, and more specifically those connected with status or image, are likely to play a role in commute trips.

We found contradicting results for the impact of having a local PT subscription. Such a subscription increases the likelihood of using shared (electric) bicycles and e-scooters in the urban context, yet slightly decreases the choice for suburban shared cycling modes and demand-responsive taxi services. We were not able to substantiate these findings, but we assume commitment to use PT plays a role. The urban findings might reveal that committed travellers are open to shared modes for improving their trips. Yet, this effect could be absent in the suburban context with typically a lower level of PT service and an increased likelihood to substitute PT with other transport options.

Another difference between the contexts consists of the replacement of current cycling in the activity-connected first and last mile. For urban destinations, current activity-connected cyclists are more likely to replace this cycling with shared urban e-bikes in contrast to PT users with a suburban destination.

Also the preferences of weekend travellers differ between urban and suburban destinations. For urban destinations, the willingness to share is lower during the weekends compared to weekdays. This effect was not present in the suburban context. Moreover, shared vehicles and demand-responsive taxi services are increasingly preferred during the weekends. We argue that weekend trips tend to have a less structural nature since most commute and education trips take place during weekdays. Hence, the drive to improve travel performance is lower. On the other hand, incidental trip making can also be the result of low PT accessibility. From this perceptive, the increased preference to use shared modes of suburban weekend travellers could be explained as shared modes bring more destinations within an accepted reach.

4.2. Implications for transport policy

Given our results, public transport planners need to consider providing shared modes at local PT stops; these could bring added value to a significant number of PT travellers. Yet, practitioners need to be aware of the Dutch context of this study and the dominant role of cycling in the Netherlands. Apart from this notion, and given our result that most PT travellers will not use shared modes in the first and last mile, we argue that local PT networks should be designed such that many (activity) destinations can be reached by walking. This specifically considers older PT travellers and less structural trip making (i.e. travelling during the weekends).

Nevertheless, the provision of shared modes as an integrated part of the PT system can provide added value to users. From that perspective, it is best advised to focus on the supply of shared bicycles or e-bikes as these will likely attract most users. From a financial perspective, conventional bicycles could be preferred over e-bikes as these have typically lower investment and operational costs. E-scooters might also appeal to a significant group of PT users as long as its relatively low priced. They specifically seem to address the needs of some young people and could therefore be an appealing alternative in the proximity of educational facilities. Other shared options are likely to only serve niche markets.

For transport planners, it is important to identify at which stops shared mobility options can best be provided. It is not advised to provide shared modes at all stops, as many vehicles would probably be left unused. Major PT stops and transfer hubs seem to be most suitable as the demand for shared modes can be centralized there more easily. This likely also improves the availability of shared modes. We analysed the impact of travel time for several first and last mile distance scenarios on the disutility of each potential alternative. For each alternative, the travel times belonging to these scenarios are similar to the varied travel time attribute levels in our stated choice experiment. The impact is the result of different travel time parameters and different average speeds of each mode. We calculated the sensitivities and cross-sensitivities for first and last mile travel distance changes (which lead to corresponding travel time changes) in both the urban and suburban context. The results can be seen in Table 9 where the sensitivities are provided as absolute changes in modal shares.

Here, we can see that the PT travellers are less sensitive to travel time changes in the first and last mile for most shared modes in comparison to not sharing (mostly walking). This shows that shared modes can be most competitive for longer distances. For most shared options this analysis shows theirunavailability at the PT stop which is nearest to the trip destination should not have a major impact on mode choice. In that situation, PT travellers are likely to pick-up a shared vehicle at a stop located further away. We found that urban shared e-scooters and suburban demand-responsive taxi services are relatively less sensitive for changes in travel time.

4.3. Reflection and study limitations

In our reflection on population sampling, we observe an overrepresentation of mainly working and middle-aged respondents. We argue that this effect is caused by self-selection bias. We hypothesize that heavy PT users and people who pay their own tickets (most students have “free” subsidized PT in the Netherlands) are more willing to interact in PT surveys/experiments because of their own interests. Yet, our sample statistics confirm that we cover a diverse group of travellers. We argue that using two complementary methods for reaching out to the local PT user population survey (i.e. a combined passive and active approach) helped us to improve this diversity. Despite the sample deviation, we were able to determine statistically significant results for their unique characteristics (such as trip purpose, age and income). Therefore, we expect the effect of the selection bias of our study sample to be limited. The estimated VTTs do not provoke reconsidering the validity of our sample as these are comparable with other VTTs in Dutch public transport.

A stated choice approach enables the control of the choice context and the provision of multiple choice scenarios to each respondent. Although it stimulates the collection of a large and useful amount of choice data, it also invokes some inherent pitfalls. One is that respondents may potentially perceive the choice context differently when compared to the intentions of the experiment designer. We expect this effect to be present in the data collection because it can be difficult to perceive novel modes and the emerging shared mobility paradigm when the respondent is not familiar with these. Fortunately, as already mentioned, most of the vehicles and services that are part of the experiment are already present in Dutch (urban) areas. Yet, we mitigated the impact of any remaining unfamiliarity by providing a clear scope about which information to include in the choice-making process. In addition, we provided

Table 9
sensitivities and cross-sensitivities for first and last mile travel distance changes.

URBAN	xxx	xxx	Alternative with changed first and last mile travel distances									
			Shared bicycle		Shared e-bike		Shared e-scooter		Shared e-moped		Not Sharing	
	First and last mile alternative	Reference modal share at 900 m	300 m	1500 m	300 m	1500 m	300 m	1500 m	300 m	1500 m	300 m	1500 m
	Shared bicycle	16.0 %	+3.9	−3.3	−0.2	+0.2	−0.2	+0.2	−0.2	+0.2	−3.4	+3.5
	Shared	12.6 %	−0.5	+0.4	+1.3	−1.2	−0.1	+0.1	−0.1	+0.1	−2.5	+2.5
	e-bike Shared	17.8 %	−0.9	+0.7	−0.2	+0.2	+1.2	−1.1	+1.2	−1.1	−4.0	+4.1
	e-scooter Shared	1.6 %	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	−0.2	+0.2
	e-moped Not sharing	51.9 %	−2.5	+2.1	−0.8	+0.8	−0.8	+0.8	−0.8	+0.8	+10.1	−10.3

SUBURBAN	xxx	xxx	Alternative with changed first and last mile travel distances									
			Shared bicycle		Shared e-scooter		Shared e-car		DRT Professional		Not sharing	
	First and last mile alternative	Reference modal share at 1500 m	500 m	2500 m	500 m	2500 m	500 m	2500 m	500 m	2500 m	500 m	2500 m
	Shared bicycle	22.2 %	+2.9	−2.7	−0.4	+0.3	−0.1	+0.1	0.0	+0.0	−4.6	+4.7
	Shared	12.9 %	−0.5	+0.4	+2.5	−2.2	−0.2	+0.1	−0.1	+0.1	−4.4	+5.3
	e-scooter Shared	2.9 %	0.0	+0.0	0.0	+0.0	+1.1	−0.6	0.0	0.0	−0.4	+0.5
	e-car DRT Professional driver	10.4 %	−0.1	+0.1	−0.2	+0.2	−0.1	0.0	+0.3	−0.3	−1.9	+2.1
	Not sharing	51.6 %	−2.3	+2.2	−1.9	+1.7	−0.7	+0.4	−0.2	+0.2	+11.2	−12.6

Sensitivities are provided as absolute changes in modal shares clear illustrations on the shared alternatives and how to use these. We also dealt with the risk of cognitive overload and its potential impact on the decision-making process of respondents by removing records from "non-traders" and respondents who answered unrealitically fast.

In our suburban experiment we introduced shared modes with a return obligation. We have argued that such an obligation would also be present in future suburban first and last mile sharing schemes. The implication is that PT users could also use these options beyond the first and last mile context. For example by using the same vehicle to reach work and to buy groceries on the return trip. In our reflection, this effect is likely present in our survey and would also likely be present in a real-life setting. Therefore, our suburban results need to be interpret with the possibility of PT travellers using shared mobility beyond the first and last mile context.

The context of this study being focused on first and last mile transport also raises some points of attention. The relatively short distances, and thus short travel times, of these trips mean that the difference between the travel time attribute of certain alternatives can be small which might make it imperceptible to the respondents. This is connected to the dilemma of the experiment designer of trading-off between experiment validity and representing realistic choice contexts. Yet, we argue that the impact of small travel time differences between the modes on the validity of our study is limited. An indication for the validity of our results with regards to travel time is provided by VTT calculations which approximate VTT in Dutch public transport. To add, our results indicate that more travel time parameters could have become statistically significant if we would have incorporated larger travel time ranges in the experiment. However, here realism of the choice context needs to be traded-off with the effectiveness of the experiment design. Larger travel time ranges would have led to choice tasks being less realistic to the respondent in the context of Utrecht.

5. Conclusions & research recommendations

In this final section, we first provide the main conclusions of our study. In the end, we also provide recommendations for future research on this topic.

5.1. Conclusions

This paper aimed to identify which shared modes of transport are preferred by urban and suburban PT travellers in the first and last mile. Our main methodology consisted of an online survey and SC experiment with a sample of 499 respondents (285 urban, and 214 suburban respondents) conducted in the Utrecht province, The Netherlands. We have found that shared bicycles, both conventional and electric bicycles, are generally preferred over shared e-mopeds, shared vehicles (suburban), and demand-responsive taxi services (suburban). The preference for shared bicycles (electric or not) could partially be explained by existing high cycling levels in the Netherlands. We have found that shared e-bikes are generally not preferred over non-electric bicycles. Although the preference for using shared e-scooters is comparable with shared cycling options, our results indicate that it specifically targets younger people (<26 years) and travellers towards suburban destinations. Still, a majority of the PT travellers prefers not to use a shared mode in the first and last mile. Instead, they will mainly walk to or from their destination. This effect is larger for urban destinations than for suburban destinations. We presume that the density of urban PT networks – i.e. a relative short stop and line spacing – maintains walking as an acceptable option. Shared light electric vehicles and e-cars are not practically relevant to provide in conjunction to local PT networks. We deem the calculated value of travel time of these shared modes extremely high.

Preferences for shared modes are only limitedly impacted by travel times in the first and last mile. However, the disutility of walking is relatively high compared to shared mobility beyond the direct proximity of PT stops given the higher speeds of shared alternatives.

We tested several hypotheses which were motivated by the need for addressing practical challenges in inclusive mobility. Our first hypothesis was that an increase in the PT frequency during the main part of the trip would increase the propensity of local PT users to use shared mobility in the first and last mile. We only tested this hypothesis for the urban context. The second hypothesis was that a decrease of the in-vehicle time in local PT faced by the respondent would lead to increased propensity to use shared mobility in the first and last mile. Our study rejects both hypotheses.

We also tested the hypothesis that local PT users who also have children would be more likely to use shared mobility in the first and last mile. We have accepted this hypothesis for shared bicycles, shared e-bikes and shared e-scooter in the urban context, whilst our study rejects this hypothesis for shared urban e-mopeds and each of the shared mobility options in the suburban context.

Our final hypotheses stated that perceived individual challenges in local PT (physical accessibility, understanding PT system) would increase the likelihood for not using shared modes. We did not find any statistically significant effect in both the urban and suburban context to support these hypotheses.

Our study reveals that age, current cycling behaviour and weekday/weekend travelling are the most important factors for preferring shared modes in the first and last mile. People up to the age of 26 are more willing to use these shared modes than older people. This is in general line with other studies on (uni-modal) shared mode preferences. With regards to current cycling behaviour, we have found that frequent cyclists (at least 4 days/week) are more likely to use any shared modes in the first and last mile, except for urban e-scooters and e-mopeds. Apart from cycling frequency, people who currently cycle in the home-connected leg are less likely to use shared urban bicycles and suburban non-cycling micro modes in the activity-connected leg. For weekend PT travelling, we have found that shared modes are less preferred to reach urban destinations. We did not find this effect for suburban destinations. On the contrary, we found that specifically shared vehicles are preferred in the suburban first and last mile during the weekends.

In contrast to other studies on shared mobility, we have hardly found a gender effect. Our study only shows that women have a lower preference for shared suburban non-cycling micro modes (e-scooters, e-mopeds). We expect that Dutch cycling culture had a significant impact on our experiment; cycling is well-established in the Netherlands to a point where, differently from what happens in many countries, women cycle more than men.

5.2. Recommendations for future research

Based on our results and discussion we identified several important directions for future research. First, more insights are needed about the attitudes which determine the preferences for shared modes. This requires a more qualitative research approach and the inclusion of testing attitudinal statements. Eventually, the information about attitudes could be incorporated in alternative behavioural models, such as hybrid choice models. To add, we expect that heterogeneity in user preferences can also be further quantitatively explored by using alternative methodologies such as latent class analysis. Second, even though many important categories of determinants had been included in our study, some potential explanatory variables could be further studied such as weather, season, party size and luggage. Third, our study only comprises data from existing PT users. The impact of PT integration and shared mobility on modal shift and a change in PT ridership can best be answered by also considering the travel preferences and behaviour of non-PT-users in future studies.

Furthermore, the integration of public transport and shared mobility has only been limitedly studied. Specifically, the costs and benefits related to this integration are not well explored. Information about behavioural trade-offs can be used to analyse the impact of public transport integration in terms of travel time (savings), accessibility, the number of travellers and potential modal shifts by using transport models or simulations.

To add, PT integration with shared mobility schemes which require the user to return the vehicle to the pick-up point could impose changes in spatial–temporal travel patterns. It could induce trip chaining when PT travellers use shared vehicle for conducting additional activities and combining multiple trip purposes. Such additional effects are not covered by our study but will contribute to the knowledge about how integrated PT systems would be used.

Lastly, we suggest studying shared mobility in other socio-cultural contexts. It is likely that existing travel behaviour, cultural influences, the built environment, and (cycling) infrastructure, had an important role in our research findings. Nevertheless, we do want to note that the case study that we have selected can become a benchmark for representing regions that are quite advanced in providing local and regional PT systems combined with high bicycle usage and proliferated shared mobility options.

Apart from its scientific contributions, these future research steps will support further actions to be taken by PT operators and authorities to improve the first and last mile and the overall door-to-door travel experience.

CRediT authorship contribution statement

Roy J. van Kuijk: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft. **Gonçalo Homem de Almeida Correia:** Conceptualization, Formal analysis, Investigation, Writing - review & editing. **Niels van Oort:** Writing – review & editing. **Bart van Arem:** Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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