PREFERENCES FOR SHARED MODES OF LOCAL PUBLIC TRANSPORT USERS IN THE URBAN LAST-MILE

Roy J. van Kuijk, Corresponding Author
Delft University of Technology
Faculty of Civil Engineering & Geosciences
P.O. Box 5049, 2600GA, Delft
The Netherlands
Phone: +31 (0)15 278 91 29
E-mail: r.j.vankuijk@tudelft.nl

Gonçalo Homem de Almeida Correia

Niels van Oort

Bart van Arem

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ABSTRACT
Shared transport creates an opportunity to facilitate the last mile connections of public transport (PT) trips. Nevertheless, user preferences for using such shared modes as last-mile connection have hardly been studied. To explore such preferences within urban areas we have designed and conducted a stated choice experiment in the province of Utrecht, the Netherlands. In the experiment respondents were able to choose from shared bicycles, e-bikes, e-scooters, and e-mopeds to reach their final destination from a PT stop. A sample of 285 respondents considered their last-mile mode choice of a recent PT trip in light of the new options. Results show that shared (e)-bicycles are generally preferred over e-scooters and e-moped; still a majority of the urban PT travellers prefers not to use shared modes. We also found age and cycling experience to be important determinants for using shared modes. Last-mile travel times have a limited impact on the preferences shared mobility as last mile whilst frequent PT use has a negative relationship with using shared modes.

Keywords: Shared Mobility, Mode Choice, Last Mile, Micromobility, Transit

INTRODUCTION

Public transport (PT) brings 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, the travellers needs to bridge the distance to reach the destination. These trip stages are commonly known as the first and last-mile of PT trips.

Satisfaction with PT trips is strongly related to the travel experience in the first and last-mile (*1*). Negative experiences with these trip stages could, therefore, limit the willingness for people to use PT. To improve livability and sustainability in cities, there is an on-going challenge to improve PT systems and, thus, the first and last-mile of PT trips.

Considering a trip from home to work, the first-mile is home-bound and the last-mile activity-bound. For the return trip back home this is vice versa. The work of Hoogendoorn-Lanser et al. (*2*) shows that mode choice differs between home-bound and activity-bound trip stages. One explanation is that the availability of transport alternatives generally differ. For the home-bound legs, instead of walking, many people can use privately-owned means such as bicycles or cars. These could help smoothen this specific trip component. As a consequence, the activity-bound trip part is still problematic as it cannot be easily covered by private vehicles.

In this paper, we specifically analyse first-mile trips that are home-bound and the last-mile to be activity-bound. Therefore, the last-mile throughout the paper will consists of a trip stage that takes a person from a stop (of a bus or tram) to the activity at the destination location (or vice versa). It is mainly this part of a PT trip where shared modes can potentially fill the gap left by the absence of private vehicles; they expand the set of transport means to conduct the last-mile.

Shaheen and Chan (*3*) 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 the presence of an electric (support) engine. Examples of shared micro modes are: shared bicycles, e-bikes, e-scooters, and e-mopeds. They are suitable for large-scale urban use given their small size and limited local environmental impacts (i.e. noise and pollutants).

Nevertheless, there is limited knowledge about which shared modes are preferred by travellers in the last-mile. Yan et al. (*4*) found a correlation between age and acceptance of shared bicycles in the last-mile; younger people show a higher propensity to use them. Adnan et al. (*5*) considered shared bicycles for train travellers in Belgium. Yan et al. (*6*) focused on ride-sourcing for urban PT travellers in Michigan, United States. The study of Yap et al. (*7*) included autonomous driving vehicles as a last-mile alternative for train travellers in the Netherlands.

Apart from these few studies focussing on user preferences for shared modes in the last-mile, fortunately, there are more studies having a more general scope. Most of these studies focus on the user preferences for shared bicycles and e-scooters. 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 (*8*)). We provide an overview on shared mobility preference regards only the first three aspects as they affect mode choice on a larger spatial and temporal scale.

With regards to service requirements, shared bicycles users view convenience, availability and saving money as important attributes for participating in shared bicycle schemes (*9*). The study of Bachand-Marleau et al. (*10*) shows that shared bicycles mainly replace walk and cycle trips, yet also PT trips. Fitt and Curl (*11*) report that shared e-scooters replace walk trips (58%)

and only limitedly replace cycle trips (6%). Bai and Jiao (*12*) produced e-scooter trip statistics (average distance, travel time, and speed) from two US cities and found those range between typical walking and cycling values.

Related to trip characteristics, Fishman (*13*) found shared bicycle use to peak during weekday rush hours and around midday in the weekends. Most bike-sharing scheme members use shared bicycles for commuting (*14*)(*15*). McKenzie (*16*) does not find a shared e-scooter demand pattern with commute peaks and concludes that e-scooters are used for other trip purposes. On the contrary, a German field test showed that e-scooters are most likely to be used for commute, business and leisure trips (*17*). Fitt and Curl (*11*) found more nuanced findings on shared e-scooter trip purpose. First time users are most likely using them 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.

With respect to individual characteristics, many researchers found gender to have an effect on using shared bicycles. Less than 20 percent of the trips within the London bike-sharing scheme are made by women (*18*). The percentage of women in bike-sharing schemes in Melbourne and Brisbane are, respectively, 23 and 40 percent (*9*). The limited use of shared bicycles by women likely relates to a lower inclination for cycling in general. In the UK, the USA and Australia, typically low-cycling countries, most cycle trips (65-90%) are conducted by men Buehler and Pucher (*14*). This differs from the situation in the Netherlands where many people cycle; in this country, women cycle more than men (*19*).

The literature review of Fishman (*13*) shows that shared bicycle users tend to have a higher average income, a higher education status, and a paid occupation. A Chinese survey showed that gender, current cycling level, familiarity with shared bicycles and positive attitudes towards cycling being environmental friendly have the largest impact on using shared bicycles (*20*). 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 (*10*) With regards to shared e-scooters, Jiao and Bai (*21*) found that these are mainly used by young, male and high educated people. In contrast, they found a negative relationship with household income. Degele et al. (*22*) studied the individual characteristics of shared e-scooter users in Stuttgart, Germany. They found most e-scooter users to be male and between the age of 25 and 35.

Not only shared mode attributes will have an impact on user preferences in the last-mile context. Also PT (main stage) attributes impact the last-mile distance accepted by PT travellers. Typically, researchers refer to this distance as the catchment area of a PT stop. Daniels and Mulley (*23*) show that the size of the catchment areas is related to the PT mode being egressed; people tend to accept longer egress distances for trips made by train over trips made by bus.Brand and Hoogendoorn (*24*) and Rijsman et al. (*25*) show that an increase of speed and service frequency for bus and tram is related to larger catchment areas. They also show that for longer last-mile distances, fewer people walk and more people cycle.

To recap, we found that most studies do not focus on a last-mile context. The studies which do only focus on a limited set of modes. Therefore, at this point, it is difficult to explore the trade-offs made by PT travellers in the last-mile; this hinders the possibility to understand which ones should be provided in each case. Another hiatus in research is that user preference studies tend to focus on PT trips done by train; PT trips done using a bus or tram are generally not considered. As a consequence, this leaves the exploration of shared modes as a last-mile solution for local PT largely untouched.

This paper contributes to these knowledge gaps by addressing the preferences of urban bus and tram users towards shared modes in the last-mile. Multiple types of shared modes are included: bicycles, e-bikes, e-scooters, and e-mopeds. The key methodology to explore the user preferences for these modes is by estimating discrete choice models. Input data is collected employing a stated choice experiment. Using this method, we aim to identify the shared modes of transport which facilitate the last mile of many urban PT travellers. This could improve their overall door-to-door PT travel experience. The study area covers the Utrecht province, the Netherlands. This is a suitable study area as an extensive bus and tram network is available, the use of bicycles is largely accepted, and population densities show a good diversity.

We structured this paper as follows. First, we describe the research methodology. Then, we provide more details about the data collection. Next, we provide the results of our study and discuss the main findings. Finally, we provide conclusions based on this study and set out recommendations for future research.

METHODOLOGY

This section first sets out the choice context and attribute levels of the stated choice experiment. Next, we provide more details about the experiment design.

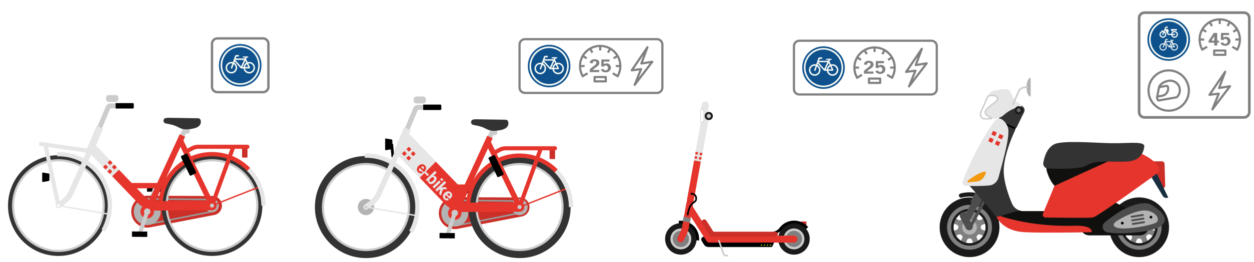

FIGURE 1 The shared modes presented to the respondents in the last-mile mode choice experiment: bicycle, e-bike, e-scooter, and e-moped

Choice context

In our choice experiment, participants reconsidered their last-mile mode choice of a recent PT trip with a bus or a tram. The shared modes shown to the respondents in this experiment were: bicycle, e-bike, e-scooter, and e-moped. We presented these modes both graphically and textually. Figure 1 shows how the shared modes were depicted to the respondents.

Respondents could also choose not to use a shared mode. In this case they could choose to use a private mode (including walking) or cancel the trip. The latter could be chosen when none of the alternatives, and their attributes, would not satisfy their travel needs.

We considered the access/payment method, pick-up/return policy, and pricing scheme to be most crucial for understanding shared mobility. These aspects have been formalized within our experiment and were mentioned to the respondents. Travelers need to use the same PT smart card as in bus or tram. The shared vehicle can be (un)locked by tapping this card onto the vehicle's card responder. Return policies for using shared modes differ between the urban and sub-urban environment. Urban users face a one-way renting policy, allowing them to leave their vehicle at any safe place near their destination. The price for using the shared modes were presented as additional to the PT fare. All shared modes had fixed prices and there were no limitations in place regarding the mileage driven and time spent with these vehicles.

Attribute levels

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

Table 1 provides an overview of the included attributes and its levels. For the last mile we varied the costs (pricing) and the travel time of the shared modes. Prices were varied such that they represented realistic market pricing. We were also interested in how PT travellers would respond to shared modes without any additional charge. We therefore decided to set one of the pricing levels for shared bicycles and e-bikes to zero. The travel times were varied such that they translate last mile distances between 300-1500 metres. We chose to present travel times to the respondents rather than travel distances; This was done as we expected that respondents relate travel impedance more to travel time.

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 reference trip value. The PT in-vehicle travel time was either set equal or 25 percent lower value with respect to the reference trip.

TABLE 1 Attribute levels varied in the stated choice experiment

	Shared Bicycle	Shared E-bike	Shared E-scooter	Shared E-Moped	Private Mode
Last-mile attributes					
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]	
PT (main stage) attributes**					
Frequency (%)	[100,200]	[100;200]	[100;200]	[100;200]	[100;200]
In-vehicle travel time (%)	[75;100]	[75;100]	[75;100]	[75;100]	[75;100]

* = Travel time for private modes were provided with walking time as a reference

** = Reference trip of respondent is considered base level (100%)

Experiment design

We constructed this experiment design by means of the NGENE software package (*26*). Given the novelty of the research subject, we preferred an orthogonal design which enables estimating the effects independently of other included attributes. We used a orthogonal fractional factorial design for the choice experiment. This design consisted of 36 choice tasks. Therefore, we separated three different blocks out of this design in order to limit the participant's cognitive load.

We expected that many participants were not acquainted with shared mobility. They might also have issues understanding novel modes of transport, in particular e-scooters and e-mopeds. For that reason a complete introduction about the modes was provided to the participants. First, we provided a graphic overview of the included modes along with some brief characteristics about them. We listed the applicable driver requirements, traffic regulations and propulsion system. For some modes the driver needs to wear a helmet or possess a driver's license. For each mode the maximum speed and network type (e.g. foot path or bicycle lane) were mentioned. Besides, information was provided about the presence of an electric (support) engine and the need for human effort.

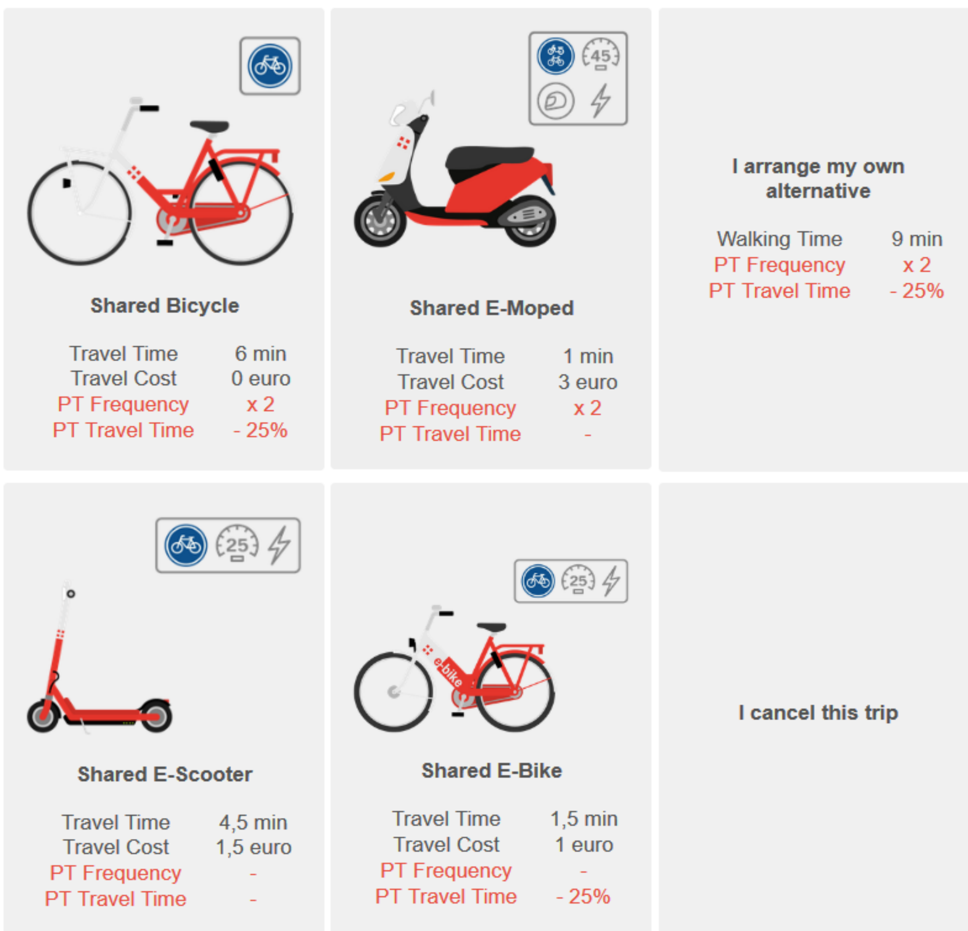

FIGURE 2 Example of one of the experiment choice tasks

Next, we showed the choice context to the respondent. We listed the attributes which were varied during the experiment and explained the meaning of each of these attributes. To strengthen the understanding of the experiment, we repeated the trip details of the reference trip. Finally, before providing the choice situations, we informed the respondent about the (parking) locations in which shared vehicles can be found and the methods regarding payment and (un)locking the shared vehicle.

We provided 12 choice situations to the respondent. Figure 2 depicts what was presented to respondents online. Alternatives which require a valid driver's license were not shown to respondents who did not possess a driver's license. After the choice experiment itself, we added an extra part to our survey. Here, respondents stated to what temporal extent they perceive difficulties with regards to visual, hearing and physical impairment. In the survey, physical impairment referred to the ability of walking and climbing stairs. We also surveyed whether the respondent experiences difficulties understanding the PT system.

MODEL SPECIFICATION AND ESTIMATION

We estimated three different types of discrete choice models and compared their performances to find the most statistically significant model representation of the respondent's stated choice behaviour. Apart from a multinomial logit (MNL) model, we estimated more complex ones such as nested logit (NL) models, panel-effect models and mixed logit (ML) models. Background information on these discrete choice model specification can be found in e.g. Train (*27*) and Hensher et al. (*28*).

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 $U_{int} > U_{jnt}$, $j \neq i$.

Eq. 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 consist of $\beta_{int}^{'}$ 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) Gumbell distributed.

$$U_{int} = V_{int} + \varepsilon_{int} = \beta_{int}^{'} * x_{int} + \varepsilon_{int}, \in C_n \tag{1}$$

NL model specifications 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.

The panel-model mixes the specification of a MNL model 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 Gumbell IID for each respondent and choice task. In our model specification, we consider the panel effect parameter α_{in} to be N(0,sigma) distributed for each alternative i and respondent n. Eq. 2. describes the utility function within the panel-effect model specification.

$$U_{int} = V_{int} + \alpha_{in} + \varepsilon_{int}^{'}, \in C_{nt} \tag{2}$$

A ML model allows for the estimation of distributions around parameters which are the result of heterogeneity of preferences between respondents. This coefficient ξ_{int} represents the distribution independently over each respondent and choice task. In our model, we consider ξ_{int} to be N(0,σ_{int}). Eq 3. describes the utility function in the ML model specification.

$$U_{int} = V_{int} + \alpha_{in} + \xi_{int} + \varepsilon^{'}_{int}, \in C_{nt} \tag{3}$$

We estimated all models using the Python Biogeme software package (*29*). We aimed to identify the model which provides the most statistically significant representation of the choice behaviour. We therefore defined a number of performance measures: the percentage of correctly predicted choices, the log-likelihood ratio and the adjusted Rho-squared as performance measures. The first is a direct measure of the predictive power, while the latter two are measures for the model's statistical fitness to the data.

We started with the estimation of a MNL model. During this process, we extended the MNL model by adding parameters until the log-likelihood ratio stopped improving significantly. This MNL model was considered the best MNL model. Next, we introduced the variables which provided significant parameters in the MNL model in the specifications of the panel-model and the ML model. The more complex structure of these models causes some parameters to become insignificant. We therefore left these parameters out and reintroduced some of them such that we could not significantly improve the log-likelihood ratio anymore. In all estimated models, "not using shared modes" was defined as the reference alternative with its alternative-specific constant fixed to zero.

DATA COLLECTION

This section describes the context in which the data collection took place. Next, we provide the statistics of the people who participated in the survey.

Case study: province of Utrecht

We collected our survey data in the province of Utrecht, the Netherlands. This province is densely populated (904 $inh./km^2$) and is located in the centre of the Netherlands. Many of the 1,34 million people inhabitants live in cities such as Utrecht, Amersfoort or Veenendaal.

The province of Utrecht possesses a large local public transport network. As such, it complements the extensive network of train services which provides direct connections to many Dutch regions. Within the cities and their direct surroundings, local PT is provided mainly through bus services, yet there are also a few tram services available. Most of these are provided on high frequency schedules (>6 vehicles/hour).

We have conducted our survey from January 20 until February 17, 2020 which did not include the covid-19 health crisis. Only people who had done a local PT trip in Utrecht over the last three months were included in the survey. We used two different methods to approach these PT users. One method consisted of a short in-vehicle survey in order to establish the composition of the PT user population. Then, these participants were invited by e-mail for a follow-up survey which included the stated choice experiment. In addition, we launched a website for direct access to the experiment, divulged by digital adds shown on the in-vehicle displays.

The Qualtrics tool (*30*) 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 activity location. We cross-referenced this information with a database from the Dutch census consisting of postal codes and a 5-level urbanization classification (*31*). We considered PT trips to class 4 and 5 (urbanized and strongly urbanized) activity-locations to be urban. PT trips to acitivity-locations with a lower urbanization classification have not been considered in this study.

Sample statistics

Our stated choice experiment was answered by a sample of 285 urban respondents. We have compared these sample statistics with the composition of the PT user population which was found by means of the previously mentioned short in-vehicle survey. This survey consists of 2363 travelers and, therefore, provides a good representation of the population of local PT travelers in the province of Utrecht. Table 2 provides an overview of the sample composition.

The sample statistics show that survey participants tend to be older than the average population. Our sample under represents 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 than in the population; the sample consists of fewer education trips. Instead, the travelers 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 practice where more women can be found in local PT. The number of travelers with a high income is under-represented in our sample. We consider the deviation between population and sample as self-selection bias. We argue that travelers who are more interested in local PT (e.g. frequent PT users, dependency on local PT) are more likely to participate in our survey.

RESULTS AND DISCUSSION

First the performances of the estimated discrete choice models are compared. Thereafter, we provide the model estimation results from the best performing model.

Model performance comparison

We estimated a MNL model, a Panel-effect model and a ML model. We compared the performance of each of these models in order to find the model specification which describes the choice data the best. The model performances were compared by means of the following measures: Log-likelihood ratio, Rho-squared, Adjusted rho-squared, and the number of correctly predicted choices. The comparison of the model performances is set out in Table 3.

We found that the performance of the MNL and ML model to be comparable. Because the ML model provides additional information (heterogenity in preferences and a panel effect) we consider the ML model to have the best performance.

TABLE 2 Sample statistics of the respondents compared to the average in-vehicle in the province of Utrecht, the Netherlands

	Local PT travelers Utrecht	Urban sample
Gender		
Male	43%	48%
Female	57%	52%
Age		
<18 years	17%	4%
18-25 years	42%	27%
26-45 years	23%	31%
46-65 years	14%	29%
>65 years	4%	9%
Gross monthly income		
< 2000 euro	64%	47%
2000-4000 euro	10%	33%
> 4000 euro	26%	20%
Household composition		
Single-adult, children	8%	4%
Single-adult, no children	29%	34%
Multi-adult, children	33%	21%
Multi-adult, no children	29%	41%
Driver's license possession		
Yes	56%	70%
No	44%	30%
Private car access		
(Almost) always	35%	52%
Sometimes	27%	22%
(Almost) never	38%	26%
Trip purpose		
Commute	34%	39%
Education	33%	18%
Visit family/friends	11%	11%
Leisure	7%	5%
Shopping	5%	5%
Business	6%	10%
Medical reasons	2%	10%
Other	1%	2%

TABLE 3 Overview on the performance measures of the considered model specifications

	MNL	Panel-effect	ML
Sample size	3420	3420	3420
Included parameters	67	42	43
Initial log-likelihood	-5020.15	-5020.15	-5020.15
Final log-likelihood	-3154.301	-3264.36	-3185.129
Likelihood ratio test	3731.427	3511.310	3669.771
Rho-squared	0.372	0.35	0.366
Adjusted Rho-squared	0.358	0.341	0.357

Mode characteristics

Table 4 provides the results of the estimated model. 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. We found all constants, except for shared e-scooters, to be negative and significant. This indicates that most shared modes have a certain variance in utility that cannot be explained by the explanatory variables. In general, we think that attitudinal beliefs contribute most to this unexplained utility. The alternative-specific constant is the least negative for e-moped, yet also the constant for e-bike is less negative than the constant for the non-electric bicycle has. Apparently, it is more difficult to explain all variance in utility for e-bikes than for bicycles. It could be that limited experience with e-bikes plays a role here. Van Cauwenberg et al. (*32*) mention that perceptions on safety, battery range, social stigma ("e-bike is cheating") and the weight of e-bikes could also be important factors.

To add, the panel effect σ_{Panel} are also large for each shared mode, except for the shared e-scooter. This shows that the choices made by an individual respondent are correlated for these modes. The σ_{Panel} for shared bicycles and e-bikes are so large that the sum of $\beta_{Constant}$ and σ_{Panel} can be larger than zero, implying that the unexplained utility of these alternatives can be larger than for the non-sharing alternative. This shows that for some people there is a larger chance they will prefer one of the cycling modes over not sharing. Both the e-scooter constant and panel effect were near-zero and non-significant. Therefore we consider both values to be zero.

We found that travel time only significantly affects the use of shared bicycles and not using a shared mode. It could be that the last mile itself causes most disutility, with the distance covered therefore being less important. Another explanation might be that the travel time ranges of the other modes are smaller, such that people do not perceive a significant difference between travel time variations.

Model results also show that travel costs have a negative impact on the likelihood of using a shared mode. The effect size was largest for shared e-bikes and e-mopeds. It could be that users of shared bicycles and e-scooters perceive these modes to add more value and are therefore less sensitive for pricing changes. Research on the use of e-scooters suggests that users might not only pay for transport, yet also for the fun related to using e-scooters (*17*)(*11*).

TABLE 4 Estimation results from the ML model specification

	Shared Bicycle		Shared E-bike		Shared E-scooter		Shared E-moped		Not Sharing	
	coef.	t-test	coef.	t-test	coef.	t-test	coef.	t-test	coef.	t-test
Mode Charact.										
β_{ASC}	-5.56	-2.36**	-17.0	-2.53**	-0.259	-0.360**	-51.3	-2.21**		
σ_{Panel}	6.97	2.85**	-16.5	-2.61**	-0.360	-1.02	-29.3	-2.39**		
β_{Costs}	-0.917	-5.42**	-2.19	-2.69**	-0.614	-3.03**	-1.62	-2.14**		
β_{Time}	-0.14	-4.06	-0.13	-1.50						
Individual Charact.										
$\beta_{Cyclehigh}$	0.884	3.52**	2.18	2.37**						
β_{PThigh}	-0.259	-1.12			-1.29	5.53**				
$\beta_{Incomelow}$	1.10	3.72**			-1.41	-6.36**				
β_{Young}	4.78	2.24**	14.0	2.54**	1.33	4.02**	13.3	2.11**		
σ_{Young}	-8.20	-3.13**	10.7	2.37**						
β_{Old}	-4.48	-3.03**			-1.46	-5.02**	4.48	1.67*		
$\beta_{D.Walk}$									-0.673	2.15**
$\beta_{D.Underst.}$									0.726	2.80**
Trip Charact.										
$\beta_{Commute}$					-0.913	-3.56**	5.14	2.24**		
$\beta_{Subscription}$	0.740	2.87**	0.751	1.21	1.19	5.53**	6.93	1.84*		
$\beta_{Weekend}$	-0.765	-2.32	-1.71	-1.90*	-2.30	-4.79**				
$\beta_{Cyclefirst}$	-1.54	-2.71**								
$\beta_{Cyclelast}$			5.42	2.51**			20.4	2.06**		

Base = not sharing
** = significant on a 95% confidence level. * = significant on a 90% confidence level

Individual characteristics

The final model results show that age is a strong determinant for choosing a shared mode in the last mile. We found that younger people (< 26 years) are more likely to use a shared mode; in contrast to older people (>45 years) who are less likely to use a shared mode. The one exception is the use of e-mopeds by older people; the respective coefficient has a positive value. We found that including heterogeneity in preferences for young people improved the model performance.

This is in the general line of other studies on shared mobility (*4, 21, 22*). Attitudes and capabilities which are more prevalent among young people could provide an explanation for this age effect. Alonso-González et al. (*33*) studied the attitudes towards other emerging transport paradigms: demand-responsive transport and mobility-as-a-service. They 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. In addition, these groups seem to be more tech-savvy as they feel very comfortable in using mobile apps for using transport services.

Furthermore, we found that having a low income (<2000 euro) relates positively with the preference for shared bicycles. On the contrary, our results show a negative correlation between lower incomes and the preference for shared e-scooters. This could be explained by the travel costs attribute ranges for e-scooter being larger and higher than for the bicycle. In some scenarios, the shared bicycle was available without any additional charge which could attract travellers who have less money to spend. Other studies show a negative correlation between income and the propensity to use shared e-scooters and e-mopeds (*21*)(*34*). It is uncertain whether this effect will also hold in the last-mile context. Aguilera-García et al. (*34*) state that people with higher incomes will replace shared e-mopeds by privately-owned vehicles as soon as they are able to afford these. This substitution behaviour which will likely not be present in the context of the last-mile; PT travellers already chose to use public transport in the first place. For that reason, it is likely that their last-mile mode choice is determined by the same mode and trip attributes as their initial choice for PT was based upon.

The situation on income and shared bicycles seems to be more nuanced. Fishman (*13*) found a positive relationship between income and the use of shared bicycles. Although, he also found the ability to save money to be an important driver to use shared bicycles. 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 cheap alternative in the last-mile.

We were not able to establish a gender effect based on the collected data. In contrast to other studies on shared mode preferences Fishman et al., Buehler and Pucher, Goodman and Cheshire (*9, 14, 18*). Also here, we expect that the Dutch cycling culture plays an important role. The findings of Ton et al. (*35*) seem to underpin this statement. In their elaborate study on Dutch active mode choice behaviour also no gender effect was found.

We also found mobility behaviour to be an important choice determinant. Travellers who also cycle regularly (min. 4 days/week) are more likely to choose a shared (e-)bicycle. This result seems plausible given that people are specifically appealed by modes they are already using. In addition, people who regularly use PT are less likely to use a shared bicycle or e-scooter. We expect habits and the commitment towards PT to play an important role for this group. Consequently, they might have a more reserved attitude towards sharing. We expect habits and the commitment towards PT to play an important role for this group. Many studies show that uni-modal trips by shared bicycles often are a replacement for PT trips (*9*)(*13*)(*15*)(*36*). This indicates that many PT travellers prefer substituting PT completely by using a bicycle rather than combining these two modes.

Lastly, we found some relationships between experiencing difficulties in PT and the preference for not using a shared mode. PT travellers who experience difficulties with walking are more likely to conduct the last mile using a shared mode. A reasonable explanation is that shared modes can be an alternative for walking. However, we did not find a particular shared mode favoured by people who experience walking issues. Travellers who experience difficulties understanding the PT system are more likely to conduct the last mile without using a shared mode. We expected this result as the use of shared modes adds complexity to the trip.

Trip characteristics

We first found that trip purpose affects the likelihood of using shared modes. People travelling to work show a lower preference to use a shared e-scooter, yet a higher preference to use an e-moped than people with other trip purposes. The effect found for shared e-scooters seems to be in contrast with previous studies; most of them emphasize that many trips by e-scooter are made for commuting purposes (*11, 15, 17*). We think that attitudes, and more specifically with regards to status or image, are likely to play a role for commute trips

Model results also show that having a local PT subscription increases the likelihood of using any shared mode. One explanation might be that they are committed to using PT and are open to shared modes for improving their trips. As these people only pay out-of-pocket cost for the shared modes, they might feel a lower financial burden to include shared modes in their trip.

Next, we found that weekend travellers have a lower preference for using a shared mode than traveller during weekdays. This effect is the strongest for e-scooters. It is likely that weekend trips are being less frequent which lowers the need for improving the travel performance.

Furthermore, our results show that travellers who made a transfer between local PT services (bus-to-bus for example) are less likely to use a shared e-scooter of e-moped in the last-mile. It might be that these travellers do not want to increase their trip complexity by using other modes.

Moreover, current cycling in the first and last-mile impacts the preference of using a shared mode. People who cycled from their origin location to a PT stop are less likely to use a shared bicycle in the last mile. Contrastingly, last-mile cyclists are more likely to use an shared e-moped or e-bike. We argue that travellers do not want to cycle on both trip ends, as this might require a greater amount of physical effort. On average, last-mile cyclists cover a longer distance than last-mile walkers (*24*)(*25*). For that reason they might feel a higher need to improve the last-mile by using a shared mode.

CONCLUSION

The aim of this paper was to identify which shared modes of transport are preferred by urban PT travellers in the last mile. The integration of these modes with local PT could improve the overall door-to-door travel experience. Up to now, trade-offs between multiple shared modes, specifically in the context of the last-mile, have only been limitedly considered in scientific literature. We estimated discrete choice models based on data from an stated choice experiment. In the experiment, respondents reconsidered their last-mile mode choice in a recent PT trip made by bus or tram. The sample was collected among 285 urban PT travellers in the province of Utrecht, the Netherlands.

We found that shared bicycles, both conventional and electric bicycles, are generally preferred over e-scooters and e-mopeds. A majority of the urban PT travellers, however, prefers not to use a shared mode in the last-mile. Those travellers will mainly walk to their destination. These results indicate that PT travellers do not necessarily want to avoid physical exercise. This is likely also the result of the limited distance which needs to be covered in the urban last-mile. This could also explain the low propensity to use shared e-scooters and e-mopeds in the last mile.

The preference for shared (e-)bicycles could partially be explained by existing high cycling levels in the Netherlands. Shared e-bikes are generally not preferred over non-electric bicycles. However, current cycling behaviour has a stronger effect on the preference for shared e-bikes than for bicycles; this is the case for frequent cyclists and people who already cycle in the last-mile.

Our study confirms the importance of age on user preferences for shared modes, which was also found in other studies. We found a strong relationship between age and the preference for shared modes; people up to the age of 26 are more willing to use shared modes in the last-mile than older people. In addition, we were able to find a strong heterogeneity in preferences among this group of young PT travellers. This shows that shared modes are not necessarily adopted by all young people.

We found that frequent PT users are less likely to use shared modes for their last mile. We expect this is caused by their existing travel habits; they might not be open to consider alternatives for the current last-mile travel behaviour. Interestingly, we found that having a PT subscription increases the probability to use shared modes.

As being said already, existing cycling behavior is an important determinant for using shared modes in the last mile. Regular cyclists are more likely to prefer shared (e-)bicycles over other shared modes. In case PT travellers already cycle in the first mile, they are less likely to use a shared bicycle in the last mile. A possible explanation is that a local PT trip with cycling on both sides of the trip is less attractive to many people than travelling directly by a bicycle. However, if travellers currently use a privately-owned bicycle in the last mile, they are more likely to shift to use a shared e-bike or e-moped in this trip stage. These modes might better meet the needs of these travellers, while leaving out the need for having a privately-owned bicycle available at the egress stop.

In contrast to other studies, we did not find a gender effect. We expect that Dutch cycling culture had a significant impact on our experiment; cycling is well-established in the Netherlands such that, other than in many countries, women cycle more than men. We also did not find a relationship between commuting as travel purpose and increased preferences for shared modes in the last mile. Although, PT trips made during the week are more likely to be combined with a shared mode in the last mile than weekend trips. This suggests that PT trips made on a more structural basis are more likely to be combined with a shared mode in the last mile.

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. We, however, do not advise to provide these at all stops, as many vehicles would probably be left unused. Major PT stops and transfer hubs seem to be most suitable as demand for shared modes can be centralized here more easily. Compared to decentralized distribution, this will induce longer last-mile travel times, but our results show that this is not very important for users of shared modes in this trip stage.

We advise to focus on conventional shared bikes as this will likely attract the most users. The supply of shared e-bikes would specifically help to replace the use of private bicycles in the last mile. This is interesting if there is a need to lower the demand for bicycle parking at PT stops and stations, specifically if existing parking capacity is insufficient. Both e-scooters and e-mopeds are likely to only serve niche markets. Although, the e-scooter might address the needs of some young people. We advise to follow-up developments on the e-scooter markets; it is not unlikely that e-scooters will appeal to a larger group and for more structural trip purposes.

Based on these conclusions we identified a number of important directions for future research. Most importantly, more insights are needed with regard to the attitudes which determine the preferences for shared modes. This requires a more qualitative research approach and the inclusion of testing attitudinal statements. In addition, it is important to address the found heterogeneity in user preferences. This will further support the actions to be taken by PT operators and authorities to improve the last-mile and the overall door-to-door travel experience. This could for example be done by latent class analysis. Further, we would advise exploring shared mode preferences in different contexts. It is likely that the built environment, infrastructure and cycling infrastructure had an important role in our research findings. Specifically, we suggest studying shared mode preferences outside the urban context and in a low-cycling context.

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