

What drives the utility of shared transport services for urban travellers? A stated preference survey in German cities

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ABSTRACT

The supply of shared mobility solutions has been increasing during the last years, so has the popularity of Mobility-as-a-Service. Both promise an easy access to and usage of shared vehicles or shared rides. Nevertheless, usage of these services remains low in German cities. Hence, the question arises: what determines the utility of travellers regarding shared modes and how is this different to conventional modes? To answer this, we conduct a stated preference experiment amongst 1,445 respondents (8,670 observations). The sample is drawn from residents of the 83 largest cities in Germany. We consider four shared (e-scooter-, bike-, carsharing, and ridepooling) and three conventional modes (walking, private car, and public transport). We estimate a mixed logit model and calculate the respective value of travel time (VoT) as well as the value of access, egress, and parking search time. The importance of the individual attributes is analysed drawing on a part-worth analysis. Further, we calculate average treatment effects to show simulated mode-choice probability changes. We find that costs are more important than travel time for carsharing and ridepooling whilst they are equally important for the remaining modes. For shared services, access is more important than egress. Moreover, among the shared services, e-scootersharing shows the highest VoT (23.73 EUR/h), followed by bikesharing (18.53 EUR/h). Finally, cost changes to private cars and public transport show the highest simulated shifting potential with carsharing profiting most from cost increases in these two modes.

1. Introduction

The supply of shared mobility services has been on the rise in recent years (ITF, 2020). The umbrella-term Mobility-as-a-Service (MaaS) has also increasingly gained public attention globally (Schikofsky et al., 2020). This holds for Germany, too: with Jelbi, there is already one MaaS-platform in Berlin (Jelbi, 2019). Another platform in the region around Karlsruhe has been launched (Regiomove, 2021). Despite this growth in supply, the usage of shared services or MaaS is still rather low (Nobis and Kuhnimhof, 2018). Why is that? This paper addresses this question for German cities by analysing key service characteristics determining the usage of shared mobility in a stated preference (SP) experiment. For this, we quantify the difference in modal choice behaviour between the “conventional” modes, i.e. private car, public transport (PT), and walking and the new shared modes, i.e. e-scooter, bike- and carsharing, and ridepooling. We thereby provide insights into strengths and weaknesses of shared modes, which are the baseline for possible policy frameworks supporting modal shifts from private cars

towards shared modes. In a first step, we elaborate on recent work about the four shared modes considered in our analyses.

1.1. Recent work about bike- and e-scootersharing

Two of the four shared services analysed here, e-scooter- and bike-sharing, comprise what is referred to as shared micromobility. Micromobility targets to cover short distance trips as well as the first or last kilometer (Abduljabbar et al., 2021; Adnan et al., 2019; Wu and Kim, 2020). Vehicles used for micromobility are light-weight, small and do not reach speeds of above 45 kph (Abduljabbar et al., 2021). Bicycles and scooters belong to the vehicles of this category, regardless of whether they are human-powered or electric (Abduljabbar et al., 2021). They can be privately owned or shared, the latter of which gives users short-term access to these modes (Shaheen et al., 2020). The shared micromobility landscape has grown rapidly in recent years and includes various services: station-based (or docked) and free-floating (or dockless) bikes or e-bikes as well as e-scooters (Reck et al., 2021). Our

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analyses include shared standing electric scooters as well as shared human-powered or electric bicycles.

As Reck et al. (2021) point out, previous work about shared micromobility either deals with the supply- or the demand-side with the latter focusing on internal, external or trip-related questions. Internal questions deal with users' socio-demographics. External ones consider, amongst others, the built environment or the weather. Trip-related questions target destinations, distance, and time of day (Reck et al., 2021). This paper focuses on external demand-side factors, specifically on the characteristics of the service and trips themselves. Further, bikesharing has been on the agenda of previous work for much longer than e-scootersharing as the latter has only recently been added to the travelers' choice set (Reck et al., 2021). In particular, e-scootersharing is used for shorter trips with average distances of 0.7 km (Reck et al., 2021) and maximum distances of 3.2 km (Smith and Schwieterman, 2018). Bikesharing, on the other hand, is used for slightly longer trips averaging in the range of 1.3 to 3.1 km (Reck et al., 2021; Lazarus et al., 2020). Due to its size and speed, shared micromobility increases accessibility (Abduljabbar et al., 2021) to PT (Shaheen et al., 2013; Abduljabbar et al., 2021; Bai and Jiao, 2020) and social equity by facilitating less mobile user groups' participation in social life (Milakis et al., 2020; Sanders et al., 2020).

Regarding shift potentials, bikesharing enables a reduction in car usage (private and taxi), an increase in cycling and support for or complement to public transit (Martin and Shaheen, 2014; Guidon et al., 2019; Link et al., 2020). However, free-floating bikesharing can also substitute walking for trips under 1 km or the bus for trips below 2.5 km (Gao et al., 2021), especially in case of pedelecs (Campbell et al., 2016). Car trips are only replaced in 1% of the cases (Link et al., 2020). E-scooters are seen as a convenient and faster alternative to walking, replacing substantially more walking than private car trips (Sanders et al., 2020). Although distances vary between free-floating and station-based bikesharing trips, reasons to try and use any of the systems are similar, namely high bicycle (station) availability and a user-friendly smartphone application (Link et al., 2020; Maas et al., 2020; Bachand-Marleau et al., 2012). However, the supply density of shared micromobility modes shows a 'plateau effect', i.e. decreasing marginal utility gains with increasing densities (Reck et al., 2021). Low costs and quality of bicycles are no significant factors to use bikesharing (Link et al., 2020). Whilst a potential competition is found for non-members of free-floating e-scootersharing and station-based bikesharing, a complementary relationship is found for members of the two services (Younes et al., 2020). Reck et al. (2021) find that with increasing trip length, the probability of choosing e-scootersharing decreases whilst the probability of choosing e-bikesharing (free-floating and station-based) increases. Moreover, higher battery charge increases choice probability although the impact is small, whereas price increases negatively effect micromobility mode choice (Reck et al., 2021). Regarding mobility tool holdings, a PT pass as well as a carsharing membership positively affect bikesharing memberships (Link et al., 2020).

1.2. Recent work about carsharing

Compared to shared micromobility, carsharing has been on the market for much longer with its first implementation dating back to 1948 in Zurich (Harms and Truffer, 1998). Despite recent new types of carsharing, the fundamental principle remains the same: individuals have access to a fleet of vehicles and can book and use them as needed (Shaheen et al., 1998). Today, free-floating, station-based and combined schemes exist (Becker et al., 2017; Rotaris et al., 2019). Like bikesharing and e-scootersharing, vehicles are shared sequentially (Bösch et al., 2018). While free-floating carsharing is especially used for saving time relative to other modes, station-based carsharing is used when a car is required for a specific purpose (Becker et al., 2017). Both schemes include shift potentials away from the private car (Becker et al., 2018; Clewlow, 2016; Jochem et al., 2020; Namazu and Dowlatabadi, 2018;

Rotaris et al., 2019; Zhou et al., 2020a). Also, car ownership is a crucial predictor for adopting free-floating and station-based carsharing (Yoon et al., 2017; Zhou and Kockelman, 2011). For German cities, Giesel and Nobis (2016) find reductions of car ownership by 7% and 15% for free-floating and station-based carsharing, respectively. Moreover, a 1% decrease in cost results in a 0.34% increase of the probability of choosing carsharing (Carroll et al., 2017). Using data from college students in Rome and Milan, Rotaris et al. (2019) show that the combination of lower costs and electric cars can increase the share of users from 2% to 10–15%. Moreover, carsharing membership is found to increase usage of PT and active modes by a factor of 1.4–1.5 (Göddeke et al., 2021). Applying a greater level of detail, Le Vine et al. (2014) find that station-based carsharing complements PT while free-floating carsharing substitutes it.

1.3. Recent work about ridepooling

Ridepooling is an on-demand service enabling the customer to book a ride (Alonso-González et al., 2020a; Shaheen and Cohen, 2018) leading to simultaneous sharing of the vehicle (Bösch et al., 2018). The pooling refers to the service characteristic that the user might have to share the ride with other passengers (Alonso-González et al., 2020a). If the possibility of sharing a ride with strangers is not given, this service is today referred to as ridehailing (Lavieri and Bhat, 2019b). Comparing ridepooling and ridehailing, Kang et al. (2021) find that users are willing to pay 0.62–1.32 USD (0.53–1.12 EUR¹) to not have to pool the ride. Vij et al. (2020b) find cost to be the most important attribute towards using ridepooling or ridehailing. They estimate values of 0.28 AUD (0.18 EUR²) per km and more for passengers to avoid pooling the ride. Furthermore, detour time or additional pickups of passengers are found to be barriers to using the service (Lavieri and Bhat, 2019b; Yan et al., 2019), even greater ones than the pooling with strangers itself (Lavieri and Bhat, 2019b). Using a discrete choice experiment, König and Grip-penkoven (2020) show that ridepooling as a user-centered service meets the requirements of potential users. Reduced waiting and in-vehicle time is another strength of ridepooling (Yan et al., 2019). Compared to the private car, ridehailing complements it more than it competes against it (Habib, 2019). Even though findings differ (Malalgoda and Lim, 2019), this might also hold for PT (Hall et al., 2018; Vij et al., 2020b; Yan et al., 2019). Previous work also indicates substitution effects towards active modes or PT with the effect being more severe in the case of ridepooling (Lavieri and Bhat, 2019a).

Previous work about integrating different (shared) modes into one analysis often focuses on MaaS, portfolio choices, and bundle choice (e.g. Becker et al., 2020; Guidon et al., 2020; Ho et al., 2020; Mulley et al., 2020; Vij et al., 2020a). Work on mode choice regarding different shared transport services as well as private car and PT is scarce (Wilkes et al., 2021; Miramontes et al., 2017), particularly for Germany. As Reck et al. (2021) point out, current analyses can be extended specifically with respect to micromobility mode choice by including user-specific attributes such as mobility tool ownership. Comparing single services and bundles, (Guidon et al., 2020) also conclude that more information about the respondents should be added to the choice models in order to better understand mode choice towards shared services. Moreover, the authors suggest to integrate additional modes.

We address this research gap by integrating four shared, including micromobility, and three conventional modes into a stated choice experiment and paying particular attention to mobility tool holdings of the respondents. Our SP-design contains all relevant shared transport services as well as private cars and PT. In doing so, we provide a direct comparison between these modes and, thus, shed light on the differences in mode choice behaviour regarding the alternatives in urban contexts in

¹ Exchange rate 1 USD = 0.85 EUR as of 13.07.2021.

² Exchange rate 1 AUD = 0.63 EUR as of 13.07.2021.

2. Material and methods

2.1. Survey instrument

To answer the questions raised above, we use SP-experiments. Here, respondents face hypothetical scenarios of mode-choice, which allows analysing trade-offs between modes (Alonso-González et al., 2020b; Louviere et al., 2010). Mode-choice experiments, also including shared services, are regularly implemented by using SP-designs (Alonso-González et al., 2020b; Guidon et al., 2020; Jin et al., 2020; Liao et al., 2020; Márquez et al., 2019; Schmid et al., 2018; Shen et al., 2020; Yoon et al., 2017; Zhou et al., 2020b).

Sampling took place via an online-panel (Norstat Germany) and respondents were located in larger cities or metropolises at the time of the survey. Focusing on the urban environment, the selection of cities is based on the RegioStaR7 scheme and includes those of categories 71 (metropolis) and 72 (regiopolis and large cities, BMVI, 2020). This is motivated by the supply of shared services, which is still highly concentrated in larger cities. In total, 83 cities were part of the sampling process. The map in Fig. 1 shows the surveyed cities.

The sample was selected using fixed quotas for age, gender, and education to match the German urban population as in Eurostat (2020). In total, $N = 1,779$ respondents answered the survey from 27th of August until 25th of September 2020. Hence, the Covid-19 pandemic might have affected the results, which we elaborate on in the discussion. All persons with a driver's license were eligible for this survey. To create realistic choice situations, respondents were randomly selected into one of two sub-samples. One dealt with short- (SD), the other with medium-distance (MD) trips and respective alternatives in the SP-experiments (see Section 2.2). The two sub-samples do not significantly differ in terms of quotas selected for the sampling process. The data preparation process is shown in the data flow chart in Fig. 2. The 'SP data (SD)' and 'SP data (MD)' data sets contain all information of the choice sets (i.e. attribute levels) and the respective choices of the respondents. We combine these data sets in order to build a data set ('SP data') comprising all choices of all respondents. Subsequently, we merge the personal data, i.e. socio-demographics and mobility tool holdings, to 'SP data' in order to generate one data set covering all information needed for model estimation and postestimation as well as further analyses.

Table 1 provides an overview of the sample's key socio-demographics and mobility tool holdings. Numbers are compared to the largest data set for transport behaviour in Germany "Mobilität in Deutschland" ("Mobility in Germany", MiD, BMVI, 2019). The

Table 1

Socio-demographic and mobility tool ownership characteristics of the sample.

Characteristic	Level	Sample	MiD 2017	Test of difference
Gender	Female	49.2 %	51.2 %	$p = 0.15$
Age	18–29	7.6 %	19.7 %	$p < 0.01$
	30–39	16.3 %	18.0 %	
	40–49	23.3 %	16.1 %	
	50–59	22.1 %	16.5 %	
	60–67	14.9 %	10.0 %	
	> 67	15.8 %	19.7 %	
Net income of household	< 500 EUR	2.0 %	0.01 %	$p < 0.01$
	500–1,999 EUR	36.0 %	18.2 %	
	2,000–3,999 EUR	44.0 %	41.6 %	
	≥ 4,000 EUR	18.0 %	39.5 %	
Location is metropolis		61.3 %	55.4 %	$p < 0.01$
No. of cars in household		1	1	$p = 0.40$
Bike accessibility in household		always	2 per household	–
PT pass		41.6 %	34.2 %	$p < 0.01$

respective sub-population residing in the classified cities is taken as basis for the comparison. To allow statements about the German population within the RegioStaR 71 and 72 cities, we use the respective expansion factors as weights. The χ^2 goodness of fit and the t-test is used to analyse the differences. 49.2 % of this sample are female compared to 51.2 % in the comparison data. The age distribution shows that our sample is slightly older (averaging 50.9 vs. 48.6 years) with a lower share of people aged 18–29. Considering the net income of the household, our sample has more lower income respondents. More people with little or no salary might have been motivated by the incentive during the pandemic. The share of people living in a metropolis is larger in our sample (61.3 % vs. 55.4 %). In both data sets, there is on average one private car per household. Holding a PT pass is more popular within our sample (41.6 %). This might be a consequence of the lower income shares since these more frequently have a PT pass in Germany (BMVI, 2019).

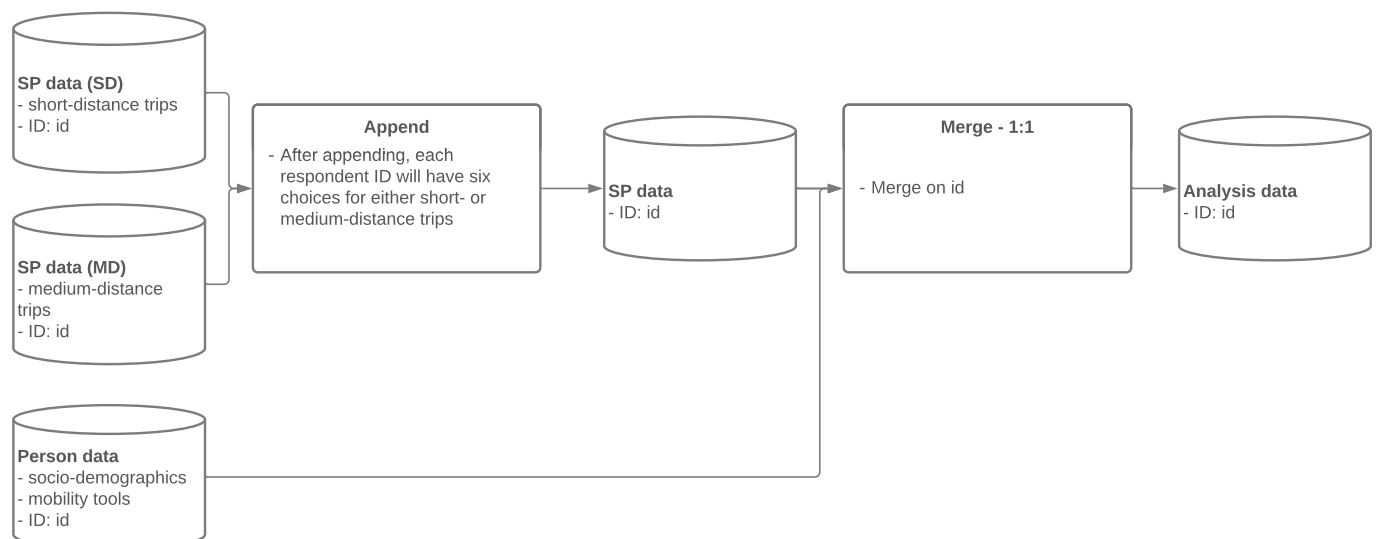


Fig. 2. Data flow chart of the data preparation process.

2.2. Stated preference design

The SP-design contains six choice situations and four alternatives per subject. It is integrated in a survey containing additional information regarding respondents' socio-demographic characteristics and mobility tool ownership. Trips are intra-urban leisure trips in the city of residence. The SP-design for SD contains e-scootersharing, bikesharing, walking, and the private car. The SP-design for MD contains carsharing, ridepooling, PT, and the private car. Subjects were introduced to the two shared modes included in their choice sets (i.e. either e-scooter- and bikesharing or carsharing and ridepooling) and the setting of the choice situation (place of residence, intra-urban, leisure, no luggage). In order to receive mode-choice decisions, respondents were told to not worry about being a member of any service or not.

Tables 2 and 3 show the SP-designs. Trip length was kept equal per choice set. In the respective urban population, almost 90 % of all urban trips in Germany are between 0 and 20 km (BMVI, 2019). 54.4 % of all trips are 4 km or less (BMVI, 2019). 35.5 % of all trips are between 4 and 20 km (BMVI, 2019). Choosing lengths of 0.5–4 km as SD and 2–20 km as MD trips, we hence cover almost 90 % of the trip length range in German cities.

Table 2 shows the attribute levels for the SD trips. To analyse travel time in greater detail, we differentiate between net travel, access, egress, and search for parking time in minutes. Travel time is integrated into similar experiments on shared mobility in previous work (Carroll et al., 2017; Ciari, 2012; Li and Kamargianni, 2019; de Luca and Di Pace, 2015; Schmid et al., 2019). We calculate the net travel time based on average speeds of the modes (BMVI, 2019). Additional intermediate levels of trip length are included to avoid generating linear relationships between trip length and travel time. As e-scooters are not included in BMVI (2019), these travel times are calculated using pedelecs. For access and egress times, values are based on previous experiments (Becker et al., 2020; Wu et al., 2019). The scheme of the two shared services could be station-based or free-floating as both is available to the users. For station-based services, parking search time is 0. Availability is introduced since e-scootersharing and bikesharing usually do not offer a pre-booking service but only a short reservation. Hence, there is no guarantee for the user that the vehicle is still available by arrival. Travel costs are calculated based on real values in accordance with the respective travel time. For the private car, costs are estimated based on the total costs of ownership (ADAC, 2020). As for travel time, the levels are set to randomly fluctuate around the actual value to avoid linear relationships. For bikesharing, respondents were offered a bike or a pedelec. Due to possible range anxiety for electric vehicles (Ghamami et al., 2020),

Table 2

Stated preference design for short-distance (SD) trips: attributes and attribute levels used in survey.

Attribute	E-Scootersharing	Bikesharing	Foot	Private Car
Length		0.5, 1, 2, 4		
Travel time [min]	2, 5, 9, 13, 16, 18	3, 5, 11, 15, 18, 21	7, 14, 27, 35, 44, 55	1, 2, 4, 5.5, 7, 8
Access time [min]	2, 5	2, 5	–	2, 5
Egress time [min]	1, 3	1, 3	–	1, 5, 10
Search for parking time [min]	0, 1	0, 1	–	1, 4, 8
Availability	10, 50, 100	10, 50, 100	–	–
Cost [EUR]	1.3, 1.8, 2.4, 3, 3.7, 4.5	1, 1.5, 2, 2.5, 4, 5	–	0.2, 0.5, 0.9, 1.4, 1.8, 2.5
Scheme	station-based, free-floating	station-based, free-floating	–	–
Engine	–	bike, Pedelec	–	–
Range [km]	1, 4, 10	1, 4, 10	–	–

Table 3

Stated preference design for medium-distance (MD) trips: attributes and attribute levels used in survey.

Attribute	Carsharing	Ridepooling	PT	Private Car
Length		2, 5, 10, 20		
Travel time [min]	4, 10, 19, 25, 32, 39	4, 11, 22, 29, 36, 44	6, 14, 29, 39, 48, 58	4, 10, 19, 25, 32, 39
Access time [min]	1, 5, 10	1, 2, 5	1, 5, 10	1, 2, 5
Egress time [min]	1, 5, 10	1, 2, 5	1, 5, 10	1, 5, 10
Search for parking time [min]	0, 3	–	–	1, 4, 8
Waiting time [min]	–	3, 5, 8	3, 5, 8	–
Detour time [min]	–	3, 6, 9	–	–
Cost [EUR]	4, 5, 7, 9, 12, 15	3.1, 7, 10.5, 15.5, 22, 31	1, 1.7, 2.7, 4.9, 7, 10	0.2, 0.5, 0.9, 1.4, 1.8, 2.5
Scheme	station-based, free-floating, hybrid	–	–	–
Crowding [%]	–	0, 10, 50, 100	0, 10, 50, 100	–
Transfer	–	–	0, 1, 2	–

range is included into the experiment for e-scooters and pedelecs.

The selection of attributes for MD trips follows a similar logic and is shown in Table 3. The total time of travel is distinguished by net travel, access, egress, search for parking and, in case of ridepooling and PT, waiting and detour (ridepooling only) time. Waiting time is added for PT and ridepooling since the vehicle usually takes some time to arrive at the user's location (Alonso-González et al., 2020c; Yan et al., 2019). For ridepooling, detour times to collect or drop other passengers might occur (Yan et al., 2019). As for SD trips, costs are calculated based on real values and for PT based on a comparison of rates (ADAC, 2019). Choosing ridepooling or PT can result in sharing the vehicle with strangers (Márquez et al., 2019). Hence, crowding as a percentage of occupied seats is integrated. With the number of transfers for PT, we include the potential necessity of changing vehicles.

For calculating the design, we use the software Ngene (Choice-Metrics, 2018). Due to the size of the design, we chose a D-efficient design with eight blocks and six choice situations per block (Rose and Bliemer, 2009). An illustration of one choice situation is shown in Fig. 3. To keep potential bias from the order of choice situations at a minimum, choice situations shown to the respondents are randomly drawn from one block.

3. Model estimation

To model respondents' decision making, we use a mixed logit model. Compared to multinomial logit, mixed logit models overcome some limitations (Train, 2009): most importantly, mixed logit models allow random taste variation and correlation in unobserved factors (Train, 2009). As derived by Train (2009), the utility of subject n from choosing alternative j is $U_{nj} = \beta'_n x_{nj} + \epsilon_{nj}$. Using this formulation allows the coefficients β_n to vary over subjects and hence to incorporate the subject's tastes. Where x_{nj} are the observed variables, ϵ_{nj} is a random term. The probability for the unconditional choice of alternative i is $P_{ni} = \int \left(\frac{e^{\beta'_i x_{ni}}}{\sum_j e^{\beta'_j x_{nj}}} \right) f(\beta) d\beta$. As the probabilities P_{ni} do not have a closed form, draws from the mixing distribution are taken to approximate them via simulation (Ortúzar and Willumsen, 2011). We use 5,000 Sobol draws for simulation (Czajkowski and Budziński, 2019).





				
Entscheidung 1 von 6				
Wegstrecke: 1,0 km				
Reisezeit	5 min	5 min	27 min	2,0 min
Zugangszeit zu Fuß	5 min	2 min		2 min
Abgangszeit zu Fuß	1 min	3 min		10 min
Kosten	2,40 €	1,50 €		0,90 €
Parksuchzeit	1 min	1 min		1 min
Antrieb		Pedelec		
Verfügbarkeitswahrscheinlichkeit	50 %	10 %		
Betreibermodell	Stationsbasiert	Stationsfrei		
Mindestreichweite	4 km	4 km		
Ihre Wahl:	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Fig. 3. Graphical illustration of SP-design exemplary for short-distance (SD) trip mode-choice.

To estimate the mixed logit model, we use the following utility function formulation, which is extended or reduced in variables and coefficients depending on the mode: alternative-specific estimates, i.e. constant, travel time, detour time, operation scheme for carsharing, and number of transfers for PT are indexed with the respective alternative abbreviation. Access and egress are estimated for the shared services and private car. The remaining attributes are jointly estimated on the basis of occurrence in the respective alternatives. As we are specifically interested in the implications of different mobility tools, we integrate respondents' holding thereof in the utility function. We include the number of accessible private cars, the accessibility to private bicycles, and two binary variables signaling whether a pass for PT or a subscription to a MaaS-platform is held. Here, the e-scootersharing utility function is shown. Those for the remaining modes can be found in the Appendix.

$$\begin{aligned}
 U_{ES} = & \beta_{ES} + \beta_{time_{ES}} * time_{ES} + \beta_{access_{shared}} * access_{ES} + \\
 & \beta_{egress_{shared}} * egress_{ES} + \beta_{parking} * parking_{ES} + \beta_{cost} * cost_{ES} + \\
 & \beta_{availability} * availability_{ES} + \beta_{scheme_{SD}} * scheme_{ES} + \beta_{range} * range_{ES}, \\
 \text{with} & \\
 & \beta_{ES} = \beta_{ES_0} + \beta_{age_{ES}} * age + \beta_{car_{ES}} * hh_{car} + \beta_{bike_{ES}} * hh_{bike} + \\
 & \beta_{pipass_{ES}} * pipass + \beta_{maas_{ES}} * maas + \sigma_{ES} * \zeta_2, \\
 & \beta_{cost} = -e^{\beta_{cost_0} + \sigma_{cost} * \zeta_1}
 \end{aligned} \quad (1)$$

To better understand the different travel time components (TC), i.e. access, net travel, egress, and parking search time, we calculate the value of travel time components (VoTC). It shows the travellers'

willingness to pay in order to shorten the respective travel time component (Agarwal et al., 2020). Hence, it exhibits the trade-off travellers face between the travel time component and the cost of the trip. For the calculation, we draw on the theory of the economics of time as developed by DeSerpa (1971) and follow the approach by Baek et al. (2021):

$$VoTC = \frac{\partial U_{cost}}{\partial TC} = \frac{\frac{\partial U}{\partial TC}}{\frac{\partial U}{\partial cost}} = \frac{\beta_{TC}}{\beta_{cost}} \quad (2)$$

Thereby, we are able to compare VoTC values between the single (shared) modes. As we use random draws ζ_1 for the cost coefficient, this is estimated on the subjects' individual level. Hence, we receive VoTC values for each respondent to the survey.

To analyse the substitution patterns in greater detail, average marginal effects are estimated for the change in choice probability per mode. The percentage-point change for the probability of choosing one alternative given a percentage change in the m -th attribute of another variable is

$$E_{ni, x_{nj}^m} = -x_{nj}^m \int \beta^m L_{nj}(\beta) \left[\frac{L_{ni}(\beta)}{P_{ni}} \right] f(\beta) d\beta, \quad (3)$$

with β^m being the m -th element of β . We do so by simulating the base choice probabilities using the model parameters on the individual level. We repeat this procedure after an increase or decrease by a certain percentage or a change from 0 to 1 for the binary variables and, thus, receive the treatment choice probabilities. The average treatment effects

are then calculated by taking the difference between both values on the individual-level and averaging these over all subjects per mode.

To estimate the models, we use the R-package `mixl` (Molloy et al., 2021) as it allows an integrated formulation and estimation of choice models at high computational speeds.

4. Results and discussion

4.1. Model estimates

The results of the mixed logit model are summarized in Table 4 with all coefficients showing the expected direction, except for pedelecs.

Regarding travel time, ridepooling offers the smallest (−0.02), yet statistically not significant, and walking the highest negative value

(−0.21). With −0.12, e-scootersharing is closest to walking. Bikesharing (−0.09) and carsharing (−0.03) reveal lower disutility values. Compared to PT (−0.07), the travel time of ridepooling seems to be more enjoyable to subjects. This may be due to less (unknown) fellow passengers for the ridepooling service. The private car offers a travel time value (−0.06) below ridepooling and carsharing. As ridepooling includes a driver, travel time might not be perceived to be as negative. Interestingly, the effect of driving a private and hence familiar car does not lead to a less negative travel time coefficient compared to carsharing, but the contrary. Further analyses of the value of travel time are carried out to shed more light on this (Section 4.3).

Our results show similar patterns as previous work regarding the coefficients' rank order whilst providing a more comprehensive set of alternatives. In a long-term study, Weis et al. (2021) find that the travel

Table 4
Results of the mixed logit model for mode-choice.

	E-scootersharing	Bikesharing	Walking	Private car	Carsharing	Ridepooling	PT
Time							
Travel time [min]	−0.116*** (0.023)	−0.090*** (0.016)	−0.212*** (0.012)	−0.057*** (0.014)	−0.030** (0.012)	−0.019 (0.012)	−0.065*** (0.007)
Access time [min]	−0.040*** (0.009)	−0.040*** (0.009)		−0.034 (0.032)	−0.040*** (0.009)	−0.040*** (0.009)	−0.040*** (0.009)
Egress time [min]	−0.030** (0.013)	−0.030** (0.013)		−0.042*** (0.014)	−0.030** (0.013)	−0.030** (0.013)	−0.030** (0.013)
Detour time [min]						−0.018 (0.051)	
Parking search time [min]	−0.040** (0.017)	−0.040** (0.017)		−0.040** (0.017)	−0.040** (0.017)		
Cost							
Cost [EUR/trip]	−1.886*** (0.194)	−1.886*** (0.194)		−1.886*** (0.194)	−1.886*** (0.194)	−1.886*** (0.194)	−1.886*** (0.194)
σ_{cost}	−1.414*** (0.136)	−1.414*** (0.136)		−1.414*** (0.136)	−1.414*** (0.136)	−1.414*** (0.136)	−1.414*** (0.136)
Supply characteristics							
Availability [%]	0.006*** (0.002)	0.006*** (0.002)					
Scheme free-floating (reference: station-based)	0.418*** (0.102)	0.418*** (0.102)			0.172 (0.220)		
Scheme hybrid (reference: station-based)					−0.070 (0.233)		
Vehicle characteristics							
Pedelec		−0.321* (0.176)					
Battery range [%]	0.006 (0.018)	0.006 (0.018)					
Crowding [%]						−0.001 (0.001)	−0.001 (0.001)
Transfers							−0.298*** (0.079)
Alternative-specific constants							
Constant	−1.574 (0.990)	−1.199 (0.968)	4.551*** (0.912)		−3.078*** (0.814)	−2.785*** (0.993)	−1.205 (0.774)
Age	−0.051*** (0.013)	−0.041*** (0.013)	0.020 (0.013)		−0.027** (0.011)	−0.041*** (0.014)	0.013 (0.010)
Bike accessibility	1.811*** (0.488)	2.345*** (0.458)	0.495 (0.406)		1.621*** (0.415)	1.130** (0.505)	0.900** (0.351)
Car accessibility	−0.858*** (0.300)	−1.026*** (0.304)	−1.216*** (0.288)		−1.164*** (0.231)	−1.015*** (0.228)	−1.556*** (0.252)
Public transit pass	1.621*** (0.410)	1.799*** (0.384)	1.640*** (0.390)		2.555*** (0.376)	2.476*** (0.456)	3.651*** (0.337)
MaaS subscription	1.377*** (0.480)	1.172** (0.467)	−0.228 (0.468)		1.114*** (0.406)	2.234*** (0.460)	1.241*** (0.386)
σ_j	1.315*** (0.268)	1.587*** (0.242)	−2.933*** (0.254)	3.498*** (0.205)	0.315 (0.493)	0.908*** (0.289)	1.792*** (0.170)
ζ_{pool}				0.776*** (0.027)			
Respondents	1,445						
Choice observations	8,670						
LL(null)	−15,159.798						
LL(choice model)	−5,643.207						
AICc	11,427.030						

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

time coefficient for walking has the highest absolute value. In a simulation, Becker et al. (2020) also apply the highest value to walking. In both studies, bike or bikesharing comes in second, which ranks third in our case. However, e-scootersharing is not analysed in Weis et al. (2021) and Becker et al. (2020). Baek et al. (2021) find e-scootersharing to be less cumbersome than walking. Reck and Axhausen (2021) find that users of dockless e-scootersharing evaluate travel time to be more important than bikesharing users. In Weis et al. (2021) and Becker et al. (2020), bike is followed by private car and PT. Although the difference in travel time parameters between these two modes is rather small in our work, the rank order is reversed. However, the order is comparable to what Habib (2019) finds. Moreover, due to the Covid-19 pandemic, in-vehicle travel time for PT might be negatively affected by the potentially higher infection risk and the discomfort of having to wear masks. Mor-sche et al. (2019) find equal values for carsharing and ridepooling while we find carsharing to be slightly higher than ridepooling.

Comparing travel time ratios of the single modes relative to walking, our findings are predominantly comparable to the previous work described above and particularize specific aspects. For PT, Weis et al. (2021) find ratios between 0.35 and 0.80 (depending on trip purpose) whereas the ratio found here is 0.31. Baek et al. (2021) show a ratio of 0.64 for e-scootersharing whilst we find 0.55. In this work, bikesharing lies at 0.42 whilst Becker et al. (2020) use a ratio of 0.57. Ridepooling offers a ratio of 0.09 here with Becker et al. (2020) using 0.07. For the private car, we find a ratio of 0.27, which is 0.39–1.05 in Weis et al. (2021). While Becker et al. (2020) use a ratio of 0.48 for the private car and carsharing, our findings indicate a ratio of 0.14 for carsharing.

We now turn to access and egress time. Access time causes higher disutility in case of shared services (−0.04) compared to privately owned vehicles (−0.03). Here, the coefficient for access time to shared services is statistically highly significant whilst that for the private car is not. This might reflect that shared services have to be “searched” for on the streets whilst the parking location of private cars is usually known, which reduces uncertainty. The opposite result is revealed regarding egress time. Here, the shared services offer a lower disutility (−0.03) than the private car (−0.04). Presumably, this exhibits the effect that shared vehicles can be left anywhere or at reserved spots, which offers more possibilities to get closer to the destination. The parking search time also shows that having to spend time at the end of the journey causes rather high disutility. For e-scooters and bikes, this holds especially due to the size of the vehicles that can be easily parked anywhere in case of free-floating schemes. For station-based carsharing, parking spots are reserved and increasingly more cities in Germany begin to classify carsharing parking areas. As a door-to-door service, ridepooling reduces egress time as a part of its value proposition.

The coefficient of detour time of ridepooling (−0.018) is similar to the travel time coefficient (−0.019) and not significant. Hence, subjects do not seem to distinguish between these two kinds of travel time. For the pooling efficiency, and thus the business model, this is promising.

The cost coefficient is log-normal distributed (−1.89, which translates to −0.15). When integrating shared services, Becker et al. (2020) use a similar value (−0.13). Due to the individual differences between subjects (σ_{cost} is significant), we will use the individual cost coefficients to calculate the VoTC in chapter 4.3.

Considering supply characteristics, vehicle availability (0.01) as well as the free-floating scheme (0.42) for e-scooter- and bikesharing exhibit statistically significant positive coefficients. Hence, regulators’ idea to offer station-based e-scootersharing might not be what (potential) users want. Not having to care where a station is seems to be highly valuable to subjects. The coefficients indicating the carsharing schemes show an interesting result: free-floating is better off (0.17) whilst the hybrid scheme is worse off (−0.07) compared to a station-based service (serves as reference). However, the coefficients are not significant. Due to the focus on leisure trips, subjects might have thought of round-trips such that the advantage of hybrid schemes is ineffective here.

For the services’ vehicle characteristics, the sign of the pedelec

coefficient is unexpected (−0.32). Subjects evaluate the traditional bike to be more utility generating than a pedelec. They could be more sceptical towards pedelecs as they might not know how to exactly use them. Low battery ranges as reason can be ruled out (0.01 and not significant).

Whilst crowding shows the expected sign, it is almost zero (−0.001) and statistically not significant. As expected, transfers in case of PT show a negative sign (−0.30), which translates into 4.6 min worth of travel time.

Mobility tools held by subjects show an interesting pattern: whilst the number of cars shows negative coefficients, the regular bicycle availability, public transit pass, and a MaaS-subscription (only exception is walking) offer positive coefficients. With the private car as base category, we conclude that a more active and multimodal mobility style increases chances of selecting a shared service.

With ζ_{pool} , we account for the pooled nature of the data sets. As it is significantly different from one, it indicates that the data sets exhibit different variances. The σ accounts for both kinds of heterogeneity, scale and taste. These are significant for all alternatives but carsharing. Thus, subjects show individual preferences in evaluating the attributes. To integrate these individual differences, we conduct post-estimation analyses next.

4.2. Importance of single attributes

To analyse the parameters’ contributions to the overall utility of the respective mode, and hence their importance, we conduct a part-worth analysis. To do so, we multiply the means of the attribute levels with the respective coefficient value for each subject and take the average. Results of the most important attributes can be obtained from Fig. 4.

Cost and travel time are most important across all modes. Whilst shared micromobility services exhibit lower values for the importance of cost than the private car, carsharing and ridepooling show higher values. For the latter two, costs are the most important utility driver. This might reflect the fact that on a trip-basis, they usually are more expensive than a private car but offer (almost) the same travel time. This might be one consequence of private car costs often being hidden or not considered in the perceived cost that drives travellers’ decisions (Brazil et al., 2019). For shared services, the price is tagged directly to the minute/hour, the kilometer or even the whole trip and hence more transparent. E-scootersharing and bikesharing show similar values for cost and travel time, revealing that these two attributes contribute to the overall utility of the service in a comparable size. PT also shows similar values for cost and travel time.

Access and egress times as well as the time required to find a parking place follow travel cost and time in importance, though the latter to a lower extent. Bikesharing and e-scootersharing again show similar values across modes with access taking a larger part of the utility than egress. Carsharing and ridepooling reveal the same pattern. Yet, for ridepooling, the part-worth of access is considerably larger than egress. The same holds for PT, although on a higher level. For the private car, the opposite is true, as already observed with respect to the model coefficients. Here, the egress time obtains a larger part of the utility than access. As elaborated above, this might be an effect of the possibility to park shared e-scooters and bikes more closely to the destination. Since ridepooling and PT require a halt only, these might in most cases be closer to the destination compared to the private car as well. Also for parking search time, the private car shows the highest part-worth. The same logic as with egress time might apply here since carsharing vehicles either have reserved parking places at the station or marked spots. With respect to the private car, egress and parking search time show similar values whilst those for the shared services exhibit smaller values for parking than egress.

For the shared micromobility modes, vehicle availability is more important than access and egress time. Shared e-scooters and bikes cannot be reserved (in contrast to carsharing vehicles), which might

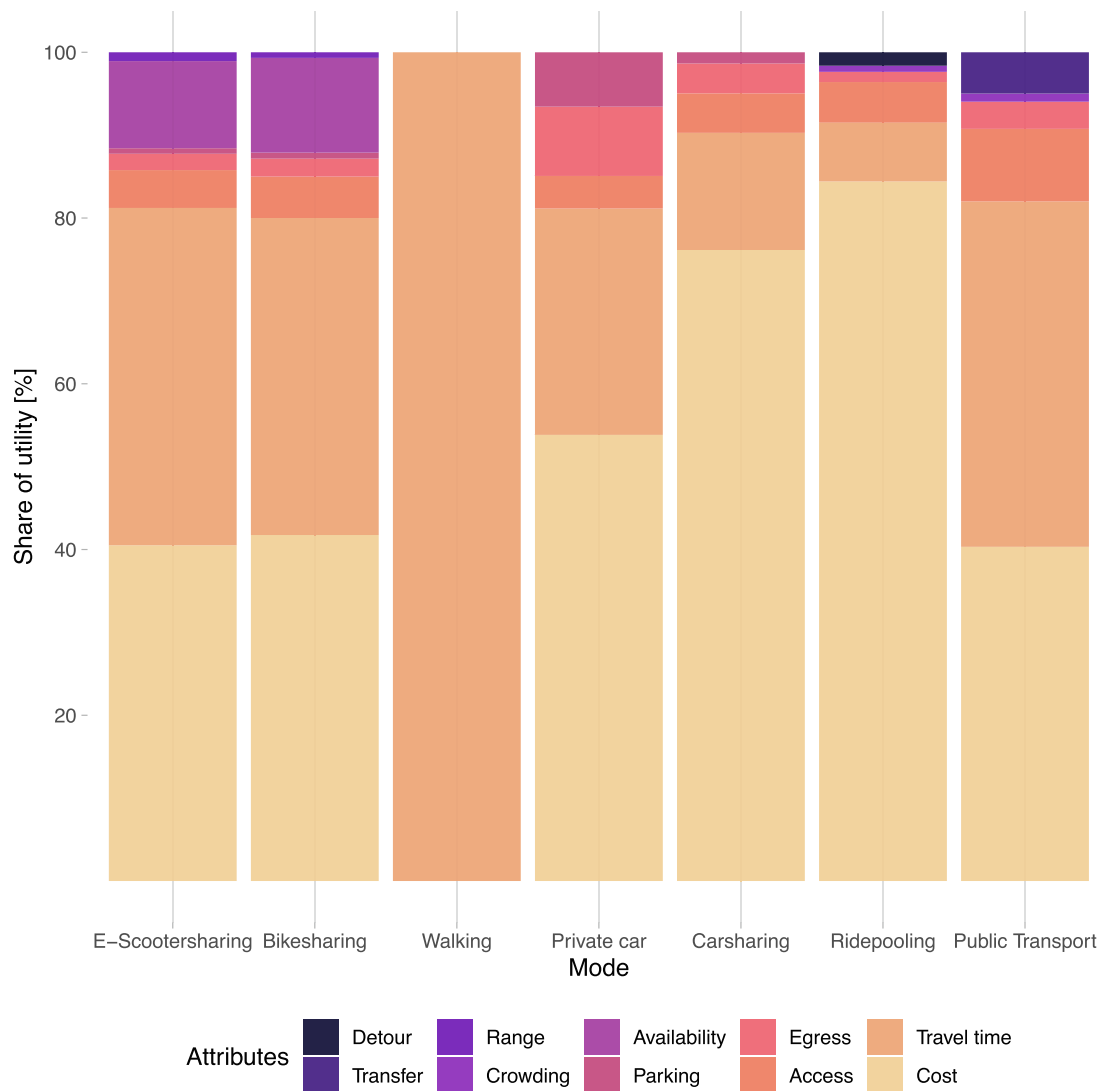


Fig. 4. Importance of single attributes on subjects' utility via part-worth analysis.

explain why availability is crucial to subjects whereas access and egress is more important in the case of carsharing. In comparison, the remaining battery range for e-scooters and pedelecs in bikesharing is less important but still more important than parking search time.

For PT, the number of transfers also comes into play, whilst the same holds true for the detour time regarding ridepooling, yet to a lower extent. Regarding PT, transfers offer a value between access and egress. The same is true for detour time concerning ridepooling. Despite the global pandemic, crowding in PT and ridepooling show the smallest values in comparison to the other attributes of the respective modes. However, the pandemic might also be the reason for this finding: due to less travellers in PT (Zehl and Weber, 2020) and regulations about keeping a physical distance to other people, crowding might have been no problem at the point of the survey. Moreover, the SP-design did not include overcrowding, thus an occupancy that exceeds the regular capacity of the vehicles. Hence, as long as crowding is below this threshold, respondents do not appear to perceive this as a major disutility driver.

As cost and travel time are most important across all modes, we look more closely at the value of time in the next step of our analysis.

4.3. Value of time

In order to deepen the understanding of the time-related differences between the individual services and modes, we calculate the VoTC (see Section 3) for the different elements of the overall travel time. These are net travel, access, egress, and parking search time (access time for private cars and detour time is omitted due to their lack of statistical significance in the model). Although travel time for ridepooling is not highly statistically significant ($p = 0.11$), we include it into the analysis for reasons of comparability.

Fig. 5 shows boxplots of the VoT for all transport modes in EUR/h. Walking tops the range with 43.45 EUR/h, followed by the shared micromobility modes. With 23.73 EUR/h, the VoT for e-scootersharing is higher than what was recently found by Baek et al. (2021) with 16.02 EUR/h.³ However, the authors specifically investigated last-mile trips whereas we refer to whole trips as baseline. Bikesharing shows a VoT-median of 18.53 EUR/h, followed by PT with 13.33 EUR/h. Thus, the non-car based modes exhibit the highest VoT. The private car exhibits a higher value (11.69 EUR/h) than carsharing (6.23 EUR/h). As

³ Exchange rate 1 KRW = 0.0008 EUR (mean of rolling year, 15.02.2021, www.finanzen.net).

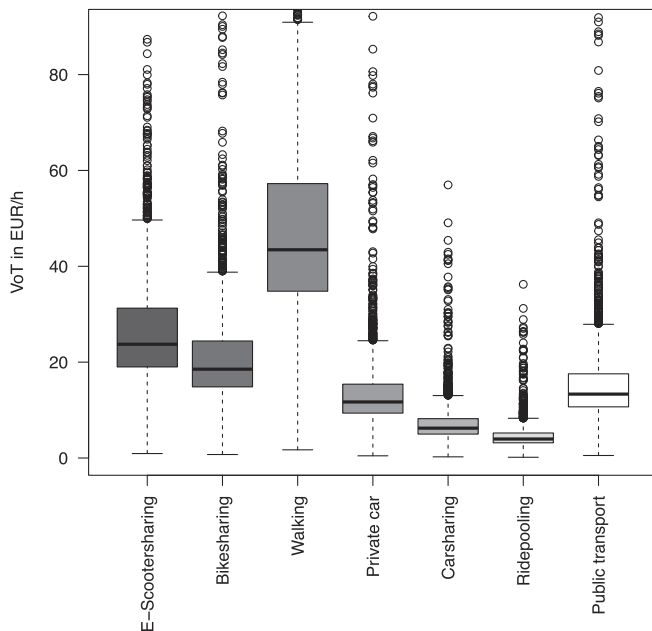


Fig. 5. Value of travel time for each transport mode in EUR/h.

mentioned, the VoT for ridepooling (3.96 EUR/h) has to be interpreted with care as its travel time coefficient could not be shown to be statistically significant. Nevertheless, the difference towards PT is noticeable. It seems that the on-demand service in smaller vehicles makes ridepooling more attractive to subjects.

For VoA, VoE, and VoP, Fig. 6 shows the results for the shared services and private car (egress and parking search time only). Interestingly, the VoA for shared services (8.20 EUR/h) is very similar to the VoE of the private car (8.50 EUR/h) as well as the VoP (8.30 EUR/h). The VoE for the shared services lies below with 6.20 EUR/h.

As shared micromobility services, specifically the new form of e-scootersharing, have yet to prove their economic sustainability, the VoTC estimates from this study might put further pressure on the business models proposed so far. Subjects show rather high values and are,

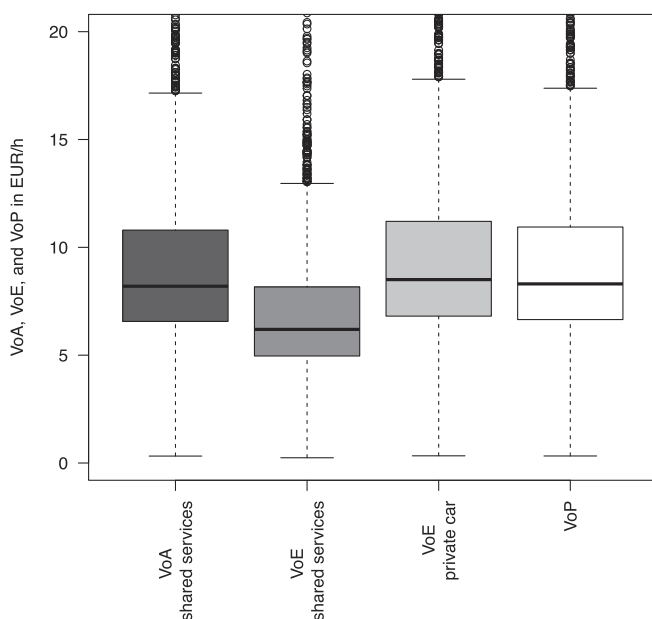


Fig. 6. Value of access (VoA) and egress (VoE) time for shared services and private car and parking search time (VoP) in EUR/h.

hence, interested in reducing the travel time components. Carsharing and ridepooling draw a more promising picture as they are well below the modes they are best comparable to (private car and PT, respectively). However, when viewed from a position of e-scooter- and bike-sharing substituting walking (Kopplin et al., 2021), these services might fill a need of urban travellers.

As shown in Section 4.2, cost is similarly important to utility as travel time. Hence, in the next section, we analyse the effects of cost changes to the mode-choice probabilities. We also account for respondents' mobility tool holdings.

4.4. Average treatment effects

To investigate the effects of different cost levels (i.e. consumer price) as well as free-floating, a public transit pass, regular bike accessibility at home, and a MaaS subscription on the choice probabilities of the respective modes, we calculate average treatment effects. The results for changed cost can be obtained from Fig. 7 and those for the binary variables from Table 5.

With cost changes of the private car, all other modes change in choice probabilities (see Fig. 7A). In Fig. 7B and C, the modes of the SD- and in Fig. 7D–F those of the MD-experiment are shown. The %pts.-changes are calculated based on the range of –50% to 150% in steps of 25%.

Fig. 7A shows that for a cost reduction of the private car, the choice probability for PT reacts most with a reduction of –2.3%pts. and an increase of 6.4%pts. for a 50% reduction and 150% increase in cost, respectively. On the other modes, a change in cost of the private car has a smaller effect. For a 150% increase in cost, the choice probability for carsharing increases by 1.1%pts., for bikesharing by 0.5%pts., for ridepooling by 0.3%pts., and for e-scootersharing by 0.2%pts. The probability for choosing the private car decreases by 9.9%pts.

For e-scootersharing, the maximum increase in choice probability is 0.6%pts. and the maximum decrease is –0.8%pts. as Fig. 7B shows. In comparison to Fig. 7C, these results show that a change in costs of e-scootersharing leads to smaller demand effects for bikesharing than vice versa. Changing costs of bikesharing by –50% results in a reduction of choice probability for e-scootersharing of –0.1%pts. whilst an increase by 150% results in a 0.3%pts. change. With an equal change of costs for e-scootersharing, the bikesharing choice probabilities decrease by –0.2%pts. and increase by 0.3%pts., respectively. For e-scooter- and bikesharing, the effects for the private car are greatest: with respect to the former, private car choice probabilities change in the range of –0.3%pts. to 0.3%pts. Regarding bikesharing, the changes lay between –0.5%pts. and 0.8%pts.

Looking at PT in Fig. 7D, greatest changes occur for the private car. Increasing costs by 150%, PT's choice probability decreases by –5.4%pts. which is rather low. However, subjects indicate the second highest taste heterogeneity for PT and the part-worth analysis shows travel time to be slightly more important than cost. Thus, subjects seem to either have a rather strong preference for PT or weigh travel time as more important than cost, which translates into low change probabilities with respect to cost changes. The preference for PT might be strengthened by the fact that PT is a mode that is not easily shifted from due to potentially low income (Nazari Adli et al., 2019; Di Ciommo and Shiftan, 2017). A cost increase by 150% leads to an average treatment effect of 4.3%pts. for the private car. Carsharing profits by an increase of 0.8%pts. and ridepooling of 0.3%pts. A cost decrease for PT by 50% leads to a loss in choice probability for the private car by –3.0%pts., for carsharing by –0.3%pts., and for ridepooling by –0.1%pts.

Reducing costs for carsharing by –50% results in an increase of choice probability by 2.4%pts. (Fig. 7E). An increase in costs by 150% leads to a reduction in choice probability by –1.1%pts. It can be seen that cost changes are evaluated very differently depending on whether it is a decrease or an increase. A 50% increase in costs results in –0.6%pts. which is much lower compared to the increase in choice probability for an equal cost reduction. Increasing costs for carsharing by 150% would

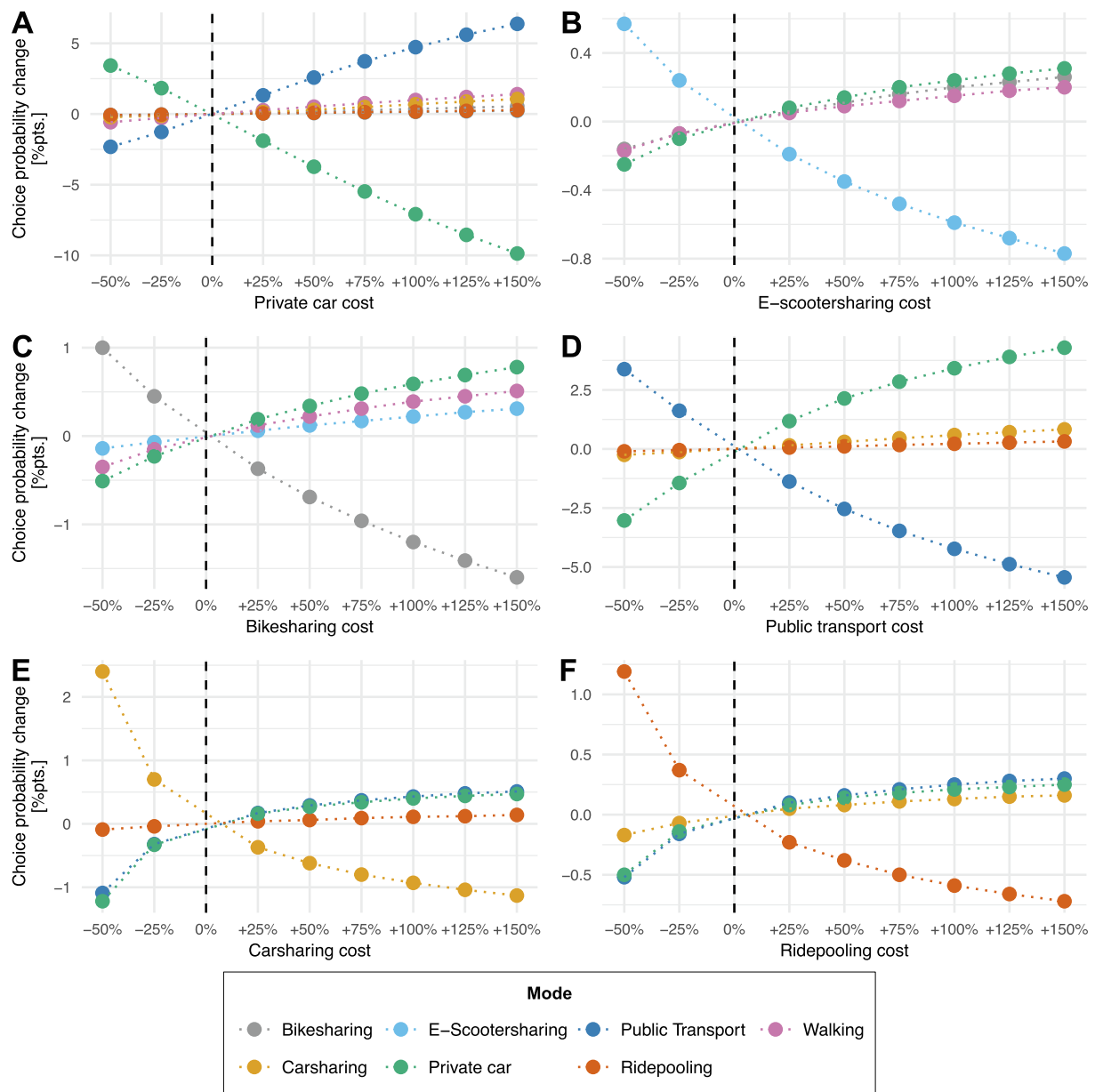


Fig. 7. Average treatment effects of cost, i.e. consumer price, on the choice probability of the modes.

Table 5

Average treatment effects of the operation scheme, public transit pass, and MaaS subscription on the choice probability of the modes [%pts.].

Variable	Bikes sharing	E-Scooters sharing	PT	Walking	Car sharing	Private car	Ridepooling
Free-floating bikes sharing	1.12	-0.21	–	-0.38	–	-0.53	–
Free-floating e-scooters sharing	-0.21	0.60	–	-0.16	–	-0.24	–
Public transit pass	2.64	0.87	14.74	3.90	0.99	-23.60	0.45
MaaS subscription	2.94	1.76	3.71	-2.64	0.35	-7.92	1.81
Regular bike accessibility	4.15	1.21	2.45	-0.51	1.31	-9.00	0.39

result in a 0.5%pts. increase in choice probability for the private car and PT and a 0.1%pts. increase for ridepooling.

Regarding changing costs for ridepooling, Fig. 7F shows similar dynamics for the service itself as in the case of carsharing (Fig. 7E). Decreasing the costs by -50% results in a 1.2%pts. increase in choice probability. Increasing the costs by 50% leads to a -0.4%pts. decrease and increasing the costs by 150% leads to a -0.7%pts. decrease in choice probability. From this cost increase, PT would benefit most (+0.3%pts.), followed by the private car (+0.3%pts.), and carsharing

(+0.2%pts.).

With respect to the operating scheme of e-scooter- and bikes sharing as well as subscription-based tickets (PT pass and MaaS subscription), changes in choice probability can be obtained from Table 5. Regarding free-floating for bikes sharing, choice probability is increased by 1.1% pts. for the service itself, whilst it reduces those of private car (-0.5% pts.), walking (-0.4%pts.), and e-scooters sharing (-0.2%pts.). The effect is lower in case of e-scooters sharing (+0.6%pts.). The PT pass shows the largest effect regarding the private car (-23.6%pts.), followed by a

regular bike accessibility (−9.0%pts.), and a MaaS subscription (−7.9%pts.). Whilst the effect of the PT pass and a MaaS subscription on PT is straightforward, their effects on bikesharing, e-scootersharing, and ridepooling is noteworthy. For these three services, the MaaS subscription shows a larger effect than the PT pass. Carsharing is the only shared service that shows this pattern reversed. The MaaS subscription also leads to a −2.6%pts. reduction in the probability to choose walking. Thus, it shows the highest negative value across the variables studied. Regular bike accessibility has effects on bikesharing (+4.2%pts.) and PT (−2.5%pts.).

5. Conclusions

This paper applies a mixed logit model and SP data to estimate the mode-choices of subjects living in German cities between e-scooter-, bikesharing, walking, and private car or carsharing, ridepooling, PT, and private car, respectively. Based on the choice modelling, we determine the importance of single attributes as well as the value of travel time components and average treatment effects. We are thus able to gain new insights on the modal-choice behaviour of subjects and its implications for policy makers and service providers.

First, whilst for bike- and e-scootersharing, cost and travel time are equally important, the former is highly more important in the case of carsharing and ridepooling. The travel time and cost coefficients found in this study are comparable to similar recent work investigating the modes analysed in the present context (Becker et al., 2020; Morsche et al., 2019; Weis et al., 2021). Access time is more important for shared modes compared to the private vehicle, whilst the opposite holds true for egress. Availability of e-scooters and bikes in shared systems is a utility driver. Detour times in ridepooling services are not as relevant as the travel time itself and are of minor importance to the subjects.

Second, with the shared micromobility modes, i.e. e-scooter- and bikesharing, subjects are able to reduce their VoT compared to walking, which might be an indication towards mode-shifting. These two modes substantially reduce travel times for intra-city trips although still exhibiting high VoT values. This is in line with recent studies on VoT and potential shifting behaviour of travellers (Baek et al., 2021; Kopplin et al., 2021). Moreover, we find free-floating to significantly enhance the utility of subjects. Reck et al. (2021) find docked (e-) bikesharing to be preferred for peak-hours and dockless e-scootersharing for off-peak hours. Our work supports the latter finding but also points at a target conflict for regulatory bodies or city planners regarding which system is to be promoted and implemented in the end. Carsharing and ridepooling show lower VoT values than the private car and PT. Again, this offers a potential for mode-shifting. With the availability being utility driving and the VoA for shared services being higher than for the private car, easy accessibility and ubiquitous supply can reduce the threshold towards shared micromobility modes and is of higher importance than egress.

Third, cost changes to the private car and PT are most effective regarding the simulated probabilities to switch to another mode. Considering shared modes, carsharing profits most from cost increases in private cars and PT. Bikesharing profits from increasing costs of the private car. Interestingly, e-scooter- and bikesharing show similar reaction patterns when increasing or decreasing the other mode, respectively. One shortcoming of this study is that we do not have the private bike as mode to which to compare the results, specifically those for bikesharing.

For policy, these findings indicate that the accessibility to shared micromobility modes and their operation schemes are a balancing act and contain a target conflict: on the one hand, accessibility is key to include them into the local transport system. On the other hand, they might offer shifting potential from walking, which would result in more vehicle traffic and would be more energy-intensive. In addition, operation schemes have their strengths for different trip purposes and different times of day. Consequently, regulation might think about

stricter usage of geofences in order to allow pick-up and parking of these modes in specific zones only. These zones could encompass PT stations in order to strengthen the integration of modes and foster multimodal travel. This, in consequence, might induce mode-shifting from the private car. However, our statements are limited to the urban context. Rural areas may exhibit different patterns and require different strategies to integrate modes and offer alternatives to the private car.

For providers of the particular services, different aspects are of importance for the individual services: the shared micromobility modes gain in utility by offering a free-floating scheme to a higher extent than carsharing. This implies that the operations for re-balancing the fleets for micromobility services are crucial to making the business models of these modes viable. From a customer perspective, the cost structures of the business models offer some degree of freedom as the decrease in choice probabilities is rather modest in reaction to cost increases. This should be a good sign for providers who still have to show that these services can be offered with a viable business model, even more so if a rather probable market consolidation takes place.

This work opens avenues for future research in three ways: first, as the used data covers residents of cities only, future work might want to compare our findings to services in more rural areas. Second, as we did not provide an opt-out alternative, we forced the subjects to make a decision between the modes presented. Future research could focus on the interaction between these modes, also because these regularly are components of MaaS platforms and bundles and supply of the services. Revealed preferences might enrich the understanding of shared mobility usage as well. For the underlying logic of the service supply, a business model point of view might be helpful in order to generate and model services that are viable. Third, this work is limited in its generalizability due to selecting leisure as the trip purpose for the SP-experiment. This limitation is a result of paying attention to the response burden of the survey as well as the Covid-19 pandemic and its general recommendation for home office where possible. Future work might extend the range of trip purposes and the impact towards mode choice.

CRedit authorship contribution statement

Konstantin Krauss: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Project administration. **Michael Krail:** Conceptualization, Validation, Resources, Writing - review & editing, Supervision, Funding acquisition. **Kay W. Axhausen:** Conceptualization, Methodology, Validation, Writing - review & editing, Supervision.

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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Appendix A

A.1. Utility functions

Bikesharing

$$U_{BS} = \beta_{BS} + \beta_{time_{BS}} * time_{BS} + \beta_{access_{shared}} * access_{BS} + \beta_{egress_{shared}} * egress_{BS} + \beta_{parking} * parking_{BS} + \beta_{cost} * cost_{BS} + \beta_{availability} * availability_{BS} + \beta_{scheme_{SD}} * scheme_{BS} + \beta_{range} * range_{BS} + \beta_{pedelec} * pedelec_{BS}, \quad (A.1)$$

with

$$\begin{aligned} \beta_{BS} &= \beta_{BS0} + \beta_{age_{BS}} * age + \beta_{car_{BS}} * hh_{car} + \beta_{bike_{BS}} * hh_{bike} + \\ &\beta_{ptpass_{BS}} * ptpass + \beta_{maas_{BS}} * maas + \sigma_{BS} * \zeta_3, \\ \beta_{cost} &= -e^{\beta_{cost0} + \sigma_{cost} * \zeta_1} \end{aligned}$$

Walking

$$U_{WA} = \beta_{WA} + \beta_{time_{WA}} * time_{WA}, \quad (A.2)$$

with

$$\begin{aligned} \beta_{WA} &= \beta_{WA0} + \beta_{age_{WA}} * age + \beta_{car_{WA}} * hh_{car} + \beta_{bike_{WA}} * hh_{bike} + \\ &\beta_{ptpass_{WA}} * ptpass + \beta_{maas_{WA}} * maas + \sigma_{WA} * \zeta_4, \end{aligned}$$

Carsharing

$$U_{CS} = \beta_{CS} + \beta_{time_{CS}} * time_{CS} + \beta_{access_{shared}} * access_{CS} + \beta_{egress_{shared}} * egress_{CS} + \beta_{parking} * parking_{CS} + \beta_{cost} * cost_{CS} + \beta_{scheme_{LD1}} * scheme_{LD1_{CS}} + \beta_{scheme_{LD2}} * scheme_{LD2_{CS}}, \quad (A.3)$$

with

$$\begin{aligned} \beta_{CS} &= \beta_{CS0} + \beta_{age_{CS}} * age + \beta_{car_{CS}} * hh_{car} + \beta_{bike_{CS}} * hh_{bike} + \\ &\beta_{ptpass_{CS}} * ptpass + \beta_{maas_{CS}} * maas + \sigma_{CS} * \zeta_5, \\ \beta_{cost} &= -e^{\beta_{cost0} + \sigma_{cost} * \zeta_1} \end{aligned}$$

Ridepooling

$$U_{RP} = \beta_{RP} + \beta_{time_{RP}} * (time_{RP} + detour_{RP}) + \beta_{access_{shared}} * (access_{RP} + wait_{RP}) + egress_{RP} + \beta_{cost} * cost_{RP} + \beta_{crowding} * crowding_{RP}, \quad (A.4)$$

with

$$\begin{aligned} \beta_{RP} &= \beta_{RP0} + \beta_{age_{RP}} * age + \beta_{car_{RP}} * hh_{car} + \beta_{bike_{RP}} * hh_{bike} + \\ &\beta_{ptpass_{RP}} * ptpass + \beta_{maas_{RP}} * maas + \sigma_{RP} * \zeta_6, \\ \beta_{cost} &= -e^{\beta_{cost0} + \sigma_{cost} * \zeta_1} \end{aligned}$$

PT

$$U_{PT} = \beta_{PT} + \beta_{time_{PT}} * time_{PT} + \beta_{access_{shared}} * (access_{PT} + wait_{PT}) + \beta_{egress} * egress_{PT} + \beta_{cost} * cost_{PT} + \beta_{crowding} * crowding_{PT} + \beta_{transfer} * transfer_{PT}, \quad (A.5)$$

with

$$\begin{aligned} \beta_{PT} &= \beta_{PT0} + \beta_{age_{PT}} * age + \beta_{car_{PT}} * hh_{car} + \beta_{bike_{PT}} * hh_{bike} + \\ &\beta_{ptpass_{PT}} * ptpass + \beta_{maas_{PT}} * maas + \sigma_{PT} * \zeta_7, \\ \beta_{cost} &= -e^{\beta_{cost0} + \sigma_{cost} * \zeta_1} \end{aligned}$$

Private car

$$U_{CA} = \beta_{CA} + \phi_{pool} * [\beta_{time_{CA}} * time_{CA} + \beta_{access_{owned}} * access_{CA} + \beta_{egress} * egress_{CA} + \beta_{parking} * parking_{CA} + \beta_{cost} * cost_{CA}], \quad (A.6)$$

with

$$\begin{aligned} \beta_{CA} &= \sigma_{CA} * \zeta_8, \\ \beta_{cost} &= -e^{\beta_{cost0} + \sigma_{cost} * \zeta_1} \end{aligned}$$

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