# A stated preferences experiment to analyze bike sharing as an alternative transport mode

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### SHORT SUMMARY

Currently, parameters for neither mode- nor route choice are available in terms of bike-sharing, resulting in a lack of knowledge to implement bike-sharing systems in transport demand models. Estimating such parameters is the aim of a stated preferences experiment on choices between shared bikes, public transport, and private motorized transport. Preliminary results of a multinomial logit model on a sample of 69 non-users and users of bike-sharing systems are presented. For all modes, travel costs have a negative effect on the associated utility of transport mode. Travel time shows a negative effect for all modes, while for shared bike and public transport access and egress time has a stronger effect than time in the vehicle. For bicycling, street type has no effect, while asphalt is the most preferred type of street surface. The utility of public transport is lower with higher utilized capacity.

**Keywords:** micro-mobility, bike-sharing, multinomial logit model, stated preferences, mode choice

## 1. INTRODUCTION

Many publications on bike-sharing systems (BSS) present descriptive statistics on origin-destination matrices (Zhao et al., 2015), and user's socio-demographics (Reck & Axhausen, 2021). In terms of mode and route choices there are studies available, which consider bikes (Börjesson & Eliasson, 2012; Caulfield et al., 2012; de Dios Ortuzar et al., 2000; Hardinghaus & Papantoniou, 2020; Sener et al., 2009; Weis et al., 2021). However, none of them does consider shared bikes for which additional attributes as costs for the rent and time for accessing and egressing BSS stations are relevant. Following from that, there is a lack of data for demand model-based simulations and predictions of ecological and transport-related effects of BSS. The proposed conference contribution addresses this gap by reporting a mode choice experiment and according empirical behavioral parameters, which allow an implementation of station-based bike-sharing systems in macroscopic transport demand models.

Whereas revealed preferences (RP) (Louviere et al., 2000; Train, 2009) reflect people's actual choices in real-world situations, they include the disadvantage of being limited to existing alternatives and attributes and being subject to challenges of multicollinearity (Train, 2009). Since our mode-choice study is interested in e.g. the effect of transport prices and travel times with little variation, a stated preference (SP) experiment was created to collect people's stated mode choices in hypothetical choice situations, which allows to include controlled variation in the attributes (Louviere et al., 2000; Train, 2009). To make the situations more realistic for the participants, the choice tasks were tailored individually based on RP data. The experiment considers the alternatives bike sharing (BS), public transport (PT), and private motorized transport (PMT). The survey population includes BSS-users and -non-users.

#### 2. METHODOLOGY

#### Data

BSS-users were recruited after renting a VRNnextbike, a BSS in the South-West of Germany (VRNnextbike, n.d.). When using the smartphone app, users were presented an invitation to participate in a computer-assisted telephone interview (CATI) on their travel behavior and bike-rent habits. In the CATI survey, information on trip characteristics and purpose was collected, and the chosen route was traced via an online route planning tool (komoot, n.d.) to gather additional information such as travel time. The collected RP-data served as a basis for our mode choice experiment. This follow-up survey was presented to BSS users, who agreed to participate in the SP study. Based on the reported route, trip characteristics for the alternatives modes PT and PMT were collected using an online routing provider (*Google Maps*, n.d.) and an electronic PT-schedule service (VRN, n.d.).

BSS-non-users were recruited from a sample of randomly generated phone numbers. As RP data are not available for this subsample, quasi RP data were employed, which are based on real BSS usage data provided by the VRNnextbike and discriminated for short, middle, and long trips. In this case, data on mode alternatives are based on information of the national travel survey in Germany (MiD, 2017), taking into account the differences between major and minor cities. To design a tailored questionnaire for this subsample, each respondent was assigned to a town size group, based on his or her postal address. Secondly, every participant was sequentially assigned to a trip length (small, middle, long) and a trip purpose (leisure or mandatory activity such as work). Based on this approach, calculated quasi RP values were assigned to the participants as basis for the variation in the SP-experiment.

For both, BSS-users and BSS-non-users, the SP questionnaire was created by varying the modespecific characteristics in accordance to a predefined experimental design. The participation in the study was restricted to adults (18 years and older) owning a driver's license to make the alternative PMT realistic. The individually tailored questionnaires were created within one week after recruitment, printed, and sent via postal mail to the participants. After four weeks of non-response, reminders were sent with a copy of the questionnaire. An incentive of 20€ was provided to the respondents after returning the filled-out survey instrument.

### Experimental design

As reported above, the SP experiment employs three transport modes (BSS, PMT, PT), which are provided as labelled alternatives (Louviere et al., 2000; Rose & Bliemer, 2014) to the respondents. Mode-specific attributes were selected by referring to previous research (Axhausen et al., 2008; Börjesson & Eliasson, 2012; Hardinghaus & Papantoniou, 2020; Weis et al., 2021) and evaluated in expert interviews. All continuous attributes were varied relative to the RP data, while levels of categorical variables (BS: street type, surface type; PT: utilized capacity) were determined by the experiment design. Hereby, certain constraints had to be met: The arterial road was never presented together with macadam surface. A scheme of the mode-specific attributes and their variation is presented in Table 1.

To find a design with small standard errors of parameter estimates as possible, an *efficient* design (Rose & Bliemer, 2009, 2014) was created employing the software Ngene (ChoiceMetrics, 2018). The design resulted in 60 choice tasks split into six blocks. Each participant was assigned to one block and thus asked to complete ten choice tasks.

In the questionnaire, a detailed description of the task and attribute levels was provided to ensure equal understanding across all participants. For the same reason, pictures visualized the three levels of utilized capacity in PT (middle, high, overloaded) as suggested by Weis et al. (2021) are shown in Figure 1. An example for a choice task is presented in Figure 2.

mode	attribute	levels / variation of reference values
BS	access & egress time	-50% / -10% / +40%
	travel time (TT)	-30% / -10% / +30%
	travel costs	-100% / -35% / +20%
	street type	cycleway / side street / arterial road
	surface type	asphalt / cobblestones / macadam
PMT	travel time (TT) incl. parking search	-20% / -10% / +30%
	fuel costs	-50% / +150% / +200%
	parking costs	-50% / +100% / +200%
PT	access & egress time	-50% / -10% / +40%
	travel time (TT)	-30% / -10% / +30%
	travel cost	-100% / -35% / +20%
	utilized capacity	middle / high / overloaded

Table 1. SP experiment: mode-specific attributes and variation of levels



Figure 1. SP questionnaire: Visualization of utilized capacity in PT (Weis et al., 2021)



Figure 2. Choice task example

#### Model specification

Discrete choice data, where respondents choose between a limited number of alternatives, are commonly analysed by applying random utility maximization (RUM) theory. The theory assumes rational behavior in which respondents choose the alternative with the highest utility (Adamowicz et al., 1994; Louviere et al., 2010; Mariel et al., 2021; Train, 2009). Namely, an individual n faced with J alternatives in T choice tasks associates an indirect utility  $U_{njt}$  for an alternative j in a choice task t and chooses the alternative with the highest utility. The utility of an alternative j is therefore decomposed as

$$U_{nit} = V_{nit} + \varepsilon_{nit} = x'_{nit}\beta + \varepsilon_{nit}$$
(1)

where  $U_{njt}$  is not observed, but  $V_{njt}$  is the deterministic utility of alternative j, and  $\varepsilon_{njt}$  is a random component not included in  $V_{njt}$ . The deterministic utility  $V_{njt}$  can be specified by the term  $x'_{njt}\beta$ , where x is a vector of explanatory variables (e.g. attribute levels), and  $\beta$  are the corresponding coefficients to be estimated.

In this SP study, J=3 labelled alternatives (shared bike, car, public transport; see Figure 2) are described by K=3 to 5 attributes (see Table 1). For each alternative, a utility function  $(V_{njt})$  was specified, whereby the alternative-specific attributes were included in the equation as explanatory variables. When specifying the utility function, it is important to understand that "only the differences in utility matter", while the "scale of utility is arbitrary" (Train, 2009, p. 19). Therefore, to capture the differences in the utility of the alternatives, J-1 alternative-specific constants (ASC) were specified, whereby the estimated ASCs are interpreted relative to the omitted alternative, which is normalized to zero (Ben-Akiva & Lerman, 1985; Train, 2009). For the categorical attributes street type, surface type, and utilized capacity, the *L* levels of each attribute were transformed into *L-1* dummy variables. This means, the utility for one level per attribute is normalized to zero and serves as reference category, while the parameter estimates for the *L-1* dummy variables capture the utility differences to this reference category (Louviere et al., 2000; Mariel et al., 2021; Train, 2009). Since only the difference in utility matters, the choice of the reference category is arbitrary (Train, 2009).

#### 3. RESULTS AND DISCUSSION

A multinomial logit model (MNL) (Ben-Akiva & Lerman, 1985) was estimated in R (Hess & Palma, 2019; R Core Team, 2020) on the data of 690 observations (choice tasks) from 69 individuals. The results are presented in Table 2. It has to be kept in mind that the survey is still in the field and the presented results are preliminary. Additional information will have an impact on the significance of the results.

The estimated ASCs show the differences in utility for the mode alternatives, whereby BS was chosen as the reference category. The utility of PMT is lower than for BS ( $\beta$ =-1.392, t-value= -2.660), while it is higher for PT ( $\beta$ =0.754, t-value=1.544).

For BS, both, access and egress time to the bike station ( $\beta$ =-0.220, t-value=-7.455) and travel time with the bike ( $\beta$ =-0.125, t-value=-7.614) have a negative utility to the respondent, whereby the negative effect is larger for access and egress time than for cycling time. This was expected as ride-times in or on a vehicle are often considered less negative than waiting or access and egresstimes (see Weis et al., 2021). Also travel costs show a negative utility ( $\beta$ =-0.616, t-value=-6.667). The data does not support any differences in utility for the street type, since relative to the reference category arterial road, the estimates for side street ( $\beta$ =-0.255, t-value=-0.956) and cycleway ( $\beta$ =-0.012, t-value=-0.046) are not significantly different from zero. Relatively to macadam surface, cobblestones do not show differences in utility ( $\beta$ = -0.203, t-value=-0.810), while asphalt is a more preferred surface type, but the effect is also not significant ( $\beta$ =0.400, t-value=1.556). For PMT, travel time ( $\beta$ =-0.116, t-value=-4.872), fuel costs ( $\beta$ =-0.727, t-value=-3.342), and parking costs ( $\beta$ =-0.573, t-value=-7.047) have a negative utility for the participants.

For PT, similar to the alternatives BS and PMT, travel time shows negative utility for both, access plus egress time ( $\beta$ =-0.249, t-value=-6.715) and time in vehicle ( $\beta$ =-0.147, t-value=-6.108). Again, as for BS, access and egress time has a larger negative effect than travel time in the vehicle. A negative utility is also true for travel costs ( $\beta$ =-0.825, t-value=-6.715). With reference to a middle utilized capacity, higher utilized capacity results in utility loss (negative effects). Namely, an overloaded level of utilized capacity ( $\beta$ =-1.509, t-value=-5.505) shows a larger difference in utility to the middle level than high utilize capacity ( $\beta$ =-1.264, t-value=-4.720).

The estimated model shows an adjusted rho-squared ( $\rho^2$ ) of 0.37, which can be considered as a quite good model fit (Ben-Akiva & Lerman, 1985; Louviere et al., 2000; Train, 2009)).

mode	attribute level	estimate	t-ratio		
	ASC (shared bike)	reference			
	ASC (car)	-1.392	-2.660		
	ASC (public transport)	0.754	1.544		
BS	access & egress time [min]	-0.220	-7.455		
	TT cycling [min]	-0.125	-7.614		
	travel costs [€]	-0.616	-6.667		
	street type				
	arterial road	reference			
	side street	-0.255	-0.956		
	cycleway	-0.012	-0.046		
	surface type				
	macadam	reference			
	cobblestone	-0.203	-0.810		
	asphalt	0.400	1.556		
PMT	TT total [min]	-0.116	-4.872		
	fuel costs [€]	-0.727	-3.342		
	parking costs [€/hour]	-0.573	-7.047		
РТ	access & egress time [min]	-0.249	-6.715		
	TT in vehicle [min]	-0.147	-6.108		
	travel costs [€]	-0.825	-9.390		
	utilized capacity				
	middle	reference			
	high	-1.264	-4.720		
	overloaded	-1.509	-5.505		
n = 69 individuals; $n = 690$ observations					
Log Likelihood (0) = -758.0425; Log Likelihood (final) = -460.6758					
$\rho^2 = 0.3923$ ; adjusted $\rho^2 = 0.3699$					

Table 2. MNL estimation results for the three modes shared bike, car, and public transport

#### 4. CONCLUSIONS

At this stage of analysis, it is important to mention that the survey is still in the field. Therefore, conclusions will be derived after running the model on the full sample when the fieldwork is completed. All effects, however, show in the expected direction and are plausible in their size. Updated results will be presented at the conference.

In further steps, this study aims to estimate an MNL model with the inclusion of socio-demographics, estimation of willingness-to-pay for the alternative attributes, and value of travel time savings. Moreover, following the segmentation approach (Ben-Akiva & Lerman, 1985) and previous research on mode choice (Weis et al., 2021), separate models will be estimated for different trip purposes. After that, the estimated parameters will be implemented into transport behavior models, and scenarios for the development of BS, MPT, and PT usage will be outlined.

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