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International Comparison of Psychological Factors and their Influence on Travel Behavior

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Abstract

Previous research has shown the influence of attitudes or motives on mobility. In deciding which mobility markets may be interesting for mobility services in the future, it is therefore important to benchmark not only travel behavior but also attitudes of people. In most cases, the studies focus on one city or one country, which only leads to local insights. In contrast to that, we developed an approach which covers behavior and attitudes to measure influences between both dimensions in an international comparison on a city level. With our approach, we surveyed 1,800 people in San Francisco, Berlin, and Shanghai. These cities serve for comparison and are intended to clarify whether there are differences between the magnitude of attitudes and motives. Consequently, our research questions are: Do attitudes and motives influence travel behavior distinctively in different cultural contexts? Are there different implications on a city level? To investigate the influences on behavior and compare these results between the surveyed cities, we applied various ordered logit regression models. Based on these regression, this paper provides insights on the contributions of attitudinal and sociodemographic variables on behavior such as usage frequencies corresponding to different modes in three distinctive cities. We applied a robust survey framework for international comparisons. Results showed as expected a strong relationship between attitudes and realized behavior in terms of modal use. By analysing cities, significant differences in the magnitude of the effects among the cities but also significant similarities are observable. This study supports global comparisons and policy designing.

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Keywords: Travel Behavior; Attitudes; Motives; International Comparison

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1. Introduction

When looking at travel behavior on an international level, it is essential to know if attitudes towards modes influence behavior and if so, to what extent. Generally, we can assume that attitudes might have a proportionally high relevance when it comes to influencing individual human behavior which is not trivial to measure. Furthermore, national differences in attitudes may cause varying outputs in travel behavior. Having this in mind, it is important for international mobility market analyses as well as forecasting of on-demand mobility potentials to learn more about country-specific differences of attitudes and orientations towards modes to compare cities, countries or even continents.

In the past years, the research on attitudes and behavior in the transportation field has increased and can be generally divided into behavior- or attitude-oriented models. The behavior-oriented models are primarily rational choice models. As these "soft" attributes can play a major role in the decision-making process, it became popular to extend the classical discrete choice models with constructions of latent variables (Ashok et al. 2002, Ben-Akiva et al. 1999, Walker 2001). The attitude-oriented models are based on theoretical frameworks, such as the Theory of Planned Behavior (TPB) (Ajzen 1991), and are primarily causal models in which the causal effect of constructs is at the centre of the decision-making process. Several studies analyzed this influence on travelers' behavior (for example Bamberg et al. 2003; Dobson et al. 1978; Gärling et al. 1998; Kroesen et al. 2017). The development in both fields of research is driven by complex models such as Hybrid Choice Models (HCM) (behavior-oriented) or Structural Equation Models (SEM) (attitude-oriented). A detailed overview of applications with SEM is given by Golob (2003) and for HCM by Bouscasse (2018) and Kim et al. (2014). Due to their increasing complexity with the inclusion of additional psychological factors, they are not suitable for every application. Also simpler regression models were used to investigate the influence between psychological aspects and travel behavior (Fujii and Gärling 2003; Nobis 2006; Sönmez and Graefe 1998; Spears et al. 2013; Doherty et al. 2010). The application of sequential estimation is also frequently used, with a choice model following a factor analysis (Ben-Akiva et al. 2002). Furthermore, the complexity increases with the scope of the analysis. Existing studies dealing with the identification of relations between both dimensions mostly focus on one city or country. To our knowledge, international comparative studies are relatively rare. The existing studies confirmed an attitude-behavior relationship. In our research, we want to contribute to the results of the existing studies by adding the aspect of international comparison. Therefore, the focus of this study is on the comparison of cities with different cultural contexts. This basic idea leads us to our research questions: Do attitudes and motives influence travel behavior distinctively in different cultural contexts? Are there different implications on a city level? To compare influences of attitudes on behavior in various cities, we developed a standardized survey approach which helps us to investigate the influence comprehensively. For our study we surveyed three cities (San Francisco, Berlin, and Shanghai). In each city, we queried 600 people by using an integrated survey design, which combines travel behavior, demographic variables, and psychological factors. Therefore, we applied a so-called *travel skeleton approach*, which captures exclusively typical travel behavior. To examine the relation interdependencies between attitudes, sociodemographic variables and behavior, literature often uses HCM (Kim et al. 2014) or SEM (Urban und Mayerl 2014). Nevertheless, by aiming for a reduction of complexity and the possibility to compare various variables, we decided to perform an ordered logit model. Eventually arising problems of overestimated attitudes balance themselves out as long as no comparison with other variables (e.g., sociodemographic or behavioral variables) takes place. With the ordered logit regression model, we estimated effects on the use of different modes. In addition, we are able to consider impacts of attitudes on an international level and figure out which attitudes are relevant in the relationship against the background of different cultural and societal frameworks.

The paper is structured as follows: First, we explain the data and survey design we used for our analysis. Second, we describe the data preparation and analysis methodology. Finally, we perform ordered logit regression models to identify impacts of attitudes on realized behavior and compare them between cities in different cultural contexts.

2. Data Collection and Survey Design

The following analyses are based on a data collection approach, capturing comprehensive information about travel-related aspects such as daily and occasional travel behavior as well as attitudes towards means of transportation.

Additionally, it covers questions about peoples' car use motives. This approach collects information about activities and mode choices by using a *travel skeleton,* as described in the following section. In addition, we implemented two psychological item sets into the survey to investigate attitudes and motives of individuals. The data in this study are based on three similar surveys conducted in Berlin (Germany), Shanghai (China) and San Francisco (U.S.). The cities were chosen because, on the one hand, they represent modern cities in different cultures with many alternatives to the car. On the other hand, these countries are important sales markets for passenger cars and on-demand mobility services. For this reason, it is also interesting to consider the attitudes towards cars in urban areas. The three surveyed cities are well-developed and offer good public transport systems. In addition, each city has specific innovative transport services (e.g., Uber, Didi or DriveNow). Berlin and San Francisco are "hybrid cities", which exhibit dense public-transit-oriented urban cores, surrounded by low-density car-oriented suburban areas. Shanghai is considered more of a "non-motorized" city, with a high population density which supports the use of non-motorized transport (Institute for Mobility Research (ifmo) 2013). Furthermore, Shanghai has a comparably low car ownership rate resulting from restrictive transport policies. In these cities, we utilized the same standardized survey approach to enable comparability. We designed and implemented a computer-assisted personal interview (CAPI). The total sample size is 1,800 observations, whereby the data set consists of 600 individuals from each city. We conducted a quota sample regarding *age*, *gender*, *household size* and *net income* as a representative survey of each captured city. The survey has finally been carried out to the participants by a professional market research firm (Spiegel-Institut). On-street recruitment was used in Berlin and San Francisco. The surveys have been conducted between October 2016 and January 2017 and aimed at capturing the behavior and the psychological factors of persons above the age of 17 and, as far as possible, the whole household. We have to mention, that on-street recruitment and differences between interviewers can cause biases. Table 1 shows the characteristics of the sample concerning *gender*, *age*, *education* and *occupation*.

Table 1. Sociodemographic Characteristics of the Sample

		Shanghai	**San Francisco**	**Berlin**
Sample Size		*600*	*600*	*600*
Characteristics in %				
Gender	Male	44.33	50.50	48.50
Age	Under 35 years	34.67	28.50	33.50
	Over 59 years	14.00	25.00	23.00
Education	Bachelor degree or higher	67.17	51.83	75.50
Occupation	Full-time + part-time employed	62.83	56.33	54.17
	(Early) Retired	25.50	19.50	18.33
	Student	7.17	7.67	12.50

2.1. The Travel Skeleton Approach

To capture the observed persons comprehensively, we developed a cost-effective integrated survey design. The reason for a new design is the challenge for researchers to collect data about highly variable and complex travel behavior comprising many areas of life. The focus here is on the identification of a basic framework or *skeleton* that captures the important elements of everyday travel. Literature states the idea of using or identifying a so called *skeleton* is common in travel behavior research (Dianat et al. 2017; Doherty et al. 2002; Joh et al. 2007; Saneinejad and Roorda 2009). The *skeleton* provides a reasonable compromise between the level of detail needed and the required effort to survey travel behavior. The concept of a travel *skeleton* aims to focus on the collection of typical elements of travel behavior including their characteristics as frequencies (e.g., concerning use of modes) and also their variation during a week. The questioning of *typical* behavior – in our research referring to the frequent, daily repetition of activities across many weeks – reduces the error rate of short-term snapshots like diary oriented surveys. Thus the *skeleton approach* leads to a smaller intrapersonal variance and has the advantage of a smaller sample size to achieve the same validity. Due to the reduction of variance, a sample of 600 individuals per city was sufficient. Having possible behavioral exceptions in mind, our objective was to also capture less regular performed activities on a more abstract level. Hence, we added questions covering, e.g., day trips at the weekend and holiday trips in terms of frequencies and modal use which is not standard in traditional travel diary approaches yet. Altogether, this allows the collection of "pseudo-longitudinal" data. For more detailed explanations about the *travel skeleton approach*, please refer to von Behren et al. (2017; 2018a; 2018b) and Magdolen et al. (2019). Table 5 in section 3.2 gives a partial overview of the collected data with the *travel skeleton approach*.

2.2. Standardized Psychological Item Sets

Frequently, a high amount of mobility cannot only be explained by objective dimensions like characteristics of alternative modes or different available destinations. We assume that more of the behavior could be explained if we knew more about people's attitudes towards modes and their motivation for car use. For that reason, we added questions dealing with attitudes. In our survey approach, we used a tested and internationally accepted set of questions about attitudes, social and personal norms (Hunecke et al. 2007; Hunecke et al. 2010). Table 2 shows the psychological items used. The item set consists of 27 questions based on a five-point Likert scale. The item set of Hunecke has the advantage that there is a strong focus on sustainable modes such as public transportation and bicycle. Especially when considering cities, these modes are a strong alternative to the car. In addition, we utilized a standardized and well-tested item set regarding motives on car use (Steg 2005; Steg et al. 2001; Riegler et al. 2016). Previous studies have shown that car use respectively car ownership is associated with different other functions (Steg 2005; Steg et al. 2001; Riegler et al. 2016) beyond the instrumental values like, e.g., the symbolic and affective motives. Therefore, we supplemented our survey approach with a well-tested item set to examine the influence of these motives on revealed behavior as well. The item set is displayed in Table 2 (CM-variables).

Table 2. Used Attitude-questions of two Psychological Item Sets

Item categories	*Items*	*Questions*
Public transportation privacy	PTP1	In public transportation people sometimes come too close to me in an unpleasant manner.
	PTP2	In public transportation my privacy is restricted in an unpleasant manner.
Public transportation autonomy	PTA1	I can structure my everyday life very well without a car.
	PTA2	I can take care of what I want to with public transportation.
	PTA3	It is difficult for me to travel the ways I need to go in everyday life with public transportation instead of by car.
	PTA4	If I want, it is easy for me to use public transportation instead of a car to do my things in everyday life.
Public transportation excitement	PTE1	I appreciate public transportation, because there is usually something interesting to see there.
	PTE2	I can easily use the traveling time on the bus or train for other things.
	PTE3	I like to ride buses and trains, because I don't have to concentrate on traffic while doing so.
	PTE4	I can relax well in public transportation.
Public transportation intention	PTI1	It is my intention to use public transportation instead of a car for the things I do in everyday life.
	PTI2	I have resolved to travel the ways I need to go in everyday life using buses and trains.
Subjective norm	SN1	People who are important to me think it is good if I would use public transportation instead of a car for things I do in everyday life.
	SN2	People who are important to me think that I should use public transportation instead of a car.
Personal norm	PN1	Due to my principles, I feel personally obligated to use eco-friendly means of transportation for the things I do in everyday life.
	PN2	I feel obligated to make a contribution to climate protection via my choice of transportation.
Car excitement	CE1	Driving a car means fun and passion for me.
	CE2	Driving a car means freedom to me.
	CE3	When I sit in the car I feel safe and protected.
	CE4	Being able to use my driving skill when driving a car is fun for me.

Perceived mobility necessities	PMN1	My everyday organization requires a high degree of mobility.
	PMN2	I constantly have to be mobile in order to comply with my everyday obligations.
Bicycle excitement	BE1	I like to be out and about by bike.
	BE2	I can relax well when riding a bike.
	BE3	I ride a bicycle because I enjoy the exercise.
Weather resistance	WR1	I don't like to ride my bike when the weather is cool.
	WR2	I also ride my bike when the weather is bad.
Car use motive	CM1	I feel free and independent when I drive a car.
	CM2	A car can communicate status and prestige.
	CM3	The characteristics of a car can show who and what I am.
	CM4	It doesn't matter to me what vehicle type I drive.
	CM5	The functioning of a car is more important to me than the make of a car.
	CM6	A car is primarily a means to an end for me.
	CM7	I like to drive a car.
	CM8	There are dream cars that I would like to drive once.
	CM9	You can draw conclusions about a person from the car.
	CM10	The make of a car is important to me.
	CM11	I only use a car to get from A to B.

Likert scale: 1 = does not apply; 2 = rather does not apply; 3 = applies in part / does not apply in part; 4 = rather applies; 5 = applies

3. Data Preparation and Methodology

Regarding the survey design, we have the possibility to analyze behavior and attitudes of the same persons, relationships between both dimensions and correlations with nationalities. Our analysis to investigate these relationships consisted of an ordered logit regression model. Before we performed the regression, few preparations of the data were needed. Therefore, we applied explorative principal axis factor analysis (PAF) to reduce information about attitudes and norms towards modes and motives for car use and to find unobservable latent variables. In this section, we also present intermediate results, which were used in the subsequent ordered logit regression.

3.1. Factor Analysis

First of all, we performed a PAF with 25 items out of 27 items about attitudes and norms from Table 2. Two items (*Car excitement 1* and *4*) had to be excluded due to missing values in Shanghai. The direct inclusion of the manifest items as explanatory variables in the later regression model is not possible, since the fact that they are afflicted with measurement errors is ignored. Instead, latent variables (factors) are used. In factor analysis items can be combined to factors in case they have a large loading (>0.4) on the same factor (Backhaus et al. 2016). According to the Kaiser criterion, only factors with an eigenvalue greater than one are included for further analysis (Hunecke et al. 2010; Prillwitz and Barr 2011). Based on the PAF we received six factors (see Table 3): *Public transportation orientation (PTO)*, *Bicycle excitement (BE)*, *Norm (N)*, *Public transportation privacy (PTP)*, *Perceived mobility necessities (PMN)* and *Car excitement (CE)*. Results are comparable with findings from Magdolen et al. (2019). Apart from the items about motives of car use, these six latent variables (factors) with information on attitudes built a primary interest in our study.

Table 3. Factor Analysis of Attitudes towards Modes and Norm

Attitudes and norms						
Factors / latent variables	*Public transportation orientation (PTO)*	*Bicycle excitement (BE)*	*Norm (N)*	*Public transportation privacy (PTP)*	*Perceived mobility necessities (PMN)*	*Car excitement (CE)*
Cronbach's alpha	*α=0.93*	*α=0.92*	*α=0.80*	*α=0.72*	*α=0.81*	*α=0.60*
Indicators in PCA						
Public transportation excitement 1	0.73460	.	.	.	.	.
Public transportation excitement 3	0.67940	.	.	.	.	.
Public transportation autonomy 2	0.65059	.	.	.	.	.
Public transportation intention 2	0.64691	.	.	.	.	.
Public transportation excitement 4	0.64564	.	.	.	.	.
Public transportation excitement 2	0.63933	.	.	.	.	.
Public transportation intention 1	0.61339	.	.	.	.	.
Public transportation autonomy 4	0.48855	.	.	.	.	.
Public transportation autonomy 1	0.42252	.	.	.	.	.
Public transportation autonomy 3	.	.	.	.	.	.
Bicycle excitement 1	.	0.91334	.	.	.	.
Bicycle excitement 3	.	0.90143	.	.	.	.
Bicycle excitement 2	.	0.89899	.	.	.	.
Weather resistance 2	.	0.66958	.	.	.	.
Personal norm 1	.	.	0.85542	.	.	.
Personal norm 2	.	.	0.85399	.	.	.
Subjective norm 2	.	.	0.49214	.	.	.
Subjective norm 1	.	.	0.43376	.	.	.
Public transportation privacy 2	.	.	.	0.81212	.	.
Public transportation privacy 1	.	.	.	0.73268	.	.
Weather resistance 1	.	.	.	.	.	.
Perceived mobility necessities 2	.	.	.	.	0.85610	.
Perceived mobility necessities 1	.	.	.	.	0.80753	.
Car excitement 3	.	.	.	.	.	0.71738
Car excitement 2	.	.	.	.	.	0.57017
Criteria of extraction						
Criterion	*Numbers of factors*					
Kaiser Criterion	6					
Scree Test	6					

Based on the 11 items (*CM1-CM11*) of the theoretical framework of car use motives from Steg (2001; 2005), we also performed a second PAF and received three factors representing our latent variables about motives. Table 4 shows the intermediate results of the PAF and the criteria of extraction. Items with high loadings describe the received factors.

In summary, the factors are called *Symbolic* for the first factor, *Emotional* for the second factor and *Instrumental* for the third factor. Results are comparable with Riegler et al. (2016). The factor *Symbolic* means possessing a car can show a persons' characteristics. The second factor, *Emotional*, describes whether people like to drive a car. Lastly, the factor *Instrumental* shows if people only use a car to get from one place to another.

Table 4. Factor Analysis with Items about Motives of Car Use

Car use motives			
Factors / latent variables	*Symbolic*	*Emotional*	*Instrumental*
Cronbach's alpha	$\alpha=0.86$	$\alpha=0.81$	$\alpha=0.74$
Indicators in PCA			
Car use motive 9	0.78456	.	.
Car use motive 3	0.76946	.	.
Car use motive 2	0.72947	.	.
Car use motive 10	0.54911	.	.
Car use motive 7	.	0.89576	.
Car use motive 1	.	0.82796	.
Car use motive 8	.	0.50970	.
Car use motive 6	.	.	0.72882
Car use motive 11	.	.	0.66820
Car use motive 5	.	.	0.60026
Car use motive 4	.	.	0.54505
Criteria of extraction			
Criterion	*Numbers of factors*		
Kaiser Criterion	3		
Scree Test	3		

3.2. Ordered Logit Regression Model

For investigating relation interdependencies between attitudes, sociodemographic variables and behavior, literature often suggests HCM (Kim et al. 2014) or SEM (Urban and Mayerl 2014) but even simpler regression models are used (Fujii and Gärling 2003; Nobis 2006; Sönmez and Graefe 1998; Spears et al. 2013; Doherty et al. 2010). Model requirements make it challenging to compare attitudes or latent variables, as only a few items can be considered for reasons of complexity. When using an ordered logit model, influences on the behavior are partly overestimated. This plays only a minor role in the comparison of countries. However, one has to be careful when comparing the influences of attitudes with influences of behavior or sociodemographic characteristics. This can be distorted by overestimation. For the objective of this paper to compare attitudes, this point also fades partially into the background. To reduce complexity and to have the possibility to compare various variables directly with each other, we decided for an ordered logit regression model on responses to different frequency classes of means of transportation use against the explanatory variables defined in Table 5. By means of the *skeleton approach* we were able to estimate for each person the frequency of their use of different modes. Afterwards, the results were categorized into four classes:

1: several times a week or more often
2: several times a month until once a week
3: once a month or less
4: never

For our international comparison, we examined the influences on the mode choice. In our study we consider car as driver, public transportation and bicycle use. As a result, we consider a non-motorized mode as well as individual and public transport. We have chosen bicycle use as an active mode versus walking, as the walking trips are difficult to capture when questioning the typical behavior in the *travel skeleton approach*. In addition, Hunecke´s item set does not include psychological items for walking. Consequently, our dependent variables are *car driver class*, *public transportation class* and *bicycle class* (see Table 5). These variables have now four instead of two possible outcomes, we cannot apply a normal, i.e., binary logit regression model. The core categories itself are qualitative and have a reasonable sequential order where a higher value is indeed 'smaller' – i.e., indicates using the mode less often – than the previous one, making the answer discretely on an ordinal scale. Thus an ordered logit model was chosen for every regression we carried out in this paper (Wooldridge 2010).

Let Y_i be an ordered response – in our case the aforementioned class of modes of transportation – taking on the values $\{0, 1, 2, \ldots, j, \ldots, J\}$ for some known integer J. This type of regression model allows us to determine the nonlinear probability $Pr\ (Y_i = j \mid X_{i,k})$ that the latent dependent variable Y_i^* will cross a certain estimated threshold or cut points $\alpha_1 < \alpha_2 < \ldots < \alpha_j < \ldots < \alpha_J$ with respect to changes in our independent variables $X_{i,k}$ and can in general be described as follows:

$$Y_i^* = \sum_{k=1}^{K} \beta_{i,k} \cdot X_{i,k} + \varepsilon_i \qquad with \quad \varepsilon_i \mid X_{i,k} \sim N(0,1)$$

where Y_i^* represents the estimated latent dependent variable. We can define:

$$\begin{aligned} Y_i &= 1 \quad if \quad -\infty = \alpha_0 \le Y_i^* \le \alpha_1 \\ Y_i &= 2 \quad if \quad \alpha_1 < Y_i^* \le \alpha_2 \\ Y_i &= 3 \quad if \quad \alpha_2 < Y_i^* \le \alpha_3 \\ Y_i &= 4 \quad if \quad \alpha_3 < Y_i^* \le \alpha_4 = +\infty \end{aligned}$$

Thus, in our model with four different classes *(1, 2, 3, and 4)* we have three cut points α_j $(J = 3)$ to be estimated. The conditional (response) probability that observation n will select class j is then:

$$p_{i,j} = \Pr\left(Y_i = j \mid X_{i,k}\right) = \Pr\left(\alpha_{j-1} < Y_i^* \le \alpha_j\right) = \frac{\exp^{\alpha_j - \sum_{k=1}^{K} \beta_{i,k} \cdot X_{i,k}}}{1 + \exp^{\alpha_j - \sum_{k=1}^{K} \beta_{i,k} \cdot X_{i,k}}} - \frac{\exp^{\alpha_{j-1} - \sum_{k=1}^{K} \beta_{i,k} \cdot X_{i,k}}}{1 + \exp^{\alpha_{j-1} - \sum_{k=1}^{K} \beta_{i,k} \cdot X_{i,k}}}$$

with all α_j- and $\beta_{i,k}$-parameters being estimated by Maximum Likelihood (MLE). For our regression model, we chose different control variables $X_{i,k}$. Table 5 shows the control variables with description which we used for the ordered logit regression. Apart from sociodemographic variables on an individual (e.g. *gender*, *age*, *occupation* status) and household (e.g. *household type*, *household size*) level, we considered variables on travel behavior such as *trips per day* and, of course, our variables of interest, the psychological factors described in Table 3 and Table 4, respectively. Hence, we estimated the following latent variable model:

$$\begin{aligned} Y_i^* = {} & \boldsymbol{\beta_1} \cdot Psychological\ factors + \boldsymbol{\beta_2} \cdot Car\ use\ motives\ + \boldsymbol{\beta_3} \cdot Travel\ behavior\ characteristics + \\ & \boldsymbol{\beta_4} \cdot Sociodemographic\ characteristics\ (personal\ level) + \boldsymbol{\beta_5} \cdot Sociodemographic\ characteristics\ (household\ level) \end{aligned}$$

whereas we included car use motives only in regressions with *car driver class* as the dependent variable, and i denotes the dependent class variable, i.e., *car driver*, *public transportation*, or *bicycle*. It is important to point out that we are not solely interested in the estimated parameters of the regression itself or the expected value of Y_i^* given $X_{i,k}$ – $E(Y_i^* \mid X_{i,k})$ – since Y_i^* is an abstract construct. Instead, we are interested in the above mentioned response probabilities $Pr\ (Y_i = j \mid X_{i,k})$.

Table 5. Used Variables for Ordered Logit Regressions

	Variable	*Description*
Class variable (user frequency)	Car driver class	Car use several times a week or more often = 1 Car use several times a month until once a week = 2 Car use once a month or less = 3 No car use = 4
	Public transportation class	Public transportation use several times a week or more often = 1 Public transportation use several times a month until once a week = 2 Public transportation use once a month or less = 3 No public transportation use = 4
	Bicycle class	Bicycle use several times a week or more often = 1 Bicycle use several times a month until once a week = 2 Bicycle use once a month or less = 3 No bicycle use = 4
Travel behavior	km per day	Average number of kilometers per day
	Trips per day	Average trip rate per day
	Leisure activity days per week	Number of days in which leisure activities take place during a week
	Frequent day trips dummy	More than 3 day trips per year = 1; 3 or less day trips per year = 0
Sociodemographics (personal level)	Age	Age of the person being surveyed
	Male dummy	Male = 1; Female = 0
	High education dummy	Associate of Arts or Associate of Science degree (A.A. or A.S.), Bachelor degree, Master degree, Doctoral degree = 1; Otherwise = 0
	Occupation dummy	Employed full-time or employed part-time = 1; Other occupation status = 0
	Retired dummy	Retired person = 1; Not retired person = 0
	Own bicycle dummy	Person with an own bicycle = 1; Person without an own bicycle = 0
Sociodemographics (household level)	Household type	1-2 people in a household with at least one professional and no children = 1 1-2 people in a household with no professional and no children = 2 Household with children under 18 = 3 3 or more people in a household with no children = 4
	Household size	Number of people in a household
	High net income dummy	Household with a monthly net income above US$ 5,000 (adjusted purchasing power) = 1 Household with less than US$ 5,000 monthly net income (adjusted purchasing power) = 0
	Cars per household	Number of cars per household
	Satisfaction parking dummy	Household with a high satisfaction with the parking facilities at home = 1 Household with a low satisfaction with the parking facilities at home = 0
	Abandoned car dummy	Household reduced car stock in the last 5 years by at least one car = 1 Household did not reduce car stock in the last 5 years = 0

In order to test if our variables of interest are significantly correlated with modes of transportation classes on a general basis, i.e., worldwide – approximated by using our three observed cities – we firstly perform ordered logit regressions with all our observations (i.e., of all the cities) in the sample. Second, since we are interested in the estimated response probabilities at various values of $X_{i,k}$ rather than the values of Y_i^* itself, we cannot solely rely on the value of the estimated parameters $\boldsymbol{\beta}$ indicating the average marginal effect of a unit increase in our variables of interest. Even when comparing different models, the estimators for $\boldsymbol{\beta}$ are not directly comparable, but sign and significance are: The direction of the effect of $X_{i,k}$ on the probabilities $Pr\ (Y_i = j \mid X_{i,k})$ is unambiguously determined by the sign of $\boldsymbol{\beta}$ obtained in the ordered logit regression. Therefore, we additionally estimated marginal effects to illustrate what effect a unit increase in our variables of interest (i.e., the latent variables) on average has on the predicted probability to switch to mode of transportation class 1, 2, 3, or 4, respectively. Third, to reveal if our variables of interest have different effects in different cities, we performed further subsample regressions. For our analysis we used the latest statistical software Stata® Version 15.1.

4. Results

4.1. Descriptive Analysis

Table 6 shows the absolute and relative frequencies of the use of the modes by classes (1, 2, 3, and 4) and city (*SFO*, *BER*, and *SHA*), respectively. Since we conducted our survey within these vivid cities, almost 70 % of the people being surveyed use a car once a week or less and every second participant never uses a car. This effect is mainly driven by the Shanghai subsample (73 % in class 4), where car-ownership is restricted. We expect a relatively low frequency of using public transportation in San Francisco, given that the transit system is less developed in comparison to both Berlin and Shanghai. The absolute frequency distribution of bicycle class is comparable to car driver class, whereas similar relations between Berlin and Shanghai persist. However, in San Francisco, almost 70 % do not use a bicycle, and only about one in ten uses it at least several times a week.

Table 6. Descriptive Analysis of User Frequency

		Frequency classes					
User frequency	Obs.	1 (Several times a week)	2 (Once a week or less)	3 (Once a month or less)	4 (Never)	Median (frequency)	Std. Dev.
Car driver class	**1,800**	**535 (30 %)**	**178 (10 %)**	**189 (10 %)**	**898 (50 %)**	**3**	**1.323**
SFO	*600*	*237 (40 %)*	*71 (12 %)*	*89 (15 %)*	*203 (33 %)*	*2*	*1.309*
BER	*600*	*178 (29 %)*	*76 (13 %)*	*87 (15 %)*	*259 (43 %)*	*3*	*1.290*
SHA	*600*	*120 (20 %)*	*31 (5 %)*	*13 (2 %)*	*436 (73 %)*	*4*	*1.227*
Public transportation class	**1,800**	**874 (49 %)**	**308 (17 %)**	**290 (16 %)**	**328 (18 %)**	**2**	**1.172**
SFO	*600*	*156 (26 %)*	*62 (10 %)*	*123 (21 %)*	*259 (43 %)*	*3*	*1.241*
BER	*600*	*359 (60 %)*	*109 (18 %)*	*104 (17 %)*	*28 (5 %)*	*1*	*0.922*
SHA	*600*	*359 (60 %)*	*137 (23 %)*	*63 (10 %)*	*41 (7 %)*	*1*	*0.922*
Bicycle class	**1,800**	**530 (29 %)**	**212 (12 %)**	**233 (13 %)**	**825 (46 %)**	**3**	**1.301**
SFO	*600*	*65 (11 %)*	*49 (8 %)*	*78 (13 %)*	*408 (68 %)*	*4*	*1.025*
BER	*600*	*233 (39 %)*	*102 (17 %)*	*117 (19 %)*	*148 (25 %)*	*2*	*1.218*
SHA	*600*	*232 (39 %)*	*61 (10 %)*	*38 (6 %)*	*269 (45 %)*	*3*	*1.385*

4.2. Influences of Attitudes, Norms and Motives on Mode Choice

Ordered logit regression modeling was used to determine which psychological factors influence travel behavior. Table 7 shows the results of the regression of the whole sample. The results are divided into two analyses per mode of transportation. The first regression (columns (1), (3), and (5)) captures all independent variables except for *public transportation class* and *bicycle class*, for which the variables for car use motives have not been included. The second regression (columns (2), (4), and (6)) is a reduced model, which only covers variables of primary interest concerning modes to confirm results. If the estimator is negative, an increase of the independent variable leads to a more frequent usage of the considered modes. Positive values describe the opposite effect. One goal of our analyses is to find variables of attitudes which are internationally valid to compare cities from different countries.

Results show highly significant influences on realized car usage by *Car excitement (CE)* and *Public transportation orientation (PTO)*. A higher *CE* and a lower *PTO* leads to a more frequent car use. One important part of the latent variable *PTO* with a high factor loading (see Table 3) is the *Public transportation autonomy (PTA)*. If people can organize their everyday travel without a car, car use will be reduced. The *Perceived mobility necessities (PMN)* has no influence on the probability to use a car in the whole sample. The *Norm (N)* has only an influence in the reduced model (see column (2) in Table 7). People with a higher *Norm* are less likely to use a car. In the use of *public transportation (PT)*, the *Norm* plays a decisive role. The probability of using *PT* increases with a higher *Norm* to use more sustainable means of transport. In addition, motives for car use also have a high impact on behavior. High emotional or instrumental motives for car use increase car usage to a large extent. Interestingly, emotional motives had a higher impact on usage than instrumental motives for car use. This has to be interpreted in connection with *CE*, both (emotional motives and excitement) have to be regarded as similar issues. Motives for car use were only considered in the model for car usage. The reduced model with the variables of interest for car usage confirms the estimators in an isolated consideration regarding magnitude, sign, and significance. As expected, there is also a high significant influence from owning a car in the household.

Table 7. Ordered Logit for Means of Transportation Use

	Dependent variable	**Car driver class**		**Public transportation class**		**Bicycle class**	
	Independent variables	(1)	(2)	(3)	(4)	(5)	(6)
Psychological factors / attitude and norm	Car excitement (CE)	-0.591*** (0.137)	-0.893*** (0.118)	0.390*** (0.105)		0.390*** (0.114)	
	Public transportation orientation (PTO)	0.366*** (0.091)		-1.715*** (0.099)	-1.848*** (0.092)	0.232** (0.099)	
	Bicycle excitement (BE)	0.237** (0.101)		0.125 (0.097)		-1.673*** (0.112)	-1.676*** (0.111)
	Perceived mobility necessities (PMN)	0.034 (0.091)	-0.041 (0.083)	0.586*** (0.088)	0.538*** (0.087)	0.032 (0.095)	
	Norm (N)	0.038 (0.094)	0.156* (0.088)	-0.204** (0.089)	-0.222*** (0.084)	-0.099 (0.098)	-0.102 (0.091)
	Public transportation privacy (PTP)	-0.177* (0.091)		-0.306*** (0.089)	-0.177** (0.082)	-0.096 (0.098)	
Car use motives	Symbolic	0.479*** (0.091)	0.400*** (0.089)				
	Emotional	-0.979*** (0.119)	-0.839*** (0.113)				
	Instrumental	-0.433*** (0.088)	-0.431*** (0.087)				
Travel behaviour	km per day	-0.005** (0.002)	-0.006** (0.002)	0.000 (0.002)	0.000 (0.002)	0.004 (0.003)	0.004 (0.003)
	Trips per day	-0.156** (0.065)	-0.174*** (0.064)	-0.132** (0.062)	-0.146** (0.062)	-0.009 (0.070)	-0.022 (0.068)
	Leisure activity days per week	-0.031 (0.040)	-0.023 (0.040)	0.103*** (0.038)	0.108*** (0.038)	-0.071* (0.042)	-0.065 (0.042)
	Frequent day trips dummy	-0.134 (0.151)	-0.182 (0.150)	0.013 (0.148)	0.026 (0.148)	-0.001 (0.157)	0.009 (0.155)

Sociodemographics (personal level)	Age	-0.029*** (0.006)	-0.030*** (0.006)	0.024*** (0.006)	0.024*** (0.006)	0.003 (0.006)	0.003 (0.006)
	Male dummy	-0.620*** (0.130)	-0.590*** (0.128)	0.306** (0.123)	0.393*** (0.121)	0.053 (0.135)	0.091 (0.134)
	High education dummy	-0.398*** (0.136)	-0.444*** (0.134)	-0.045 (0.133)	-0.041 (0.133)	-0.022 (0.148)	-0.032 (0.146)
	Occupation dummy	-0.589*** (0.182)	-0.653*** (0.180)	0.286 (0.184)	0.266 (0.183)	-0.397** (0.198)	-0.386** (0.194)
	Retired dummy	0.989*** (0.302)	0.957*** (0.299)	0.001 (0.278)	-0.045 (0.276)	-0.403 (0.328)	-0.426 (0.327)
	Own bicycle dummy	-0.240 (0.177)	-0.010 (0.137)	-1.002*** (0.172)	-0.890*** (0.129)	-3.633*** (0.203)	-3.612*** (0.202)
Sociodemographics (household level)	Household type	0.028 (0.075)	0.026 (0.074)	0.006 (0.072)	0.007 (0.072)	-0.129 (0.082)	-0.120 (0.081)
	Household size	0.162** (0.071)	0.148** (0.071)	-0.006 (0.070)	-0.028 (0.069)	-0.118 (0.081)	-0.145* (0.080)
	High net income dummy	-0.244 (0.153)	-0.202 (0.152)	0.529*** (0.148)	0.506*** (0.148)	0.162 (0.170)	0.122 (0.168)
	Cars per household	-1.662*** (0.122)	-1.628*** (0.121)	0.317*** (0.098)	0.424*** (0.094)	0.534*** (0.114)	0.632*** (0.108)
	Satisfaction parking dummy	-0.023 (0.129)	-0.000 (0.128)	0.333*** (0.125)	0.345*** (0.124)	-0.177 (0.139)	-0.144 (0.137)
	Abandoned car dummy	0.268 (0.172)	0.298* (0.171)	0.640*** (0.177)	0.708*** (0.175)	0.164 (0.192)	0.221 (0.189)
Model fit	Observations N	1,427	1,427	1,427	1,427	1,427	1,427
	McFadden's R-squared	0.345	0.338	0.387	0.383	0.473	0.469
	Log likelihood	-1,148.075	-1,160.354	-1,115.190	-1,122.607	-936.147	-942.579
	Likelihood ratio χ^2 (k)	1,211.570	1,187.010	1,410.120	1,395.290	1,678.260	1,665.400
	Probability (P) > χ^2	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors are in parentheses. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Apart from the effect on car usage, *PTO* also has a significant influence on *PT* use with a much higher magnitude and in a reverse direction. The highest significant impact on *PT* usage is caused by the *PTO*. The *PMN* works in the opposite direction. People who claim to be mobile at all times are less likely to use *PT*. These people may have considered that they cannot meet these requirements with *PT* due to a lack of flexibility. It is interesting, however, that a high value nevertheless increases the probability of *PT* use. People seem to accept the lack of privacy. At the same time, a high value for *Public transportation privacy (PTP)* increases car use. People who have a problem with the lack of privacy are more likely to use the car.

The bicycle usage is strongly dependent on *Bicycle excitement (BE)*. A higher *BE* leads to a more frequent use of the bicycle. The bicycle usage is also affected by the *Norm* of people, but the value is not significant. It should also be mentioned that the results show a high significant impact on the use of bicycles by owning a bicycle.

4.3. Marginal Effects

Additionally to our regression model, we considered the marginal effects of the psychological factors on the realized use frequencies of modes of transportation (see Table 8). The marginal effect illustrates what effect an increase by one unit in our variables of interest (i.e., the latent variables) on average has on the predicted probability to switch to mode of transportation class 1, 2, 3, or 4, respectively, leaving the rest of the variables in the model at their corresponding means. It is important to mention – as described above – that lower mode of transportation classes denote a more frequent usage. The marginal effects were only calculated for the reduced models (2), (4), and (6).

Car excitement (CE) showed the highest predicted probability change for class 1 of all used psychological factors concerning car usage. An increase in *CE* of one unit from its mean increases the probability of being in *car driver class* 1 by 15.0 % and reduces the probability to switch to class 4 by 19.6 %. All marginal effects of *CE* regarding the car usage are highly significant. In terms of the different levels of sensitivity in different frequency classes, we can identify typical car-friends and car-rejecters. Therefore, these two groups have the strongest effects at both ends of the user frequency classes. This interpretation was confirmed by the marginal effects of the *emotional* and *instrumental* motives which have also high marginal effects. An increase of the *symbolic* motives reduces the probability to be in classes 1 and 2. A high *symbolic* value is not accompanied by a high usage. This can already be seen in Table 7. *Public transportation orientation (PTO)* showed the highest predicted probability change for class 1 of all used psychological factors. An increase in *PTO* of one unit from its mean increases the probability of being in *public transportation class* 1 by 40.7 % and reduces the probability to switch to class 3 by 30.6 %. Bicycle usage is highly influenced by *Bicycle excitement (BE)*. A one unit decrease in *BE* increases the probability by 38.7 % to never use a bicycle in the typical behavior. The highest predicted positive probability change is observable at *BE* in class 2. This underlines that the bicycle is not a universal mode for all activities and trip purposes.

Table 8. Marginal Effects on Travel Behavior

Dep. var.		Car driver class				Public transportation class				Bicycle class			
	Value	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*
Indep. var.		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Psychological factors / attitude and norm	CE	15.0%*** (2.1%)	6.9%*** (1.2%)	-2.4%*** (0.8%)	-19.6%*** (2.6%)								
	PTO					40.7%*** (2.1%)	-1.4% (2.0%)	-30.6%*** (2.2%)	-8.6%*** (0.9%)				
	BE									8.6%*** (0.9%)	16.8%*** (1.7%)	13.3%*** (2.6%)	-38.7%*** (2.8%)
	PMN	0.7% (1.4%)	0.3% (0.6%)	-0.1% (0.2%)	-0.9% (1.8%)	-11.8%*** (1.9%)	0.4% (0.6%)	8.9%*** (1.6%)	2.5%*** (0.5%)				
	N	-2.6%* (1.5%)	-1.2%* (0.7%)	0.4% (0.3%)	3.4%* (1.9%)	4.9%*** (1.9%)	-0.2% (0.2%)	-3.7%*** (1.4%)	-1.0%*** (0.4%)	0.5% (0.5%)	1.0% (0.9%)	0.8% (0.7%)	-2.3% (2.1%)
	PTP					3.9%** (1.8%)	-0.1% (0.2%)	-2.9%** (1.4%)	-0.8%** (0.4%)				
Symbolic		-6.7%*** (1.5%)	-3.1%*** (0.8%)	1.1%*** (0.4%)	8.8%*** (2.0%)								
Emotional		14.1%*** (1.9%)	6.5%*** (1.1%)	-2.2%*** (0.7%)	-18.4%*** (2.5%)								
Instrumental		7.2%*** (1.4%)	3.4%*** (0.8%)	-1.1%*** (0.4%)	-9.5%*** (1.9%)								

Standard errors are in parentheses. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

4.4. City Comparison

Table 9 shows ordered logit regression results grouped by the three captured cities. Control variables consist of all variables except psychological factors and car use motives. After additionally analyzing odds ratios and marginal effects, we can indicate comparability between the cities regarding the magnitude of their coefficient.

As in Table 7, the coefficients on *Car excitement (CE)* are all negative and statistically highly significant, meaning that the higher *CE* is, the more likely people choose the car, which is unsurprising. The magnitude of the coefficient in the Berlin subsample is smaller than in San Francisco and Shanghai. Regarding a fair public transportation system in Berlin and as being the city with the lowest car-ownership rates in Germany, the car is not of a particular value for travel needs. The highest *CE* effect is observable in Shanghai. We can also observe high influences of *CE* on bicycle use intensities in San Francisco. This reflects that people with higher *CE* do not like to cycle. The influence of car conviction is maybe higher and drivers with a high affinity exclude other options more strongly. The car also has sufficient flexibility to meet people's everyday needs. In addition, in all cities *Bicycle Excitement (BE)* has a high impact on bicycle usage. Referred to *BE*, we indicated a reversed influence on bicycle use. The highest influence is observable in Berlin. Berlin favors cycling because of its topography and the weather conditions in contrast to the other two cities. In Shanghai, *BE* also has a positive influence on *PT* use. The strong growth of bike-sharing systems makes intermodal trip chains more attractive. The bicycles are used as access to *PT*. In contrast, we indicate that people with high *Perceived mobility necessities (PMN)* cannot assure their travel needs at all time. *PMN* is positively associated to *car driver class* in Berlin. People with high mobility requirements use the car more frequently. In Shanghai, a reverse effect can be observed. However, this may also be due to existing traffic problems in Shanghai. People who always have to be mobile make better use of the *PT*, which is well-developed in the inner area of Shanghai. The effect on *PT* use is weaker by *PMN* in Shanghai. This is a large difference to the other cities, where people with a need for mobility are less likely to use *PT* than cars. The *Public transportation orientation (PTO)* has in all three cities a statistical significant influence on *PT*. This raises also the question of how the Chinese assess the use of the subway. Here the subways are sometimes more crowded. In many cases, there is no alternative for people in Shanghai. Consequently, one has to make him- or herself comfortable with the situation. In addition, Chinese people have a different view of privacy, because the required personal space is culturally different. People from individualistic cultures, such as the U.S., usually demand more personal space than people from collectivistic cultures (Ri 2018). This is also confirmed by the latent variable *Public transportation privacy (PTP)*. People who made unpleasant experiences in the *PT* also use it more often and accept the situation as there seems to be no suitable alternative for some trips. The opposite effect can be observed in San Francisco. This leads to the question if people lack experience with the *PT* and they only believe that people come too close to them unpleasantly. But it could also be due to cultural differences that we cannot comprehensively capture here. The *Norm (N)* has no significant influence on the usage, but a high influence is observable in San Francisco against the car, in Berlin towards the *PT* and in Shanghai towards cycling.

Concerning the model fit parameters of the ordered logit regressions, it is important to note that all model chi-squared values were significant at corresponding levels less than 0.01 percent, with probabilities (P) > $\chi 2$ = 0.000 in all regressions in this paper. The continuously high likelihood ratio chi-squares with a p-value of 0.000 tell us that our model as a whole is statistically significant, as compared to the null model with no predictors. The McFadden R-squared (pseudo R-squared) is also given in the respective model fit section: All values are in between 0.277 and 0.555, meaning that we cannot use these models flawlessly to predict the use of different modes of transportation with certainty. Nevertheless, our regression results show which factors are reliably important, i.e., are (highly) significantly correlated with our dependent variables, which is the primary focus of this study.

Table 9. Ordered Logit Regression by Cities

	Dependent variable	Car driver class			Public transportation class			Bicycle class		
	City	*SFO*	*BER*	*SHA*	*SFO*	*BER*	*SHA*	*SFO*	*BER*	*SHA*
	Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Psychological factors / attitude and norm	Car excitement (CE)	-1.462*** (0.182)	-1.002*** (0.169)	-2.716*** (0.438)	0.185 (0.182)	0.580*** (0.199)	0.940*** (0.248)	0.821*** (0.230)	0.146 (0.187)	0.153 (0.263)
	Public transportation orientation (PTO)	0.207 (0.137)	0.397** (0.163)	0.422 (0.374)	-1.936*** (0.170)	-1.944*** (0.210)	-2.210*** (0.286)	0.433*** (0.167)	-0.003 (0.188)	0.190 (0.321)
	Bicycle excitement (BE)	0.119 (0.183)	0.264* (0.152)	0.364 (0.303)	0.035 (0.196)	0.275 (0.176)	0.320 (0.196)	-1.900*** (0.222)	-2.470*** (0.217)	-1.589*** (0.252)
	Perceived mobility necessities (PMN)	0.037 (0.162)	-0.343** (0.147)	0.458 (0.344)	0.600*** (0.161)	0.685*** (0.168)	0.385* (0.204)	0.224 (0.188)	-0.211 (0.160)	0.323 (0.241)
	Norm (N)	-0.143 (0.145)	-0.085 (0.146)	-0.046 (0.454)	-0.067 (0.149)	-0.165 (0.171)	0.125 (0.294)	0.032 (0.172)	-0.001 (0.163)	-0.257 (0.359)
	Public transportation privacy (PTP)	-0.510*** (0.156)	-0.172 (0.139)	-0.017 (0.448)	0.385** (0.164)	-0.180 (0.160)	-0.671** (0.293)	-0.163 (0.194)	0.070 (0.158)	0.334 (0.338)
	Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model fit	Observations N	531	462	434	531	462	434	531	462	434
	McFadden's R-squared	0.367	0.277	0.555	0.446	0.377	0.323	0.500	0.504	0.472
	Log likelihood	-430.559	-434.340	-176.162	-372.365	-310.731	-315.169	-265.943	-305.834	-263.070
	Likelihood ratio χ^2 (k=22)	498.680	332.960	439.23	599.090	376.080	300.870	529.420	622.490	470.110
	Probability (P) > χ^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors are in parentheses. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

5. Conclusions

For a comprehensive analysis of mobility markets, the consideration of behavior and attitudes is a basic prerequisite to identify future potentials for mobility services and transport planning in general. To analyze the influence of attitudes on travel behavior between cities (mobility markets), we applied an integrated survey approach combining revealed travel behavior and underlying psychological factors. Instead of providing a trip diary, we used a *skeleton approach* to capture and identify typical travel behavior. Psychological factors are employed using psychological item sets from existing research. Using the data, we performed ordered logit regressions to identify influences between attitudes and realized behavior. The study concentrates on the comparison between cities in different cultural contexts. Based on a survey, the three cities Berlin, Shanghai and San Francisco were compared.

Results have shown the signs of influences on the behavior are similar. However, differences in magnitude become clear. In particular, the analysis of *Car excitement (CE)* shows differences. In Shanghai and San Francisco, the *CE* has a significantly greater influence on car use. But we must emphasize the fact that Berlin is not typical for German cities in this respect either. However, this also applies to Shanghai or San Francisco if one compares the cities with Wuhan or Houston as an example. In this context, the difference in culture becomes clear. In Berlin, in contrast to the other cities considered, *Perceived mobility necessity (PMN)* plays an important role. If people think they have to be mobile, then they are more likely to use a car. A reverse effect is visible in Shanghai. Affinity to the car has a negative influence on the use of bicycles in all three cities. Especially people in San Francisco are less likely to use bicycles with increasing car affinity. This strong effect is not visible in Berlin and Shanghai. Results have also shown an influence of privacy on the use of *PT* in San Francisco. People whose privacy is disturbed have a lower probability of using *PT*. This is where transport planners should start and also improve privacy in *PT*. Car- or ridesharing tries to offer such an opportunity.

The study also shows the need for comparative international studies. The focus here should be on comparability. Comparability at a more abstract level naturally leads to restrictions in interpretation. These limitations should be taken into account when interpreting the results. Nevertheless, the results of the study show discrepancies and similarities between cities. These results can be used for transport planners or mobility companies to point out possible potentials which are not currently reflected in the realized behavior. Further, our findings are transferable to similar cities with similar transport services and cultural backgrounds. In our study we have examined cities which are already well-developed in their countries. The comparison of the pure number of inhabitants or city size is not enough. Rather, the transport offer in the city must be compared for transferability. However, for example the transfer of results regarding attitudes towards cycling must take into account climatic and topographical peculiarities. At this point the influences can deviate strongly.

Further research should address possible reverse causality effects between our dependent and explanatory variables, meaning that realized behavior could cause changes in attitudes. In our model, the influence of sociodemographic characteristics on psychological factors cannot be investigated either. More complex models must be used for these relationships. An international comparison of this relationship should also be targeted. To what extent more complex models such as HCM or SEM must be used for this is part of future research. Finally, additional cities and countries should be surveyed to overcome concerns about sample selection. In particular, the comparison of strongly car-oriented cities with the already surveyed modern cities such as Shanghai, San Francisco, and Berlin is of great interest.

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References

Ajzen, Icek (1991): The theory of planned behavior. In *Organizational Behavior and Human Decision Processes* 50 (2), pp. 179–211. DOI: 10.1016/0749-5978(91)90020-T.

Ashok, Kalidas; Dillon, William R.; Yuan, Sophie (2002): Extending Discrete Choice Models to Incorporate Attitudinal and Other Latent

Variables. In *Journal of Marketing Research* 39 (1), pp. 31–46. DOI: 10.1509/jmkr.39.1.31.18937.

Backhaus, Klaus; Erichson, Bernd; Weiber, Rolf; Plinke, Wulff (2016): Faktorenanalyse. In Klaus Backhaus, Bernd Erichson, Wulff Plinke, Rolf Weiber (Eds.): Multivariate Analysemethoden: Springer Berlin Heidelberg, pp. 385–452.

Bamberg, Sebastian; Ajzen, Icek; Schmidt, Peter (2003): Choice of Travel Mode in the Theory of Planned Behavior. The Roles of Past Behavior, Habit, and Reasoned Action. In *Basic and Applied Social Psychology* 25 (3), pp. 175–187. DOI: 10.1207/S15324834BASP2503_01.

Ben-Akiva, Moshe; McFadden, Daniel; Gärling, Tommy; Gopinath, Dinesh; Walker, Joan; Bolduc, Denis et al. (1999): Extended Framework for Modeling Choice Behavior. In *Marketing Letters* 10 (3), pp. 187–203. DOI: 10.1023/A:1008046730291.

Ben-Akiva, Moshe; Walker, Joan; Bernadino, Adriana; Gopinath, Dinesh; Morikawa, Taka; Polydoropoulou, Amalia (2002): Integration of Choice and Latent Variable Models. In Hani Mahmassani (Ed.): In perpetual motion - Travel behavior research opportunities and application challenges. 1st ed. Amsterdam, New York: Pergamon, pp. 431–470.

Bouscasse, Hélène (2018): Integrated choice and latent variable models: A literature review on mode choice. Working Papers GAEL n° 07/2018, checked on 4/24/2019.

Dianat, Leila; Habib, Khandker Nurul; Miller, Eric J.; Transportation Research Board (2017): Modeling Non-Work/School Activity Patterns in a Week-Long Activity-Based Model Using Skeleton Schedule Constraints. In Transportation Research Board (Ed.): TRB 96th Annual Meeting Compendium of Papers. Washington, D.C.

Dobson, Ricardo; Dunbar, Frederick; Smith, Caroline J.; Reibstein, David; Lovelock, Christopher (1978): Structural models for the analysis of traveler attitude-behavior relationships. In *Transportation* 7, pp. 351–363. DOI: 10.1007/BF00168036.

Doherty, Noeleen; Dickmann, Michael; Mills, Timothy (2010): Mobility attitudes and behaviours among young Europeans. In *Career Dev Int* 15 (4), pp. 378–400. DOI: 10.1108/13620431011066259.

Doherty, Sean T.; Miller, Eric J.; Axhausen, Kay W.; Gärling, Tommy (2002): A Conceptual Model Of The Weekly Household Activity-Travel Scheduling Process.

Fujii, Satoshi; Gärling, Tommy (2003): Application of attitude theory for improved predictive accuracy of stated preference methods in travel demand analysis. In *Transportation Research Part A: Policy and Practice* 37 (4), pp. 389–402. DOI: 10.1016/S0965-8564(02)00032-0.

Gärling, Tommy; Gillholm, Robert; Gärling, Anita (1998): Reintroducing attitude theory in travel behavior research: The validity of an interactive interview procedure to predict car use. In *Transportation* 25 (2), pp. 129–146. DOI: 10.1023/A:1005004311776.

Golob, Thomas F. (2003): Structural equation modeling for travel behavior research. In *Transportation Research Part B: Methodological* 37 (1), pp. 1–25. DOI: 10.1016/S0191-2615(01)00046-7.

Hunecke, M.; Haustein, S.; Böhler, S.; Grischkat, S. (2010): Attitude-Based Target Groups to Reduce the Ecological Impact of Daily Mobility Behavior. In *Environment and Behavior* 42 (1), pp. 3–43. DOI: 10.1177/0013916508319587.

Hunecke, Marcel; Haustein, Sonja; Grischkat, Sylvie; Böhler, Susanne (2007): Psychological, sociodemographic, and infrastructural factors as determinants of ecological impact caused by mobility behavior. In *Journal of Environmental Psychology* 27, pp. 277–292. DOI: 10.1016/j.jenvp.2007.08.001.

Institute for Mobility Research (ifmo) (Ed.) (2013): Megacity Mobility Culture - How Cities Move on in a Diverse World. Berlin, Heidelberg: Springer Berlin Heidelberg (Lecture Notes in Mobility).

Joh, Chang-Hyeon; Arentze, Theo A.; Timmermans, Harry (2007): Identifying Skeletal Information of Activity Patterns by Multidimensional Sequence Alignment. In *Transportation Research Record: Journal of the Transportation Research Board* (2021), pp. 81–88. Available online at http://dx.doi.org/10.3141/2021-10.

Kim, Jinhee; Rasouli, Soora; Timmermans, Harry (2014): Hybrid Choice Models: Principles and Recent Progress Incorporating Social Influence and Nonlinear Utility Functions. In *Procedia Environmental Sciences* 22, pp. 20–34. DOI: 10.1016/j.proenv.2014.11.003.

Kroesen, Maarten; Handy, Susan; Chorus, Caspar (2017): Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. In *Transportation Research Part A: Policy and Practice* (101), pp. 190–202. DOI: 10.1016/j.tra.2017.05.013.

Magdolen, Miriam; von Behren, Sascha; Chlond, Bastian; Hunecke, Marcel; Vortisch, Peter (2019): Combining attitudes and travel behavior - A comparison of urban mobility types identified in Shanghai, Berlin and San Francisco. In Transportation Research Board (Ed.): TRB 98th Annual Meeting Compendium of Papers. Washington, D.C.

Nobis, Claudia (2006): Carsharing as Key Contribution to Multimodal and Sustainable Mobility Behavior: Carsharing in Germany. In *Transportation Research Record: Journal of the Transportation Research Board* (1986), pp. 89–97. Available online at http://dx.doi.org/10.3141/1986-14.

Prillwitz, Jan; Barr, Stewart (2011): Moving towards sustainability? Mobility styles, attitudes and individual travel behaviour. In *Journal of Transport Geography* 19, pp. 1590–1600. DOI: 10.1016/j.jtrangeo.2011.06.011.

Ri, Li (2018): Politeness in Chinese-American non-verbal intercultural communication. International Workshop on Advances in Social Sciences

(IWASS). Available online at https://webofproceedings.org/proceedings_series/ESSP/IWASS%202018/IWASS1231237.pdf.

Riegler, Sebastian; Juschten, Maria; Hössinger, Reinhard; Gerike, Regine; Rößger, Lars; Schlag, Bernhard et al. (2016): Carsharing 2025 - Nische oder Mainstream? Institut für Mobilitätsforschung (ifmo).

Saneinejad, Sheyda; Roorda, Matthew (2009): Application of sequence alignment methods in clustering and analysis of routine weekly activity schedules. In *Transportation Letters: The International Journal of Transportation Research* 1 (3), pp. 197–211. DOI: 10.3328/TL.2009.01.03.197-211.

Sönmez, Sevil F.; Graefe, Alan R. (1998): Determining Future Travel Behavior from Past Travel Experience and Perceptions of Risk and Safety. In *Journal of Travel Research* 37 (2), pp. 171–177. DOI: 10.1177/004728759803700209.

Spears, Steven; Houston, Douglas; Boarnet, Marlon G. (2013): Illuminating the unseen in transit use: A framework for examining the effect of attitudes and perceptions on travel behavior. In *Transportation Research Part A: Policy and Practice* 58, pp. 40–53. DOI: 10.1016/j.tra.2013.10.011.

Steg, Linda (2005): Car use: Lust and must. Instrumental, symbolic and affective motives for car use. In *Transportation Research Part A: Policy and Practice* 39 (2-3), pp. 147–162. DOI: 10.1016/j.tra.2004.07.001.

Steg, Linda; Vlek, Charles; Slotegraaf, Goos (2001): Instrumental-reasoned and symbolic-affective motives for using a motor car. In *Transportation Research Part F: Traffic Psychology and Behaviour* 4 (3), pp. 151–169. DOI: 10.1016/S1369-8478(01)00020-1.

Urban, Dieter; Mayerl, Jochen (2014): Strukturgleichungsmodellierung. Ein Ratgeber für die Praxis. 1. Aufl. Wiesbaden: Springer VS.

von Behren, Sascha; Heilig, Michael; Bönisch, Lisa; Chlond, Bastian; Vortisch, Peter (2018a): How Attitudes Effect On-Demand Mobility Usage – an Example from China. In International Association for Travel Behaviour Research (IATBR) (Ed.): 15th International Conference on Travel Behavior Research. Santa Barbara, 15.-19.07.2018.

von Behren, Sascha; Minster, Clotilde; Esch, Johanna; Hunecke, Marcel; Chlond, Bastian (2017): Assessing Car Dependence: Development of a Comprehensive Survey Approach Based on the Concept of a Travel Skeleton. In International Steering Committee for Travel Survey Conferences (ISCTSC) (Ed.): 11th International Conference on Transport Survey Methods. Esterel, Canada, September 24-29, 2017.

von Behren, Sascha; Minster, Clotilde; Magdolen, Miriam; Chlond, Bastian; Hunecke, Marcel; Vortisch, Peter (2018b): Bringing travel behavior and attitudes together: An integrated survey approach for clustering urban mobility types. In Transportation Research Board (Ed.): TRB 97th Annual Meeting Compendium of Papers. Washington, D.C.

Walker, Joan Leslie (2001): Extended Discrete Choice Models - Integrated Framework, Flexible Error Structures, and Latent Variables. Dissertation. Massachusetts Institute of Technology, Massachusetts. Department of Civil and Environmental Engineering. Available online at https://its.mit.edu/sites/default/files/documents/WalkerPhD.pdf.

Wooldridge, Jeffrey M. (2010): Econometric analysis of cross section and panel data. Cambridge, Mass.: MIT Press.