BRINGING TRAVEL BEHAVIOR AND ATTITUDES TOGETHER: AN INTEGRATED SURVEY APPROACH FOR CLUSTERING URBAN MOBILITY TYPES

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ABSTRACT

Implementing measures to improve transportation systems requires detailed knowledge of potential travelers' behavior and underlying psychological factors. Traditional travel surveys often provide information about travel behavior only. Crucial aspects such as information about attitudes and norms are usually not considered. However, this information is relevant to gain knowledge about acceptance of planned measures, e.g., new mobility offers. Our research tries to overcome these challenges by elaborating an integrated survey approach. To this aim, we combine questions on mobility patterns, using a travel skeleton, and questions related to people's norms and attitudes. We conducted a travel survey in selected German cities and clustered data to define and identify different urban mobility types. For this, we brought together travel behavior as well as attitudes and norms. Our results showed the importance of both aspects, as travel behavior does not necessarily correspond to people`s attitudes (e.g., people who like driving a car, but using transit). Our clusters distinguished both: travel behavior and attitudes. Among those clusters are for example *convinced cyclists* or *eco-modes oriented pragmatics*. The clustered data indicates how to efficiently address travelers in order to introduce measures such as new mobility offers.

INTRODUCTION

To define, implement and assess efficiency of transportation measures, a sound knowledge of travel behavior, travelers' requirements as well as information about their attitudes towards different modes is required. However, in most cases, a very detailed survey approach, which covers all relevant aspects, is essential. Traditional travel surveys are usually expensive and they often do not capture all relevant aspects of travel behavior, such as survey elements on attitudes towards different means of transportation. Beside cost aspects, extensive survey designs also imply considerable respondent burden. Consequently, understanding the travel behavior and evaluating the efficiency of any transport related measures suffers from a lack of information. Another crucial deficit of conventional survey approaches covering only one day is the missing information about the variability in behavior, multimodality and long-distance traveling. Furthermore, the information in these cross-sectional surveys covers only the effective i.e. realized travel behavior. Explanations for the use (or non-use) of a given mode are usually not available.

Travel behavior surveys dealing with so many different research aspects cannot be structured as common travel behavior household surveys. Thus, we developed the idea of the travel skeleton approach. We are not asking for detailed information about trips but rather about the determinants of travel, such as the frequency and locations of peoples' activities, segmented for different purposes. These determinants serve as a "skeleton". The data does not result in detailed key figures such as in-depth modal split share of all trips of a random day. Instead we aimed to capture the determinants of individual travel behavior. Further, we combined this survey about travel behavior with a well-tested set of questions concerning attitudes towards travel modes, social norms and preferences. Existing research only uses travel behavior data without underlying psychological frameworks.

Altogether, this survey approach functions as a universal compromise. On the one hand, it provides data for understanding of people's behavior. On the other hand, information about norms and attitudes, e.g. the reasons for their behavior, is collected.

The first objective of our research is to develop an integrated survey tool in order to collect information about inhabitants' mobility with a manageable length and flexibility. Additionally, the application of the collected data should help to segment urban populations in terms of (urban) mobility types. Our research question is: Does this kind of combined approach provide enough information to sufficiently assess transportation measures?

In this paper, we present our survey approach in combination with the travel skeleton and psychological questions as an innovative, integrative tool. The survey was administered to 850 randomly selected people living in specific urban neighborhoods in Hamburg and Berlin. To test our research question, we segmented people based on cluster analysis and were able to define different urban mobility clusters. These clusters include behavior as well as attitudes and social norms of the individuals.

LITERATURE REVIEW

Travel behavior can be analyzed by reducing the complexity of different individuals' behavior. Well known in market research, segmenting data in groups with similar characteristics has recently become an established approach in travel behavior research as well. To obtain these groups, cluster analysis methods are often used. Considering influences on travel behavior of different peer groups is essential to develop targeted strategies to offer suitable infrastructure and services, or generally spoken, travel solutions. This can affect people's mode choice and traveling.

Wulfhorst et al. (*1*) conducted a cluster analysis to identify types of megacities worldwide with regard to different mobility cultures. Based on a factor analysis with diverse indicators (e.g. land use, quality of transport systems), the study highlighted specific local conditions of megacities as an important influence on mobility patterns. Klinger et al. (*2*) classified German cities by a mobility culture approach. Various indicators were involved in the segmentation, showing presumed interactions of objective and subjective indicators (e.g. urban form, mobility-related perceptions). Both studies show segmentation as an appropriate approach in geographic transport research to identify distinct city clusters.

Furthermore, clustering of individuals by revealed behavior is useful to gain an overall understanding of travel behavior. There is a consensus amongst researchers about relevance and impact of infrastructural and sociodemographic factors on the one hand as well as attitudinal factors on the other hand. The latter originates from the theory of planned behavior (TPB) by Ajzen (*3*). He states a dependency between attitudes and travel mode choice. Hence, there are several approaches to include attitudes in the analysis of travel behavior. Besides clustering methods, applications including attitudes as latent variables in discrete choice, hybrid choice and structural equation models emerged (*4; 5*). Kroesen et al. (*6*) present an detailed overview of studies with varying approaches to analyze attitudes and travel behavior. Attitudes are usually measured and thus made quantitatively easy to handle using a Likert scale (*7–9*).

For clustering, various variables can be used. This includes psychological factors standing for attitudes or indicators representing issues of travel behavior. One of the main goals is to combine cluster analyses with attitudes which mostly result from surveys comprehending a modified TPB (*7; 9; 10*). Hunecke et al. (*8*) conducted a regression analysis to underline the meaning of psychological variables compared to demographic and infrastructural variables. Redmond (*11*) combined lifestyle and personal factors in a cluster analysis and compared the results with an cluster analysis with attitudinal factors. Prillwitz and Barr (*12*) conducted an attitude-based cluster analysis besides a cluster analysis based on individual travel behavior. Both approaches obtained four clusters, which were then linked to each other. Besides the variables used to identify the clusters, various characteristics help to understand the different types (resulting clusters) of travel behavior. Depending on the data, sociodemographic and psychological attributes, aspects of travel behavior as well as residential location characteristics may be involved.

Consequently, more research work on bringing together attitudes and behavior in a cluster analysis is crucial, because a combination of both dimensions can identify clusters with dissonances. Our paper closes this research gap by performing a cluster analysis with both dimensions.

DATA AND SURVEY DESIGN

The following analyses are based on a data collection approach, which can be considered unique, since we capture and combine comprehensive information about many travel related aspects. These aspects consist of daily and occasional travel behavior (including longitudinal aspects such as variability, multimodality and long-distance traveling) and attitudes towards different means of transportation (including social and individual norms).

The "Urban Travel Monitor" (UTM) is a data collection and data provision project funded by the BMW Group. BMW aims to develop a survey approach, which can be applied in different cultural contexts, collects data in a compact and universal form and allows for the capturing of many aspects and indicators. Therefore, we implemented an innovative survey design in order to compare markets and identify households or individuals open to new offers for car sharing from an objective and subjective perspective. Objective perspective indicates for example a low level of car use, i.e. that the car ownership is not essential for many car owners. Subjective perspective means for example a psychological disposition to change travel behavior and car ownership status.

Data collection

The data in this study are based on a survey in Germany and was conducted in two urban districts in Berlin and Hamburg. In this survey, we used a computer assisted personal interview. To make the interview more diversified and less monotonous for the interviewees, we combined it with a part for self-completion (questions regarding attitudes towards modes). The surveys were part of two neighborhood development projects in both districts, which included measures to increase the amenity values of public space. The sample consisted of 563 individuals in Hamburg and 287 individuals in Berlin. The survey took place in both cities from May to November 2016. The survey aimed at capturing behavior and psychological factors of people above the age of 17 and, as far as possible, the whole household. The characteristics of the investigated neighborhoods are very similar: they are both located near the city centers, having good public transportation accessibility but poor parking facilities and good access to shopping and recreational facilities. Lacking parking facilities especially lead to the idea of a survey about travel behavior to improve their situation with new mobility services such as bikes or car sharing.

The sampling procedure was random: every person of the investigated neighborhoods had the chance to participate in the survey. The survey institute recruited the participants by means of different motivations (e.g. incentives) in cooperation with civic associations in the neighborhoods. Apart from the randomness, the samples showed an approximate similarity regarding gender, age and household size distribution in the investigated neighborhoods.

The travel skeleton approach

To capture comprehensive data, we developed an innovative integrated survey design. The collection of data on travel behavior is a sophisticated challenge for researchers, as this data is usually highly variable. With increasing complexity of a survey, the respondents´ burden rises and the samples become more expensive regarding recruiting. Altogether, these reasons mean considerable constraints for research. Regarding data, it is important (at least in order to examine the applicability of sharing concepts) to capture both long-distance travel behavior as well as everyday travel behavior. When measuring determinants of this behavior (e.g. socio-economically existing options for modes and destinations), it is also necessary to consider the spatial settings and the attitudes behind the revealed behavior. Surveys about travel behavior and its determinants usually emphasize only one certain aspect. This means a one-off application of collected data according to the research idea. Hence, the idea of the travel skeleton comprises a streamlined, efficient and universal approach. Using and identifying a so called "skeleton" is common in the research of travel behavior (*13–16*). The travel skeleton-idea aims to concentrate on collecting typical and relevant elements and determinants of travel behavior including their characteristics such as frequencies and variabilities. This information determinates behavior of individuals, because also less regular activities can be captured. This approach leads to a smaller intrapersonal variance in the sample, which implies a smaller sample size. The captured variability in the sample is mostly interpersonal. The much smaller sample size can be considered as a central advantage of this approach. Furthermore, we aimed to capture less regularly performed activities on a more abstract level, e.g. day trips over the weekend or holiday trips. Such information usually lacks in traditional travel diary approaches. Altogether, this allows the collection of "pseudo-longitudinal" data. It is a reasonable compromise between the level of detail needed and the effort required to collect the data. In principle, longitudinal data collection approaches such as the German Mobility Panel (MOP), which captures one week, allow to identify typical frequencies and (at least partially) the levels of variability of certain types of activities. For long-distance travel studies, it is common to ask retrospectively at a certain time. Another possibility is to ask for typical frequencies and characteristics of activity types, both covering the longitudinal range. In summary, a fundamental knowledge about typical characteristics, frequencies and variations of different types of activities for everyday and long-distance travels helps to identify a set of questions to create a "pseudo-longitudinal" database.

We formulated questions according to socio-demographic and socio-economic self-assessment of the participants. Furthermore, we asked for context information about frequently visited destinations in daily travel (e.g. the accessibility with alternative modes) to illustrate and characterize the options for variations. As an add-on to the travel skeleton, we asked the participants about the use (and principle knowledge) of on-demand mobility services.

Often travel behavior cannot be explained entirely by the "objective" situation, i.e. the characteristics of alternative modes or different available destinations. We assume that behavior can be further explained knowing more about peoples' attitudes towards modes. For that reason, we complemented the survey with questions about attitudes, adding a tested and internationally accepted set of questions about attitudes, social and individual norms as an optional element (*8*).

INDICATORS

Regarding our survey design, we were able to use information on behavior and attitudes of the same individuals in our analyses. However, the skeleton approach comprises a lot of different information on different levels. For a clustering approach, this vast amount of information needs a densification, in order to keep the clustering feasible and manageable. Therefore, we generated adequate indicators of behavior and attitudes. In the following section, we introduce and describe the selected indicators for the cluster analysis. Next, we describe the cluster analysis to determine homogenous groups for different attitudes and behavior.

Travel behavior

The idea of clustering types of mobility has to concentrate on relevant aspects, in which individuals are likely to show a certain level of variation. Hence, we had to compress the available information in order to reduce the complexity of the behavior of individuals within the sample. In our analyses, we decided to use three indicators to describe the revealed travel behavior. In the decision process, we attempted to cover different facets of behavior. First, we calculated an indicator that shows the "complexity" of the persons' daily life regarding their activities during a typical week (first indicator). The second indicator reflects the mode choice of the participants. Furthermore, we considered daily mileage as a standard indicator for "volume of travel" (third indicator). The generated indicators are listed and described as follows.

The first indicator is called "Complexity of daily life" (CDL) and considers the quantity of activities as well as the variability of activities. Variability means how many different activities take place. To calculate a measure of instability in behavior, we used the Herfindahl-Hirschman-Index (HHI) (*17; 18*). The HHI as used by Mallig and Vortisch (*17*) is defined as

$$H = \sum_{i=0}^{N} {s_i}^2$$

whereby s_i is the share of category i. The HHI can assume values between $\frac{1}{N}$ and 1. To calculate the CDL, we used the shares of specific activities (work, leisure, chauffeuring, errands and shopping) in proportion to all performed activities in a week. For our indicator we normalized the HHI to the range of [0;1] (*17*). In addition, we reversed the values for a complexity indicator:

$$H^* = 1 - \left[\frac{H - \frac{1}{N}}{1 - \frac{1}{N}}\right]$$

Through this reversion, we received a measure of instability of activities. High values near 1 mean a high complexity of daily life and values near 0 a low complexity in performed activities.

The second indicator used was a system variable, which included the mode choice of individuals. The indicator presents the use of different modes on a scale between environmental-friendly (bicycle and public transportation) on the one side and the car on the other. We named this variable "System variable eco-modes versus car" (SVEC). It considers the user frequency of bicycle and public transportation on the one hand and car usage on the other hand. The indicator ranges between 0 and 1. A value near 1 is equivalent to a high car use and a very low use of eco-modes. A very low value shows a high eco-mode usage and a low car usage. This indicator reduces the complexity of the mode choice by showing only the decision between car and eco-modes.

We chose the daily mileage expressed in kilometers ("Kilometer per day" – KPD), as the last indicator. Based on the travel skeleton, we estimated the daily mileage from the information of typical activities and their average distance. This estimated value is not comparable with mileage information of travel diaries, because more or less random activities and trips are not considered in the travel skeleton. However, the information was appropriate for an interpersonal comparison, which is one of the objectives of this paper.

Attitudes towards modes

Besides the indicators of travel behavior, we generated three indicators of attitudes towards different modes. For that reason, we used a standardized item set with 27 questions based on a Likert scale (*8; 19*). TABLE 1 shows the 27 items used. The Likert scale is the approach most widely used to scale responses in survey research of attitudes. We scaled each attitudinal statement from 1 to 5. It allows using the results as quasi-metric values and carry out common mathematically operations like calculating an arithmetic mean. We formed ten categories as variables out of the 27 items by calculating the mean of each item group (see TABLE 2).

Based on these 10 variables we performed a principal component analysis (PCA) to reduce the number of involved variables in the subsequent cluster analysis. This method is used in many studies concerning travel aspects (*10; 8; 12*). This is in a strict sense not a factor analysis, but it is useful to decrease the (mostly vast amount of) data to a few components (*20*). Variables can be combined within the same factor in case they have a large loading (*21*). Often, only factors are included in further analysis in case their eigenvalue is above one (*8; 12*). The so-called Kaiser criterion is fulfilled, when only factors with eigenvalue above one are included. To improve results of the PCA a varimax rotation was used (*8; 7*). It simplifies the factor structure of a group of items. It helps to find a distinct and interpretable result by receiving a factor solution in which the variables either have a large or small loading on one component (*20*). Apart from the Kaiser criterion, we calculated the useful number of factors by well-recognized criteria respectively tests such as Scree-Test, Horn's Parallel Analysis and Minimum Average Partial (MAP) Test (*20; 22*). The Parallel test of Horn creates a random dataset by using the same amount of observations as the original data set and compares the eigenvalues of the random data set with the original data. In case the eigenvalues of the PCA are smaller than the eigenvalues from the random data, the components are mostly random noise. Therefore, the number of components is appropriate when the eigenvalues of the PCA are barely larger than the eigenvalues of the random data. The MAP-Test shows the amount of common variance remaining in the data after extracting *n* components. For further information of the described methods an extended overview is given in Ledesma et al. (*22*). In addition, we checked the quality of the factor analyses by using different quality measures (Kaiser´s Measure of Sampling Adequacy (MSA) and the Bartlett's Test of Sphericity). Both measures confirmed a sufficient quality of the factor analysis (*23; 24*).

TABLE 2 shows the results of the tests and the quality measures. Regardless of the criteria used, the interpretation of the components is essential. In many cases, it is preferable to choose more components as advanced methods recommend, if the interpretation in subsequent analyses is easier. Based on the importance to interpret the results, we decided to use three components of the attitudes. The factors are called public transportation affinity (PTAF) for the first factor, bicycle affinity (BA) for the second factor and car affinity with perceived mobility necessities (CAPMN) for the third factor. TABLE 2 shows the factors and their loadings. The third factor was important for interpretation as it included information about car attitudes of the participants.

TABLE 1 Used attitude-questions of the psychological item set

Category / variable	***Items***	***Questions***
Public transportation privacy (PTP)	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 (PTA)	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 (PTE)	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 (PTI)	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 (SN)	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 (PN)	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 (CE)	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 (PMN)	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 (BE)	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 (WR)	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.

TABLE 2 Results and criterions of the Principal Component Analysis (PCA)

Used items for the Principal Component Analysis (PCA)			
Category / variables	*Mean*	*Std Deviation*	*95% confidence interval for mean*
Public transportation privacy (PTP)	2.60	1.14	[2.52;2.67]
Public transportation autonomy (PTA)	2.17	1.10	[2.09;2.24]
Public transportation excitement (PTE)	3.25	0.98	[3.18;3.31]
Public transportation intention (PTI)	3.34	1.27	[3.25;3.42]
Subjective norm (SN)	2.96	1.17	[2.88;3.04]
Personal norm (PN)	3.54	1.18	[3.46;3.62]
Car excitement (CE)	2.91	1.13	[2.84;2.99]
Perceived mobility necessities (PMN)	3.44	1.22	[3.35;3.52]
Bicycle excitement (BE)	3.62	1.35	[3.53;3.72]
Weather resistance (WR)	2.79	1.41	[2.70;2.89]
Principal Component Analysis (PCA) - Rotated Factor Pattern (Varimax)			
Components of PCA	*factor 1*	*factor 2*	*factor 3*
Public transportation privacy (PTP)			0.402
Public transportation autonomy (PTA)			0.571
Public transportation excitement (PTE)	0.721		
Public transportation intention (PTI)	0.776		
Subjective norm (SN)	0.689		
Personal norm (PN)	0.667		
Car excitement (CE)			0.600
Perceived mobility necessities (PMN)			0.732
Bicycle excitement (BE)		0.874	
Weather resistance (WR)		0.821	
Criteria of extraction and quality for PCA			
	Numbers of components	*Value*	*Pr > Chi-Square*
Criteria of extraction			
Kaiser Criterion	3		
Scree Test	2 - 3		
Horn’s Parallel Analysis	2		
Velicer’s MAP test	2		
Criteria of quality			
Kaiser´s Measure of Sampling Adequacy (MSA)		0.73>0.6 (middling)	
Bartlett’s test of Sphericity		χ^2 (850) = 1847.91	p***

METHODS

After assessing the constituent attitudinal variables by factor analysis and selection of the behavioral variables as described above, we conducted a cluster analysis to identify distinguish, homogeneous urban mobility types. For this, we combined behavioral and attitudinal indicators to obtain clusters based on both dimensions. With this approach, we aimed to identify clusters with a dissonance between travel behavior and attitudes towards modes, for example a positive attitude towards environment-friendly modes but a domination of car use. Especially, when combining these two dimensions (behavior and attitude) in one cluster analysis, a balanced consideration (equal amount of attitudinal and behavioral variables) is a precondition. Before starting the cluster analysis, all used indicators were standardized (with a mean of zero and a variance of one). To develop clusters that include highly similar cases but differ strongly in their characteristics with other generated clusters, we used the Ward method. This method is accepted as adequate clustering method in the existing literature (*7; 10*). The Ward method is a hierarchical approach, which assigns any registered case to an own cluster first. During the process, the method gradually merges those two clusters, which produce the lowest increase in variance. The central challenge for the researcher is then to decide retrospectively what number of clusters meets the most meaningful solution. To select the number of clusters, there is no specific method or value applicable. However, statistical assistance is provided by a dendrogram. The final decision which number is best solution is then taken by the researchers. The most important aspect is the level of differentiation between the clusters and the interpretation of their characteristics.

For clustering data, the software tool SAS was used. Before we clustered the individuals, we checked the correlation between the indicators used. Only a low correlation with $r < 0.5$ was visible. In order to select the number of clusters, we performed different tests. We looked at the Cubic Clustering Criterion (CCC) and the value of Pseudo F. CCC showed a value larger than two for eight clusters and the Pseudo F statistic had a local maximum for five clusters. We chose eight clusters due to the analysis of the dendrogram and the higher CCC-value, showing more organization in the data as expected by equal distribution. In addition, we checked, without significant results, the option of using seven or six clusters.

RESULTS

Eight groups could be identified by the cluster analysis. TABLE 3 displays all the cluster centers regarding the indicators used to derive the clusters. In addition, further variables with their average or distribution are shown to describe the clusters. For the cluster analysis, several outliers or observations with poor quality were deleted (altogether 10% of the total sample). 759 respondents provided usable data for the cluster analysis.

The received clusters have different cluster sizes, varying from 42 to 134 observations. FIGURE 1 shows the final cluster centers for each cluster based on the z-transform. Obviously, the clusters have different characteristics, especially the first, sixth, seventh and eighth cluster. Only the second cluster has low characteristic values. This can be interpreted as the “middle” or "average", because the individuals do not show high scores concerning the used indicators. In the following, we describe the received clusters by highlighting special characteristics. TABLE 3 summarizes the following descriptions. The variables to describe the clusters are separated in two sections. The first section shows sociodemographic variables of people and their households. The variable gender shows the proportion of females in the clusters. The variable employment is divided in full-time (FT) and part-time (PT) workers and gives information about the proportion of employed individuals in the cluster. The second section consists of variables regarding travel behavior such as trips per day and frequency of usage of different means of transportation.

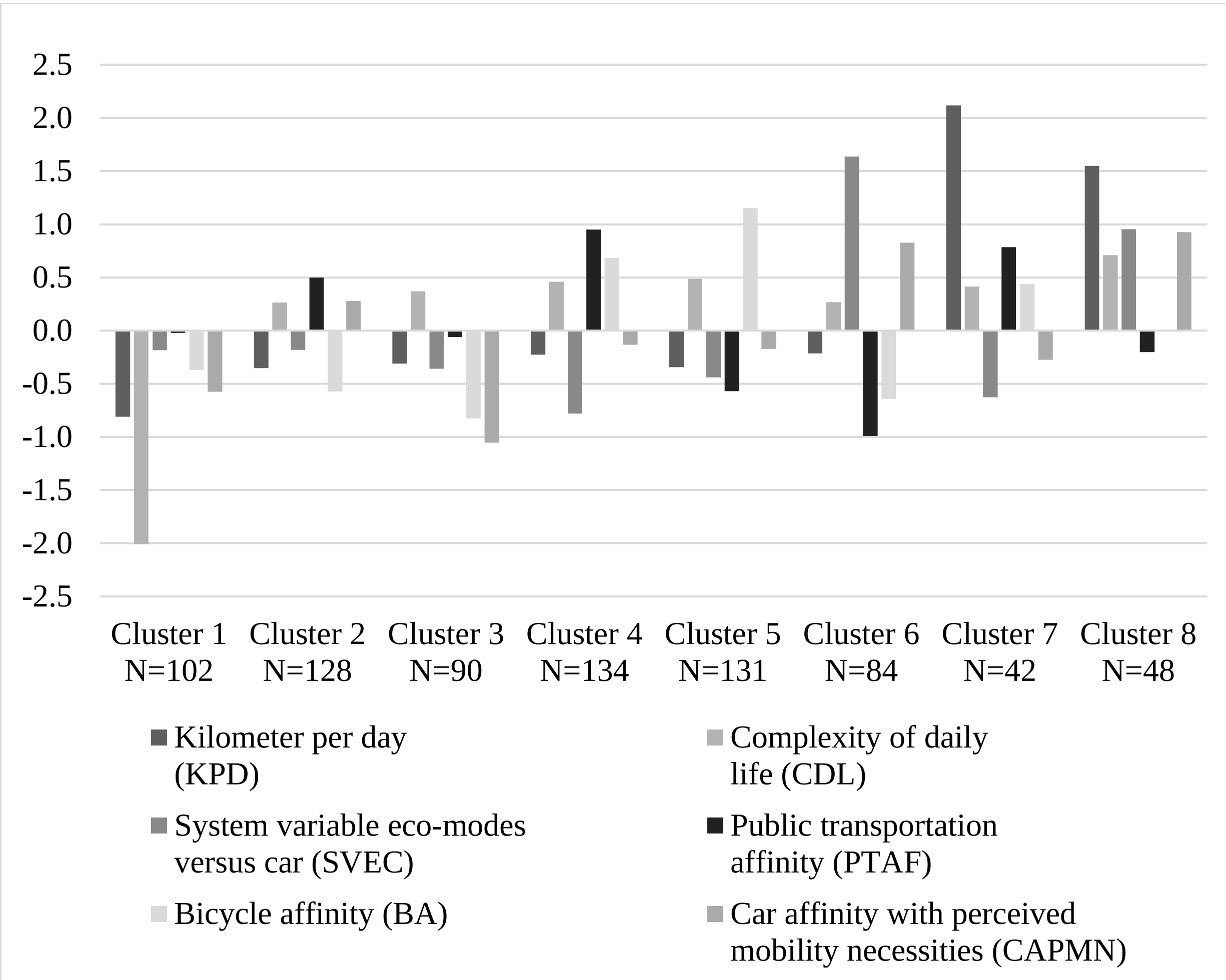

FIGURE 1 Final cluster centers for each of the clusters shown graphically

Furthermore, the variable intensity of long-distance travels is an indicator based on retrospective information on daytrips (during the last three months) and journeys with overnight stays (during the last year). The indicator can assume scores between 0 and 1. A score near 1 signifies high intensity and vice versa.

The *(neutral) low mobiles* (CL 1) show a very low complexity in daily life mobility. Individuals of this group have few activities regarding frequency and diversity. This correlates with a small amount of kilometers per day. Low car orientation with perceived mobility necessities characterizes (the attitudes of) this group. This matches with the very low car rate per household (0.29). The people of this group stay mostly inside their quarter. There is a small demand for mobility offers. For this group, it is more important to improve the situation inside the quarter regarding pedestrian walkways or shopping facilities.

The *transit-oriented multimodal* individuals (CL 2) have a high public transportation affinity in combination with a multimodal behavior. This group uses all means of transportation (bicycle, public transportation and car) at least several times a month. In particular, they use the public transportation several times a week. This group mainly consists of women and has a comparably low mean age. Persons of this group have even lower kilometer and trip rates than the average, but a necessity of mobility at the same time. This group is young and employed and uses appropriate and suitable modes of transportation for their activities with a slight preference of public transportation. An extended car sharing offer could be suitable to persuade people to abandon their cars.

Another cluster obtained in the cluster analysis is the cluster p*ublic transit users without necessity of mobility* (CL 3). These individuals have a high aversion against bicycles and cars. They have the highest mean age, the smallest household size and use public transit several times a week. This group has learned to use public transportation and to solve daily requirements with this mode. However, their daily complexity is lower. In general, this group would highly benefit from further improvements of the public transportation system. Regarding their age, they could profit from a greater accessibility and user-friendliness of public transportation.

The fourth cluster is called *eco-modes oriented pragmatics* (CL 4). This cluster has the highest public transportation affinity, a high bicycle orientation and uses both eco-modes (public transportation and bicycle) at least several times a week, whereby the bicycle usage is higher, since they use it daily on average. Their daily complexity is not low, but with their pragmatism, they can combine the eco-modes to complete their tasks. Car usage is very infrequent, which is shown through a small car rate. Based on a higher intensity of long-distance travels this group may use their car for daytrips or journeys with overnight stays. This group would benefit from improving cycle paths and secured parking lots for bicycles in their neighborhoods.

The *convinced cyclists* (CL 5), the fifth cluster, differs from the fourth cluster, although both clusters use bicycles a lot. The *convinced cyclists* have a very low public transportation affinity and the highest bicycle orientation. The complexity of daily life as well as the trip rate per day is high. This cluster consists of larger households (family-households). In daily life, they use the bicycle for their activities. Public transportation and cars are used infrequently. The peculiarity of this cluster in contrast to others is the high intensity of long-distance travels. This group of people lives in a field of tension between everyday life and adventure in terms of daytrips or journeys. They can profit from improved bicycle paths and special car sharing tariffs and car offers (e.g. minibuses) for long-distance travels with overnight stays.

The sixth cluster is called *convinced car users* (CL 6). This group has an extremely high aversion against public transportation and bicycle. Individuals use only the car for their activities, as shown in the variable SVEC. The complexity of daily life and their intensity is average. We assume that they do not reflect their behavior, not knowing better alternative modes for their activities. Another means of transportation besides the car is not imaginable for this group. The rate of cars per household is the highest of all at 1.19. Within this group a dissonance can be identified: Other modes could frequently be a good alternative, i.e. those people do not really need a car. However, car affinity is high. Altogether they are more car dependent on a subjective level.

The next cluster, the *green travel oriented high mobiles* (CL 7) has the highest value regarding KPD. They like to use public transportation and must use it for their activities, e.g. work. The trip rate per day is high, too. Most persons in this cluster are employees (86%). They also use bicycles for activities with shorter distances. Their car orientation is lower and their car usage is very low. This group can manage their demand of long-distance travels in everyday life by using public transportation. They benefit from a developed railway-system and an accessibility of long-distance trains, which is the case in the centrally located districts.

Finally, the *captive performers* (CL 8) have the highest complexity regarding activities in combination with the highest car orientation with perceived mobility necessities. In addition, the cluster has the highest employment rate of all clusters. This group differs from the *convinced car users*, because the *captive performers* need their car to organize their daily life. The *convinced car users* do not have such a highly perceived mobility necessity. People of cluster 8 are more car dependent (in objective terms) due to their activities as other groups in the sampling. Especially, this group of people benefits from a better parking situation in the quarter. In contrast to the *convinced car users*, they use bicycles and public transportation for short-distances trips. In appropriate situations, they use other modes than the car for their activities. An overview of all clusters is given in TABLE 4.

The clusters have about the same size~~s~~ in Hamburg and Berlin in proportion to the amount of observations. None of the clusters was dominated by people from one city, except for the first cluster with a higher proportion from Berlin. This confirmed the assumption that both neighborhoods in Hamburg and Berlin are very similar. In summary, the results show an interpretable clustering. The integrated approach by bringing travel behavior and attitudes together provided useful information such as the difference of objectively independent and dependent car users.

TABLE 3 Description of the clusters

	CL 1 N=102	**CL 2 N=128**	**CL 3 N=90**	**CL 4 N=134**	**CL 5 N=131**	**CL 6 N=84**	**CL 7 N=42**	**CL 8 N=48**
Indicators to derive clusters (Cluster centers)								
Complexity of daily life (CDL)	-2.01	0.27	0.37	0.46	0.49	0.27	0.41	0.71
System variable eco-modes versus car (SVEC)	-0.18	-0.18	-0.36	-0.78	-0.44	1.64	-0.63	0.95
Kilometer per day (KPD)	-0.81	-0.35	-0.31	-0.23	-0.34	-0.21	2.12	1.55
Public transportation affinity (PTAF)	-0.02	0.50	-0.06	0.95	-0.57	-0.99	0.79	-0.20
Bicycle affinity (BA)	-0.37	-0.57	-0.83	0.68	1.15	-0.64	0.44	-0.01
Car affinity with perceived mobility necessities (CAPMN)	-0.57	0.28	-1.06	-0.13	-0.17	0.83	-0.28	0.93
Selected indicators of travel behavior and personal characteristics to describe each cluster								
Sociodemograhic								
Gender (female in %)	59	66	50	63	54	44	45	46
Age (median)	47	43	50	42	47	45	47	45
Cars per Household (mean)	0.29	0.54	0.37	0.31	0.47	1.19	0.40	0.92
Household size (mean)	2.13	2.02	1.84	2.14	2.48	2.10	2.36	1.88
Working persons (FT+PT) (in %)	46	58	60	69	79	71	86	90
Retired persons (in %)	28	26	29	13	12	19	2	2
Travel behavior								
Trips per day (mean)	1.3	3.2	3.3	3.3	3.5	3.1	3.6	4.0
Frequency* of car usage (mean)	5.2	4.4	5.2	5.4	4.7	1.5	5.1	2.3
Frequency* of public transportation usage (mean)	2.4	2.0	2.0	2.1	3.4	4.0	2.1	3.3
Frequency* Bicycle usage (mean)	3.7	3.3	3.4	1.5	1.2	4.0	1.8	2.5
Intensity of long-distance travels	0.12	0.40	0.38	0.45	0.46	0.37	0.47	0.47

* Frequency: 1 = daily, 2 = Several times a week, 3 = Once a week, 4 = Several times a month, 5 = Once a moth, 6 = Less often than once a month, 7 = Never.

TABLE 4 Cluster profiles of the analysis

CL	Cluster name	%	Cluster description
1	(Neutral) Low mobiles	13.44	■ Low daily trip rates with low kilometers per day ■ Lowest complexity of daily life ■ Lowest car orientation ■ Low level of employment and high level of retired persons ■ Mostly households with no cars, more females and a higher average age
2	Transit-oriented multimodals	16.86	■ No strong characteristic values visible ■ Higher public transportation affinity ■ High frequency of public transportation usage (several times a week in average) ■ Mostly females and a low average age
3	Public transit users without necessity of mobility	11.86	■ Very low bicycle affinity ■ Lowest car affinity with perceived mobility necessities ■ Oldest cluster and smallest household size in average ■ Low rate of cars per household and lower portion of employed person
4	Eco-modes oriented pragmatics	17.65	■ Highest public transportation affinity ■ Very high bicycle usage and high public transportation usage ■ Lowest car use ■ More females, youngest cluster and low rate of cars per household ■ Multiperson households in average
5	Convinced cyclists	17.26	■ Highest bicycle affinity ■ Highest bicycle usage with a daily use in average ■ Largest household size in average and high employment rate ■ Many trips per day
6	Convinced car users	11.07	■ Lowest public transportation affinity and very low bicycle affinity ■ Highest car usage ■ High car affinity with perceived mobility necessities ■ Highest rate of cars per household (more than one car in average) ■ High employment rate and a moderate rate of retired persons
7	Green travel oriented high mobiles	5.53	■ Highest kilometer pro day and high trip rates ■ Very low car usage ■ High public transportation and bicycle usage ■ High complexity of daily life ■ Large household size and very high employment rate ■ Low car affinity with perceived mobility necessities
8	Captive performers	6.32	■ Highest complexity in daily life ■ Highest car affinity with perceived mobility necessities ■ Highest trip rates ■ High car use and middle public transportation or bicycle usage ■ Highest employment rate and high rate of cars per household

CONCLUSIONS

Detailed information about peoples' travel behavior and underlying psychological factors are essential to improve transportation systems. For design processes, the implementation and the assessment of customer oriented transport solutions (e.g., emerging technologies such as car sharing), travelers' requirements and their likely acceptance of these solutions need to be known. Therefore, information from trip diaries provided by traditional household surveys are often not sufficient. In addition to the travel requirements, psychological factors are also crucial. However, these are usually not considered.

Therefore, we developed an integrated survey approach combining revealed travel behavior and underlying psychological factors (social norms and attitudes towards modes). Instead of providing a trip diary, we used a "skeleton approach" to capture travel behavior. Avoiding information about single trips, we asked for the frequency and locations of peoples' activities during a typical week, segmented for different purposes. These determinants serve as a "skeleton" identifying the typical behavior. We call this approach "travel skeleton". Psychological factors are captured using an additional questionnaire. Testing the validity of our combined approach, we did a cluster analysis. We first defined six indicators. Three of them summarized information on travel behavior (distance traveled, complexity of travel and activities, and the modal utilization); three of them summarized information on psychological factors (attitudes towards bicycle, transit, and car). In a second step, we used them for a successful clustering of different and distinct urban mobility types.

The integrated consideration of travel behavior and attitudes allows for the distinction of objective and subjective aspects, e.g., captive as well as voluntary car users. We could assess whether people behave consistently or not. Checks of these clusters showed some unexpected outcomes: On the one hand, we could identify clusters of persons who, at first sight, behave contradictorily, as the modal behavior is in contrast to the attitudes (e.g., people who like driving a car, but use public transit). On the other hand, we also identified clusters with consistent attitudes and realized behavior (e.g., convinced car users). These outcomes showed the advantage of our approach. It is possible to identify groups of persons with dissonances or accordance between behavior and attitudes. A practical application of the approach and the data collected is currently underway. Therein, we ask car-owning persons who have both a comparably low level of car use (low level of objective car dependency) and a lower car affinity (low level of subjective car dependency) to test car sharing temporally. Amongst the clusters we identified, a high willingness to test the car sharing approach has already been observed.

Altogether, results showed the applicability of our combined approach. Both aspects (behavior and attitudes) provide valuable insights and improve assessment of new mobility offers.

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