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Attitude-Based Target Groups to Reduce the Ecological Impact of Daily Mobility Behavior

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This study analyzes the usefulness of an attitude-based target group approach in predicting the ecological impact of mobility behavior. Based on a survey of 1,991 inhabitants of three large German cities, constructs derived from an expanded version of the Theory of Planned Behavior were used to identify distinct attitude-based target groups. Five groups were identified, each representing a unique combination of attitudes, norms, and values. The groups differed significantly from each other with regard to travel-mode choice, distances traveled, and ecological impact. In comparison with segmentations based on sociodemographic and geographic factors, the predictive power of the attitude-based approach was higher, especially with regard to the use of private motorized modes of transportation. The opportunities and limits of reducing the ecological impact of mobility behavior on the basis of an attitude-based target group approach are discussed.

Keywords: *transportation; conservation-ecological-behavior; attitudes; ecological assessment; target groups*

The emissions resulting from mobility behavior decrease the quality of life in communities and are important driving forces of climate change. Although noise, particles and other pollutants are relevant at a local and

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regional level, some gases like carbon dioxide, methane and nitrous oxide contribute to the global greenhouse effect. According to the Kyoto Protocol, industrialized countries have to reduce their greenhouse gas emissions by an average of 5.4% below 1990 levels in the first commitment period from 2008 to 2012. The transportation sector is responsible for 12% of the world's greenhouse gas emissions.

Several strategies have been proposed for the implementation of environmentally sustainable passenger transportation including increases in the efficiency of transportation technologies (Lovins & Cramer, 2004), the increasing density of housing, employment, shopping, and cultural activities (Stead & Marshall, 2001), and regulatory and fiscal measures (European Conference of Ministers of Transport [ECMT], 2004). The attractiveness of sustainable mobility can also be increased with soft policy measures, such as public awareness campaigns for sustainable mobility and social marketing for public transportation (Brög, Erl, & Mense, 2004). Application of the social marketing approach to encourage sustainable behavior requires the recognition of different target groups that describe the heterogeneous motivations and necessities of all consumers. Knowledge about the motivational basis of target groups can be used to design interventions to promote sustainable behavior more efficiently (Geller, 1989; McKenzie-Mohr, 2000).

The rationale for segmentation results from a methodological weakness of the *maximizing average effects* strategy, which is usually used for statistical analyses based on samples of the whole population. This strategy is not sensitive to the identification of correlations between variables in specific subgroups of the population. However, correlations in specific subgroups can reach such high levels of significance that they can provide important information for the design of efficient interventions that encourage behavioral change.

In this study, mobility-behavior target groups are identified on the basis of attitudes derived from the Theory of Planned Behavior (TPB; Ajzen, 1991) and from further mobility-related attitudinal dimensions relevant for travel-mode choice. This identification of target groups is aimed at identifying differentiated starting points to reduce the ecological impact of mobility behavior.

Attitudinal Variables as Determinants of Mobility Behavior

Thus far, the use of target group segments based on psychological models of the attitude-behavior relationship has been rather rare in transportation research, although there are a multitude of studies analyzing the psychological determinants of travel-mode choice. In their theoretical assumptions, most of these studies refer to TPB (Ajzen, 1991) and demonstrate that travel-mode choice can be explained by mobility-related operationalizations of attitude, subjective norm, perceived behavior control, and intention (e.g., Bamberg, Hunecke, & Blöbaum, 2007; Bamberg & Schmidt, 2003; Haustein & Hunecke, 2007; Heath & Gifford, 2002). A further relevant psychological determinant of travel mode choice is the personal norm, which is theoretically derived from the Norm Activation Model of Schwartz (1977). In contrast to the subjective norm construct of the TPB (Ajzen, 1991), the personal norm measures the intrinsic moral obligation to behave in a morally correct way. Several studies have demonstrated a positive effect of personal norm on the use of environmentally friendly travel modes (e.g., Harland, Staats, & Wilke, 1999; Hunecke, Blöbaum, Matthies, & Höger, 2001; Nordlund & Garvill, 2003). Other mobility-related attitudinal dimensions result from symbolic-affective evaluations of travel modes (Anable & Gatersleben, 2005; Ellaway, Macintyre, Hiscock, & Kearns, 2003; Hunecke, 2000; Mann & Abraham, 2006; Steg, 2005; Steg, Vlek, & Slotegraaf, 2001). Steg et al. (2001) demonstrated that symbolic-affective functions, such as excitement and prestige, as well as instrumental-reasoned functions, such as financial costs and driving conditions, are important dimensions underlying the attractiveness of car use. Examining the relative importance of different instrumental and affective journey attributes, Anable and Gatersleben (2005) found that for work journeys, more importance is attached to instrumental aspects, whereas for leisure journeys, almost equal importance is ascribed to instrumental and affective aspects, such as flexibility, convenience, relaxation, and freedom. Hunecke (2000) differentiated four basic symbolic dimensions of mobility: autonomy, excitement, status, and privacy. On the basis of these dimensions, behavior-relevant attitudes concerning different travel modes can be operationalized (Haustein & Hunecke, 2007).

Another important empirical finding indicates that the use of psychological factors, in addition to sociodemographic and infrastructural variables, can improve predictions of different aspects of mobility behavior. Van Wee, Holwerda, and Van Baren (2002) demonstrated higher explanatory power for a model including subjective preferences for certain transportation modes as compared with a model that only comprised sociodemographic and infrastructural variables. Their analyses also showed that the predictive power of preference was higher for travel-mode choice than for distance covered. One crucial limitation of this study, however, was the low reliability of the preference rating, which was only measured with one item.

Hunecke and Schweer (2006) obtained similar results in their multivariate regression analyses, predicting travel mode and destination choice in five different districts in Cologne, Germany. In their study, psychological factors were operationalized on the basis of an extended TPB (Ajzen, 1991). The results also indicated that psychological factors, as opposed to infrastructural and sociodemographic variables, were better predictors of travel mode choice than for destination choices.

Methods of Segmentation for Mobility Behavior

The segmentation approaches most often used in transportation planning are based on behavioral or sociodemographic variables. A behavior-based approach defines segments by using different travel modes along with the frequency of their use. In this way, car users and users of public transportation can be classified as either *low* or *high* users. The methodological weakness of behavior-based segments lies in their lack of an explanation for behavior. This approach can only describe mobility behavior and does not provide information about the underlying processes that determine that behavior. A segmentation approach that takes the sociodemographic characteristics of traffic participants into account avoids the limitations of behavior-based segments. Age, gender, occupation, household size, income, and car ownership are socioeconomic and demographic characteristics that are highly relevant for mobility behavior. These characteristics can be used for a detailed segmentation of the population in aggregate transport models for whole countries or continents such as Europe (De Jong, Gunn, & Ben-Akiva, 2004).

An important sociodemographic segmentation approach for mobility behavior is based on life cycles, defined by age, household size, and employment status. A target-group approach to German rail, for example, differentiates between nine different lifecycles, including students, members of households with schoolchildren, and pensioners. These lifecycle segments demonstrate strong differences in terms of travel-mode choice (Jäger, 1989).

Research on social stratification in modern societies, however, has shown that the complexity of social activities cannot be explained satisfactorily by sociodemographic variables. For this reason, the concept of lifestyle, which better defines an individual's daily range of actions, was introduced in social structure research. Lifestyles are affected substantially by individual values and attitudes and are not only determined by socioeconomic or sociodemographic variables. The lifestyle approach is particularly applied in the marketing practices of transportation companies and the automobile industry to identify differences in individual mobility behavior. The results of this commercial research are usually not published, so it is impossible to evaluate the usefulness of commercial lifestyle approaches like the Sinus-Milieus (Sinus Sociovision, 2006) in the segmentation of mobility behavior.

Segmentation by lifestyle for different aspects of mobility has been evaluated in two studies. First, Redmond (2000) separately identified 6 travel-related attitudinal types and 11 types based on personality and lifestyle characteristics. Both typologies offer different and useful insights into various aspects of travel behavior, such as the enjoyment of travel, the perceived amount of travel, the desired level of mobility, and the actual amount traveled. Redmond concluded that both typologies are superior to sociodemographic-based segments in identifying starting points for policy that would encourage changes in mobility behavior. The results of Hunecke and Schweer (2006) indicate a more differentiated picture about the use of different segmentational approaches for various aspects of mobility behavior. Here, three segmentation approaches based on sociodemographic, lifestyle, and attitudinal variables were tested for their predictive power in terms of travel mode choice and destination frequency within a subject's own city district. The attitude-based segments showed, by far, the highest predictive power for travel mode choice, whereas the sociodemographic lifecycle segmentation predicted destination choice best. The lifestyle typology indicated a better prediction for the destination choice than the attitudinal segmentation did, but for travel-mode choice it showed the weakest predictive power of the three approaches.

Attitudes are often used as constituent elements for target groups in the domain of mobility behavior but systematic approaches for target-group segmentation that are based on attitudes derived from psychological theories of attitude-behavior relationships are very rare. In the past, theoretically and methodologically sophisticated approaches for an attitude-based segmentation of mobility behavior have only been demonstrated in Anable (2005) and Hunecke, Schubert, and Zinn (2005). Both studies used an expanded version of the TPB (Ajzen, 1991) as a theoretical background to derive attitudes that are relevant for different aspects of mobility behavior. In Anable's study, 17 attitude and belief dimensions, such as moral responsibility to use the car less often, general car dependence, behavioral control, and green identity, were identified via principal component analysis. In a second step, these attitude and belief dimensions were clustered separately in two groups of persons, those who did and those who did not have access to a car as a driver or passenger. For the group with car access four segments were identified (*malcontented motorists, complacent car addicts, aspiring environmentalists,* and *die hard drivers*) and two segments were identified for the group without car access (*car-less crusaders* and *reluctant riders*). The six segments showed specific differences in mobility behavior intentions as well as in the realized mobility behavior. Anable then deduced different policy options to encourage the use of environmentally friendly modes from the knowledge about segment specific attitudes and beliefs. Hunecke et al. (2005) developed a target-group approach to support the modal shift from car to public transportation (PT). With the theoretical background of an expanded TPB (Ajzen, 1991), six attitude dimensions could be reliably measured (PT Control, PT Status, PT Excitement, PT Privacy, Car Excitement, and Ecological Norm). The impact of these six attitude dimensions on travel-mode choice, along with the acceptance of political measures that would either encourage public transportation or restrict car use, was then tested using multiple regression analyses. All six attitudes showed significant correlations to travel-mode choice or acceptance variables. Finally, the six attitude dimensions were clustered in a multi-step process, which generated six target groups: PT-oriented, PT-sensitized, pragmatics, PT-reserved, PT-averse, and uninterested. These six target groups were characterized by strong differences in the six underlying attitude dimensions as well as in travel-mode choice. In a further study, five of the six target groups were replicated using a sample of 1,500 Cologne residents (Hunecke & Schweer, 2006). Hunecke and Schweer's study (2006) demonstrated great differences for the resulting five target groups in terms of travel-mode choice.

Attitudinal Variables as Determinants of Ecological Impact

Stern (2000) introduced the distinction between an *intent* perspective and an *impact* perspective to environmental psychology. The intent perspective analyzes the motivational basis of conservation behavior, whereas the impact perspective focuses on the ecological consequences of environmental behavior.

From an impact perspective mobility behavior was analyzed in two studies by Poortinga, Steg, and Vlek (2004) and Hunecke, Haustein, Grischkat, and Böhler (2007), which showed differing results. Poortinga et al. (2004) demonstrated that the impact of environmental behavior is more strongly related to sociodemographic and household variables than to values and environmental beliefs, although these results must be interpreted considering the limitation that behavior-specific attitudes were not included in the analysis. Empirical findings from environmental behavioral research, however, indicate that behavior specific attitudes and beliefs are better predictors of behavior than values or general environmental concern (e.g., Dietz, Stern, & Guagnano, 1998; Oreg & Katz-Gerro, 2006). For this reason, the second study, conducted by Hunecke et al. (2007), measured attitudinal factors based on the TPB (Ajzen, 1991) and additional mobility-related attitude dimensions, testing their relationship to the ecological impacts of individual mobility behavior while controlling for sociodemographic and infrastructural characteristics. In a regression analysis with ecological impact as the dependent variable, sociodemographic and psychological variables were the strongest predictors of ecological impact, whereas infrastructural variables were of minor relevance.

From an impact perspective, there is only one study that has quantified the ecological impact of mobility behavior for different population segments while using attitudes to describe the resulting segments. Götz, Loose, Schmied, and Schubert (2003) calculated an ecological assessment for five mobility styles called *disadvantaged, modern-exclusives, fun-oriented, overburdened family-oriented,* and *traditional-domestics.* The mobility styles were constructed by clustering 63 items concerning preferences for lifestyle, leisure, and work. The analysis indicated that the fun-oriented mobility style emits 5.4 kg of CO_2 equivalents per person per day, more than twice as much greenhouse gas as the traditional-domestic mobility style with only 2.0 kg. Mobility-related attitudes were measured in the current study as well, but these were only used descriptively and were not considered as constituent variables in the clustering process.

The Present Study

In the present study, the ability of an attitude-based target group approach to predict the ecological impact of mobility behavior was analyzed. The operationalization of attitudes for the segmentation process has been grounded, as much as possible, to well-founded theories of attitude-behavior relationship to avoid the arbitrary nature of many attitude-based target-group approaches that have been used in transportation research and practice in the past.

Six criteria are used in marketing research to evaluate the qualification of segmentations: predictive power, actionability, measurability, stability, accessibility and efficiency (see Dibb, 1999, for a review). *Predictive power* quantifies a segment's strength in predicting the target behavior. *Actionability* refers to the identification of starting points that encourage the target behavior. *Measurability* describes the availability of data for the segmentation. *Stability* characterizes the stability of the segments over time. *Accessibility* consists of the opportunities to address marketing interventions with regard to specific segments. *Efficiency* relates the time and effort of the segmentation to its practical use in the marketing process. In the present study we focused on the segmentation criterion of predictive power, which was analyzed for an attitude-based target-group approach. It was expected that an attitudinal approach would yield a higher predictive power with respect to the ecological impact of mobility behavior than alternative approaches used in transportation research and practice. This expectation follows from multiple empirical results, indicating that mobility-related attitudes are significant predictors of travel-mode choice. The relationship between attitude and travel-mode choice has also been confirmed in studies that control for sociodemographic and infrastructural variables (Hunecke et al., 2007; Hunecke & Schweer, 2006; Van Wee et al., 2002). Concerning the high relevance of travel-mode choice for the ecological impact of mobility behavior, a strong relationship between attitude-based mobility types and the ecological impact of mobility behavior was expected in this study. The consideration of ecological impact complies with the general demand for analysis of environmental behavior in social and behavioral environmental research, from both intent and impact perspectives (Stern, 2000).

Method

Sample and Procedure

Data for this study were collected from June to December 2003 in the German cities of Augsburg, Bielefeld, and Magdeburg. The selection of these three cities was based on the spatial model of BIK (Consulting–Information–Communication).[1] According to the BIK classification, the three cities constitute core areas, a classification comparable to the Standard Metropolitan Area (SMA) label in the United States. The BIK core area category reflects urban areas that comprise 443 German communities and cover 43.3% of the German population. Three typical urban districts were then selected for each city, representing different levels of accessibility and transportation infrastructure: an inner-city district, a city-border district, and a suburban district. A description of the criteria for the three district types is presented in Table 1.

Table 1
General Criteria for Three Types of City Districts

	Characteristics		
Criteria	District 1: Inner-City District	District 2: City-Border District	District 3: Suburban District
Distance to the city center	Settlement close to the city center	Settlement at the border of the city	Settlement in the suburban area with relations to the core city (labor, leisure)
Density	High density of population and housing	Medium density of population and housing	Low density of population and housing
Housing	Mostly apartment buildings, some historical buildings	Mostly apartment buildings but also single and semi-detached houses	Mostly single and semi-detached houses
Infrastructure	High variety of commercial and public facilities (for shopping, cultural, social, leisure purposes)	Medium variety of commercial and public facilities (mainly for shopping and social purposes)	Basic needs available (mainly for shopping and social purposes)
General accessibility of the city center by foot and bike	High accessibility by both modes	Accessibility of the city center by bike	Limited accessibility
Local public transportation	Easy access to bus and tram	Connected by tram, light rail and/or bus	Connected by regional train and/or bus
Long-distance travel	Easy access to main train station	Change of bus or tram necessary	Change of bus or train necessary

The survey population was randomly produced by the cities' registration offices for each of the city districts. A total of 11,028 German citizens ages 18 to 80 received a letter describing the survey. The people were personally contacted by trained interviewers and asked if they wished to participate. The survey was conducted via standardized face-to-face interviews that lasted about 60 min each. Altogether, 1,991 interviews were carried out, with approximately 660 interviews per city and 220 interviews per city district. The response rate was 25% after correcting for address errors and for people not contacted because the desired number of interviews had already been achieved.

The sample consisted of 1,056 women (53%) and 935 men (47%) with a mean age of 46.7 years. The sample was representative for the core areas regarding age and gender, whereas the education level was above average (43.5% with higher education), which is probably due to the high percentage of students living in the selected inner-city districts and to the fact that well-educated people tend to have a greater willingness to participate.

Measures

Attitudinal variables. The constructs of the TPB (Ajzen, 1991) were measured as a basis for the psychological target-group model and supplemented with additional factors relevant for travel-mode choice.

The TPB constructs of perceived behavior control and subjective norm were measured with statements referring to the use of environmentally friendly means of transportation in place of the private car. For private car and public transportation travel modes, attitude was operationalized with statements about the symbolic dimensions of autonomy, excitement, status, and privacy. For bicycle use, only the two dimensions, autonomy and excitement, were measured because previous research has indicated that dimensions of status and privacy are not relevant for the use of bicycles in everyday life. Instead, the weather is an important contextual factor for bicycle use (Haustein, Hunecke, & Manz, 2007) and thus, weather was taken into account by measuring willingness to use a bicycle in bad weather conditions. This attitude dimension is called *weather resistance*.

In addition, the personal-norm construct of using environmentally friendly means of transportation and a new construct, *perceived mobility necessities*, were measured. All constructs were measured with two items and responses were provided on a 5-point Likert scale (1 = *do not agree at all*, 2 = *agree slightly*, 3 = *agree moderately*, 4 = *agree very much*, 5 = *agree totally*).

A principal component analysis with varimax rotation was carried out to reduce the number of psychological variables to their underlying dimensions. Retaining only factors with eigenvalues greater than one, an easily interpretable 8-factor solution was obtained, explaining 58.2% of the variance.

In Table 2, the loadings of the single items on each of the eight factors are presented. Mean scales were constructed following the resulting factor solution with one exception: Although items referring to excitement and status of public transportation loaded on the same factor, two separate scales were constructed because these two dimensions are highly relevant to the design and promotion of public transportation services and because they have loaded on separate factors in preceding studies (Hunecke et al., 2005; Hunecke & Schweer, 2006).

Values were assessed using a shortened version of the Schwartz Value Inventory (Schwartz & Bilsky, 1990) developed by Bamberg (2001). Schwartz distinguishes between 10 motivational types of values within a two-dimensional structure that is constituted by four higher order value types: openness to change versus conservation and self-enhancement versus self-transcendence (Schwartz, 1992). The openness-to-change pole includes stimulation and self-direction, whereas the opposite pole stresses the preference of tradition, security, and conformity. The self-enhancement pole deals with power and achievement, whereas self-transcendence includes universalism and benevolence. Each of the four higher order value types was measured with three items on a 9-point scale (–1 = *opposed to my values*, 0 = *not important*, 1–2 [unlabeled], 3 = *important*, 4–5 [unlabeled], 6 = *very important*, 7 = *of supreme importance*). The four value scales were constructed following the theoretically specified structure. Table 3 displays means, standard deviations, internal consistencies (Cronbach's alpha), and retest reliabilities for the calculated multi-item scales. All psychological items are listed in the appendix.

Spatial Characteristics and Accessibility to Transport Systems

The spatial characteristics of the district in which the interviewee lived, as well as the accessibility of transport systems within that district, were measured by dummy variables representing district type. District types differ systematically with regard to seven spatial and infrastructural criteria (cf. Table 1). In addition to the effect of the district types, the influence of the three cities, Augsburg, Bielefeld, and Magdeburg, on the mobility behavior was analyzed. This was done because the possibility of each city's special characteristics significantly affecting mobility behavior could not

Table 2
Results of Principal Component Analysis

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
PBC 1[1,2]	.67	–.05	.04	.00	.09	.05	–.37	.09
PBC 2	.66	–.01	.09	.02	.19	–.03	–.19	–.06
PT autonomy 1[1,2]	.54	–.25	–.11	.14	.09	.20	–.03	.08
PT autonomy 2	.71	.00	.10	.13	.13	.06	–.09	–.09
Car autonomy 1[2]	.69	–.10	.18	.06	.17	.01	–.21	.09
Car autonomy 2	–.29	.60	.10	–.05	–.01	–.04	–.07	–.28
Car privacy 1	–.07	.43	–.03	–.05	.06	–.39	–.05	–.28
Car privacy 2	–.11	.57	.11	–.10	.04	.02	–.05	–.31
Car excitement 1	–.08	.83	–.01	–.02	–.07	–.04	.06	–.02
Car excitement 2	.14	.59	–.20	.10	–.16	–.14	.05	.24
Car excitement 3	.06	.73	–.07	.06	–.05	–.13	.07	.04
Car excitement 4	–.02	.73	–.01	.06	.02	.02	.05	.03
Bicycle excitement 1	.02	–.10	.79	.07	.08	.04	–.04	.22
Bicycle excitement 2	–.10	–.02	.78	.13	.02	.08	.00	.03
Bicycle autonomy 1	.44	.11	.61	.00	–.01	–.10	.06	.10
Bicycle autonomy 2	.40	.00	.65	.06	.04	–.05	–.03	.16
PT excitement 1	.39	.11	.03	.56	–.04	.12	.19	–.02
PT excitement 2	.30	–.01	.04	.54	–.05	.33	.16	–.10
PT status 1	–.08	.00	.05	.73	.22	–.04	–.06	.09
PT status 2	.22	.03	.09	.47	.16	.01	–.09	–.16
Car status 1[2]	–.09	–.03	.08	.68	.29	–.14	–.14	.05
SN 1	.22	.08	–.10	.08	.56	–.12	.01	.00
SN 2	.09	.00	–.02	.07	.72	.06	.10	.04
PN 1	.06	–.17	.21	.16	.64	.04	.00	.07
PN 2	.22	–.10	.11	.30	.61	.02	.04	.06
PT privacy 1[1,2]	.12	–.11	.02	.02	.01	.83	–.07	.02
PT privacy 2[1,2]	–.02	–.08	.01	–.02	.00	.83	–.07	.05
PMN 1	–.32	.06	.00	–.02	.12	–.06	.81	–.03
PMN 2	–.34	.06	–.01	–.06	.07	–.08	.82	.00
Weather resistance 1[1, 2]	–.08	–.09	.25	–.06	.08	.10	–.05	.77
Weather resistance 2	.12	–.04	.43	–.03	.14	.04	–.01	.68

Note: PBC = perceived behavioral control; PT = public transportation; SN = social norm; PN = personal norm; PMN = perceived mobility necessities; shaded cells indicate highest factor loading; see appendix for an explanation of items.
1. Recoded.
2. Reversed statement used (i.e., high agreement means low parameter value).

Table 3
Description of Psychological Variables

Variables	Constructs (Number of Items)	*n*	*M*	*SD*	Cronbach's α	*r*
Public transport control	Perceived behavioral control (2)	1989	3.13	1.06	.80	.76
	Public transport autonomy (2)					
	Car autonomy (1)					
Public transport status	Public transport status (2)	1984	2.93	0.94	.59	–
	Car status (1)					
Public transport excitement	Public transport excitement (2)	1897	2.68	1.09	.58	.57
Public transport privacy	Public transport privacy (2)	1870	3.55	1.08	.72	–
Car attitude	Car autonomy (1)	1871	3.00	0.91	.80	.59
	Car privacy (2)					
	Car excitement (4)					
Bicycle attitude	Bicycle autonomy (2)	1771	3.54	0.99	.77	.55
	Bicycle excitement (2)					
Weather resistance	Weather resistance (2)	1729	2.54	1.23	.70	.66
Ecological norm	Subjective norm (2)	1962	2.60	1.00	.67	.60
	Personal norm (2)					
Perceived mobility necessities	Perceived mobility necessities (2)	1971	3.25	1.37	.84	.65
Openness to change	Openness to change (3)	1986	3.11	1.62	.76	.52
Conservation	Conservation (3)	1989	4.16	0.88	.60	–
Self-enhancement	Self-enhancement (3)	1988	4.44	1.46	.76	–
Self-transcendence	Self-transcendence (3)	1988	5.24	1.32	.80	–

Note: Only those items used to create mobility types were measured a second time after one year. Thus, retest-reliability values are provided only for these items (or the respective scales).

be ruled out. In this way, the spatial characteristics and accessibility of transport systems between each city and district were measured independently from subjective evaluations.

As the accessibility of transport systems can vary considerably within each district type, access to public transportation, as well as the distance to the next bus stop and rail station, was also determined through interviewee self-assessments. In addition, the participants were asked about the number of cars per household and whether they were in possession of a driver's license.

Demographics. Sociodemographic variables were used to construct lifecycles as an alternative approach with which the predictive power of the attitude-based target group model was compared. Furthermore, demographic variables served as control variables in regression analyses that were conducted to identify the most relevant psychological variables.

The sociodemographic variables recorded included sex, age, education, occupation (full-time or part-time employment), income, household size, number of children per household, and family type.

Mobility behavior. Different aspects of mobility behavior served as both dependent variables in regression analyses and as criteria for comparing the predictive power of different target-group models. Moreover, mobility behavior served as the basis for assessing the environmental impact of mobility behavior.

Mobility behavior was measured by the participants' evaluations of their daily activities and transportation modes. The participants were asked how often they performed 14 different activities.[2] For each activity, data about the distance covered and the transportation mode used were collected. Four mobility behavior variables were calculated and used as dependent variables: the percentage of trips conducted by private motorized modes,[3] by public transportation, and by bicycle, as well as the calculated distance traveled per person annually.

Ecological impact analyses. Ecological impact served as another criterion in the comparison of the predictive power of different target-group models. This criterion is particularly relevant for policy makers, who must define priorities in the application of measures that promote environmentally sustainable transport. In this study, the emissions of mobility-related greenhouse gases during vehicle use were examined. Greenhouse gases were calculated as CO_2 equivalents based on Global Warming Potential (Intergovernmental Panel on Climate Change [IPCC], 1996),[4] so that the effects of other gases with climatic relevance, such as methane and nitrous oxide, were weighted against the effects of the same quantity of CO_2 and thus integrated into the calculations.

As Figure 1 illustrates, there are three factors relevant to the calculation of the ecological impact of an individual's mobility behavior: the distances traveled, the technical data of the transportation mode used, and the number of passengers per vehicle (capacity rate). The distances were queried in the MOBILANZ survey, and the participants gave detailed information about the technical data of their personal vehicles (brand, model, mode of drive, cubic capacity, year of construction, existence of an air conditioning system).[5] Public transportation data were made available by transport companies and was included in the software tool and data base, TREMOD (Ifeu-Institute, 2005). TREMOD was created in 1993 at the Institute for Energy and Environmental Research (Ifeu) at the request of the German Environmental Agency. The TREMOD database considers all motorized modes from 1963 to 2005, and scenarios have also been created that extend to 2030. For each transportation mode, the kilometers covered and the specific emissions were calculated. The emissions are shown as *direct* emissions, emitted directly by the transportation mode, and as *indirect* emissions, emitted by prior energy production and distribution processes. In the MOBILANZ inquiry, motorized individual road transportation was measured in greatest detail, so that energy consumption and emissions were recorded with regard to the technical characteristics of each transportation mode (cubic capacity, age, type of road, etc.).

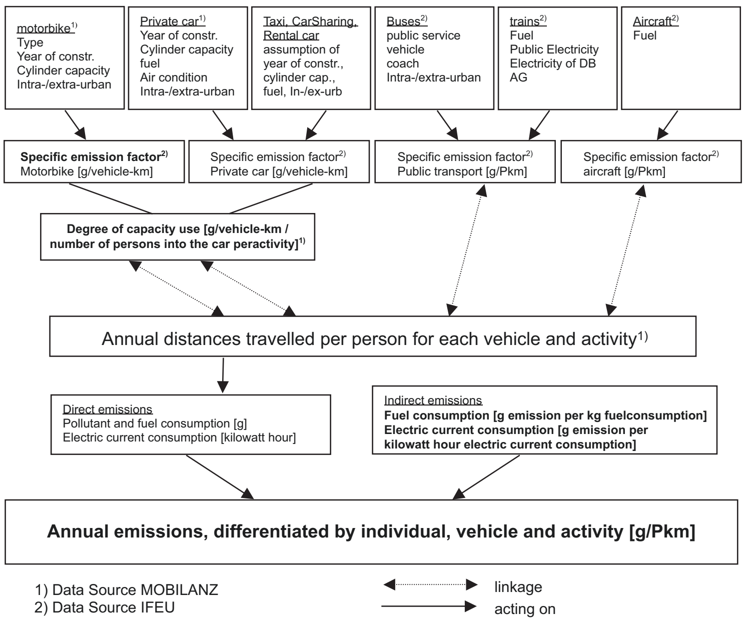
For personal cars, participants indicated the number of passengers transported. For collective vehicles, the mean capacity rates of the vehicle types in Germany for 2003 were used with buses, trams, and subways calculated at capacities of 25.0%, regional trains at 23.9%, long-distance trains at 41.3%, and aircraft at 60.0%.

In the last step, the TREMOD model was used to relate the mobility data to specific emission factors to quantify the ecological impact. Results of these calculations illustrate the annual emissions of each participant in the survey. The applied calculation used for the ecological assessment is presented in more detail in Grischkat and Hunecke (2006).

Results

In marketing research, both a priori and post hoc segmentational approaches can be distinguished (Wedel & Kamakura, 1998). In the case of

Figure 1
Calculation of the Individual Ecological Assessment



an a priori segmentation, the constituent variables of the segments as well as their variable profiles are well defined so that each respondent can be clearly assigned to one segment. In contrast, post hoc segments are identified by multivariate statistical analyses based on empirical investigations. In this study, respondents were clustered according to their similarity on multivariate profiles on any number of combinations of variables. The segments were determined from the data, whereas the number of clusters and their relative size was not known until the process had been completed. The attitude-based target-group approach, which is introduced in the following section, was constructed in a post hoc manner, whereas the two alternative models, district types and life cycles, represent a priori segmentations.

Identification of Mobility Types

Attitude-based target groups or *mobility types* were identified in two successive steps. First, the personal determinants of mobility behavior were analyzed to identify the factors with the highest predictive power. On the basis of these factors, which were used as constituent variables, a cluster analysis was used to identify the target groups.

Identification of constituent variables. Four hierarchical regression analyses were conducted to identify the most important determinants of mobility behavior. When the dependent variable was interval scaled, a linear regression was conducted. A logistic regression was carried out when the dependent variables had been dichotomized because of their unfavorable distribution. Three of the regression analyses refer to the modal split, the prediction of private motorized modes usage, public transportation and bicycle use, respectively. In addition, a regression analysis predicting the kilometers traveled by private motorized modes was carried out. Psychological, demographic, and infrastructural variables were entered as independent variables in two steps, with infrastructural and demographic characteristics entered first and psychological variables second. In this way, the additional predictive power of psychological variables became evident. Table 4 summarizes the results of all regression analyses conducted. When psychological variables were entered, explained variance increased by 7% (public transportation use) up to 25% (bicycle use). Public transport control was the strongest predictor in all regression analyses, except for the regression analysis predicting bicycle use, in which bicycle attitude was stronger.

Psychological variables were defined as constituents when they exhibited a significant impact on at least two dependent variables. This criterion was fulfilled by seven attitudinal variables: ecological norm, public transport control, public transport excitement, car attitude, bicycle attitude, weather resistance, and perceived mobility necessities (see Table 4). In addition, the value dimension of openness to change was chosen, although it was only a significant predictor of public transportation use, because Poortinga et al. (2004) found it to be the only significant psychological predictor of the ecological impact of transport-related energy use in transportation. The hierarchical regression analyses conducted ensured that only psychological variables were selected as constituent variables for the cluster process that could improve the prediction of mobility behavior if infrastructural and sociodemographic variables were controlled for. This methodological step allowed the number of psychological variables included in the cluster process to be reduced from thirteen to eight.

Cluster analysis. Cluster analyses, in general, do not offer a test to calculate the optimal number of clusters. Thus, cluster analyses using the

(text continued on p. 24)

Table 4
Review of Regression Analyses Results Predicting Different Mobility Behavior Variables

	Percentage Private Motorized Modes Usage (n = 1,433)	Public Transportation Use (*Yes/No*) (n = 1,263)	Bike Use (*Yes/No*) (n = 1,263)	Distance Traveled by Private Motorized Modes/Year[1] (n = 1,433)
	Standardized Regression Coeffcients[2]			
	Linear	Logistic	Logistic	Linear
Model 1				
Infrastructure				
City center [1 = *yes*; 0 = *no*]	–.15***	–0.20**	0.18**	–.01
Suburban area [1 = *yes*; 0 = *no*]	.07*	–0.39***	0.13	.03
Augsburg [1 = *yes*; 0 = *no*]	–.11***	0.16*	0.24***	–.02
Magdeburg [1 = *yes*; 0 = *no*]	.01	–0.10	–0.04	.08***
Driver's license [1 = *yes*; 0 = *no*]	.21***	–0.22***	0.04	.20***
Number of cars	.36***	–0.66***	–0.15*	.31***
Access to PT [1 = *not satisfied*; 5 = *very satisfied*]	–.06*	0.09	0.10	–.03
Distance to next bus stop[3]	.03	0.00	0.12*	–.01
Distance to next rail station[3]	.06*	–0.13*	–0.14*	.03
Demographic structure				
Age	–.01	–0.24***	–0.15	–.14***
Sex [1 = *male*; 0 = *female*]	.07**	–0.19**	–0.04	.03
Higher education [1 = *yes*; 0 = *no*]	–.05*	0.09	0.07	.04
People per household	–.13***	0.45***	0.13	–.14***
Children per household	.10***	–0.50***	–0.04	.06*

(continued)

Table 4 (continued)

	Percentage Private Motorized Modes Usage (n = 1,433)	Public Transportation Use (*Yes/No*) (n = 1,263)	Bike Use (*Yes/No*) (n = 1,263)	Distance Traveled by Private Motorized Modes/Year[1] (n = 1,433)
	Standardized Regression Coeffcients[2]			
	Linear	Logistic	Logistic	Linear
Living apart together relationship	–.01	0.15*	0.05	.06*
Income	.02	0.12	0.04	.05
Full-time employment [1 = *yes*; 0 = *no*]	.16***	–0.26***	0.01	.25***
Part-time employment [1 = *yes*; 0 = *no*]	.05	0.07	0.16*	.10***
Model 2				
Infrastructure				
City center [1 = *yes*; 0 = *no*]	–.10***	–0.40***	0.22*	.01
Suburban area [1 = *yes*; 0 = *no*]	.06*	–0.38***	0.17	.02
Augsburg [1 = *yes*; 0 = *no*]	–.07**	0.17*	0.15	.01
Magdeburg [1 = *yes*; 0 = *no*]	–.02	–0.02	0.03	.06**
Driver's license [1 = *yes*; 0 = *no*]	.14***	–0.09	–0.10	.15***
Number of cars	.20***	–0.44***	–0.06	.21***
Access to PT [1 = *not satisfied*; 5 = *very satisfied*]	.04	–0.10	0.02	.02
Distance to next bus stop[3]	.01	0.05	0.19*	–.02
Distance to next rail station[3]	.05*	–0.13	–0.05	.02
Demographic structure				
Age	.02	–0.22*	–0.09	–.10***
Sex [1 = *male*; 0 = *female*]	.03	–0.10	–0.12	–.01

(continued)

Table 4 (continued)

	Percentage Private Motorized Modes Usage (n = 1,433)	Public Transportation Use (*Yes/No*) (n = 1,263)	Bike Use (*Yes/No*) (n = 1,263)	Distance Traveled by Private Motorized Modes/Year[1] (n = 1,433)
	Standardized Regression Coeffcients[2]			
	Linear	Logistic	Logistic	Linear
Higher education [1 = *yes*; 0 = *no*]	–.04*	0.10	0.01	.04
People per household	–.04	0.31*	0.01	–.08**
Children per household	.04	–0.48***	0.04	.02
Living apart together relationship	.00	0.08	0.08	.06**
Income	.04	0.09	–0.01	.06*
Full-time employment [1 = *yes*; 0 = *no*]	.09***	–0.19	–0.01	.19***
Part-time employment [1 = *yes*; 0 = *no*]	.04	0.10	0.11	.09***
Psychological variables				
Ecological norm [range = 1 to 5][4]	–.09***	0.33***	0.04	–.05
Public transport control [range = 1–5][4]	–.33***	0.75***	–0.27**	–.24***
Public transport status [range = 1 to 5]	.05(u)**	0.00	0.20(u)*	.04
Public transport excitement [range = 1 to 5][4]	–.04	0.16*	0.17*	–.01
Public transport privacy [range = 1 to 5]	–.01	0.18*	0.11	.01
Car attitude [range = 1 to 5][4]	.08***	–0.18*	–0.25**	.05*
Bicycle attitude [range = 1 to 5][4]	–.05*	–0.17*	1.15***	–.03
Weather resistance [range = 1 to 5][4]	–.14***	–0.10	0.69***	–.04
Perceived mobility necessities [range = 1 to 5][4]	.09***	0.16	–0.23**	.08***
Self-enhancement [range = –1 to 7][4]	.01	0.03	–0.23**	.02

(continued)

Table 4 (continued)

	Percentage Private Motorized Modes Usage (n = 1,433)	Public Transportation Use (*Yes/No*) (n = 1,263)	Bike Use (*Yes/No*) (n = 1,263)	Distance Traveled by Private Motorized Modes/Year[1] (n = 1,433)
	Standardized Regression Coeffcients[2]			
	Linear	Logistic	Logistic	Linear
Openness to change [range = –1 to 7]	–.04	0.27**	0.12	.02
Self-transcendence [range = –1 to 7]	.03	–0.14	–0.04	.01
Conservation [range = –1 to 7]	.03	–0.04	0.03	.04
Model 1: Adjusted R^2	.38			.38
Model 2: Adjusted R^2	.58			.46
Model 1: McFadden Pseudo-R^2		.13		.05
Model 2: McFadden Pseudo-R^2		.21		.30

Note: PT = public transit; (u) = unexpected influence. Pairwise deletion of missing data was used.
1. The dependent variable "distance traveled by private motorized modes/year" was split in 10 categories of the same size so that the residuals would follow a normal distribution.
2. Standardized regression coefficients in linear regression analyses are standardized beta weights displayed by SPSS (2006). For logistic regression analyses the unstandardized coefficients were multiplied by the variables' standard derivations, as standardized coefficients are not provided by the program.
3. 1 = *0–100 m,* 2 = *100–200 m,* 3 = *250–500 m,* 4 = *500–750 m,* 5 = *750–1000 m,* 6 = *1000–1500 m,* 7 = *> 1500 m*.
4. Selected for cluster analyses. Predictors in linear regression analyses were checked for multicollinearity: variance inflation factors (VIF) of all variables were < 3.
*p < .05. **p < .01. ***p < .001.

k-means algorithm were conducted for 3- to 9-cluster solutions. The solutions were considered according to the criteria of predictive power, stability and interpretability. Table 5 presents the results of analyses of variance (ANOVAs) for the different cluster solutions with private motorized modes usage as the dependent variable. The *F* values as well as the Eta-squared values do not provide a clear best solution, for explained variance does not increase significantly with the number of clusters. Thus, as an additional criterion, the stability of the cluster solutions was analyzed. For this purpose, the sample was randomly split into two equal parts, and cluster analyses were conducted restricted to each subsample. The results of the subsamples were compared with one another and with the corresponding results of the whole sample to find the most stable solution. The 5-cluster solution proved to be the most stable because only for this solution did the analyses of the whole sample and the subsamples lead to the same result in terms of content. As a final and most important step, the interpretability of the different solutions was compared. The 4- and 5-cluster solutions displayed the best interpretability with the 5-cluster solution dividing one car-oriented type into what was later called public transport rejecters and car individualists. The 6-cluster solution resulted in two types of car individualists who only differed in their level of agreement with the constituent variables. The 7-, 8-, and 9-cluster solutions generated a type with high values in all constituent variables, seeming to lean toward an affirmative answer trend rather than a pattern of attitudes. Taking into account all three criteria, the 5-cluster solution was selected.[6]

Psychographic Profiles of Mobility Types

The five resulting mobility types were labeled public transport rejecters, car individualists, weather resistant cyclists, eco-sensitized PT-users, and self-determined mobile people. Table 6 displays cluster centers for each of the identified segments. In ANOVAs, the differences between the segments with regard to the means of the constituent variables were tested. Significant differences are indicated in Table 6 in superscript.

Public transport rejecters have a lower evaluation of PT than the other types with regard to both control and excitement. They can further be characterized by high perceived mobility necessities and a low openness to change. Although car individualists are quite similar to PT-rejecters in several dimensions, they differ particularly in their high openness to change and extremely positive evaluation of the symbolic aspects of the private car. In comparison, weather-resistant cyclists have negative scores on the

Table 5
Analysis of Variance (ANOVA) Results for 3 to 9 Clusters

ANOVA (Private motorized modes)		
Number of Clusters	*F* Value	Eta^2
3	450.87	.313
4	284.00	.301
5	216.78	.305
6	191.72	.326
7	153.06	.317
8	133.35	.321
9	121.99	.331

Table 6
Cluster Centers of Mobility Types

	1. Public Transport (PT) Rejecters (20.5%)	2. Car Individualists (21.0%)	3. Weather-Resistant Cyclists (19.4%)	4. Eco-Sensitized PT-Users (19.7%)	5. Self-Determined Mobile People (19.4%)
PT control	$-1.02^{2,3,4,5}$	$-0.58^{1,3,4,5}$	$0.26^{1,2,4,5}$	$0.90^{1,2,3,5}$	$0.53^{1,2,3,4}$
PT excitement	$-0.56^{2,3,4,5}$	$-0.24^{1,4,5}$	$-0.14^{1,4}$	$0.90^{1,2,3,5}$	$0.02^{1,2,4}$
Car attitude	$-0.19^{2,3,4}$	$0.82^{1,3,4,5}$	$-0.62^{1,2,4,5}$	$0.06^{1,2,3,5}$	$-0.18^{2,3,4}$
Bicycle attitude	$-0.73^{2,3,4,5}$	$-0.20^{1,3,4}$	$0.80^{1,2,4,5}$	$0.43^{1,2,3,5}$	$-0.29^{1,3,4}$
Weather resistance	$-0.50^{2,3,4}$	$-0.29^{1,3,4,5}$	$1.30^{1,2,4,5}$	$-0.10^{1,2,3,5}$	$-0.53^{2,3,4}$
Ecological norm	$-0.46^{3,4}$	$-0.38^{3,4}$	$0.22^{1,2,4,5}$	$1.18^{1,2,3,5}$	$-0.51^{3,4}$
Perceived mobility necessities	$0.70^{3,4,5}$	$0.60^{3,4,5}$	$-0.08^{1,2,5}$	$-0.19^{1,2,5}$	$-1.12^{1,2,3,4}$
Openness to change	$-0.49^{2,3,4}$	$0.93^{1,3,4,5}$	$0.14^{1,2,5}$	$-0.03^{1,2,5}$	$-0.61^{2,3,4}$

Note. Items in superscript indicate which means are significantly different from each other. For example, a 2 written in superscript in the first line indicates that that mobility type differs significantly from the car individualist with regard to PT control (analysis of variance, Scheffé's post hoc test, $p < .05$).

private car factor, their main characteristics being a positive attitude toward bicycle use and a high weather resistance, meaning that they are not averse to using the bicycle in poor weather conditions. Eco-sensitized PT-users show a high ecological norm and a positive evaluation of PT. Finally, self-determined mobile people have a high perceived PT control and low perceived mobility necessities, and they score negatively on openness to change. The results in Table 6 show that there is a multitude of significant differences between each of the five clusters, indicating a high external heterogeneity of the cluster solution as far as the constituent variables are concerned.

Differences of Mobility Types in Mobility Behavior

The differences in attitudes and values of the five mobility types are reflected in their mobility behavior, especially their travel-mode choice.[7] Results for the ANOVAs are presented in Table 7. PT-rejecters make the highest percentage of trips by private motorized modes, followed by car-individualists. In Scheffé's post hoc comparisons, both types differ significantly from each other ($p < .05$), and even more significantly ($p < .001$) from all other types in that respect. PT-rejecters also differ significantly from all other types as they show the lowest percentage of PT usage ($p < .01$), whereas the eco-sensitized PT-users show the highest PT usage levels ($p < .001$). The latter are also characterized by a very balanced modal split. As expected, the weather-resistant cyclists make the largest share of trips by bicycle, using it for even more trips than they use private motorized modes. In contrast, the self-determined mobile people have the highest percentage of trips by foot. These results are also confirmed by Scheffé's post hoc comparisons ($p < .001$). Regarding distances, PT-rejecters and car individualists differ significantly from the other three types by greater distances ($p < .001$). They cover more than 2 times more distance by private motorized modes annually than weather-resistant cyclists and more than 3 times more than both eco-sensitized PT-users and self-determined mobile people.

Ecological Impact of Mobility Types

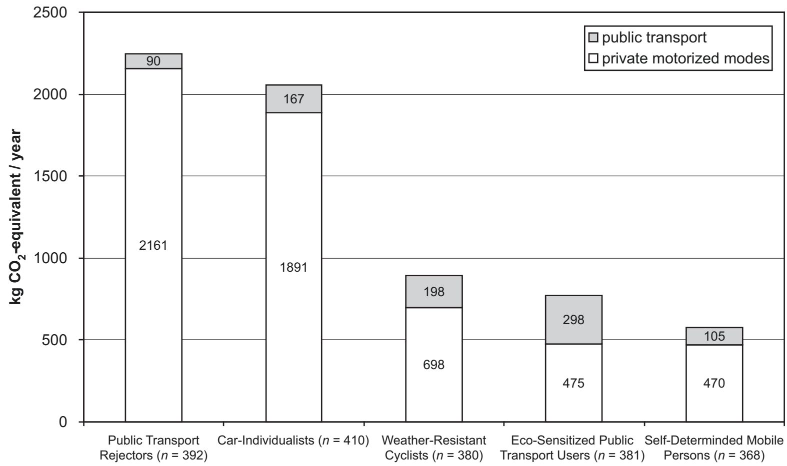
The connection between the ecological assessment and mobility types is presented in Figure 2.[8] PT-rejecters and car individualists stand out in that they produce the most total greenhouse gas emissions as well as the most greenhouse gas emissions resulting from the use of private motorized modes. In Scheffé post hoc comparisons, they differ significantly from all other types ($p < .001$). Eco-sensitized PT-users show the highest emissions resulting from public transportation use. In this respect, they differ significantly from PT-rejecters and self-determined mobile people, a fact also confirmed by Scheffé's post hoc test ($p < .01$).

Table 7
Differences in Mobility Behavior of Different Mobility Types

Mobility Behavior	Public Transport (PT) Rejecters ($n = 409$)	Car Individualists ($n = 419$)	Weather-Resistant Cyclists ($n = 387$)	Eco-Sensitized PT-Users ($n = 392$)	Self-Determined Mobile People ($n = 386$)	
Private motorized modes (mean percentage)	74.5	67.3	31.6	27.1	35.7	$F(4,1985) = 216.78^{***}$
PT use (mean percentage)	4.8	11.1	10.8	26.7	15.3	$F(4,1985) = 55.50^{***}$
Bicycle use (mean percentage)	6.0	8.0	38.9	18.0	12.7	$F(4,1985) = 140.22^{***}$
By foot (mean percentage)	14.8	13.6	18.7	28.1	36.3	$F(4,1985) = 57.98^{***}$
Distance (km) traveled by private car per year (mean, excluding holidays)	11858.8	11289.3	5210.3	3677.5	3461.4	$F(4,1984) = 46.30^{***}$

$^{***}p < .001$.

Figure 2
Ecological Assessment of Mobility Types



Comparison of Attitude-Based Mobility Types With a Geographic and Sociodemographic Target-Group Model

In the sample analyzed, two alternative segmentations were applied. Geographical target groups were determined by district type and sociodemographic target groups by lifecycle. In both approaches, the target groups are defined a priori. The geographical approach differentiates three target groups concerning spatial and infrastructural characteristics: people who live in inner-city districts, those who live in city-border districts, and those in suburban districts. These three geographical target groups differ in seven spatial and infrastructural characteristics: distance to the city center, density, housing, infrastructure, accessibility of the city center by foot and bicycle, accessibility of local public transportation, and accessibility of long-distance travel modes (see Table 1). Assignment to the geographical target groups was conducted, independently from interviews, on the basis of information about the district type in which people live.

Sociodemographic target groups were generated using the life cycle approach of Jäger (1989), developed for short-distance travel by train on the German railway system. In this approach, nine lifecycles were defined a priori. Each lifecycle represents a specific combination of four sociodemographic variables: age, household size, number and age of children in the household, and employment status (see Table 8). In this study's sample, almost all (98.3%) individuals could be assigned to one lifecycle segment by means of the sociodemographic data obtained.

An analysis of means in each district type shows that people in suburban areas use the car more often than people of other district types (see Table 9). However, people from the three district types differ only moderately in terms of distance traveled, and they do not differ significantly with regard to their resulting greenhouse gas emissions. Regarding lifecycles, people in households with children as well as people in young, two-or-more-person households use the car most often. Young people in single households and in two-or-more-person households cover the most distance by car. Consequently, both groups also have the highest greenhouse gas emissions resulting from mobility behavior, whereas pensioners have the lowest.

If we compare the statistical power (Eta squared) of the results presented in Table 9, we find that the differences are higher for mobility types than for the other two segmentation approaches. The mobility type was found to have a large effect on the use of private motorized modes, a medium-sized effect on distance traveled and a small effect on ecological impact. The other two approaches only show one medium-sized and two small effects.

Discussion

In this study, attitude-based target groups that show significant differences in ecological impact resulting from daily mobility behavior could be identified. This result can be traced back to the high predictive power of the identified attitudinal segmentation for travel-mode choice, which is one of the main influences on ecological impact, in addition to distance traveled and the technical data of the modes used. As the segmentation method focuses on maximizing the differences in travel mode choice, the high predictive power of the attitude-based target-group approach is not very surprising. It is interesting, however, that the predictive power for travel-mode choice is so much higher than that for the alternative geographic and sociodemographic approaches. In contrast, for the ecological impact the effect size is rather weak but still higher than the effects sizes of the alternative models.

It should be noted that comparison between the three target-group approaches was not entirely fair. Post hoc generation of the attitude-based approach is more likely to enhance differences in mobility behavior than

Table 8
Description of Life Cycles

Life cycles	Criteria	*n*	%
Students/apprentices	position = student, apprentice no children in the household	80	4.0
College students	position = student no children in the household	120	6.0
Young people in single households	one-person-household age < 40 no students	105	5.3
Households with at least one child younger than six years of age	children in the household of which at least one is < 6 years of age	196	9.8
Households with students	children in the household of which the youngest is ≥ 6 and < 18 years of age	292	14.7
Young households with two or more people	living together with other adults only age < 40	177	8.9
Households with adults younger than 65 years of age	living alone or together with other adults age ≥ 40 < 65	499	25.1
Households with pensioners	no one-person-household position = pensioner or age ≥ 65 and position =housewife or position = unemployed	381	19.1
Pensioners in single households	one-person-household position = pensioner or age ≥ 65 and position = housewife or position = unemployed	108	5.4
Missing data	people that could not be assigned	33	1.7
Total		1991	100.0

the two a priori segmentations. Furthermore, the attitude-based target groups contain more constituent variables. However, it can be concluded from the findings of the regression analyses that post hoc segmentations based on the spatial or infrastructural variables considered would not have been better able to predict travel mode choice or ecological impact.

To further improve the power of the attitude-based target-group approach in predicting ecological impact, the selection of constituent variables for segmentation must be more strongly concentrated on mobility aspects that concern distances traveled. The results of this study's regression analyses indicate that some of the attitudes that are important predictors for travel-mode choice are also relevant predictors for distances

Table 9
Analyses of Variance (ANOVAs) for Different Target Group Models with Eta-Squared Measures

	Private Car Use (%)	Distance Traveled by Car (km per Person per Year, Excluding Holidays)	Greenhouse Gas Emissions (Excluding Holidays)
Mobility types			
Public transport (PT) rejecters	74.5	11,858.8	2,252.2
Car individualists	67.3	11,289.3	2,072.4
Weather-resistant cyclists	31.6	5,210.3	896.2
Eco-sensitized PT-users	27.1	3,677.5	773.4
Self-determined mobile people	35.7	3,461.4	575.3
ANOVA	$F(4,1985) =$ 216.78***	$F\ (4,1984) =$ 46.30***	$F\ (4,1930) =$ 26.69***
Eta squared	.305	.086	.053
District types			
City center	34.5	7,731.0	1,373.8
City border	46.9	5,831.7	1,143.6
Suburban area	61.8	8,045.9	1,481.8
ANOVA	$F(2,1984) =$ 107.90***	$F(2,1984) =$ 5.82*	$F(2,1930) =$ 2.02
Eta squared	.098	.006	.002
Lifecycles			
Students/apprentices	39.9	7,093.2	1,557.6
College students	28.6	7,778.8	1,674.4
Young people in single households	49.1	11,901.1	2,164.8
Households with at least one child younger than 6 years of age	54.4	6,990.9	1,114.5
Households with students	59.9	8,816.8	1,491.8
Young households with two or more people	58.5	11,839.8	2,240.8
Households with adults younger than 65 years of age	49.5	7,914.3	1,678.7
Households with pensioners	42.1	2,982.1	405.1
Pensioners in single households	21.0	2,032.0	416.3
ANOVA	$F(8,1951) =$ 22.43***	$F(8,1951) =$ 13.42***	$F(8,1900) =$ 9.41***
Eta squared	.085	.052	.038

Note. Small effect size: 0.01; medium effect size: 0.06; large effect size: 0.14 (Cohen, 1988) covered by car, such as the variables public transport control and perceived mobility necessities. Nevertheless, additional research is needed to identify further attitudinal variables related to destination choice.

Evidence for the predictive power of an attitude-based post hoc segmentation leads to the question whether it is also possible to define attitudinal target groups a priori. The only way to achieve this aim is to identify relevant attitude dimensions that can be used as constituent variables for the segmentation process. To negotiate the potentially arbitrary nature of attitudinal variables that define target groups, the operationalization of attitudes must be based on empirically proven theories of attitude-behavior relationships. The comparison of results from the present study with those of Anable (2005) shows preliminary success with this approach. Both studies use an expanded version of the TPB as a theoretical framework for the operationalization of the attitudes used in the segmentation process, and both studies come to quite similar conclusions with respect to basic attitude dimensions. The variables perceived behavior control, general car dependence, and attitudes to cycling identified by Anable measure the same attitudinal beliefs as the variables *public transport control, car attitude,* and *bicycle attitude* in this study. In Anable's study, moral and social norms were measured as independent variables. In the present study's data, these norms were measured in relation to the common dimension *ecological norm*. Attitudes concerning car use were also operationalized more differentially by Anable. The same is true for the domain of public transportation use in the present study. With further research, it seems that the identification of attitudinal dimensions for use in a priori segmentations will be possible. Given that these attitudes have yet to be identified, there is currently no chance to derive a priori attitude-based target groups, for the resulting target groups strongly depend on the number and kind of constituent variables. This issue is also visible upon comparison of the target groups resulting from the present study and those identified by Anable (2005). In spite of a high similarity between the underlying attitude dimensions, the target groups show large differences. Anable's decision to form separate clusters of individuals with and without car access is one reason for these differences. After this a priori differentiation, the resulting target groups were no longer comparable with the target groups of the present study, which were identified without a priori decisions.

The present study only analyzes predictive power as a criterion for target-group segmentation. Based on this study alone, policy makers cannot fully assess the use of attitude-based segmentations for the fostering of ecological mobility behavior. For a complete evaluation of all of the advantages and disadvantages of different target group approaches, further criteria such as actionability, measurability, stability, accessibility, and efficiency must be considered (Dibb, 1999). Table 10 gives an evaluative overview of the three target-group approaches considered with reference to these six criteria.

The table reveals that none of the three approaches can claim absolute superiority. In addition to high predictive power, a strong advantage of the attitude-based approach is its actionability. Attitudinal target groups provide the information necessary for the identification of starting points for soft policy measures, such as public awareness or social marketing campaigns, because attitude profiles can be used for the selection and preparation of target group specific information. For example, PT-rejecters and car individualists are both segments characterized by a low perceived ability to use public transportation, but differ in terms of their evaluation of the private car. Thus, for each group, different forms of information and services are required to achieve a shift from the private car to public transportation. Alternatively, the attitudinal profiles of each target group can be used to change attitudes by means of persuasive communication strategies. Spatial or sociodemographic factors like city topology or a person's age, in contrast to attitudes, cannot be changed by behavioral interventions.

With respect to the segmentation criteria of measurability, stability, and accessibility, the attitudinal approaches have disadvantages when compared with sociodemographic and geographic segmentations (cf. Table 10). The efficiency criterion strongly depends on the field of application and therefore does not lend itself to a general evaluation. Instead, it is possible to specify fields of application in which each of the three target-group approaches can be applied most effectively in supporting sustainable mobility.

One question still remains regarding the application of target-group approaches to encourage sustainable mobility behavior. In policy making, quantifications of greenhouse gas emissions serve as the central indicators for evaluations of climate protection measures. Mobility-related greenhouse gas emissions, however, come from many different sources and are attributable to the effects of many aspects of mobility behavior such as travel-mode choice, age of the vehicle used, number and character of holiday trips, and so on. Presently, it remains unclear whether an aggregate indicator of greenhouse gas emissions, such as the one used as the dependent variable in the analyses of this study, is an appropriate indicator for the derivation of climate protection measures in transport planning practice. Future research should focus on determining which aggregation level of ecological impact is needed for the realization of effective climate protection measures. The results of the present study demonstrate that attitude-based approaches do not only provide important information for measures that aim to reduce greenhouse gas emissions on an aggregate level, but also for different aspects of mobility behavior, especially travel mode choice.

Table 10
Evaluation of the Three Target-Group Approaches

Marketing Criteria	Geographic (Spatial Characteristics and Traffic Infrastructure)	Sociodemographic (Lifecycles)	Psychological (Attitudes, Norms, and Beliefs)
Predictive power	Medium: private car use Low: distances traveled by car and respective greenhouse gas emissions	Medium: private car use Low: distances traveled by car and respective greenhouse gas emissions	High: private car use Medium: distances traveled by car Low: greenhouse gas emissions
Actionability	Provides information for spatial and infrastructural planning. The perception and evaluation of the spatial and infrastructural environment by users is not considered	Measures can be related to basic needs of life cycles. Somewhat high variance in mobility behavior within single life cycles Constituent sociodemographic characteristics cannot be changed	Knowledge of the individual determinants of mobility related decisions provides starting points for spatial and infrastructural measures as well as new mobility services. Individual processes relevant to mobility behavior can be affected by information and communication centered (soft policy) measures
Measurability	High reliability for spatial characteristics if measured by experts Self-reporting often influenced by bias	High reliability even when characteristics are self-reported	Reliability varies between psychological variables. Measurement errors can be explicitly quantified

(continued)

Table 10 (continued)

Marketing Criteria	Geographic (Spatial Characteristics and Traffic Infrastructure)	Sociodemographic (Lifecycles)	Psychological (Attitudes, Norms, and Beliefs)
Stability	Extremely high stability	Characteristics very stable at the population level Characteristics change over time at the individual level during the lifecycle	Very low stability. Characteristics vary with changes in life situation and environment
Accessibility	Direct local accessibility	Indirect accessibility for typical activities and media used	Standardized interviews are necessary for direct accessibility
Efficiency	Expert measurement of all relevant characteristics for each person is very extensive and therefore cannot be realized Surveys typically ask participants for the specific spatial and infrastructural characteristics of their residential environment	Data is often not available in the form of official statistics Sociodemographic characteristics are measured in surveys by default	An exact classification requires a questionnaire with 20 to 25 items An approximate classification can be made with a lower number of indicator items
Best field of application	Long-term planning of traffic infrastructure	Promotion of mobility services that can be tailored to specific life cycles (e.g., ticket for senior citizens)	Soft policy interventions to promote travel modes (e.g., social marketing for public transportation)

Appendix

		Items
Ecological norm	Subjective norm	People who are important to me think that I should use public transportation instead of my private car.
	Subjective norm	People who are important to me would support me in using public transportation instead of the private car.
	Personal norm	For environmental reasons I feel obliged to leave the car unused in everyday life as often as possible.
	Personal norm	Due to my personal values I feel obliged to use environmentally friendly modes like buses or trams for my regular trips.
Public transport control	Perceived behavioral control, recoded	For me, using public transportation instead of the private car would be difficult in everyday life.
	Perceived behavioral control	Using public transportation instead of a private car would be easy for me if I wanted to.
	Public transport autonomy, recoded	If I used public transportation only, I would feel restricted in my freedom of movement.
	Public transport autonomy, recoded	Using public transportation, I can do everything I want to do.
	Car autonomy	I can lead my everyday life without a private car.
Public transport status	Public transport status	I'm impressed by people who cover a lot of distances by public transportation.
	Public transport status	I think that using public transportation is trendy.
	Car status, recoded	I look up to people who arrange their every day life in such a way that they do not posses a private car.
Public transport excitement	Public transport excitement	I like public transportation because there are a lot of interesting things to see.
	Public transport excitement	For me using public transportation is relaxing.

(continued)

Appendix (continued)

		Items
Public transport privacy	Public transport privacy	When using public transportation, my privacy is limited in an unpleasant way.
	Public transport privacy	When I use public transportation, other people come close to me in an unpleasant way
Car attitude	Car autonomy	Driving a car means freedom to me.
	Car privacy	I like driving a car because I can decide with whom I drive.
	Car privacy	In my private car I feel safe and secure.
	Car excitement	Driving a car means fun and passion to me.
	Car excitement	Sometimes I enjoy driving without a special destination.
	Car excitement	Driving a car is sometimes a pleasant challenge to me.
	Car excitement	I enjoy applying my driving competence.
Bicycle attitude	Bicycle excitement	I love riding my bike.
	Bicycle excitement	Riding my bike is relaxing.
	Bicycle autonomy	By bike I can get anywhere.
	Bicycle autonomy	I can reach many of my important destinations by bike.
Weather resistance	Weather resistance, recoded	I don’t like riding my bike when the weather is chilly.
	Weather resistance	I ride my bike even in bad weather conditions.

(continued)

Appendix (continued)

		Items
Perceives mobility necessities	Perceives mobility necessities	The organization of my everyday life requires a high level of mobility.
	Perceives mobility necessities	I have to be mobile all the time to meet my obligations.
Values	How important is . . . to you as a guiding principle of life?	
Openness to change	. . . having an exciting life . . .	
	. . . having a diversified life . . .	
	. . . being daring . . .	
Conservation	. . . social order . . .	
	. . . national security . . .	
	. . . family safety . . .	
Self-enhancement	. . . being ambitious . . .	
	. . . being competent . . .	
	. . . being successful . . .	
Self-transcendence	. . . unity with nature . . .	
	. . . saving the environment . . .	
	. . . respect for nature . . .	

Notes

1. This spatial differentiation model is the most accepted analytical model for the structural organization of area in Germany (Hoffmeyer-Zlotnik, 2000). The model's main indicators are population density and workplaces (inhabitants + employees / square kilometer). These indicators reflect the intensity of interaction within regions, which is essential for transportation issues (Aschpurwis + Behrens GmbH, 2001).

2. The 14 purposes belong to 4 categories: (1) work (work/training, trips to second home because of work), (2) shopping (shopping, one-stop shopping), (3) private errands (trips to administration, the dropping off and picking up of children, supply of relatives/dependents), (4) leisure time activities (shopping, meeting a partner, meeting friends and relatives, visits to cultural events, sports/association, allotment gardens, day trips).

3. Private motorized modes include motorized two-wheelers, private cars, car sharing, cars rentals, and taxis.

4. The Global Warming Potential is defined as the ratio of the time-integrated radiative forcing from the instantaneous release of 1 kg of a trace substance relative to that of 1 kg of a reference gas (IPCC, 2001, p. 385). The considered time horizon is 100 years and CO_2 is the reference gas. For the gases considered: 1 kg methane (CH_4) is equivalent to 21 kg CO_2 and 1 kg nitrous oxide (N_2O) is equivalent to 310 kg CO_2 (IPCC, 1996).

5. For alternative transit modes like cars used for car sharing, rental cars, and taxis, the following assumptions were made: car-sharing cars were assumed to be small, rental cars of middle class, and taxis were assumed to be upper-class vehicles. Public transport data were made available by the transportation companies and are included in the database for motorized traffic in Germany TREMOD, which was created by the Ifeu-Institute in Heidelberg, Germany. TREMOD was also used as a basis for specific emission factors (see Figure 1).

6. Cluster analyses were conducted with three software tools: ClustanGraphics 5.26 (2002), ConClus 3.0 (Klein, 2001) and SPSS 14 (2006). The Clustan and ConClus solutions were almost identical, whereas SPSS solutions differed from the Clustan and ConClus solutions. In the end, the Clustan solution was selected because the allocation of people to the five clusters on the basis of the constituent variables was slightly better, which was measured by a discriminant analysis.

7. With regard to basic mobility behavior data (e.g., number and availability of the private car), the results of this survey were quite similar to both of the two representative Germany mobility surveys (MiD; Infas & DIW, 2003; Mobility Panel, BMVBW; Zumkeller, Chlond, & Kuhnimhof, 2002). However, with 2.9 trips per person per day, the number of trips in this study was lower than the MiD result of 3.3 and the Mobility Panel result of 3.5 trips per day. This is due to the different methods used. In contrast to MiD and the Mobility Panel that used the target-date method for data collection, mobility behavior was measured in the current study by retrospective questioning, which has the disadvantage of susceptibility to memory effects.

8. Differences between means in Figure 2 and results for total greenhouse gas emissions for mobility types in Table 9 are due to the use of air traffic, which is not included in Figure 1 because of its negligible relevance for daily mobility behavior.

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