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Values, attitudes and travel behavior: a hierarchical latent variable mixed logit model of travel mode choice

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Abstract Values lie at the heart of an individual's belief system, serving as prototypes from which attitudes and behaviors are subsequently manufactured. Attitudes and behaviors may evolve over time, but values represent a set of more enduring beliefs. This study examines the influence of values on travel mode choice behavior. It is argued that personal values influence individual attitudes towards different alternative attributes, which in turn impact modal choices. Using data from a sample of 519 German commuters drawn from a consumer panel, the study estimates an integrated choice and latent variable model of travel mode choice that allows for hierarchical relationships between the latent variables and flexible substitution patterns across the modal alternatives. Results from the empirical application support the value-attitude-behavior hierarchical model of cognition, and provide insights to planners and policy-makers on how better to sell public transit as a means of travel.

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Introduction

It is widely agreed that the current pattern of human growth is unsustainable, and that a determined effort needs to be made to persuade individuals with regards to their travel behavior to forego driving in favor of greener modes of transportation (Ewing et al. 2008; Schafer et al. 2009; Sperling and Gordon 2009). Though the deleterious effects of the car on health and environment are well documented, and increasingly well publicized, vehicle use continues to proliferate. The failure of policies attempting to achieve modal shifts has been ascribed by many researchers to an incomplete understanding of the cognitive process underlying the formation and persistence of individual preferences (Bamberg et al. 2003; Anable 2005; Steg 2005). Travel behavior studies rooted in psychology and the social sciences have demonstrated that more abstract psychological constructs, such as attitudes, values, norms, perceptions, affects and desires, are integral to an individual's choice of travel mode (Jensen 1999; Hagman 2003; Verplanken et al. 2008). Though the role of instrumental factors such as travel times and travel costs in determining mode choice is well recognized, and the influence exerted by individual attitudes towards less tangible attributes such as comfort and convenience has gained considerable attention in the last two decades (see, for example, Morikawa et al. 2002; Kuppam et al. 1999; Vredin Johansson et al. 2006; Yañez et al. 2010), a comprehensive framework akin to the Theory of Planned Behavior (Azjen 1991) or the Theory of Interpersonal Behavior (Triandis 1977) that recognizes the influence of each of these psychological constructs on travel mode choice has not yet been operationalized in practice, due largely to methodological and computational limitations. In this study, we focus our attention on both attitudes and values and how they might be incorporated within the framework of a traditional travel mode choice model, thereby advancing the state of the art one step closer towards a more holistic representation of travel mode choice behavior.

Values are defined as enduring beliefs that a specific mode of conduct is personally or socially preferable to an opposite or converse mode of conduct (Rokeach 1973). Values lie at the very heart of an individual's belief system: they reflect the most basic characteristics of adaptation and serve as prototypes from which attitudes and behaviors are subsequently manufactured (Homer and Kahle 1988). Therefore, while attitudes and behaviors are prone to change and evolve over time, values represent a set of more stable and persistent beliefs that transcend objects, situations and issues (Rokeach 1973; Feather 1990; Schwartz 1992). The domain of travel behavior analysis has been dominated by studies on attitudes, and the impact of values on travel behavior has garnered much less attention. Several studies that have examined individual mode choice have acknowledged the need to incorporate the influence of values explicitly (Bamberg 1996; Lanzendorf 2002; Choo and Mokhtarian 2004; Zhao 2009). Decisions that might appear at the outset to be irrational can often be explained when the influence of values is appropriately accounted for (Steg 2005; Gatersleben and Uzzell 2007; Páez and Whalen 2010). For example, individuals who cherish feelings of power and pleasure might continue to drive, even when driving is not the cheapest, fastest or safest mode of travel for a particular trip, because they crave the sense of control and freedom afforded by the act of driving. Similarly, individuals with a heightened notion of cleanliness and personal hygiene might be disinclined to use transit, irrespective of its level-of-service, because they perceive buses and trains as not the most sanitary of travel modes. In light of these and other examples, it is argued that the inclusion of values in traditional travel demand modeling frameworks could provide greater information about the cognitive shifts that must be achieved before any commensurate changes in actual observable travel behavior can be expected to follow.

There is a rich and variegated history to the use of values in studies in psychology and the social sciences for explaining individual attitudes and behaviors (see, for example, Kluckhohn 1951; Rokeach 1973; Williams 1979). In general, results for direct value-behavior relationships in the literature have proven to be modest at best (see, for example, Kassarjian and Sheffet 1991; Kristiansen and Hotte 1996). However, research that has examined the mediated impact of values on behavior through intervening constructs, such as the value-attitude-behavior hierarchy proposed by Homer and Kahle (1988), has been far more fruitful. Figure 1 depicts the structure of the value-attitude-behavior hierarchical[1] model of cognition. As per the theory, a small number of more or less stable values give rise to hundreds of more mutable attitudes, which in turn manifest themselves as myriads of different behaviors. The objective of this study is to develop an integrated choice and latent variable (ICLV) model (McFadden 1986; Ben-Akiva et al. 2002) of travel mode choice that captures explicitly the additional influence of values on individual travel behavior. Consistent with the value-attitude-behavior hierarchical model of cognition, we posit that personal values influence individual attitudes towards alternative attributes, which subsequently impact travel behavior.

Though numerous studies on travel behavior have employed the ICLV framework (Vredin Johansson et al. 2006; Yañez et al. 2010), they have tended to simplify significantly the cognitive theories motivating the use of these models, and much of the behavioral richness captured originally in these theories through the complex interplay between different latent psychological constructs has often been lost as a consequence of these simplifications. Studies that have incorporated hierarchical relationships between latent variables (Temme et al. 2008; Zhao 2009; Tudela et al. 2011) have often been forced by the limitations of existing estimation software, such as Mplus, to use the multinomial logit kernel and overlook choice model frameworks that allow for more flexible errors structures, such as the mixed logit model. The mixed logit model is a highly pliable model form that can approximate any random utility model (McFadden and Train 2000). Unlike the multinomial logit model, it allows for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (Train 2009). To the best of our knowledge, ours is the first study to simultaneously estimate a latent variable mixed logit model with hierarchical relationships between the latent variables. The model framework developed in this study is both statistically robust and firmly grounded in behavioral theory. Results from an empirical application confirm the value-attitude-behavior hierarchical causal representation, and provide insights that could prove helpful to the design of policies aimed at encouraging the use of public transport.

The paper is organized as follows: Section 2 describes the dataset. Section 3 lays out the methodological details of the ICLV model framework developed in the study. Section 4 discusses estimation results and policy implications. Section 5 concludes the paper by summarizing our contributions, findings, limitations and directions for future research.

[1] Throughout the paper, the word 'hierarchical' is *not* used in the Bayesian sense of the word.

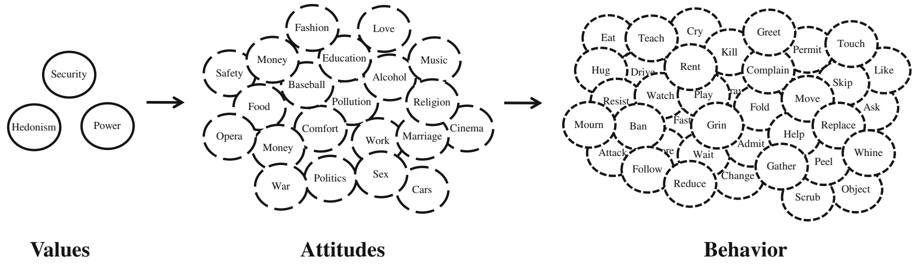

Fig. 1 An illustrative representation of the value-attitude-behavior hierarchical model. In moving from left to right, the constructs become more numerous and context-specific, and less stable

The dataset

Data for our analysis came from a sample of German consumers between 17 and 76 years of age. Following a survey pre-test with 20 subjects, 907 respondents were drawn from a consumer panel of a major international market research company. The survey was administered in a computer-aided telephone interview. Panelists were recruited following a demographic quota sampling approach based on age, gender, household size, size of city/place of residence, and profession as a proxy for status. The sample distribution on demographic variables, shown in Table 1, did not significantly deviate from the population distribution. The survey response rate of the invited panelists was 45 %.

The questionnaire consisted of five major parts: In the first section, respondents were asked demographic questions needed for quota sampling. The second section included questions about personal mobility. Respondents were asked about the possession of a driver's license, of seasonal tickets for public transport alternatives (bus, streetcar, integrated public transport system, railroad), and about possession of cars. For each individual in the dataset three travel modes were defined: drive only, drive to public transit, and public transit only. Accordingly, the distance to the nearest stations of various public transport alternatives (if available) and the time needed for daily trips to work with public transport as well as by car had to be estimated. In the third section, we asked about attitudes towards transport modes for daily trips to work. Building on Vredin Johansson et al. (2006), we developed measurement indicators for the three attitude dimensions: flexibility, convenience/comfort, and ownership. Respondents had to rate attitudinal questions relating to these three dimensions on five-point Likert-scales ranging from not important at all to very important. Operationalizing attitudes as attribute importances is in line with the literature in the transportation field (e.g. Ben-Akiva et al. 2002; Vredin Johansson et al. 2006) and research on the value-attitude hierarchy (e.g. McCarty and Shrum 1994). However attitudes may be defined differently in other disciplines. In the fourth section, we asked respondents about their mode choice for daily trips to work or education. Respondents had to indicate whether they predominantly used car, public transport, or a combination of both.

The survey closed with a section where we measured respondents' value orientations with the portraits value questionnaire (PVQ) from Schwartz et al. (2001). Respondents had to indicate their similarity to person descriptions (portraits) gender-matched with the respondent on six-point rating scales ranging from very unlike to very much alike. Though the PVQ that was used to measure respondents' values identifies ten motivationally distinct value constructs (Schwartz et al. 2001), we restricted our attention to the following three:

Table 1 Descriptive statistics stratified by travel choice mode

Description	Drive only (412 observations)		Drive + public transit (57 observations)		Public transit only (50 observations)	
	Mean	Std dev	Mean	Std dev	Mean	Std dev
Gender (females = 1)	0.50	0.50	0.40	0.50	0.52	0.51
Age (years)	40.12	13.04	40.32	14.71	39.50	13.81
Net monthly Income (Euros)	2,640	1,352	2,395	1,205	2,242	979
# Cars in household	1.96	0.78	1.39	0.56	0.92	0.80

power, hedonism and security. Power is defined as concern for social status and prestige, and control or dominance over people and resources; hedonism denotes interest in pleasure and sensuous gratification for oneself; and security refers to safety, harmony and stability of society, of relationships, and of the self. These three constructs capture three of the four principal axes defined by Schwartz et al. (2001): self-enhancement, openness to change and conservatism. A detailed description of the measurement models for both the attitude and value constructs as well as results of confirmatory factor analyses can be found in the online archive.

For 43 % of the respondents in our sample, daily trips to work/education were not applicable (e.g., they were homemakers, unemployed or retired) or alternative travel modes did not exist (e.g., they did not possess a driver's license or had no car in the household). After deletion of these cases (see Vredin Johansson et al. 2006 for a similar approach), our analytic sample consisted of 519 respondents.

Model framework

In the general formulation of the ICLV model, two components can be distinguished: a multinomial discrete choice model and a latent variable model. Each of these sub-models consists of a structural and a measurement component. In the discrete choice component, the alternatives' utilities may depend on both observed and latent characteristics of the alternatives and the decision makers. Consistent with the random utility maximization model, utility as a theoretical construct is operationalized by assuming that individuals choose the alternative with the greatest utility. The latent variable part is rather flexible in that it allows for both simultaneous relationships between the latent variables and MIMIC-type models where observed exogenous variables influence the latent variables. Such a specification enables the researcher to disentangle the direct and indirect effects of observed as well as latent variables on the alternatives' utilities. The latent variables themselves are assumed to be measured by multiple indicators representing, in our case, the respondents' answers to Likert-scale survey questions.

The proposed model framework is illustrated in Fig. 2. Consistent with the value-attitude-behavior hierarchical model of cognition, we postulate that personal values towards power, hedonism and security influence an individual's attitudes towards comfort and convenience, flexibility, and ownership of different alternatives, which in turn influence the individual's travel mode choice. Over the following subsections, we specify the functional form for the different components of the model framework. For a more general treatment the reader is referred to Ashok et al. (2002); Walker and Ben-Akiva (2002), and Bolduc et al. (2005).

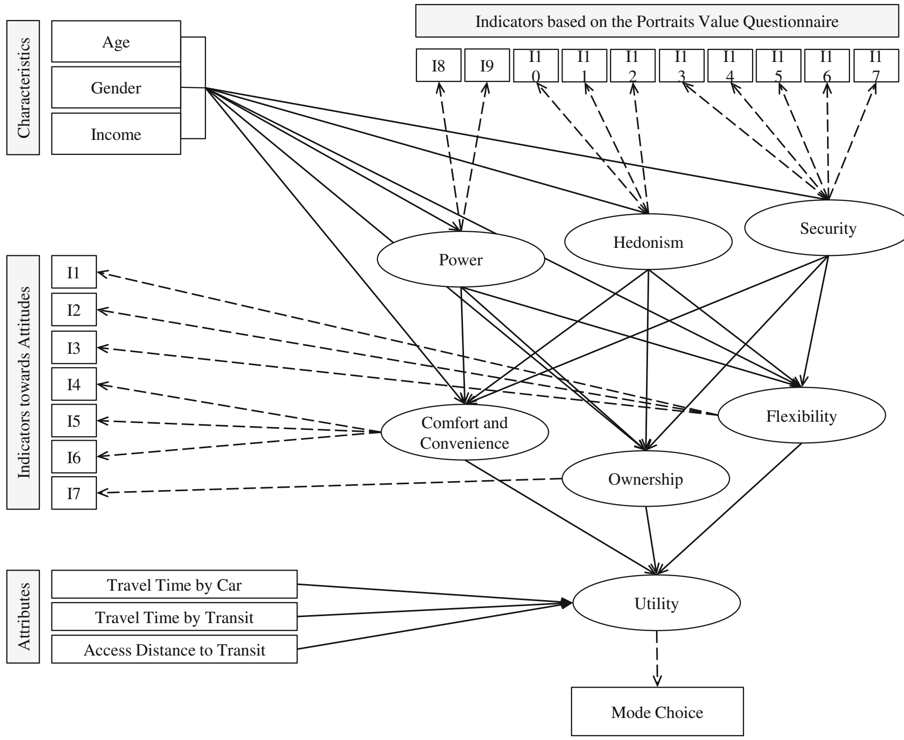

Fig. 2 ICLV model of travel mode choice as posited by the value-attitude-behavior hierarchy of cognition

The latent variable sub-model

Sociodemographic characteristics denoting age, gender, and income largely determine an individual's life circumstances in terms of his socialization, his social roles, his life stage, and his expectations. Differences in life circumstances in turn affect the salience of values (Prince-Gibson and Schwartz 1998; Schwartz 2003; Schwartz and Rubel 2005). Accordingly, the structural equation for each of the three values is defined below:

$$\mathbf{val_n} = \boldsymbol{\Gamma}\mathbf{z_n} + \boldsymbol{\eta}_\mathbf{n},$$

where $\mathbf{val_n}$ denotes the (3×1) vector of values for individual n, and $\mathbf{z_n}$ denotes the (4×1) vector of individual characteristics: age, gender, income and a regression constant equal to one. The (3×4) matrix $\boldsymbol{\Gamma}$ denotes the unknown regression coefficients, and $\boldsymbol{\eta}_\mathbf{n}$ is a (3×1) vector of random disturbances assumed to be i.i.d. multivariate normal with mean zero and a (3×3) diagonal covariance matrix given by $\boldsymbol{\Sigma}_\eta$ whose non-zero elements are parameters to be estimated.

Several studies have shown that an individual's attitudes towards attributes such as comfort and convenience, flexibility, and reliability are affected by sociodemographic variables (see, for example, Ben-Akiva et al. 2002). In addition to sociodemographic variables, we hypothesize that personal values also influence individual attitudes. Therefore, the structural equation for each of the three attitudes can then be written as follows:

$$\mathbf{att_n} = \mathbf{Az_n} + \mathbf{Bval_n} + \boldsymbol{\sigma}_\mathbf{n},$$

where $\mathbf{att_n}$ denotes the (3×1) vector of attitudes for individual n. The (3×4) matrix $\mathbf{A}$ and the (3×3) matrix $\mathbf{B}$ denote the unknown regression coefficients, and $\boldsymbol{\sigma}_\mathbf{n}$ is a (3×1) vector of random disturbances assumed to be i.i.d. multivariate normal with mean zero and a (3×3) diagonal covariance matrix given by $\boldsymbol{\Sigma}_{\boldsymbol{\sigma}}$ whose non-zero elements are parameters to be estimated.

Model identification requires that the latent variables **val** and **att** be operationalized by multiple manifest indicators **I**. The indicators in our case are responses to Likert-scale survey questions regarding the level of agreement with statements, as described in Sect. 2. For each of the six latent variables, one or more distinct indicators are used. In all, the measurement model comprises sixteen indicators, listed in Table 1 in the online appendix. A linear regression model is used for describing the mapping of indicators onto the latent variables. For example, in constructing the latent variable $\mathbf{val_{Pow}}$, or values towards power, two indicators, denoted $\mathbf{I_{Pow}}$, were used, resulting in the following measurement equation:

$$\mathbf{I_{Pow,n}} = \boldsymbol{\alpha}_\mathbf{Pow} + \boldsymbol{\gamma}_\mathbf{Pow}\mathrm{val}_{\mathrm{Pow,n}} + \boldsymbol{\lambda}_\mathbf{Pow,n},$$

where $\mathbf{I_{Pow,n}}$ is a (2×1) vector denoting individual n's responses to the two Likert-scale questions measuring values towards power (see online appendix), $\boldsymbol{\alpha}_\mathbf{Pow}$ is a (2×1) vector of linear regression intercepts, $\boldsymbol{\gamma}_\mathbf{Pow}$ is a (2×1) vector of loadings, and $\boldsymbol{\lambda}_\mathbf{Pow,n}$ is a (2×1) vector of measurement errors assumed to be i.i.d. multivariate normal across individuals with mean zero and a (2×2) diagonal covariance matrix given by $\boldsymbol{\Sigma}_{\lambda_\mathbf{Pow}}$ whose non-zero elements are also parameters to be estimated. For the measurement sub-model to be identifiable, one component each of $\boldsymbol{\alpha}_\mathbf{Pow}$ and $\boldsymbol{\gamma}_\mathbf{Pow}$ has to be fixed so as to set the location and scale[2] for $\mathbf{val_{Pow}}$. Measurement equations for each of the remaining five latent variables are similarly formulated.

The discrete choice sub-model

The random utility maximization model is based on the assumption that a decision-maker n $(\mathrm{n} = 1, \ldots, \mathrm{N})$, faced with a finite set $\mathrm{C_n}$ of mutually exclusive alternatives i $(\mathrm{i} = 1, \ldots, \mathrm{I_n})$, chooses the alternative j which provides the greatest utility $\mathrm{U_{nj}}$. The utility of each alternative $\mathrm{U_{ni}}$ is described as some function of explanatory variables that comprises the systematic part of the utility function, $\mathrm{V_{ni}}$, and some stochastic component, represented by the disturbances ϵ_{ni}:

$$\mathrm{U_{ni}} = \mathrm{V_{ni}} + \epsilon_{\mathrm{ni}}$$

In our case, an individual's choice set is composed of three alternatives: drive only, drive to public transit and public transit only. Employing a more compact vector form, we get:

$$\mathbf{U_n} = \mathbf{V_n} + \boldsymbol{\epsilon}_\mathbf{n},$$

where $\mathbf{U_n}$, $\mathbf{V_n}$ and $\boldsymbol{\epsilon}_\mathbf{n}$ are all (3×1) vectors. The systematic component of the utility function for any alternative is postulated as a linear function of observable attributes of the modal alternatives, and latent individual attitudes towards modal attributes. Sociodemographic characteristics of the decision-maker, when included linearly in the utility

[2] The scale of the latent variable could alternatively be fixed by constraining the diagonal elements of $\boldsymbol{\Sigma}_{\boldsymbol{\eta}}$ and $\boldsymbol{\Sigma}_{\boldsymbol{\sigma}}$, as mentioned in Daziano and Bolduc (2013). However, the two ways are statistically equivalent, and it is usually left to the analyst to choose whichever form is more convenient.

functions as alternative-specific variables or through interactions with level-of-service attributes, were found to be statistically insignificant. It appears that their impact is absorbed by the attitudinal variables, as a consequence of which they are omitted from the final specification:

$$\mathbf{V}(\mathbf{x_n}, \mathbf{att_n}; \boldsymbol{\beta}) = \mathbf{x_n}\boldsymbol{\beta}_\mathbf{x} + \mathbf{att_n}\boldsymbol{\beta}_\mathbf{att}$$

where $\mathbf{x_n}$ is a (3 × 5) matrix of alternative attributes that includes travel time by car, travel time by public transit, access distance to public transit and two alternative-specific constants (with the reference alternative being drive only), and $\mathbf{att_n}$ is the (3 × 6) matrix of individual attitudes towards flexibility, comfort and convenience, and ownership interacted with alternative-specific binary variables for two of the three alternatives (drive to public transit and public transit only, with drive only being held as the reference alternative). The influence exerted by the explanatory variables on the utility of each alternative is reflected by the (11 × 1) vector $\boldsymbol{\beta} = (\boldsymbol{\beta}_\mathbf{x}, \boldsymbol{\beta}_\mathbf{att})$, where $\boldsymbol{\beta}_\mathbf{x}$ and $\boldsymbol{\beta}_\mathbf{att}$ are (5 × 1) and (6 × 1) vectors, respectively. As mentioned earlier, when values were included directly in the utility functions for the choice model they were not found to have a statistically significant effect. Therefore they haven't been retained in the structural component of the final mode choice sub-model.

To account for possible correlation between alternatives, we employ a cross-nested normal error component logit-mixture (NECLM) model, where drive only and drive to public transit are grouped under one nest, and drive to public transit and public transit under the other. Therefore, the stochastic component $\boldsymbol{\epsilon}_\mathbf{n}$ can be decomposed as follows:

$$\boldsymbol{\epsilon}_\mathbf{n} = \mathbf{F}\boldsymbol{\zeta}_\mathbf{n} + \boldsymbol{\nu}_\mathbf{n},$$

where $\boldsymbol{\nu}_\mathbf{n}$ is a (3 × 1) vector of error components assumed to be i.i.d. univariate extreme-value across individuals with location parameter set to zero and scale parameter set to one, and $\boldsymbol{\zeta}_\mathbf{n}$ is a (2 × 1) vector of error components assumed to be i.i.d. multivariate normal across individuals with mean zero and a (2 × 2) diagonal covariance matrix $\boldsymbol{\Sigma}_\zeta$ whose non-zero entries are error correlation coefficients to be estimated, and $\mathbf{F}$ is a (3 × 2) matrix such that element f_{ij} equals one if alternative i belongs to nest j, and zero otherwise. Assuming that individuals in the sample are utility maximizers, i.e. they choose the alternative that gives them the highest utility, yields the widely-used NECLM form (see, for example, McFadden and Train 2000) for an individual's conditional probability:

$$\begin{aligned} \mathrm{P}(\mathbf{y_n}|\mathbf{x_n}, \mathbf{att_n}) &= \prod_{j \in C_n} \mathrm{P}\left(y_{nj} = 1|\mathbf{x_n}, \mathbf{att_n}\right)^{y_{nj}} \\ &= \prod_{j \in C_n} \left(\int_{\zeta_n} \frac{\exp\left(\mathbf{x_{nj}}\boldsymbol{\beta}_\mathbf{x} + \mathbf{att_{nj}}\boldsymbol{\beta}_\mathbf{att} + \mathbf{F_j}\boldsymbol{\zeta}_\mathbf{n}\right)}{\sum_{i \in C_n} \exp(\mathbf{x_{ni}}\boldsymbol{\beta}_\mathbf{x} + \mathbf{att_{ni}}\boldsymbol{\beta}_\mathbf{att} + \mathbf{F_i}\boldsymbol{\zeta}_\mathbf{n})} \mathbf{f}_\zeta(\boldsymbol{\zeta}_\mathbf{n}) \mathrm{d}\boldsymbol{\zeta}_\mathbf{n} \right)^{y_{nj}}, \end{aligned}$$

where $\mathbf{y_n}$ is the (3 × 1) vector of observed choices such that y_{nj} equals one if decision-maker n chose alternative j, and zero otherwise, $\mathbf{F_j}$ is the j^{th} row of the matrix $\mathbf{F}$, $\mathbf{f}_\zeta(.)$ is the probability distribution function for $\boldsymbol{\zeta}_\mathbf{n}$, and P(.) denotes the probability function.

The likelihood function

Since all information about the latent variables is contained in the multiple observed indicators, the joint probability of the choice and latent variable indicators conditioned on the exogenous variables is considered in constructing the likelihood function. Assuming that the random errors $\boldsymbol{\eta}$, $\boldsymbol{\sigma}$, $\boldsymbol{\lambda}$ and ϵ are independent, integrating over the joint distribution of the latent variables and taking the product over all decision-makers leads to the following multidimensional integral form to the likelihood function for the sample population, $\mathrm{P}(\mathbf{y}, \mathbf{I}|\mathbf{x}, \mathbf{z}; \boldsymbol{\theta})$, given by:

$$\prod_{n=1}^{N} \int_{\mathbf{val_n}} \int_{\mathbf{att_n}} \mathrm{P}(\mathbf{y_n}|\mathbf{x_n}, \mathbf{att_n}) \mathbf{f_I}(\mathbf{I_n}|\mathbf{att_n}, \mathbf{val_n}) \mathbf{f_{att}}(\mathbf{att_n}|\mathbf{z_n}, \mathbf{val_n}) \mathbf{f_{val}}(\mathbf{val_n}|\mathbf{z_n}) \mathrm{d}\mathbf{att_n} \mathrm{d}\mathbf{val_n}$$

where $\boldsymbol{\theta} = \left(\boldsymbol{\alpha}, \boldsymbol{\beta}, \gamma, , \mathbf{B}, \boldsymbol{\Gamma}, \boldsymbol{\Sigma}_{\eta}, \boldsymbol{\Sigma}_{\sigma}, \boldsymbol{\Sigma}_{\lambda}, \boldsymbol{\Sigma}_{\zeta}\right)$ is the set of all model parameters to be estimated, and the probability density functions $\mathbf{f_I}(.)$, $\mathbf{f_{att}}(.)$ and $\mathbf{f_{val}}(.)$ correspond to the measurement and structural components of the latent variable model, respectively. Maximizing the likelihood function written above yields the vector of parameter estimates. All our models were estimated simultaneously using Python Biogeme, an open source freeware designed for the estimation of discrete choice models using maximum simulated likelihood methods (Bierlaire 2003).

Estimation results and policy implications

Though a number of different model specifications were tested, we present here the estimation results for the best specification, described in the previous subsection, as determined by various statistical measures. In particular, there are three ways in which the influence of values on travel mode choice can be incorporated within the ICLV framework: (1) through their indirect influence on attitudes; (2) through their direct influence on the utilities of different travel modes; and (3) through both their indirect influence on attitudes and their direct influence on the utilities of different travel modes. Consistent with the value-attitude-behavior hierarchical model of cognition, a comparison between these three specifications deemed the first to be the most appropriate for the dataset at hand.

For the sake of brevity, we exclude estimation results for the measurement component of the latent variable sub-model. However, it will be useful to keep in mind the measures that were used to construct each of the six latent variables while interpreting the parameter estimates. We begin by examining the parameter estimates for the structural component of the values sub-model, enumerated in Table 2. As was hypothesized in the previous subsection, sociodemographic variables do exert some interesting effects on personal values. Power is clearly more salient for men than for women, a result that is consistent with research in psychology (Schwartz and Rubel 2005). Both age and income are negatively related to hedonism as a guiding personal value. Again, this result is consistent with published research (Schwartz and Rubel 2005). Furthermore, the strong positive effect of age on security supports the contention that age is positively related to conservation values. This hypothesis derives from the fact that older people are more likely to be in stable relationships and to have developed habitual behaviors that they adhere to, and are less likely to seek exciting changes and challenges (Schwartz 2003).

Table 3 lists estimation results for the structural component of the attitudes sub-model. The results clearly confirm that personal values impact attitudes towards mode choice and thereby provide strong empirical support for the value-attitude hierarchy. Hedonism has its strongest positive effect on ownership, and convenience and comfort, but to a lesser extent also drives our measure for flexibility. While the effect of hedonism on attitudes toward

Table 2 Estimation results for the structural component of the values sub-model

Variable	Estimate	Std error	t-stat	*p* value
Values toward power				
Mean	3.371	0.200	16.82	0.00
Age (years)	0.008	0.004	2.18	0.03
Gender (binary variable equals 1for females)	−0.290	0.097	−2.98	0.00
Net monthly income (Euros)	0.003	0.019	0.17	0.87
Standard deviation of error component	1.000	0.063	15.82	0.00
Values toward hedonism				
Mean	5.539	0.168	33.07	0.00
Age (years)	−0.015	0.003	−4.98	0.00
Gender (binary variable equals 1for females)	−0.111	0.081	−1.38	0.17
Net monthly income (Euros)	−0.039	0.015	−2.62	0.01
Standard deviation of error component	0.828	0.050	16.72	0.00
Values toward security				
Mean	3.683	0.153	24.04	0.00
Age (years)	0.022	0.003	6.86	0.00
Gender (binary variable equals 1for females)	0.071	0.064	1.11	0.27
Net monthly income (Euros)	−0.018	0.012	−1.50	0.13
Standard deviation of error component	0.578	0.061	9.51	0.00

convenience and comfort may be expected, the explanation for its influence on attitudes toward ownership is somewhat less straightforward. Respondents who put a high relevance on owning the transport mode might also associate other, more pleasure-related aspects and activities with it (e.g., enjoy driving the vehicle they own, being undisturbed by unwanted others, etc.). Security orientation has a strong positive impact on all three attitudes towards transport mode choice. This result makes sense since all three attitudes—ownership, convenience/comfort, and flexibility—prevent the individual from making unexpected, potentially undesirable experiences in transport mode choice. The influence of power on attitudes is relatively weak compared to the effects exerted by the other two value constructs. However, respondents for whom power is a particularly salient value ascribe a comparatively higher relevance to flexibility and ownership, as one would expect given that power values express a desire for social status, prestige as well as control or dominance over people and resources (Schwartz and Bilsky 1990). To summarize, our results concerning the value-attitude relationships possess face validity and clearly support the value-attitude hierarchy. The relationship between attitudes and sociodemographic variables is somewhat weak in comparison to the effect of the value constructs. The fact that sociodemographic variables are sources of value priorities and thereby impact attitudes towards mode choice via the value constructs might explain the weaker results for direct effects.

We move on to the parameter estimates for the mode choice sub-model, listed in Table 4. All variables, latent and observed, were included linearly in the utility specification. Though interactions between attitudinal variable and level-of-service attributes can offer additional insights, they were not tested to keep the model specification as parsimonious as possible. The effects of observable alternative attributes are largely consistent with published literature. As for the effect of attitudes on mode choice, we find that the desire for flexibility significantly increases the propensity to avoid any means of public

Table 3 Estimation results for the structural component of the attitudes sub-model

Variable	Estimate	Std error	t-stat	*p* value
Attitudes toward flexibility				
Mean	2.551	0.326	7.83	0.00
Values toward hedonism	0.087	0.040	2.18	0.03
Values toward security	0.184	0.066	2.81	0.00
Values toward power	0.077	0.033	2.33	0.02
Age (years)	−0.005	0.003	−1.71	0.09
Gender (binary variable equals 1for females)	0.093	0.053	1.73	0.08
Net monthly income (Euros)	0.046	0.010	4.44	0.00
Standard deviation of error component	0.420	0.044	9.54	0.00
Attitudes toward convenience and comfort				
Mean	0.756	0.516	1.47	0.14
Values toward hedonism	0.151	0.047	3.24	0.00
Values toward security	0.447	0.092	4.85	0.00
Values toward power	0.062	0.033	1.87	0.06
Age (years)	−0.002	0.003	−0.82	0.41
Gender (binary variable equals 1for females)	0.040	0.054	0.73	0.47
Net monthly income (Euros)	0.001	0.010	0.13	0.89
Standard deviation of error component	0.305	0.045	6.76	0.00
Attitudes toward ownership				
Mean	−0.224	0.620	−0.36	0.72
Values toward hedonism	0.230	0.076	3.03	0.00
Values toward security	0.385	0.123	3.13	0.00
Values toward power	0.101	0.060	1.69	0.09
Age (years)	0.008	0.005	1.61	0.11
Gender (binary variable equals 1for females)	0.198	0.105	1.89	0.06
Net monthly income (Euros)	0.027	0.018	1.49	0.14
Standard deviation of error component	0.213	0.150	1.42	0.16

transport and to exclusively use the car for daily work trips. Therefore, information campaigns that market initiatives such as park and ride should focus on features of public transit that depict its flexibility in a positive light. These could include, wherever applicable, services such as customized real time alerts, demand-responsive route deviations, special commuter lines, off-peak operations etc. In turn, importance of a convenient and comfortable commute increases the probability of choosing public transport. This likely has to do with the hassles of driving, such as peak-hour congestion and lack of parking space, and the corresponding conveniences of riding public transit, such as being able to read a book. In light of this, provision of additional facilities such as free wireless Internet on board commuter trains can make individuals more sensitive to the convenience and comfort of public transit. If a commuter finds it important to own the transport mode, he is less likely to use public transport by itself. However, with regards to a choice between driving exclusively and driving to public transit, the effect of ownership is statistically insignificant, as one would expect, since both alternatives require possession of or access to a car.

Table 4 Estimation results for the mode choice sub-model

Variable	Estimate	Std error	t-stat	*p* value
Alternative-specific constants				
Drive only	0.000	–	–	–
Drive to public transit	2.311	2.150	1.07	0.28
Public transit only	3.011	2.578	1.17	0.24
Level of service attributes				
Travel time by car (minutes)	−2.300	0.655	−3.51	0.00
Travel time by public transit (minutes)	−1.660	0.517	−3.21	0.00
Access distance to public transit	−0.132	0.049	−2.69	0.01
Attitudes				
Flexibility				
Drive to public transit	−1.210	0.527	−2.30	0.02
Public transit only	−1.633	0.632	−2.58	0.01
Convenience and comfort				
Drive to public transit	1.242	0.739	1.68	0.09
Public transit only	1.908	1.010	1.90	0.06
Ownership				
Drive to public transit	−0.878	0.650	−1.35	0.18
Public transit only	−1.390	0.880	−1.58	0.11
Error components				
Car nest	0.765	0.498	1.54	0.12
Transit nest	0.058	0.277	0.21	0.83

A comparison between observable level-of-service attributes and latent attitudinal variables finds the latter to have a greater influence on aggregate travel mode shares. For example, our model predicts that a 10 % increase in attitudes towards comfort and convenience across the sample population will reduce the market share for car by 8.4 %, where a 10 % increase could be taken heuristically to represent a modest improvement in attitudes.[3] In comparison, a 10 % increase in car travel times across the sample population is expected to reduce the market share for car by a meager 0.9 %. Individual attitudes may change through situational forces such as those mentioned in the previous paragraph in the short-term and through changes in values brought on about by family learning and socialization in the long-term. While the mode choice sub-model provides useful information on how better to market public transit, the structural component of the attitudes sub-model offers guidance on how each of these different policies might best be implemented. All three attitudinal constructs are significantly and positively explained by the three value constructs, suggesting that the indirect influence of each of the value constructs on the relative appeal of public transit can be decomposed into these three constituent competing effects. Interestingly, the cumulative indirect effect of values toward security on the comparative attractiveness of public transit is negligible. In fact, values toward hedonism have the strongest negative indirect effect on transit ridership levels, followed by

[3] Since latent variables can be both negative and positive, a 10 % improvement in the latent variable is simulated by adding 10 % of the absolute value to the same. In other words, if x and x' denote the original and the new value of the latent variable, respectively, then $x' = x + 0.1|x|$.

values toward power. Therefore, policies aimed at reducing car use that employ measures such as increased pricing or legal enforcement might have a detrimental effect on values towards power and hedonism, which through their bearing on the attitudinal constructs might adversely impact travel mode choice behavior. Non-invasive policies such as dispensing free transit passes to existing car users, on the other hand, offer a more peaceable alternative that is likely to prompt greater success. As evidenced by studies by Fujii and Kitamura (2003) and Abou-Zeid and Ben-Akiva (2012), such measures can indeed prompt changes in individual attitudes towards different travel modes. And though neither study explicitly controlled for values, our model framework suggests that these changes were likely brought about by commensurate changes in personal values.

Lastly, we examine the estimates for the error components for the two nests. Neither parameter is significant at the 10 % level: the parameter for the transit nest has a p value of 0.83, and the parameter estimate for the car nest has a p value of 0.12. Though a p value of 0.12 might be somewhat high, it merits repeating that our sample comprised only 519 individuals. Moreover, error components for an analogous model without latent variables were found to be even less significant. An explanation for why standard errors on the estimates should decrease after the addition of latent variables isn't readily apparent, and as a precautionary measure we have retained the error components in the final specification.

Conclusions

We set out to develop an ICLV model of travel mode choice that maps the influence of values and attitudes on observable individual travel behavior. Past studies that have used ICLV models often reduced cognitive theories that first motivated the development of these models to simpler abstractions that were easier to operationalize. In trading behavioral richness for computational tractability, these studies ignored more complex relationships between different latent psychological constructs, such as the value-attitude hierarchy explored in our work. Studies that have employed hierarchical representations have been compelled by the limitations of available estimation software, such as Mplus, to use the multinomial logit kernel for the choice model (Temme et al. 2008; Zhao 2009; Tudela et al. 2011). The multinomial logit kernel is a simple but often unrealistic representation of individual behavior, as best exemplified by its independence from irrelevant alternatives property. Additionally, it cannot capture variations in attribute preferences that are unobservable or purely random.

Our work overcomes these limitations through the simultaneous estimation of a hierarchical latent variable mixed logit model of travel mode choice. The general structure of our ICLV model consists of a mode choice sub-model where the utility of different alternatives is specified as a function of both observable variables, such as attributes of the alternatives, and latent variables, in our example attitudes. The latent variable sub-model allows for relations between latent variables and observable variables, as well as causal relationships between the latent variables themselves as hypothesized by the value-attitude hierarchy. The mixture distributions in our case are introduced to allow for more flexible substitution patterns in order to surmount the independence from irrelevant alternatives property of the traditional multinomial logit model. Though the parameters associated with the mixture distributions are not found to be statistically significant for the dataset at hand, the model framework is truly general in that the mixture distributions could just as easily be used for incorporating heterogeneity through random taste variation or, in the case of panel datasets, correlation in unobserved factors over time. Advances in computational power and simulation methods have triggered rapid growth in the development and application of mixed logit models to travel behavior studies. Metropolitan Planning Organizations have been using nested logit for a number of years (see, for example, San Francisco County's state of the art activity-based model, the San Francisco Chained Activity Modeling Process), and it is only a matter of time before travel demand models graduate to mixed logit as well. By integrating more complex latent variable frameworks with flexible choice model structures, our study allows for the influence of latent variables such as values and attitudes to be represented within the planning process in a behaviorally realistic manner.

Empirical results validate the proposed hierarchical model of cognition: personal values denoting power, hedonism and security are found to affect individual attitudes towards flexibility, comfort and convenience, and ownership, which in turn influence mode choice behavior. When these same value constructs were included directly in the choice model, they were not found to have a statistically significant effect. Our findings further indicate that attitudinal variables measuring concern for flexibility, comfort and convenience, and ownership exert greater influence on travel mode choice behavior than more traditional level-of-service variables such as travel times. These results provide valuable information about the cognitive process underlying the formation of modal preferences for commute trips for our sample population and their influence on aggregate market shares that could prove useful to the design of policies seeking to discourage driving.

Given the absence of constructs such as habits, norms and affects in the model framework, we cannot admittedly be certain about the policy implications derived from the model. That being said, no model can ever offer a complete picture of decision-making. Existing models of travel mode choice in the literature and in practice that conform to the traditional travel demand model paradigm have gone as far as to incorporate the influence of attitudes, but the impact of other constructs has largely been ignored. Compared to these, our study proposes a model that is more complete. Future research intends to leverage advances in data collection methods and model estimation routines to include additional constructs within the framework presented here.

Unfortunately, nobody is selling transit the way automakers are selling cars. Driving a car is routinely equated in advertising campaigns with greater professional success and a happier personal life (Steg 2005). By insinuation, public transit is for the poor, the unemployed, and the less fortunate. The examples mentioned in the previous section illustrate some of the many ways in which findings from the methodological framework developed in this study can provide insights to planners and policy-makers on how better to sell public transit as a means of travel, insights that wouldn't otherwise be available with more traditional travel demand models.

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