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Accounting for sensation seeking in route choice behavior with travel time information

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ABSTRACT

The purpose of this paper is to demonstrate that latent variables, with the focus on sensation seeking concepts, incorporated in new technique of route choice modeling, improve our analyzing of route choice behavior with pre-trip travel time information. The application of a hybrid discrete choice model framework integrates a latent variable model and a route choice model by combining their measurement and structural equations. The model is estimated based on data from a laboratory experiment and a field study of a simple network. The results show that certain sensation seeking domains (e.g., thrill and adventure seeking) alongside traditional variables (e.g., travel time information) enrich our understanding and provide more insight into route choice behavior. Furthermore, observed personal variables, such as gender and marital status, may serve as causal indicators to sensation seeking variables.

1. Introduction

Advanced traveler information systems (ATIS) or road traffic information (RTI), using pre-trip or en-route real-travel-time information, are rapidly penetrating all modes of transportation. These systems include various technologies and media, e.g., navigation systems with Global Positioning System (GPS), variable message signs (VMS), radio broadcasting, and are well recognized as an efficient mean to realize improved utilization of the transportation network by affecting travel and driver behavior. Drivers may respond to these systems and to the information provided through changing one's departure time, destination, speed, mode, activity, but most common by altering routes (Bekhor, Ben-Akiva & Ramming 2002; Bonsall, 2002; Emmerink, Nijkamp, Rietveld & Ommeren 1996; Kenyon & Lyons, 2007; Koski, 2002; Kwan, Dijst, & Schwanen, 2007; Wachs, 2002).

Drivers' route choice behavior, in particular given relevant road information, involves many aspects and various factors, e.g., behavior modeling, drivers' attitudes towards communication and technology and the systems reliability (Chen & Jovanis, 2005; Emmerink et al., 1996; Polydoropoulou, Ben-Akiva, & Kaysi, 1994). The ultimate route choice decision is inherently a multiple-objective, decision-making process. That is, many factors other than the conventional measurement variables (e.g., travel time and cost, distance) are involved and have a major impact on the driver's decision process (Abdel-Aty, Kitamura, & Jovanis, 1997; Jan, Horowitz, & Peng, 2000; Li, Guensler, & Ogle, 2005; Polydoropoulou et al., 1994; Srinivasan & Mahmassani, 2000). For example, Adler (2001) claimed that the benefits of having route guidance diminished when drivers became more familiar with the travel network. Bogers, Viti, and Hoogendoorn (2005) and Ben-Elia, Erev,

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and Shiftan (2008) constructed simulation experiments to explore the influence of information, learning and habit on choices between two routes.

The several factors affecting route choice behavior are traditionally dealt with by incorporating appropriate variables and complex error structures in random utility models (RUM) (Chorus et al., 2007; Katsikopulos, Duse-Anthony, Fisher, & Duffy, 2002; Prashker & Bekhor, 2004; Prato, 2009). One of the updated established methods is the hybrid choice model, which integrates many types of discrete choice modeling methods (Ben-Akiva et al., 2002; Walker, 2001) to account for both latent and observed variables. Latent features such as habits, familiarity and available information and their impact on route choice were presented in Papinski, Scott, and Doherty (2009) and in Kaplan and Prato (2012), who also discussed the gap between the behavioral paradigm of choice set formation and its representation in route choice modeling. The latent variables were used in the choice set generation phase by revealing constraint thresholds from considered choice sets. Recently, Prato, Bekhor, and Pronello (2012) illustrated a hybrid choice model which integrates latent variables in route choice models and consists of measurement and structural equations. Measurement equations relate latent variables to measurement indicators and utilities to choice indicators. Structural equations relate travelers' characteristics to latent variables and observable route attributes as well as unobservable latent variables to utilities. Their results illustrate that considering latent variables (e.g., memory, habit, familiarity, spatial ability, time saving skills) alongside traditional variables (e.g., travel time, distance, and congestion level) provides insight into and enriches the comprehension of route choice behavior.

A broad array of disciplines (e.g., psychology, economics, marketing, transportation engineering) has shown a general interest in enhancing discrete choice models by considering the incorporation of psychological factors affecting decision making (Ben-Akiva et al., 2002). In this regard, interesting is the notion of sensation seeking, which is commonly used in behavioral science. Sensation seeking is defined as "the need for varied, novel, and complex situations and experiences, and the willingness to take physical and social risks for the sake of such experiences" (Zuckerman, 1994). Sensation seeking also expresses a tendency to maintain current or previous decisions. This is generally represented by travel habit and inertia which explain a significant part of the undertaken trip pattern (Bogers et al., 2005; Golledge, 2001, chap. 3; Mahmassani & Jou, 2000; Srinivasan & Mahmassani, 2000).

Sensation seeking, especially one of its four classic domain formulation – Thrill and Adventure Seeking (TAS) – which reflects sensation seeking in the area of sports and physical activities, was found in numerous studies to be positively related to reckless and risky driving behavior (Dahlen, Martin, Ragan, & Kuhlman, 2005; Jonah, Theissen, & Au-Yeung, 2001; Prato, Toledo, Lotan, and Taubman Ben Ari (2010); Roberti, 2004; Schwebel, Severson, Ball, & Rizzo, 2006; Zuckerman & Neeb, 1980).

Literature shows few attempts to incorporate sensation seeking in route choice behavior. Albert, Toledo, and Ben-Zion (2011) found that individuals who scored higher on the TAS tend to switch their routes more frequently. They also pointed out another domain of sensation seeking – Boredom Susceptibility (BS) – which represents intolerance for repetition and routine of any kind. Individuals who scored higher on the BS were likely to switch their routes more frequently and chose a bypass route more often. Shiftan, Bekhor, and Albert (2011) did not find TAS nor BS to have a significant impact on route choice behavior but indicated that a third domain of sensation seeking – Experience Seeking (ES) – in the sensory and cognitive domain, plays a role in route choice behavior; for individuals with more experience seeking (who prefer new experiences), the probability of using a route with smaller travel time variance decreases. When experience seeking increases (that is, individual prefer new experiences) an individual tends to choose a riskier route in terms of greater travel time variance. While not exhaustive, both studies, which used the traditional types of RUM models, clearly suggest that more attention should be paid on addressing the role of sensation seeking in route choice behavior.

The contributions of the present paper are twofold: the first is further improvement of the line of research reflecting new generation of models of route choice behavior following the hybrid discrete choice model methodology as described in details in Prato et al. (2012). The approach presented here consolidating the hybrid choice model's use and applicability. The second is the introduction of new concepts of latent variables which reflect domains of sensation seeking. According to our hypothesis, these variables play an important role in understanding route choice behavior with pre-trip travel time information. The paper aims to demonstrate that sensation seeking concepts, incorporated in new techniques of route choice modeling, will significantly improve our understanding of route choice behavior with pre-trip travel time information. Furthermore, observed socio-economic and personal characteristics, such as gender and age, may serve as causal indicators to sensation seeking variables (e.g., age is known as negatively related to TAS). These causal indicators not only may improve model fit and add insights into the analysis, but also could be used for route choice predictions.

The rest of the paper is organized as follows: Section 2 presents the data collection and describes the experiment. Section 3 described the framework and insights of the proposed route choice model. Section 4 presents the estimation of route choice models. Section 5 presents the discussion and conclusions.

2. Data collection

The methodology for collecting the data is explained in details in Shiftan et al. (2011) and is briefly outlined here. The data set included two elements: a route choice assignment and a questionnaire which aims to identify observed and latent variables that influenced individual's behavior in the route choice assignment.

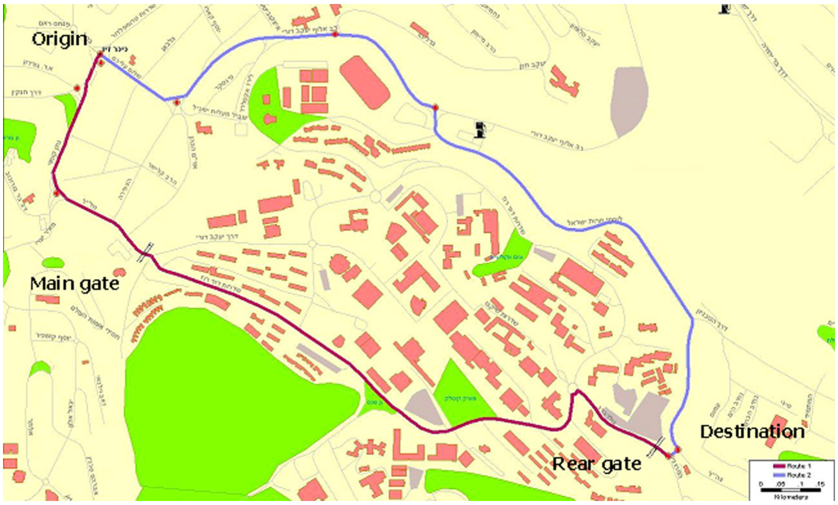

Fig. 1. The study network.

The sample consists of 131 undergraduate students from two academic institutions. This sample is more extensive than the one presented in the previous work described in Shiftan et al. (2011) as more participants were recruited; however, sample characteristics are similar in both studies. 92 (70%) of the sample were students at Holon Institute of Technology which is located in the center of Israel and 39 (30%) were students at the Technion – Israel Institute of Technology, located in Haifa, in the north of Israel. Their socio-economic characteristics were found to be similar. The majority of the sample participants were singles, aged 22–29 years old, held a driving license for 3–10 years. 40% of participants were female.

The route choice assignment has been performed throughout a field study and via an in-laboratory experiment, both presenting the same tasks and the same real-world network. As shown in Shiftan et al. (2011) these two types of data can be combined. The study network is illustrated in Fig. 1. Route B (the blue[2]) has a time advantage, while route A (the red) has a variance advantage; therefore route B is considered to be riskier compared to route A, in terms of greater travel time variance. Each participant performed the route choice task in 20 trials; in all trials except of the first the participants were provided with travel time information in the two alternative routes and were asked to choose a route.

The questionnaire main purpose was to identify the observed and latent factors which may be comprised in the route choice model. The questionnaire included items regarding socio-economic characteristics such as age, gender, marital status and so on. In order to identify sensation seeking we used the general frame of the Sensation Seeking Scale (SSS), form V (Zuckerman, 1994). The SSS is estimated on the basis of a questionnaire that includes 10 for each domain, presented in a random order in the format of a "forced choice".

The domains included were:

- Thrill and Adventure Seeking (TAS) – Desire for outdoor sports and physical activities involving unusual sensations and risks. It can be summarized as a positive answer to "I sometimes like to do things that are a little frightening".
- Experience Seeking (ES) – in the sensory and cognitive domain. Referring to new sensory or mental experiences through unconventional choices. An example of a statement expressing sensation seeking in this domain: "I like to explore a strange city or town by myself, even if it means getting lost."
- Boredom Susceptibility (BS) – represents intolerance for repetition and routine of any kind (e.g., work) and a restless reaction to unvarying situations. An example of a statement expressing sensation seeking in this domain: "The worst social sin is to be a bore".

Similarly, we defined a new concept – domain with ten indicators that might reflect sensation seeking in the area of travel characteristics such as time and comfort (TC). These indicators were based on previous experiences with such indicators in regard to travel behavior; see for example, Outwater et al. (2003). Examples of indicators describing this factor are "I do not avoid traveling at certain times because it is too stressful" and "I would change my mode of travel if it could save me some time." Positive responses to such statements indicate sensation seeking in this domain. Table 1 describes the 40 indicators that formed the four latent variables in the experiment.

The 40 indicators were purposely scrambled in the questionnaire and some of the questions were asked in reverse mode in an attempt to maximize the awareness of the respondents. Confirmatory factor analyses using AMOS (Arbuckle, 2001)

[2] For interpretation of color in Fig. 1, the reader is referred to the web version of this article.

Table 1
Indicators of the latent variables.

Latent variable	Indicator	Description
TAS (Thrill and Adventure Seeking)	I_3	Wish to be a mountain climber
	I_{11}	Tendency to do things that are a little frightening
	I_{16}	Tendency to take up the sport of water skiing
	I_{17}	Tendency to try surfboard riding
	I_{20}	Tendency to learn to fly an airplane
	I_{21}	Tendency to go scuba diving
	I_{23}	Tendency to try parachute jumping
	I_{28}	Tendency to dive off the high board
	I_{38}	Tendency to sail a long distance in a small but seaworthy sailing craft
	I_{40}	Enjoy the sensations of skiing very fast down a high mountain slope
ES (Experience Seeking)	I_4	Weather should not affect plans
	I_6	Explore a strange city or region by myself, even if it means getting lost
	I_9	Fancy to experience cannabis
	I_{10}	Enjoy some of the earthy body smells
	I_{14}	Try new foods that I have never tasted before
	I_{18}	Take off on a trip with no preplanned or definite routes or timetable
	I_{19}	Make friends in some of the "far-out" groups like artists or anarchists
	I_{22}	Enjoy to meet some people who are homosexual (men or women)
	I_{26}	Find the beauty in the clashing colors and irregular forms of modern paintings
	I_{37}	People should dress in individual ways even if the effects are sometimes strange
BS (Boredom Susceptibility)	I_2	Can't stand watching a movie that i've seen before
	I_5	Get bored seeing the same old faces
	I_7	Predict almost everything a person will do and say he or she must be a bore
	I_8	Don't enjoy a movie or play where I can predict what will happen in advance
	I_{15}	Looking at someone's home movies, videos, or travel slides bores me tremendously
	I_{24}	Prefer friends who are excitingly unpredictable
	I_{27}	Very restless if I have to stay around home for any length of time
	I_{31}	The worst social sin is to be a bore
	I_{34}	Like people who are sharp and witty even if they do sometimes insult others
	I_{39}	No patience with dull or boring people
TC (Time and Comfort)	I_1	Departure time shouldn't influence on cancelling a trip
	I_{12}	Knowledge of traffic congestion before making a trip isn't important
	I_{13}	Confidence of driving in in unfamiliar areas
	I_{25}	Feeling well of driving in new places
	I_{29}	Private car is the fastest means of transport
	I_{30}	No concern about possible involvement in an accident
	I_{32}	Adherence to estimated schedule
	I_{33}	No importance of the reason for trip delay
	I_{35}	Don't check flight time before traveling abroad
	I_{36}	Enjoy chatting with others when traveling

established the fit of the indicators' measures to the corresponding constructs in the model, which is presented in the next section.

3. The hybrid route choice model

This section illustrates the methodology for formulating and estimating models from the collected data. The hybrid discrete choice model framework integrates a latent variable model and a route choice model by combining their measurement and structural equations. Fig. 2, adapted from Prato et al. (2012) illustrates the hybrid route choice model.

The hybrid choice model enhances the comprehension of route choice behavior by considering latent variables which represent unobserved constructs (e.g. domain of sensation seeking) alongside observable variables which represent individual characteristics (e.g. gender) and attributes of the alternatives, (e.g., the travel time information provided).

The main difference between the model developed in this paper and the model developed in Prato et al. (2012) is related to the latent variables. While in Prato et al. (2012) exploratory factor analysis was performed to extract the latent variables, the present paper uses the latent variables (TAS, ES, BS and TC) from the literature. These variables were confirmed by performing factor analysis with the 40 indicators presented in Table 1.

Using the notation from Fig. 2, the structural equations of the choice model express the distribution of the utilities (Walker, 2001):

$$U_n = V(Z_n, X_n^*; \beta) + \varepsilon_n \quad \text{and} \quad \varepsilon_n \sim D(0, \Sigma_\varepsilon) \tag{1}$$

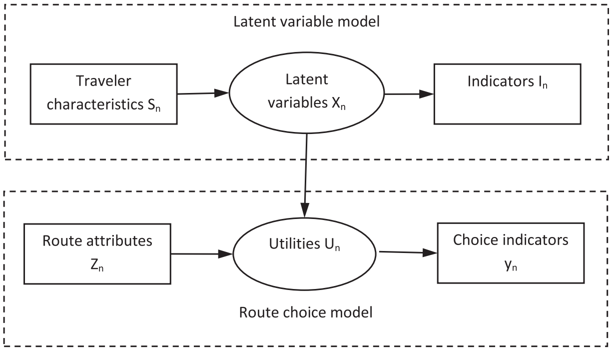

Fig. 2. Hybrid route choice model (adapted from Prato et al. (2012) and Prato et al. (2010)).

where U_n is a vector of utilities of alternative routes for individual n, Z_n is a vector of attributes of alternative routes, ε_n is a vector of error terms following distribution D with covariance matrix Σ_ε, and β is a vector of parameters to be estimated. The latent variables X_n^* are expressed by the following structural equations:

$$X_n^* = g_1(S_n;\gamma) + \omega_n \quad \text{and} \quad \omega_n \sim D(0, \Sigma_\omega) \tag{2}$$

where X_n^* is a vector of latent variables, S_n is a vector of characteristics of individual n, ω_n is a vector of error terms following distribution D with covariance matrix Σ_ω, and γ is a matrix of parameters to be estimated. In this paper, it is assumed that g_1 is a linear function.

As indicated in the previous section, the measurement equations of the latent variable model associate the latent variables to the indicators according to the correspondence in Table 1. The functional relationship of the measurement equations are given by relating the indicators to the latent variables as follows:

$$I_n = g_2(X_n^*;\alpha) + \upsilon_n \quad \text{and} \quad \upsilon_n \sim D(0, \Sigma_\upsilon) \tag{3}$$

where I_n is a vector of indicators, υ_n is a vector of error terms following distribution D with covariance matrix Σ_υ, and α is a vector of parameters to be estimated. In this paper, it is assumed that g_2 is a linear function. As observed by Raveau, Yáñez, and Ortúzar (2012) Eqs. (2) and (3) correspond to the Multiple Indicator Multiple Cause (MIMIC) model.

The choice indicators y_n are expressed as follows:

$$y_{in} = \begin{cases} 1 & \text{if } U_{in} \geqslant U_{jn} \ \forall\, j \neq i \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

In this proposed model the structural equations of the latent variable model that associate the latent variables to the individual characteristics are formulated as follows:

$$BS = \gamma_1 MARRIED + \gamma_2 CHILDREN + e\_BS \tag{5}$$
$$ES = \gamma_3 DRIVER10 + \gamma_4 WORKER + \gamma_5 MALE + e\_ES \tag{6}$$
$$TAS = \gamma_6 CHILDREN + \gamma_7 WORKER + \gamma_8 MARRIED + e\_TAS \tag{7}$$
$$TC = \gamma_9 MARRIED + \gamma_{10} CHILDREN + e\_TC \tag{8}$$

where *BS*, *TC*, *ES* and *TAS* represent the four latent variables as explained in Section 2, and *e_BS*, *e_TC*, *e_ES* and *e_TAS* respectively indicate the error terms. The five explanatory variables "*Married*", "*Male*", "*Worker*", "*Children*" and "*Driver*10" are binary variables that respectively indicate if an individual is married, male, works, has at least one child in the household and has a driver's license for 10 years or more.

The structural equations of the choice model that associate route utilities with route attributes and latent variables as perceived by individual n are expressed as follows:

$$V_{in} = \beta_0 + \beta_1 TIME_{in} + \beta_2 FIRST_{in} + \beta_3 TAS_n TIME_{in} + \beta_4 ES_n FIRST_{in} + \beta_5 TC_n TIME_{in} + \beta_6 BS_n TIME_{in} + \sigma_n \tag{9}$$

where β_0 is a constant that indicates the Technion campus route (route A); $TIME_{in}$ is the travel time of route i that was informed to individual n; $FIRST_{in}$ is a dummy variable that indicates the uninformed (first) choice of route i of individual n; the four remaining variables represent interactions of the latent (personal-specific) variables with the explanatory (alternative-specific) variables. Note that the latent variables *TAS*, *TC* and *BS* are multiplied by the variable *TIME*, while *ES* is multiplied by *FIRST*. A systematic process of considering every possible interaction term between latent variables and route attributes and examining the significance of the estimated parameters led to the significant interaction terms in the equation above.

Since the experiment involved repeated observations (first choice + 19 replications), σ_n accounts for serial correlation. Different utility specifications were tested to find the best possible utility function explaining the maximum variance in the data.

The hybrid choice probability function involves three components as follows (Ben-Akiva et al., 2002):

$$P(y_n, I_n | Z_n, S_n, \beta, \alpha, \gamma, \Sigma_\varepsilon, \Sigma_\upsilon, \Sigma_\omega) = \int_{X_n^*} P(y_n | X_n^*, Z_n, \beta, \Sigma_\varepsilon) f_2(I_n | X_n^*, \alpha, \Sigma_\upsilon) f_1(X_n^* | S_n, \gamma, \Sigma_\omega) dX_n^* \tag{10}$$

where $P(y_n|X_n^*, Z_n, \beta, \Sigma_\varepsilon)$ is the route choice probability (in this paper, a binary logit model), f_2 and f_1 are respectively the densities of the latent variables and the indicators. In this paper it is assumed a normal distribution of the error terms.

4. Model estimation results

The parameters of the hybrid choice model expressed in Eq. (6) can be estimated simultaneously by simulated maximum likelihood. Given the complexity of the model and the long time needed to obtain stable estimates, this paper reports the results of a sequential estimation first, assuming that each of the components of the probability function are independent. The estimated values of the sequential estimation are then used as initial values for the simultaneous estimation.

The first step was to perform factor analysis on the 40 indicators, using 10 indicators for each factor. The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.723, and the Bartlett test produced a chi-squared value of 242.8. Both tests are significant and in line with results from the literature on sensation seeking. Table 2 presents the component score coefficients for each of the four latent variables.

The next step was to estimate the parameters of the latent variable model. This was performed assuming that the latent variables are deterministic and calculated according to the scores presented in Table 2.

The estimation results of the structural equations of the latent variable model are presented in Table 3. As can be seen there are significant correlations between individual characteristics and latent variables. For example, individuals having at least one child in the household are less sensation seekers in the BS, TAS and TC domains.

Fig. 3 shows the correlations between each variable in the model. Note that the model presented in Fig. 3 allows for correlation between socio-economic variables and also correlation between the error terms of the latent variables. However, the simultaneous estimation will assume independency of the error terms and socio-economic variables, as with other MIMIC models in the literature.

The last step of the sequential process is the estimation of the route choice model. In order to account for repeated observations, simulated maximum likelihood method has been used for estimating the parameters of the route choice model using the BIOGEME software (Bierlaire, 2003). Table 4 presents the estimation results. The variables in Table 4 correspond to those defined in Section 3.

Table 5 presents the results of the simultaneous estimation of the hybrid choice model. The estimation was performed by simulated maximum likelihood with 1000 Halton draws, using the Python version of Biogeme (Bierlaire & Fetiarison, 2009). Some of the parameters of the measurement equations were constrained to 1 to account for proper identification and two additional parameters were constrained to zero to allow the model to reach stable results.

The estimation results show that the direction of influence of the information travel time corresponds with the expectation that the utility of each route decreases as the information indicates that travel time increases. The latent variables have been found significant. The first choice dummy shows that, on average, the participants tended to prefer their initial route choice (that is, the route that was chosen in the first trial without having any information) instead of switching to the alternative route. The impact of repetition in the route choice task is also notable in the model in a similar manner to the impact of the first choice variable.

Table 2
Score coefficients for the measurement equations.

TAS		ES		BS		TC	
Indicator	Score	Indicator	Score	Indicator	Score	Indicator	Score
I3	.205	I4	.126	I2	−.108	I1	.299
I11	.189	I6	.303	I5	.228	I12	.260
I16	.217	I9	.175	I7	.308	I13	.282
I17	.076	I10	−.118	I8	.156	I25	.377
I20	.148	I14	.383	I15	.060	I29	−.025
I21	.172	I18	.347	I24	.307	I30	.279
I23	.200	I19	.180	I27	.279	I32	.279
I28	.219	I22	.352	I31	.293	I33	.073
I38	.164	I26	.111	I34	.120	I35	.279
I40	.156	I37	.224	I39	.181	I36	.084

Table 3
Latent variable model estimation results (not including correlation terms).

Latent Variable		Individual characteristic	Estimate	S.E.	C.R.	*P*
BS	←	Married	1.728	0.639	2.705	0.007
BS	←	Children	−1.84	0.873	−2.107	0.035
ES	←	Driver10	0.689	0.37	1.862	0.063
ES	←	Worker	0.426	0.346	1.233	0.218
ES	←	Male	−0.587	0.305	−1.929	0.054
TAS	←	Children	−2.125	1.201	−1.769	0.077
TAS	←	Worker	0.772	0.486	1.587	0.113
TAS	←	Married	1.329	0.888	1.496	0.135
TC	←	Married	−0.713	0.616	−1.157	0.247
TC	←	Children	−1.292	0.842	−1.535	0.125
Number of individuals			131			
RMR – root mean square residual			0.033			
GFI – goodness of fit index			0.992			
RMSEA – root mean square error of approximation			0.000			

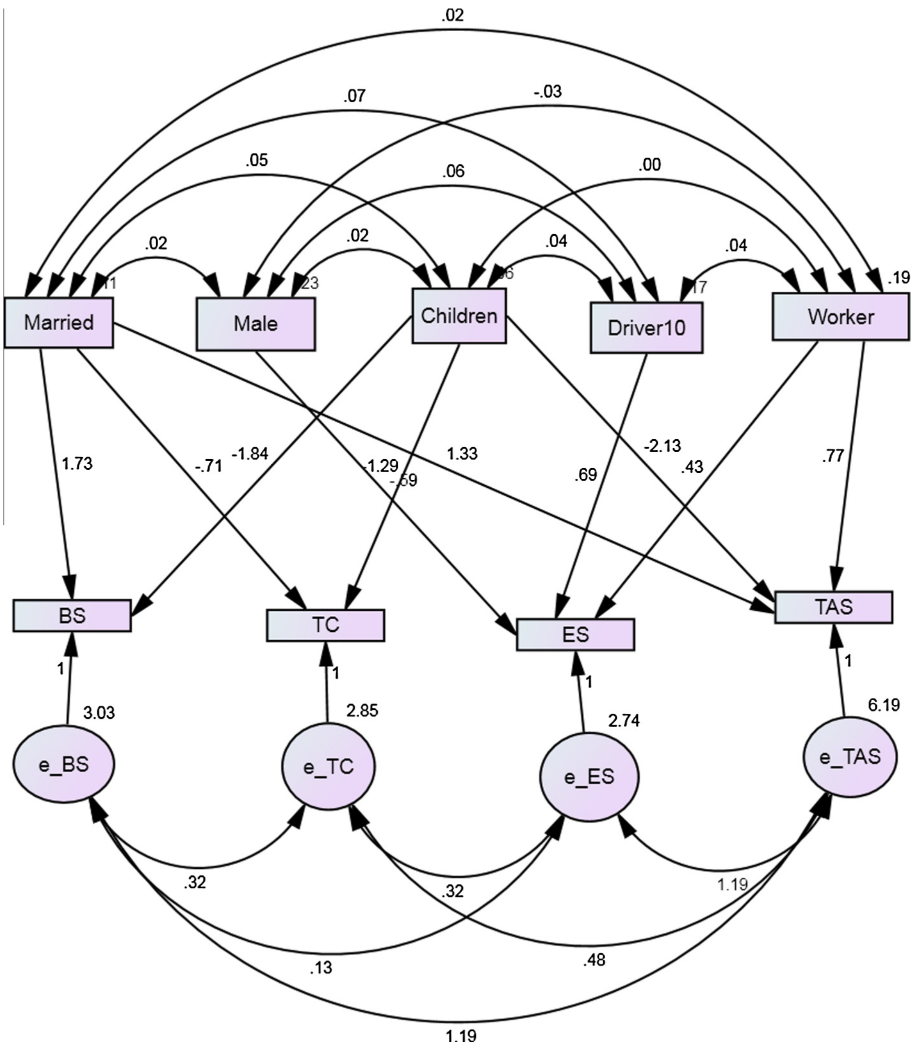

Fig. 3. Correlations among the variables in the latent variable model.

Table 4
Route choice model – sequential estimation results.

Variable	Value	Std err	*t*-test
b0_const	−1.24	0.258	−4.79
b1_infotime	−1.31	0.338	−3.88
b2_first	1.99	0.344	5.79
b3_TAS_time	−0.126	0.0317	−3.96
b4_ES_first	0.0771	0.0494	1.56
b5_TC_time	−0.133	0.046	−2.9
b6_BS_time	0.154	0.0426	3.61
SIGMA	1.73	0.155	11.1
Number of observations	2290		
Number of individuals	131		
Null log-likelihood	−1587.3		
Final log-likelihood	−914.4		
Likelihood ratio test	1346.3		
Adjusted rho-bar squared	0.419		

Table 5
Hybrid route choice model – simultaneous estimation results.

	Variable	Value	Std. err.	*t*-test
Route choice model parameters	b0_const	−1.21	0.252	−4.8
	b1_infotime	−1.90	0.173	−10.98
	b2_first	2.14	0.202	10.61
	b3_TAS_time	−1.72	0.995	−1.73
	b4_ES_first	0.112	0.101	1.11
	b5_TC_time	−0.509	0.315	−1.62
	b6_BS_time	0.1486	0.101	1.47
Latent variable model parameters	g1_married	0.301	0.0792	3.8
	g2_children	−1.31	0.137	−9.56
	g3_driver10	0.00563	0.00799	0.70
	g4_worker	0.139	0.00566	24.55
	g5_male	−0.112	0.00625	−17.85
	g6_children	−0.28	0.027	−10.36
	g7_worker	0.171	0.00681	25.17
	g8_married	0.195	0.0232	8.4
	g9_married	−1.01	1.04	−0.97
	g10_children	1.29	1.9	0.68
Measurement model parameters	TAS_I3	1		
	TAS_I11	−3.25	0.294	−11.03
	TAS_I16	5.19	0.368	14.1
	TAS_I17	0		
	TAS_I20	−6.2	0.399	−15.56
	TAS_I21	−1.98	0.269	−7.36
	TAS_I23	8.07	0.473	17.07
	TAS_I28	2.88	0.286	10.07
	TAS_I38	−3.56	0.31	−11.49
	TAS_I40	−1.23	0.258	−4.76
	BS_I2	1		
	BS_I5	−1.36	0.119	−11.44
	BS_I7	0.91	0.0892	10.2
	BS_I8	−0.0425	0.0493	−0.86
	BS_I15	0.771	0.0775	9.95
	BS_I24	−1.58	0.136	−11.66
	BS_I27	0.463	0.063	7.35
	BS_I31	1.63	0.141	11.53
	BS_I34	−0.371	0.0579	−6.39
	BS_I39	−0.697	0.074	−9.43
	ES_I4	1		
	ES_I6	−6.38	0.356	−17.91
	ES_I9	7.04	0.384	18.33
	ES_I10	1.62	0.228	7.1
	ES_I14	−3.94	0.278	−14.14
	ES_I18	−3.62	0.274	−13.24
	ES_I19	−8.29	0.431	−19.23
	ES_I22	2.58	0.255	10.1

Table 5 (*continued*)

	Variable	Value	Std. err.	*t*-test
	ES_I26	0.0588	0.219	0.27
	ES_I37	6.33	0.357	17.74
	TC_I1	1		
	TC_I12	0		
	TC_I13	2.68	0.246	10.88
	TC_I25	3.29	0.261	12.61
	TC_I29	−0.0371	0.218	−0.17
	TC_I30	−0.926	0.221	−4.19
	TC_I32	0.0662	0.216	0.31
	TC_I33	−1.56	0.227	−6.88
	TC_I35	−4.61	0.299	−15.42
	TC_I36	−2.6	0.246	−10.57
Error terms	SIGMA_1	−1.06	0.102	−10.33
	e_BS	0.844	0.0577	14.63
	e_ES	0.0102	0.00431	2.38
	e_TAS	−0.0231	0.00699	−3.3
	e_TC	0.256	0.8	0.32
Goodness of fit	Number of Halton draws			1000
	Number of parameters			56
	Number of observations			2290
	Number of individuals			131
	Initial log-likelihood			−65,306
	Final log-likelihood			−58,714
	Likelihood ratio test			13182.7
	Adjusted rho-bar squared			0.101

The results of sensation seeking are interesting. Three of the sensation seeking variables play an important role in the model: TAS, TC and BS. TAS_time is a considerable factor and has a negative coefficient. This indicates that when the TAS score increases (i.e., more sensation seeking in this domain), the utility of each route decreases. This result is expected: as mentioned in the introduction, individuals with higher TAS tend to risky driving behavior; therefore one could expect that these individuals also will tend to choose risky and uncommon routes.

The coefficient of TC_time is significant in the model. Similar to the effect of TAS, this variable, which also has a negative coefficient, indicates that the utility of each route decreases with more sensation seeking in this domain. That is, when sensitivity to the route's travel conditions decreases (higher score in this domain), the utility of each route decreases as well.

The coefficient of BS_time is also significant, even though its impact is not intuitive. Contrary to expectations and to the other sensation seeking variables, this coefficient is positive. This indicates that the utility of each route increases as BS score increases. It should be noted that high score on BS reflects intolerance for repetition and restless reaction to unvarying situations. An explanation for this may be that BS, unlike the other factors of sensation seeking, represents a trait which is consistent across age and does not decline throughout an individual's lifetime (Roberti, 2004; Zuckerman & Neeb, 1980). In this regard our sample, comprised from students, may indicate that young posse high score on BS which is associated with risky and uncommon routes, but this should be further investigated among other populations and age groups.

Note that the route choice parameter estimates are similar in both sequential and simultaneous estimations, but the latent variable estimates are different for the sequential and simultaneous estimations. Daziano and Bolduc (2013) note that if the identification constraints are the same, then the same measurement scale for the latent variables and (relatively) comparable point estimates should be obtained (see for example Raveau, Daziano, Yáñez, Bolduc, & Ortúzar, 2010). The explanation for the differences in latent variable parameters is related to the fact that the factor analysis results presented in Table 2 (and used in the sequential estimation) were estimated without constraining the indicators, and the scores were as input values for the subsequent steps.

5. Conclusions

This paper provides insight into route choice behavior by estimating a hybrid choice model. The contributions of the paper are twofold: the first is the application of the hybrid choice model as described in details in Prato et al. (2012) which reflects new generation of models of route choice behavior. The second is the introduction of new concepts of latent variables, e.g. initial preference towards a route (the first choice variable in the analysis) and domains of sensation seeking. The results confirm our hypothesis that these variables play an important role in route choice behavior with pre-trip travel time information. The paper extends the common characteristics used route choice behavior analysis: with these concepts incorporated in new technique of route choice modeling our understanding of route choice behavior with pre-trip travel time information is improved.

Sensation seeking, especially TAS domain, was found pertinent to route choice behavior. In general, the utility of a common route in a simple network decreases as TAS increases. A novel domain of sensation seeking introduced in this paper – TC

– was found significant in route choice behavior with a similar effect to TAS. BS domain of sensation seeking was also found important though its impact is not intuitive. While the role of sensation seeking in driving behavior is established (see for example, Dahlen et al., 2005; Prato et al., 2010; Schwebel et al., 2006) there were recently few attempts which indicate its potential to route choice behavior (Albert et al., 2011; Shiftan et al., 2011) and the present paper supports its importance also based on newly route choice analysis tools.

As expected, traditional variables used in route choice analysis under information (e.g., travel time information) were found to be important in route choice behavior. Furthermore, observed personal variables, e.g., gender, age, which traditionally are incorporate in modeling as socio-economics characteristics, were found applicable to serve as indicators to sensation seeking variables and therefore to improve the model's applicability and add insights into the analysis. Consequently, this suggests that the impact of ATIS and RTI on route choice behavior may be better predict and designed accordingly, e.g. different attitudes to various individuals.

Note that the modeling approach in this paper, similar to Prato et al. (2012) can be used when applying the model for analysis or forecasting. The issue is that the measurements (indicators) are only known for the estimation sample and will not generally be known for a forecast situation. However, the strength of this approach is that the measurements are not needed for a forecast; once the explanatory variables of the route choice model and the latent variable model are estimated, then these variables can be used directly in the forecast, as pointed out by Brey and Walker (2011).

The results presented here are based on a laboratory and field experiment comprised of a fairly homogenous population in a simplified travel network. Therefore, the results obtained cannot be considered very robust, and more studies in this direction should be performed. These studies should be based on the approach presented here which consolidates the hybrid choice model and enables dealing with other well recognized latent variables (e.g. learning effect) within this framework.

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