Stated consideration and attribute thresholds in mode choice models: a hierarchical ICLV approach

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Abstract

Consideration of alternatives, as many other aspects related to the decision-making process, is not observable and challenging to measure. Even when supplementary information is collected during stated choice experiments, its use as an additional explanatory variable is discouraged due to potential endogeneity issues, measurement error and limited suitability for forecasting. To overcome these limitations, we propose an Integrated Choice and Latent Variable model where consideration of an alternative is treated as a latent variable. The novelty of the presented model is that the latent variable for consideration of an alternative itself is a function of another set of latent variables that represent thresholds applied by the decision maker to individual attributes (such as travel time and cost). The proposed hierarchical relationship between *latent thresholds* and *latent consideration* enables us to explain a share of otherwise purely random heterogeneity, and identify the structural drivers of consideration. The latter is of interest to policymakers and private operators.

Keywords

Hierarchical ICLV, stated consideration, stated threshold

1. Introduction

One of the strongest assumptions underlying mode choice studies is that all available alternatives are considered. This might not be a reasonable assumption because individuals are often not aware of all alternatives and/or employ simplifying choice heuristics. Past work suggests that ignoring consideration effects can have severe implications on parameter estimates and forecasting (Williams and Ortúzar, 1982;

Swait, 1984). Namely, biased parameter estimates and forecasts may lead to incorrect policy and managerial decisions (Pancras, 2010; Draganska and Klapper, 2011).

The challenge with consideration of alternatives, as part of the decision-making process, is that it cannot be observed and challenging to measure (i.e. at least not directly or without error). Previous studies mainly inferred consideration solely on the basis of the observed choice behaviour (Gaudry and Dagenais, 1979; Swait and Ben-Akiva 1987a, 1987b; Basar and Bhat, 2004), or related consideration to some observed attributes of the alternatives (Cascetta and Papola, 2001; Cantillo and Ortúzar, 2005; Martinez et al., 2009).

A handful of scholars, generally when using stated choice (SC) surveys, have collected additional information covering aspects related to consideration, such as availability (Ben-Akiva and Boccara, 1995) and acceptability (Hensher and Ho, 2015) of alternatives, or self-imposed thresholds for individual attributes (Swait, 2001). Indeed, the answers to these questions do not give an exact or error free measure of the underlying behavioural processes. In the present paper, we use an Integrated Choice and Latent Variable (ICLV) model (McFadden, 1986; Ben-Akiva et al., 2002; Bolduc et al., 2005), which recognises this property of the data.

The ICLV approach has been extensively used in many fields (e.g. transport, health, and environment) to incorporate either psychological factors such as attitudes and perceptions (see, e.g., Soto et al., 2018; Kløjgaard and Hess, 2014; Mariel and Meyerhoff, 2016) or respondents' processing strategies (Hess and Hensher, 2013) into choice models. In this paper, we provide a novel use of the ICLV framework by incorporating consideration effects through inter-related latent variables. In particular, *latent thresholds* for attributes are used to explain *latent consideration* of the alternatives. These latent variables are in turn used to help explain mode choice behaviour. The inclusion of the latent variables in the overall framework is made possible by additional information collected during a SC survey on the decision-making process in the form of *stated thresholds* and *stated consideration*. We adopt the term 'hierarchical ICLV' model as introduced by Paulssen et al. (2014), because the *latent threshold* only affects individual choices indirectly through *latent consideration*. There is a strong behavioural mechanism supporting such a hierarchical relationship since the consideration of alternatives is likely to be driven by the presence of thresholds for individual attributes.

In the proposed approach *latent consideration* is used to reduce the utility, and therefore choice probability, of the alternatives. A similar 'discounting' approach has been proposed by Fotheringham (1988) in the context of consumer store choice, and by Cascetta and Papola (2001) and Martinez et al. (2009) in transport contexts, even though these authors related consideration to observable (as opposed to latent) characteristics of the alternatives. This discounting approach represents a convenient alternative to the traditional *two-stage* modelling of consideration and choice (Manski, 1977), given that it does not require enumerating (and modelling) of all possible consideration sets (i.e. combinations of alternatives).

Our work unveils the strong behavioural link between consideration of alternatives and thresholds for attributes, and their role in the decision making-making process. We illustrate a mechanism through which these links can be captured with the use of additional information collected during standard surveys. The remainder of the paper is structured as follows. In Section 2, we describe the available data, coming from a SC experiment on transport mode choice on the Rome-Milan corridor, in Italy. Section 3 lays out the empirical strategy and explains the proposed models. In Section 4, we report and discuss the estimation results. Finally, in Section 5, we draw conclusions from our study.

2. Data

We use data from a SC experiment that was administered in April and May 2016 to a sample of travellers on the Rome-Milan corridor (approximately 600 km). Here, seven alternatives (i.e. modes of transport) are available to travellers. The alternatives vary significantly in terms of travel time and travel cost (Table 1). Accordingly, it is reasonable to assume that some travellers might *a priori* disregard alternatives based on self-imposed thresholds for specific attributes.

Table 1 Alternatives' core characteristics at the time of the SC experiment

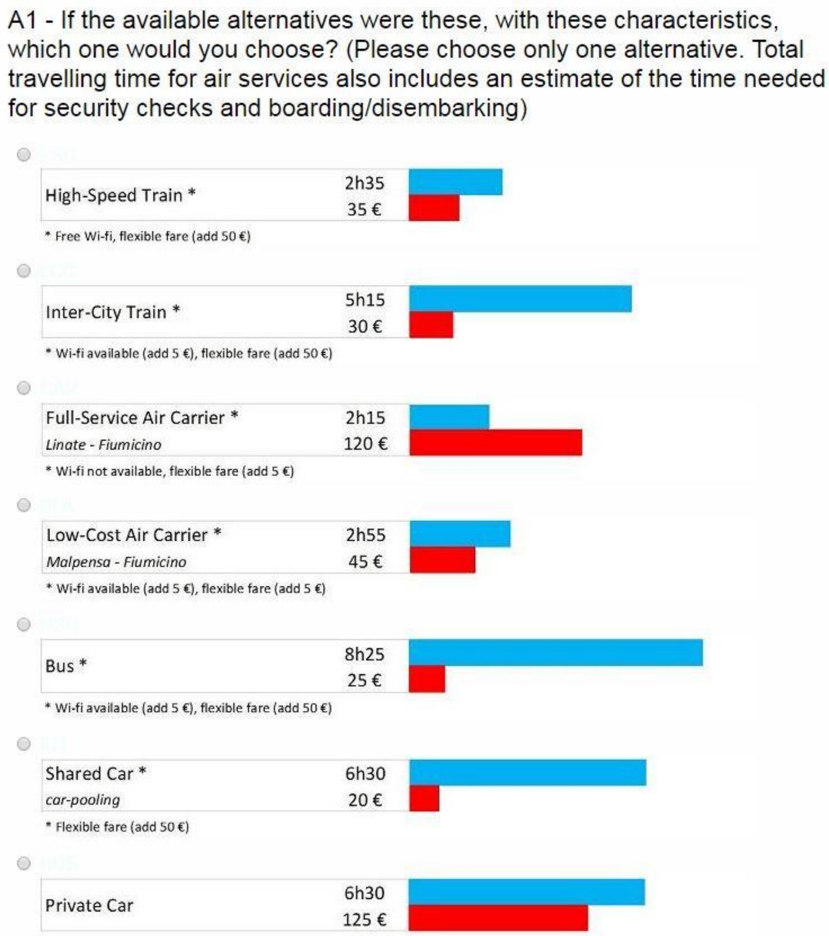
	Travel time (h/min)		Travel cost (€)	
Alternatives	*min*	*max*	*min*	*max*
High Speed Rail	2h55	4h28	19.9	209
Inter-City Rail	6h27	6h50	9	79
Full Service Air Carrier	2h20[1]		55.71	244.71
Low Cost Air Carrier	2h25[1]		44.73	267.23
Bus	7h25	10h45	1	29
Car-pooling[2]	5h41		25	45
Private car[3]	6h22		99 (41 toll/58 fuel)	

Source: Operators' websites; Note: 1 - includes an estimate of in-flight and boarding time as reported by www.goeuro.com; 2 - www.blablacar.it; 3 - www.viamichelin.com.

A total of 209 on-site face-to-face *Tablet Assisted* surveys were administered to travellers going from Rome to Milan (or *vice versa*) while waiting on the platform for their train (57%), at the bus stations for their bus (17%), or in the proximity of the airports (12%). A smaller portion of surveys was administered online (8%), and in two service stations on the A1/E35 highway, located around halfway between Rome and Milan, in the proximity of Bologna (6%). Each respondent completed 6 choice tasks, which were designed to mimic a real purchasing decision through an online journey planner. To this end a similar layout to the one displayed by the website www.goeuro.com (Figure 1) was used. To avoid possible ordering effects, we randomised the order of the presented alternatives across respondents. The attributes of the alternatives selected for the SC experiment were travel time, travel cost, ticket flexibility, and the level of connectivity on-board (Wi-Fi). The attributes all referred to a standard one-way trip between Rome and Milan.

Due to software limitations it was not possible to customise the design around respondents' most recent trip. The attribute levels presented in Table 1 were therefore designed around the *current ranges* (as displayed on operators' websites) and values which are expected to be feasible in the near future. The use of generic values is justifiable by the use of the same origin and destination across all respondents. We generated the choice tasks using a Bayesian D-efficient experimental design, with priors drawn from the literature or based on our expectations (Rose et al., 2008).

Figure 1 The layout of the choice tasks



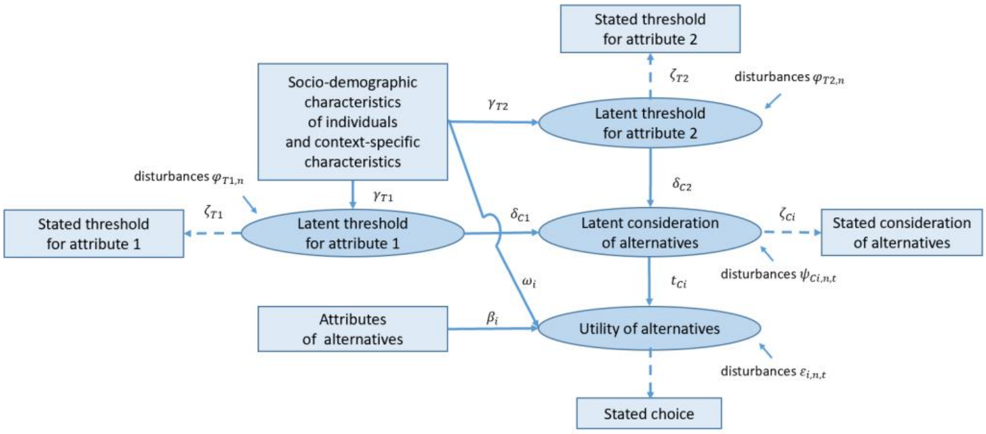
Besides choices, information on consideration of the different modes of transport was collected after each choice task. High-speed rail (HSR) obtained the highest average reported consideration (74%), followed by low-cost air carrier (LCC, 37%), and full-service air carrier (FSC, 31%). Private car obtained the lowest level of reported consideration (14%). Across respondents, the average number of considered alternatives in the 6 choice tasks is 2.26 (with an average standard deviation of 0.56). Moreover, there is little variation in the alternatives considered across choice tasks. For example, IC, bus, or car-pooling, are found to be either considered or not considered in at least 4 out of 6 choice tasks by 70% of respondents. This suggests that, for some alternatives, consideration is not context-specific and driven by *a priori* beliefs/knowledge for specific journeys.

In addition to stated consideration, the existence of thresholds on travel time and cost was also collected for each individual. The average reported value for the threshold on travel time was close to 6 hours (5h57min), while that on travel cost was 123€. Across respondents and choice tasks, the reported thresholds for travel time and travel cost were ‘respected’ in 85% and 91% of choices, respectively. This gives some measure of the reliability of this information, but the presence of some ‘violations’ supports the treatment of the thresholds as latent (i.e. acknowledging error in the stated thresholds) as well as the use of a probabilistic approach (rather than deterministically excluding alternatives that exceed thresholds).

3. Methodology

In the proposed hierarchical ICLV model structure - illustrated in Figure 2 - *latent thresholds* for attributes are used to explain the *latent consideration* of each alternative, which is then in turn used in the choice model. The model structure contains latent variables for thresholds, for example, one for time and one for cost, where these are explained on the basis of socio-demographic and context-specific characteristics. At the second layer, there are then mode-specific latent variables for consideration, where these again are a function of observable characteristics but are also informed by the latent threshold variables. Latent consideration then enters into the choice model via a discount factor on the utilities. We will now explain the individual model components in turn.

Figure 2 The proposed 'hierarchical ICLV' model



Note: Items in rectangles can be directly observed by the analyst while Items in the ellipses are unobserved. The broken arrows indicate measurement components, while plain arrows indicate structural components.

3.1 Structural model for latent variables

The structural equation for the *latent threshold* $\alpha_{Tk,n}$ for attribute *k* (where, for example, *k=1* for time and *k*=2 for cost) and respondent *n*, which is assumed to be constant across choice situations, is defined by (Equation 1):

$$\alpha_{Tk,n} = \gamma_{Tk} Z_{Tk,n} + \varphi_{Tk,n} \tag{1}$$

where $Z_{Tk,n}$ denotes a vector of socio-demographic (e.g. gender/income/age of the respondent) or context specific characteristics (e.g. nature of the trip), γ_{Tk} measures their impact on the *latent threshold* for attribute *k*, and $\varphi_{Tk,n}$ represents the error term. The latter is assumed to follow a standard normal distribution across attributes and respondents.

Latent consideration of an alternative *i* and respondent *n* is assumed to be a function of the relevant *latent thresholds* $\alpha_{Tk,n}$, as well as of socio-economic and trip characteristics, $Z_{Ci,n}$, (Equation 2). This allows for the possibility that, besides the role of thresholds (i.e. of its structural drivers) in explaining consideration of similar alternatives (for example, in terms of travel time or cost), there are further characteristics of the individuals which are able to explain why specific alternatives are considered or not.

$$\alpha_{Ci,n} = \sum_{k=1}^{K} \delta_{Ck}\alpha_{Tk,n} + \gamma_{Ci}Z_{Ci,n} + \psi_{Ci,n} \quad (2)$$

In this equation, δ_{Ck} and γ_{Ci} measure the impact of the *latent thresholds* and of the socio-economic characteristics, respectively, and $\psi_{Ci,n}$ represents a standard normally distributed error term across alternatives and respondents.

Latent consideration is specified at the person level because responses to the stated consideration questions suggest consideration is not context-specific and driven by a priori beliefs/knowledge for specific journeys (see Section 2). Ideally, one would compare the *latent thresholds* against the presented attribute levels in each equation. A simplified model is however presented, where the *latent thresholds* are implicitly contrasted against (constant) a priori beliefs. On the Rome-Milan corridor, the available alternatives can be categorised in two groups with respect to travel time or cost (e.g. 'fast' and 'slow', 'cheap' and 'expensive'), and this is assumed to guide consideration of the alternatives.

3.2 Measurement model

The stated threshold for attribute *k* and respondent *n*, $I_{Tk,n}$, is used as indicator for the *latent threshold*. When the indicator for the threshold takes the form of a continuous variable (as it would be the case with thresholds for travel time and travel cost), it can be modelled by the following measurement equation (Equation 3):

$$I_{Tk,n} = \theta_{Tk} + \zeta_{Tk}\alpha_{Tk,n} + \eta_{Tk,n} \qquad (3)$$

where θ_{Tk} is a constant, $\alpha_{Tk,n}$ is the latent variable for the threshold for attribute k, ζ_{Tk} measures its impact on the value of the corresponding stated threshold. $\eta_{Tk,n}$ is the error term, which follows a zero-mean normal density with a standard deviation of $\sigma_{I_{Tk}}$, which is to be estimated. Using zero-centered thresholds and latent variables obviates the need to estimate the constant θ_{Tk}.

The probability of having a threshold is therefore given by the normal density function (Equation 3.4):

$$P_{(I_{Tk,n}|\alpha_{Tk,n})} = \frac{1}{\sqrt{2\pi\sigma_{I_{Tk,n}}{}^2}}\, e^{-\frac{(I_{Tk,n}-(\theta_{Tk}+\zeta_{Tk}\alpha_{Tk,n}))^2}{\sigma_{I_{Tk,n}}{}^2}} \qquad (4)$$

Stated consideration for alternative *i,* respondent *n*, and choice situation *t*, $I_{Ci,n,t}$, is used as the indicator for *latent consideration*. This indicator is a binary variable, and the probability of consideration over the sequence of choice tasks takes the form of a binary logit (Equation 5):

$$P\left(I_{Ci,n}|\alpha_{Ci,n},\alpha_{Tk,n}\right)$$
$$= \prod_{t=1}^{T}(\lambda_{(I_{Ci,n,t}=0)}\left(\frac{1}{1+\ e^{\theta_{Ci}+\zeta_{Ci}\alpha_{Ci,n}}}\right)$$
$$+\lambda_{(I_{Ci,n,t}=1)}\left(\frac{e^{\ \theta_{Ci}+\zeta_{Ci}\alpha_{Ci,n}}}{1+\ e^{\theta_{Ci}+\zeta_{Ci}\alpha_{Ci,n}}}\right)) \quad (5)$$

where $\lambda_{(I_{Ci,n,t}=0)}$ is a dummy variable which takes value 1 when the alternative is stated to be considered, and 0 otherwise, θ_{Ci} is a constant, $\alpha_{Ci,n}$ is the latent variable for consideration, and ζ_{Ci} measures its impact on the value of stated consideration. Even though indicators for stated consideration were collected at the choice-level, these have been modelled using *latent consideration* specified at the respondent level as explained before.

3.3 Choice model

The choice component is consistent with the Random Utility Maximisation (RUM) theory (McFadden, 1974). In the proposed approach, the modelled component of utility of alternative *i,* for respondent *n* in choice occasion *t*, $V_{i,n,t}$, depends on both observed and latent characteristics, where the latter are deemed to account for the consideration stage in respondents' decision-making process (Equation 6):

$$U_{i,n,t} = V_{i,n,t}\ + \varepsilon_{i,n,t}\ = \varsigma_{i,n} + \beta_i X_{i,n,t} + \omega_i Z_n + \tau_{Ci}\log\left(a^{*}{}_{Ci,n}\right) + \varepsilon_{i,n,t} \qquad (6)$$

where $X_{i,n,t}$ is a vector of attributes of alternative *i* for respondent *n* and choice situation *t*, whose impact on utility is measured by a vector of estimated parameters β_i, Z_n is a vector of socio-demographic characteristics of respondent *n*, whose impact on utility (which differs across alternatives) is measured by a vector of estimated parameters ω_i, and $\varepsilon_{i,n,t}$ is the error. $a^*{}_{Ci,n}$ is the transformed *latent consideration* variable $\alpha_{Ci,n}$. The transformation in 7 is required to bound the variable between 0 and 1 and thereby discount the utility of unconsidered alternatives through the use of a log-transform. The impact of this discount factor on utility is measured by τ_{Ci}.

$$a^*{}_{Ci,n} = \frac{1}{(1+exp(-\alpha_{Ci,n}))} \qquad (7)$$

When $a^*{}_{Ci,n}$ is closer to 0, the utility will be heavily discounted, given that $\log(a^*{}_{Ci,n}) \rightarrow -\infty$ as $\rightarrow 0$. When the alternative is very likely to be considered, and therefore $a^*{}_{Ci,n}$ approaches 1, no discounting of utility is enforced. Therefore, *latent consideration* effectively accounts for the role of consideration by giving a lower choice probability to alternatives that are unlikely to be considered.

We also introduce random alternative-specific constants for all but one alternatives, $\varsigma_{i,n}$, with mean μ_{ς_i} and standard deviation σ_{ς_i}, such that $\varsigma_{i,n}$ = μ_{ς_i}+ $\sigma_{\varsigma_i}\xi_{i,n}$, where $\xi_{i,n}$ follows a standard normal distribution over respondents. Assuming that the error terms for all alternatives are i.i.d. type I extreme value distributed, the probability that alternative *i* is chosen by respondent n – amongst the *J* available alternatives in the set C_n – over the sequence of choice situation *t* can be represented by the standard logit probability (Equation 8):

$$P\left(Y_{i,n,t} |\, a^*{}_{Ci,n}, \alpha_{Tk,n}, X_{i,n,t}, Z_n, \varsigma_n\right) = \prod_{t=1}^{T} \frac{e^{V_{i,n,t}}}{\sum_{j\, \in C_n} e^{V_{j,n,t}}} \qquad (8)$$

The joint LL function for the proposed 'hierarchical ICLV' model is given by (Equation 9):

$$LL = \sum_{n=1}^{N} \ln \left[\left(\int_{\alpha_{Tk,n}} \int_{a^{*}_{C,n}} \int_{\varsigma_n} P(I_{Tk,n}|\alpha_{Tk,n})\, P(Y_{i,n,t}|a^{*}_{Ci,n}, \alpha_{Tk,n}, X_{i,n,t}, Z_n, \varsigma_n) P(I_{Ci,n}|\alpha_{Ci,n,}, \alpha_{Tk,n}) \right. \right.$$
$$\left. \left. \mathrm{f}(\varsigma_n|\mu_\varsigma, \sigma_\varsigma)\mathrm{g}(\alpha_{Ci,n}|\alpha_{Tk,n}, Z_{Ci,n})\mathrm{h}(\alpha_{Tk,n}|\, Z_{Tk,n}) d\varsigma_n da^{*}_{C,n,t} d\alpha_{Tk,n} \right) \right] \quad (9)$$

The repeated choice nature of both consideration and choice data is taken into account through the use of a panel mixed multinomial logit (MMNL) model and the estimation of robust standard errors (cf. Daly and Hess, 2011). The models are all estimated using maximum simulated likelihood and 1000 Modified Latin Hypercube Sampling draws[1] (MLHS, Hess et al., 2006).

4. Results and discussion

The present paper serves as proof of concept of accounting for consideration of the alternatives using a hierarchical ICLV framework. In this study we assume that only a subset of the alternatives, namely IC, bus, and car-pooling, are 'partially' considered by the respondents.[2] These alternatives are much slower and cheaper than HSR, FSC, and LCC and we thereby assume consideration decisions are only driven by the presence of thresholds on travel time. This means that latent consideration for the slower alternatives are here explained by only one latent

[1] This number of draws resulted in stable models, i.e. by increasing the number of draws we did not observe any improvement in the final LL.

[2] This therefore means that latent consideration is not included in the utility function for the remaining alternatives, meaning that these are always 'fully' considered, whereas the other alternatives are discounted, but still receive a positive choice probability.

threshold, i.e. that for the travel time attribute. Our assumptions are supported by both the stated consideration and choice data[3], which suggest that respondents are less likely to a priori discard the remaining (faster and more expensive) alternatives from consideration.

[3] On the one hand, the average self-reported levels of consideration for HSR, FSC, and LCC are larger than those for IC, bus, and car-pooling (HSR: 74%; FSC: 31; LCC: 37%; IC: 24%; Bus: 25%; Car-pooling: 21%). On the other hand, HSR, FSC, and LCC have been chosen at least once by 94% of respondents, which would suggest that these alternatives were not a priori discarded, while the remaining alternatives were chosen at least once only by 52% of respondents. Private car deserves a separate discussion. The information on stated consideration for this alternative was contradictory in several circumstances, i.e. a share of respondents stated to consider private car even when this was unavailable for them. For this reason, we decided not to use this information; nevertheless, we took information on car availability into account in the modelling, making car deterministically available/unavailable accordingly.

Table 2 Estimation results

	Model 1		Model 2		Model 3	
STRUCTURAL MODELS	*est*	*rob t-rat(0)*	*est*	*rob t-rat(0)*	*est*	*rob t-rat(0)*
Latent threshold travel time						
γ Business			-0.147	-1.97	-0.052	-0.40
γ Age 35+			-0.423	-5.96	-0.464	-3.20
Latent consideration IC						
δ Latent Threshold IC			1.778	6.02	1.898	3.95
Latent consideration BUS						
δ Latent Threshold Bus			2.177	4.96	2.470	5.76
γ Paid myself (vs employer and relatives)			0.458	2.99	0.426	1.53
γ Income 2000+ € or na			-0.539	-3.58	-0.440	-1.79
Latent consideration CAR POOLING						
δ Latent Threshold CAR POOLING			0.908	3.89	2.104	2.47
γ Female			-0.347	-2.96	-0.295	-1.45
γ High-education (university level)			0.273	1.93	0.237	1.11
γ Income 2000+ € or na			-0.449	-4.03	-0.507	-2.05
MEASUREMENT MODELS						
Stated threshold						
ζ Latent threshold travel time			0.256	10.44		
σ Stated threshold travel time			0.375	16.84		
Stated consideration IC						
ζ Latent threshold travel time IC			1.149	5.72		
θ Stated consideration IC			-2.263	-10.75		
Stated consideration BUS						

ζ Latent threshold travel time BUS			1.368	5.71		
θ Stated consideration BUS			-3.122	-9.67		
Stated consideration CAR POOLING						
ζ Latent threshold travel time CAR POOLING			2.307	6.14		
θ Stated consideration CAR POOLING			-3.149	-8.98		
CHOICE MODELS						
ASC choice IC	-1.072	-1.85	1.080	1.88	1.714	2.80
ASC choice FSC	1.569	1.91	1.715	2.06	1.658	1.87
ASC choice LCC	0.133	0.14	0.434	0.43	-0.047	-0.04
ASC choice Bus	-1.103	-1.34	1.871	2.28	2.136	2.36
ASC choice Car-pooling	-1.443	-1.91	1.179	1.68	0.428	0.50
ASC choice Private Car	-6.239	-1.90	-8.736	-1.88	-7.015	-1.99
Wi-fi free (HRS, IC, FSC, LCC, Bus)	0.141	0.93	0.244	1.66	0.210	1.34
Wi-fi €5 (HRS, IC, FSC, LCC, Bus)	0.071	0.58	0.089	0.70	0.055	0.41
Flexible ticket (free)	0.364	2.81	0.390	3.00	0.457	3.31
Flexible ticket (€5)	0.345	2.92	0.389	3.27	0.395	3.27
Travel time train (HSR, IC)	-0.008	-3.76	-0.008	-3.69	-0.009	-4.18
Travel time air (FSC, LCC)	-0.012	-3.32	-0.012	-3.27	-0.012	-3.05
Travel time Bus/Car-pooling	-0.009	-5.64	-0.008	-5.32	-0.009	-5.87
Travel time Private Car	0.003	0.39	0.004	0.59	0.002	0.31
Travel cost	-0.045	-9.16	-0.047	-8.88	-0.051	-7.85
Travel cost, income na	-0.037	-5.75	-0.043	-5.68	-0.043	-5.13
Paid employer (travel cost)	0.023	4.32	0.026	4.47	0.027	3.91
Income elasticity (travel cost)	-0.221	-3.92	-0.181	-3.22	-0.241	-3.73
Access/egress time main airports	-0.030	-4.37	-0.031	-4.60	-0.032	-4.40
Access/egress time secondary airports	-0.013	-2.25	-0.016	-2.25	-0.014	-2.01
Fidelity card (FSC)	1.897	4.81	2.045	5.06	2.059	4.92

Age 25-34 (IC, Bus, Car-Pooling)	-0.830	-1.75	-0.511	-1.39	-0.533	-1.02
Age 35+ (IC, Bus, Car-Pooling)	-1.602	-2.89	0.183	0.37	0.504	0.62
Business (FSC, LCC)	-0.468	-1.70	-0.507	-1.73	-0.501	-1.66
Business (IC, Bus, Car-pooling)	-1.344	-2.79	-0.637	-1.67	-1.195	-1.86
High-education (all but HSR)	-0.477	-1.88	-0.471	-1.94	-0.672	-2.22
Female (FSC, LCC)	0.570	2.03	0.594	2.00	0.561	1.78
τ Latent Consideration IC			5.859	5.84	6.474	3.14
τ Latent Consideration BUS			14.150	4.38	15.937	2.97
τ Latent Consideration CAR POOLING			6.868	5.62	5.743	2.83
Random coefficients standard deviations						
ASC choice IC sd	-2.037	-6.01	0.491	1.48	-0.050	-0.71
ASC choice FSC sd	1.187	3.80	1.277	4.08	1.289	3.97
ASC choice LCC sd	-1.389	-6.48	1.430	6.06	-1.648	-6.53
ASC choice Bus sd	2.452	8.87	1.073	2.64	0.392	1.39
ASC choice Car-pooling sd	1.547	4.96	0.538	1.82	0.214	0.48
ASC choice Private Car sd	-4.414	-3.18	4.873	2.41	-3.647	-5.05
LL(final, complete model):	-1263.23		-2563.49		-1186.60	
LL(final, choice model only):	-1263.23		-1198.69		-1186.60	

Estimation results are summarised in Table 2. Model 1 represents a MMNL model with normally distributed alternative specific constants (ASC) over respondents. This model assumes all alternatives are fully considered and thereby represents the standard practice. Model 2 is the proposed 'hierarchical ICLV' model which accounts for latent consideration effects by 'discounting' the utility of a subset of alternatives (i.e. IC, bus, and car-pooling). Model 3 is the reduced-form model of Model 2. This is also a MMNL model in which we do not make use of the indicators (i.e. stated threshold and stated consideration), but still include the discounting factor (unlike Model 1). This discounting factor is a function of the same set of observed explanatory variables used in the structural equations for latent threshold and latent consideration in Model 2. The estimation of this reduced-form model is aimed at unveiling the actual benefits of using supplementary information (Vij and Walker, 2016).

In Model 1, the estimates for the ASCs reveal a strong preference for FSC over HSR, which was used as the reference alternative in our models.[4] The opposite occurs for IC, car-pooling and private car. Standard deviations, which reflect the degree of heterogeneity for the ASCs at the respondent level, are all significant; in particular, we notice that those for IC, LCC, bus, and car-pooling are larger than the respective mean values.

We estimated four coefficients for travel time, namely one for the rail alternatives (HSR and IC), one for the air alternatives (FSC, LCC), one for the slow and low-cost alternatives (bus and car-pooling), and one for the private car alternative. These

[4] This alternative has been chosen as baseline even though car-pooling was found to be the minimum variance alternative (Walker et al., 2007). We opted for this inferior solution given that, in the proposed model formulations, consideration effects are directly included in the utility level though latent considerations.

coefficients show the right (negative) sign and are all statistically significant, except for private car. This result can be explained by the fact that this alternative was chosen in very few occasions (21 out of 1254 choices). Coefficients for access/egress time for airports are also negative and significant, while those for train and bus stations were found to be in-significant.

We interacted travel cost with income in a non-linear way and estimated the income elasticity (10). Given that not all respondents reported their income, we estimated separate cost sensitivities (without an income effect) , one for those who disclosed this information (‘*Travel cost*’), and one for those who did not (‘*Travel cost, income na*’).[5]

$$\begin{aligned}\beta_{travel\_cost_n} = ((\beta_{travel\_cost\_income\_yes_n} * (\left(\frac{income_n}{average_{income}}\right)^{lambda\_income_n}) \\ * (income\_yes\_dummy_n)) \\ + (\beta_{travel\_cost\_income\_na_n} * (1 - income\_yes\_dummy_n)) \\ + (\beta_{paid\_employer_n} * paid\_employer\_dummy_n)) \qquad (10)\end{aligned}$$

The travel cost coefficients have the expected (negative) sign and are both significant; the negative, and significant value for the income elasticity implies that the (absolute) sensitivity to travel cost decreases with increases in income. The shift on the cost sensitivity for those respondents whose trip was paid by the employer ($\beta_{paid\_employer_n}$) is positive and statistically significant, implying that they care less about travel cost (i.e. the travel cost coefficient is less negative) than those who

[5] Income information was collected using income classes, and we used class-midpoints to compute both income and average income.

paid the trip themselves or whose trip was paid by some family members.[6] Model 1 also shows that respondents are more likely to select alternatives for which they can get a flexible ticket at a reasonable price (i.e. free or up to 5€). Surprisingly, the presence of Wi-Fi onboard was found to be insignificant.[7] As expected, respondents who are in possession of a loyalty card are more likely to choose the FSC alternative. Those aged 25+ are less likely to choose IC, bus, and car-pooling over HSR compared to their younger counterparts. The HSR alternative is the most likely alternative to be chosen by respondents on a business trip and those educated to at least the university level. We additionally observe a strong preference for the air alternatives over HSR by female travellers.

Model 2, the 'hierarchical ICLV' model, has three separate components. First, in the structural models, the latent threshold for the travel time is described as a function of observable exogenous variables. The latent consideration for IC, bus, and car-pooling is described as a function of the latent threshold for the travel time and an additional set of observable exogenous variables. Second, in the measurement models, the aforementioned latent variables are linked to the stated threshold for travel time and to stated consideration for IC, bus, and car-pooling (i.e. indicators) respectively. Third, in the choice model, the utility for the alternatives is specified on the basis of attributes of observable exogenous variables and latent consideration.

[6] In particular, the coefficient for travel cost for the former respondents turns out to be less than a half than that for the latter.

[7] Although insignificant, coefficients for Wi-Fi on board were retained in final estimation given that this attribute was modelled in the SC experiment design, differently from access/egress time, for which information was collected afterwards.

In the structural model for the latent travel time threshold (see Equation 1), it can be seen that the latent threshold on the travel time attribute is lower for those on a business trip and aged at least 35. Consistent with our expectation, the δ parameters indicate that latent consideration for IC, bus, and car-pooling is larger for those respondent with a higher latent threshold for travel time. Latent consideration for bus is lower for those who declared an income of at least 2,000 € per month, for those who did not declare their income, and for those who did not pay the trip themselves. Latent consideration for car-pooling is also lower for those who declared an income of at least 2,000 € per month and those who did not declare their income, but also for female, and for less educated travellers.

In the measurement models, the ζ parameters (see Equations 3 and 4) suggest that as our latent variables increase, the probability of respondents stating a higher threshold, or to consider either IC, bus, or car-pooling, increases. In the measurement models for consideration of IC, bus, and car-pooling, negative values for the θ parameters (see Equation 5) reflect the fact that the stated consideration rates were on average lower than 50% in the sample (see footnote 3).

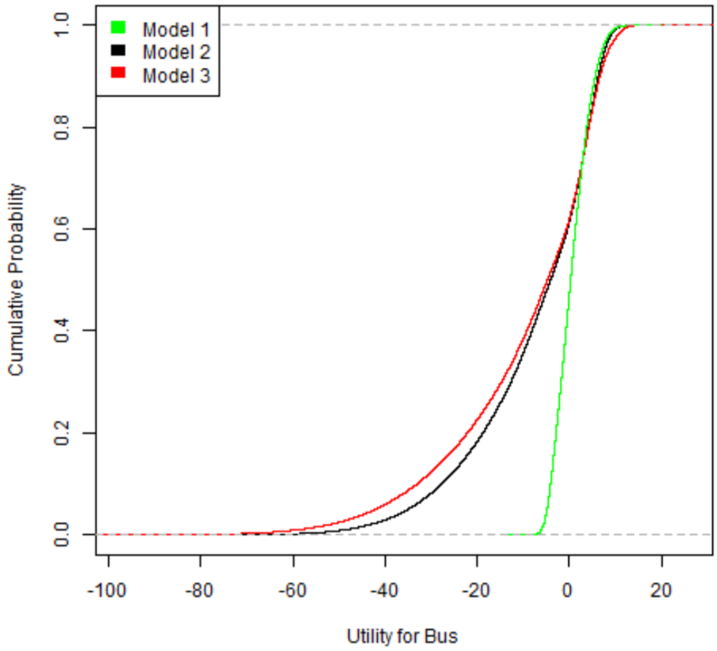
The τ parameters in the choice model measure the marginal impact of latent consideration on the utility for the supposed unconsidered alternatives, and their magnitude is simply an outcome of the functional form used; our results show that a value for the transformed latent consideration closer to unity (zero) leads to higher (lower) utility, i.e. less (more) discounting.

Models 3 is the reduced-form MMNL model of Model 2. It has the same structure of Model 2 but it does not make use of the indicators and therefore we do not estimate the measurement models. Looking at Model 3, we notice that many observable exogenous variables in the structural models are no longer significant.

This result can be explained by the circumstance that these characteristics now only explain choice (while in Model 2 these also explain the indicators via the latent threshold and latent consideration); this is particularly relevant when the same variable is also included as a free parameter in the choice model (e.g. ‘*Business*’). This confirms an efficiency gain by Model 2, resulting from the use of the additional variables explained by the measurement model components.

In Figure 3 we plot empirical cumulative distribution functions (ECDFs) for the utility values of the bus alternative according to the aforementioned formulations (Models 1-3). The ECDFs represent the proportions of observations showing specific values of the utility. In Models 2 and 3, variations in utility are mostly driven by the impact of latent consideration. Therefore, the distribution of the bus utility in these two models differs with that in Model 1, where consideration effects are not taken into account. Interestingly, for around 60% of the sample the utility of the bus alternative is strongly discounted, thus assigning a lower choice probability for this alternative.

Figure 3 ECDFs for the impact of consideration effects on utility for bus



We now discuss the implications of accounting for consideration effects on the parameters of the utility function. Relative to Model 1, the standard deviations of the ASC strongly reduce for IC, bus, and car-pooling when consideration effects are introduced. In particular, in Model 2, the standard deviation parameter becomes insignificant for IC. Differently from previous studies employing the ICLV approach (e.g. Kløjgaard and Hess, 2014; Mariel and Meyerhoff, 2016; Song et al., 2018) we are not able to quantify which share of preference heterogeneity is explained by the latent variables. This is due to the hierarchical nature of our latent variables and the transformations these are subjected to before including them in the utility function. The reduction in size of the standard deviations for the ASCs' for the 'discounted' alternatives, however, indicates that also in this case at least a share of preference heterogeneity is explained by the introduction of latent constructs.

The impact on the travel time and travel cost coefficients can be more effectively analysed in terms of Value of Travel Time (VTT) indicators (Table 3). VTT indicators are obtained for an individual who pays her/himself for the trip. Standard errors are calculated using the delta method.

Table 3 VTT (€/hour)

	Model 1		Model 2				Model 3			
	est.	*t-stat(0)*	*est.*	*t-stat(0)*	*change (2vs1)*	*t-stat (2vs1)*	*est.*	*t-stat(0)*	*change (3vs1)*	*t-stat (3vs1)*
Train	10.33	3.66	9.58	3.56	-7%	0.19	10.35	3.97	0%	-0.01
Air	16.26	3.03	15.71	3.03	-3%	0.07	13.98	2.81	-12%	0.31
Bus/Car-pooling	11.43	5.31	10.63	4.86	-7%	0.26	10.02	5.14	-11%	0.48

Overall, we observe a reduction in the VTT for all the alternatives in Models 2 and 3 relative to Model 1. The differences are, however, not significant and therefore suggest that consideration effects actually have a rather limited impact on VTT estimates.

Turning our attention to model fit, the final Log-Likelihood of the traditional MMNL model (Model 1) and the reduced-form MMNL model (Model 3) cannot be compared with that of the 'hierarchical ICLV' model (Model 2). This is due to the fact that whilst Models 1 and 3 are estimated on the choice data alone, the ICLV structure also explains respondents' stated thresholds on travel time and stated consideration for the IC, bus, and car-pooling alternatives. It is however possible to derive the final Log-Likelihood for the choice model component separately from the other components. A comparison of these measures reveal that Models 2 and 3 outperform Model 1. Vij and Walker (2016) suggest that model fit for the ICLV model and its MMNL reduced form model should be similar. A worse fit for the ICLV model (Model 2) with respect to its reduced form (Model 3) is not uncommon in the literature. In this case, the difference in fit between Model 2 and Model 3 is, however, not negligible but can be explained by the fact that the ICLV model evaluates a joint likelihood function.

5. Conclusions

The latent nature of the consideration stage, as a part of the decision-making process, implies that variations in consideration of the alternatives across individuals are not observable. Reports of consideration – or of aspects related to this stage – might indeed be collected during SC experiments. Their direct use as additional explanatory variables, to account for consideration of alternatives in the estimation of discrete choice models is, however, highly discouraged. In this paper we propose an Integrated Choice and Latent Variable (ICLV) model to account for consideration of the alternatives, with an application to transport mode choice. The ICLV approach helps circumventing the aforementioned drawbacks by treating information on respondents' processing strategies as dependent variables rather than as explanatory variables.

Our approach is 'hierarchical', in the sense that latent thresholds for attributes are used to explain latent consideration of the alternatives, reflecting what might happen in the individuals' decision-making process. These inter-related latent variables are in turn used to explain both choice outcomes and self-reported information on the decision-making process in the form of stated thresholds for attributes and stated consideration of the alternatives. Latent consideration enters the utility of the alternatives through a 'discounting' factor, which accounts for the role of consideration lowering choice probability for the supposed unconsidered alternatives.

In this study, we incorporate consideration effects only on a subset of alternative transport modes which are deemed to be hardly considered by the respondents' of a mode choice experiment on the Rome-Milan corridor. Here, seven alternatives are available, which vary substantially in terms of their characterising attributes, particularly travel time. We assume slower (but also less expensive) alternatives are not always considered, most likely due to the presence of thresholds for the travel time attribute. The assumption is supported by both stated consideration and stated choice data.

The proposed 'hierarchical ICLV' model is compared against two reference models. The first is a traditional MMNL model where consideration effects are not taken into account and all alternatives are assumed to be 'fully' considered. The second is a reduced-form MMNL model of the proposed ‘hierarchical ICLV’ model in which we keep the structural equations for the latent variables, but we do not make use of the respective indicators. The first reference model represents the current practice in most mode choice studies and we estimate the second in order to unveil the actual benefits of the proposed ICLV model.

Consistent with our expectations, results suggest that the latent threshold on travel time is lower for respondents on a business trip and for those aged at least 35. Latent consideration for IC, bus, and car-pooling is larger for those respondents with a higher latent threshold for travel time. Latent consideration for bus is also lower for richer respondents, and for those who did not pay for the trip themselves. Latent consideration for car-pooling is instead lower not only for richer travellers, but also for female and less educated travellers. The latter results could potentially be explained by safety concerns and by the fact that this mode has a very high ICT component. Latent consideration for IC, bus, and car-pooling has a significant (and positive) marginal effect on the overall utility of these alternatives; conversely, the utility for those respondents with predicted lower levels of latent consideration gets highly discounted, and choice probability for these alternatives approaches zero.

Interestingly, willingness-to-pay indicators are hardly affected by the introduction of consideration effects. Previous studies found more tangible differences in these metrics with respect to models assuming that all alternatives are ‘fully’ considered (Ben-Akiva and Boccara, 1995; Basar and Bhat, 2004). We believe that this is due to the fact that we simultaneously account for additional random heterogeneity and that we appropriately account for measurement errors in the indicators for consideration and thresholds in the ICLV model. In terms of model fit, we observe an improvement with respect to a traditional MMNL as a result of explicitly account for consideration effects. However, consistent with Vij and Walker (2016), who discuss pros and cons of any latent variable approach, we find that such improvement in fit cannot be fully ascribed to the use of the indicators.

The ICLV model shows benefits when compared with traditional RUM-based choice models. First, it enables us to explain a share of otherwise completely random heterogeneity, which can therefore be associated to latent thresholds for attributes and latent consideration of the alternatives. Second, thanks to the indicators we are able to obtain more insights into the structural drivers of consideration. This might be of interest for policymakers and private operators, and useful when applying the model.

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