ALLOWING FOR HETEROGENEITY IN THE CONSIDERATION OF AIRPORT ACCESS MODES: THE CASE OF BARI AIRPORT

Angela S. Bergantino
University of Bari
Department of Economics, Management, and Business Law
53 Largo Abbazia Santa Scolastica, Bari, Italy, 70124
Tel: +390805049038; Email: angelastefania.bergantino@uniba.it

Mauro Capurso, Corresponding Author
University of Leeds
Institute for Transport Studies and Choice Modelling Centre
34-40 University Road, Leeds, United Kingdom, LS29JT
Tel: +441133435325 Email: m.capurso@leeds.ac.uk

Thijs Dekker
University of Leeds
Institute for Transport Studies and Choice Modelling Centre
34-40 University Road, Leeds, United Kingdom, LS29JT
Tel: +441133435334 Email: t.dekker@leeds.ac.uk

Stephane Hess
University of Leeds
Institute for Transport Studies and Choice Modelling Centre
34-40 University Road, Leeds, United Kingdom, LS29JT
Tel: +441133436611 Email: s.hess@leeds.ac.uk

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ABSTRACT

Mode choice models traditionally assume that all objectively available alternatives are considered. This might not always be a reasonable assumption, even when the number of alternatives is limited. Consideration of alternatives, like many other aspects of the decision-making process, cannot be observed by the analyst, and can only be imperfectly measured. As part of a stated choice survey aimed at unveiling air passengers' preferences towards access modes to Bari International Airport, in Italy, we collected a wide set of indicators that either directly or indirectly measure respondents' consideration for the public transport alternative. In our access mode choice model, consideration for public transport services is treated as a latent variable, and enters the utility function for this mode through a 'discounting' factor. The proposed integrated choice and latent variable (ICLV) approach allows the analyst not only to overcome potential endogeneity and measurement error issues associated with the indicators, but also makes the model suitable for forecasting. As a result of accounting for consideration effects, we observe an improvement in fit which also holds in a validation sample. However, in line with the literature on latent variables, this improvement cannot be completely ascribed to the use of the indicators, which availability only contributes to identify that students are more likely to consider public transport services. Moreover, the expected increase in the modal share for this mode as a result of a reduction in its travel or headway time would be smaller.

Keywords: Consideration of alternatives, latent variables, ICLV, airport access

INTRODUCTION

The number of air travellers in the European Union has significantly increased in recent years (*1*). This growth was largely driven by low-cost carriers, which made air transport economically affordable to a larger share of the population. This expansion continuously imposes a challenge for airport managers and regional mobility planners, who have to deal with the increasing number of (infrequent) travellers, but also additional staff and accompanying persons needing to access the airport. There is no generic solution to this challenge which is valid everywhere; in addition to this, each user segment (e.g. resident *vs.* nonresident, business *vs.* nonbusiness, or airport employees) has its own needs and preferences towards airport access services (TCRP 62, 83).

Most studies investigating the drivers of airport access mode decisions have relied on revealed preference (RP) and (or) stated preference (SP) data in combination with discrete choice models. These studies were aimed at understanding the choice between existing access modes (*2, 3, 4, 5*), or focused on the implications of introducing a new access mode (*6, 7, 8*). In some cases, airport access mode decisions have been modelled jointly with airport and/or airline decisions, when multiple airports exist in the same catchment area or when the same origin-destination route is served by multiple operators (*10, 11, 12, 13*).

The underlying assumption in all these studies is that all objectively available airport access modes are effectively considered by each airport user. However, this assumption might be questioned since some access modes might be discarded *a priori*, i.e. regardless of their characteristics. For example, in the case of air travellers, trips to the airport are only the first 'leg' of a longer trip and are associated with a hard constraint, i.e. the departure time of the flight. Hence, the possible consequences of a delay in arriving at the airport may be severe. Even though unexpected delays might occur with all modes, air travellers might consider as feasible only those alternatives that they 'perceive' to have a sufficiently low risk of getting to the airport late. Other factors that might influence which alternatives are considered or not are concerns for personal safety, or the need to access a train station/bus stop which is inconveniently located with respect to their location of departure. Comfort also matters, particularly because passengers perceive the need to transfer and wait (e.g. with public transport) as a significant 'discomfort' (ACRP 4).

The assumption that individuals might consider only a subset of the available alternatives has been tested in several transport contexts, particularly route and mode choice (*14, 15*). However, to the best of our knowledge, this assumption has never been tested in the specific context of airport accessibility, which is the focus of this paper. The biggest challenge with consideration of alternatives is that this aspect of the decision-making process is not observable to the analyst.

Some researchers have tried to incorporate consideration effects into probabilistic models only on the base of the observed choices (*16 ,17, 18*). Others have explored the possibility of using supplementary information as direct (but imperfect) measures of consideration, including for example perceived availability (*19*) or acceptability (*20*) of the alternatives and self-imposed thresholds for attributes (*21*), elicited using ad-hoc questions in travel surveys. These indicators, however, might not correspond to actual levels of consideration, i.e. there is potential for measurement error, and they may be correlated with other unobserved factors, i.e. there is scope for endogeneity bias (Hess and Hensher, 2013). Given this, rather than using them as 'error-free' measures of consideration, it might be preferable to recognise that these are a function of *latent consideration*, and treat them as dependent rather than independent variables using an Integrated Choice and Latent Variable (ICLV) model. The ICLV approach has been extensively used in many fields, not only transport, to incorporate either psychological factors such as attitudes and perceptions (*25, 26, 27*) or respondents' processing strategies (*28*) into models based on random utility maximisation (RUM, CHANGE NUMBER OF REFERENCE 33). Besides allowing the analyst to overcome potential endogeneity and measurement

error issues with the indicators, the ICLV approach also allows us to make the indicators suitable for forecasting.

In this paper, we adopt the ICLV framework to measure consideration of airport access modes using three distinct sets of indicators collected as part of a stated choice (SC) survey on airport access mode choice. The first set consists of the level of agreement with various perception statements and of a preference-based ranking of the alternatives; the second refers to thresholds for attributes inferred from respondents' previous choices; the third set comprises direct reports of consideration of the alternatives. These indicators have been chosen because they represent additional sources of information which are generally collected during travel surveys (the first two sets), or because they have been used in previous studies to measure consideration of the alternatives (the third set).

In our proposed formulation, *latent consideration* explains the indicators and enters the utility of an alternative through a discounting factor. The discounting factor effectively accounts for consideration lowering the utility, and therefore choice probability, of a supposed unconsidered alternative.

Data for this study comes from a SC experiment on a sample of air travellers living in a range of 50-100 Km from Bari International Airport 'Karol Wojtyla', in Apulia (Italy). This airport recently experienced a substantial increase in travellers (*29*) as a result of the increase in the number of low-cost connections available. A direct train connects the airport with the city centre in 15 minutes; however, more peripheral areas within the Metropolitan City of Bari and the Apulian region are not as easily accessible, since the railway link to the airport is not interconnected with the main regional railway networks. Other public transport means are available (e.g. local buses), but these involve at least one interchange, are even less frequent, and their timetables are not coordinated. As a result, travellers from these areas mainly access the airport by car.

Given these premises, in this paper we estimate mode choice models in which we allow for the possibility that some air travellers might not consider public transport as a feasible alternative. Both RP and SP data is used in the estimation, and the proposed ICLV models are compared with two reference models: the first is a traditional Mixed Multinomial Logit (MMNL) model in which all alternatives are assumed to be considered. The second is a reduced-form MMNL model of the proposed ICLV models, which only infers the *latent consideration* for public transport through the observed choice data. The models are compared on the ground of the overall fit to the data, parameter estimates and out-of-sample prediction ability.

The remainder of the paper is structured as follows. We describe the available data in Section 2. Section 3 lays out the empirical strategy and explains the proposed model. In Section 4, we report and discuss the estimation results, and in Section 5 we present the validation exercise. Finally, in Section 6 we draw conclusions from our study.

DATA

The data used in this paper were gathered through pen-and-paper personal interviews (PAPI) conducted in autumn 2016 and autumn 2017. A total of 1,046 randomly selected residents in four cities in a range of 50-100 km from the airport were interviewed at their homes. Our sample comprises only air travellers, i.e. individuals who had flown through Bari International Airport at least once in the previous three months. The fulfilment of this requirement was ensured through a preliminary screening question. Official statistics on the actual profiles of the airport users are not available, and thus we are not able to assess the representativeness of our sample with respect to the target population. However, our sample is balanced across key socio-economic and demographic characteristics (e.g., sex, age, and level of education) (Table 1).

We decided to only focus on residents for three reasons. First, because they are more likely to have a private car, and therefore to use it to access the airport, whether in the '*kiss-and-ride*' or the '*park-*

and-ride' mode (i.e. 'as passengers' or 'as drivers'). Second, because they are more likely to have better knowledge of all available alternatives. Third, because they are more familiar with regional traffic patterns. Given these premises, residents represent a major potential market for public transport services (TCRP 83).

The catchment area for this airport goes far beyond the city of Bari. It comprises the geographical boundaries of the whole Apulian region and the adjacent county of Matera in the Basilicata region. It has been estimated that approximately 3,150,000 individuals can access the airport within 90 minutes (ENAC, 2010). Only 9% of these potential passengers live in the city of Bari (ISTAT, 2017), and this explains why this paper focuses on regional rather than urban mobility patterns towards the airport.

TABLE 1 Descriptive Statistics Of The Sample and of the Population in Apulian Region

Social traits/Year		**Survey 2016**	**Survey 2017**	**Region (REF)**
Sex:	Male	50.3%	48.4%	48.3%
	Female	49.7%	51.6%	51.7%
Age:	18-24	27.0%	37.3%	9.2%
	25-34	30.3%	26.7%	13.9%
	35-49	24.0%	20.1%	25.7%
	50+	18.7%	16.0%	51.2%
Education:	Up to High School	36.0%	62.3%	81.2%
	BSc+	64.0%	37.7%	18.8%
Business trip:		30.0%	18.8%	-
Student:		29.0%	48.4%	-
City:	Matera	12.7%	19.4%	-
	Altamura	64.3%	24.7%	-
	Gravina	26.3%	25.5%	-
	Corato	-	30.4%	-
Total		300	746	3,381,008

Both revealed and stated preferences were collected during the survey. The former refer to the respondents' last trip to the airport. In the SC experiment, respondents were asked to choose their preferred access mode amongst i) public transport with at least one change, ii) a direct private bus run by the airport management in cooperation with private operators, iii) car as driver, iv) car as passenger (i.e. the possibility of being dropped-off by someone else), and v) taxi. The attributes of the alternatives modelled in the SC experiment were in-vehicle travel time, out-of-vehicle travel time (i.e. the waiting time between connecting services for the public transport alternative), travel cost, and headway (i.e. the time until the next available public transport service to the airport). When the departure place is located within 50-100 km from the airport, it is reasonable to assume that passengers will use a timetable to schedule their arrival at the train station/bus stop. The headway might still be an important factor in their decision-process because if there is a reliability issue with the scheduled public transport journey, they might not be willing to wait too long at the train station/bus stop until the next ride.

Each respondent was shown 5 choice tasks which were generated using city-specific Bayesian D-efficient experimental designs (*31*), with priors inferred from a pilot study. The attribute levels were designed around the current ranges (as reported by the transport operators and www.viamichelin.com), and the order of the presented alternatives was randomised across respondents to avoid possible *left-to-right* effects (i.e. always choose the first alternative on the left).

The 2017 survey (i.e. the second wave) also collected three sets of supplementary information which could be used as indicators of *latent consideration* of the available alternatives, particularly public transport.

The first set of indicators consists of the level of agreement with perception statements towards the alternatives and of a ranking of these on the base of their overall preference. With respect to public transport, we collected responses about agreement with the following statements on a 5-points Likert scale, ranging from 1 being 'completely disagree' to 5 referring to 'completely agree':

1) *If I had to use public transport to get to the airport, I would take an earlier bus/train to make sure I will not get there late*.
2) *I do not consider the possibility of getting to the airport by public transport, because I can only be there too early or too late due to the reduced frequency*.

The second set of measures refers to respondents' past experience. Respondents were asked to report how many times they had used each of the airport access alternatives in the previous year. This information is in turn employed to infer respondents' threshold for the travel time attribute, i.e. travel time for the (used) alternative with the longest travel time is assumed to be their threshold. This indicator would give an idea of the maximum travel time the respondents are willing to accept outside the SC experiment, i.e. in real situations, and its robustness (as an indicator of a potential self-imposed threshold on travel time) would certainly increase with the number of trips made. Of course, this presents a lower limit on this threshold; just because a respondent has never chosen a mode taking longer than the slowest mode chosen in the past does not mean that the travel time for these modes exceeds that traveller's threshold. This makes the treatment of these values as indicators rather than direct measures of threshold even more important.

The third set of indicators comprises self-reports of consideration of the alternatives. Respondents were asked to reveal which alternatives they actually considered at the end of each choice task. Similar follow-up questions have been collected by Hensher and Rose (*32*) and Hensher and Ho (*20*), even though these referred to 'acceptability' of the alternatives rather than consideration. Despite being directly related to consideration, self-reports of consideration are still imperfect measures of consideration, and therefore these might not necessarily correspond to an individual's 'actual' behaviour. An additional limitation resides in the possibility that, if collected after each choice task, these follow-up questions might influence subsequent choices.

METHODOLOGY

In Figure 1 we illustrate the general ICLV model formulation, consisting of three sub-models: a structural model, where *latent consideration* is described as a function of socio-demographic characteristics of the respondent; a measurement model, which links *latent consideration* to the values of the indicators; and a choice model, where the utility for the alternatives and hence the choice is specified on the basis of attributes of observable exogenous variables and *latent consideration*.

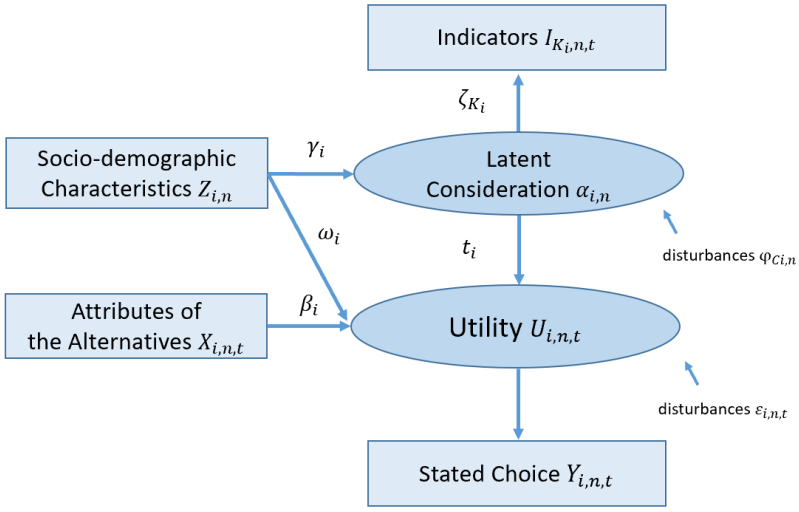

FIGURE 1 The proposed ICLV model

Note: Items in rectangles can be directly observed by the analyst. Items in the ellipses are unobserved: an error is added to to take account of this.

Structural model

In the structural equation, *latent consideration* for alternative *i* (e.g. public transport) and respondent *n*, $\alpha_{i,n}$, is defined by (1)

$$\alpha_{i,n} = \gamma_i Z_{i,n} + \varphi_{i,n} \tag{1}$$

where $Z_{i,n}$ denotes a vector of socio-demographic characteristics of the respondent whose impact on latent consideration is measured by γ_i, and $\varphi_{i,n}$ represents a normally distributed error term (*24*). Changes in the structural equation impact both the measurement model and the choice model components, given that *latent consideration* is an explanatory variable in both.

Measurement model

The measurement model links *latent consideration* (as defined by Equation 1) to its indicators. Depending on the nature of the selected indicator, distinct measurement models can be specified. In this paper we test for the use of ordinal, continuous, and binary indicators. Therefore, we specify the corresponding measurement models as an ordinal logit, a probability distribution function, and a binary logit, respectively.

Ordinal indicators

The level of agreement with statements such as those related to public transport reported in the previous Section can be recorded, for example, on a 5-point scale, ranging from 1 being ‘completely disagree’ to 5 referring to ‘completely agree’. The ranking of the PT alternative amongst the five alternatives is also treated as ordinal, with the value ranging from 1 if the alternative is the ‘most preferred’ to 5 if the alternative is the ‘least preferred’. Of course, if the ranking of multiple alternatives

were to be included in the model, an exploded logit would be more appropriate than the ordered model used here. Both level of agreement to the statement and the ranking of the alternatives can be used as indicators for *latent consideration*. The probability of observing a specific response to these ordinal indicators K relative to alternative *i* and respondent *n*, can be modelled using an ordered logit form (2):

$$P_{K_i,n}\left(I_{K_i,n} = s|\alpha_{i,n}\right) = \frac{e^{\mu_{K_i,s}-\zeta_{K_i}\alpha_{i,n}+\psi_{K_i,n}}}{1+\ e^{\mu_{K_i,s}-\zeta_{K_i}\alpha_{i,n}+\psi_{K_i,n}}} - \frac{e^{\mu_{K_i,s-1}-\zeta_{K_i}\alpha_{i,n}+\psi_{K_i,n}}}{1+\ e^{\mu_{K_i,s-1}-\zeta_{K_i}\alpha_{i,n}+\psi_{K_i,n}}} \tag{2}$$

Where $\mu_{K_i,s}$ are estimated threshold parameters, s ∈ (1,2,3,4,5) if a 5-point scale is used, $\alpha_{i,n}$ is the *latent consideration*, ζ_{Ki} measures its impact on the value of the indicator, and $\psi_{K_i,n}$ is the error term. For normalisation purposes, we set $\mu_{K_i,0}$ to - ∞ and $\mu_{K_i,5}$ to + ∞; therefore, only the intermediate four threshold values can be estimated for each indicator.
The likelihood of the observed value $I_{K_i,n}$ is then given by (3):

$$L_{I_{K_i,n}} = \sum_{s=1}^{S} \lambda_{\left(I_{K_i,n}=s\right)} \left(\frac{e^{\mu_{K_i,s}-\zeta_{K_i}\alpha_{i,n}}}{1+\ e^{\mu_{K_i,s}-\zeta_{K_i}\alpha_{i,n}}} - \frac{e^{\mu_{K_i,s-1}-\zeta_{K_i}\alpha_{i,n}}}{1+\ e^{\mu_{K_i,s-1}-\zeta_{K_i}\alpha_{i,n}}} \right) \tag{3}$$

where λ is a dummy variable which takes value 1 when the value for the indicator equals s, and 0 otherwise.

Continuous indicators
The threshold for an attribute *d* and respondent *n*, $I_{Td,n}$, can also be used as an indicator for *latent consideration*. Assuming the indicator takes the form of a continuous variable, it can be modelled by the following measurement equation (4):

$$I_{Td,n} = \ \theta_{Td} + \zeta_{Td}\alpha_{i,n} + \eta_{Td,n} \tag{4}$$

where θ_{Td} is a constant, $\alpha_{i,n}$ is the *latent consideration*, ζ_{Td} measures its impact on the value of the threshold, and $\eta_{Td,n}$ is the error term, which follows a zero-mean normal density and standard deviation of $\sigma_{I_{Td}}$. By centering the indicators on zero, i.e. subtracting the sample mean from each indicator, we obviate the need to estimate the constant θ_{Td} .
The likelihood for observing a particular threshold is given by the normal density function (5):

$$L_{I_{Td,n}} = \frac{1}{\sqrt{2\pi\sigma_{I_{Td,n}}{}^2}}\ e^{-\frac{(I_{Td,n}-(\theta_{Td}+\zeta_{Td}\alpha_{i,n}))^2}{\sigma_{I_{Td,n}}{}^2}} \tag{5}$$

Binary indicators
Stated consideration for alternative *i*, respondent *n*, and choice situation *t*, $I_{C_i,n,t}$, is our third candidate indicator for *latent consideration*. This is a binary variable, and probability of consideration takes the form of a binary logit (6):

$$P_{C_i,n,t}\left(I_{C_i,n,t}|\alpha_{i,n}\right) = \frac{e^{\theta_{C_i}+\zeta_{C_i}\alpha_{i,n}+\nu_{C_i,n,t}}}{1+e^{\theta_{C_i}+\zeta_{C_i}\alpha_{i,n}+\nu_{C_i,n,t}}} \quad (6)$$

where θ_{C_i} is a constant, $\alpha_{i,n}$ is the *latent consideration*, ζ_{C_i} measures its impact on the value of stated consideration, and $\nu_{C_i,n,t}$ is the error term. Although indicators for stated consideration are collected at the choice-level, we decided to model them using *latent consideration* specified at the respondent level, with choice specific measurement equations, to make them comparable with the other two sets of indicators. The likelihood function for this part of the model is (7):

$$L_{I_{C_i,n,t}} = \lambda_{\left(I_{C_i,n,t}=0\right)}\left(1 - P_{C_i,n,t}\left(I_{C_i,n,t}|\alpha_{i,n}\right)\right) + \lambda_{(I_{C_i,n,t}=1)}P_{C_i,n,t}\left(I_{C_i,n,t}|\ \alpha_{i,n}\right) \quad (7)$$

where λ is a dummy variable which takes a value of 1 when the alternative is stated to be considered, and 0 otherwise.

Choice model

The mode choice model uses a random utility specification, where the utility of alternative *i*, for respondent *n* in choice occasion *t* depends on both observable explanatory variables and *latent consideration* (8):

$$U_{i,n,t} = \varsigma_{i,n} + \beta_i X_{i,n,t} + \omega_i Z_n + \tau_{Ci}\log\left(a^*{}_{i,n}\right) + \varepsilon_{i,n,t}\ , \quad (8)$$

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 β_i, and Z_n is a vector of socio-demographic characteristics of respondent *n* whoseimpact on utility (which differs across alternatives) is measured by ω_i. $a^*{}_{i,n}$ is the transformed *latent consideration* variable (which has been bounded between 0 and 1 through a logit transformation to enable the use of a log-transform (9)), and its impact on utility is measured by τ_{Ci}. Finally, $\varepsilon_{i,n,t}$ is the typical type I extreme value error term.

$$a^*{}_{Ci,n} = \frac{1}{(1+\exp(-\alpha_{Ci,n}))} \quad (9)$$

According to the proposed formulation, when $a^*{}_{i,n}$ is closer to 0, the utility will be heavily discounted, since $\log(a^*{}_{i,n}) \to -\infty$ as $a^*{}_{i,n} \to 0$, and the alternative will be also given lower choice probability. When the alternative is very likely to be considered, and therefore $a^*{}_{i,n}$ approaches 1, no discounting of utility is enforced. A similar utility-discounting approach has been used by Cascetta and Papola (*34*) and Martinez et al. (*35*).

We specify a Mixed Multinomial Logit (MMNL) choice model introducing random alternative-specific constants for all but one alternative, $\varsigma_{i,n}$, with mean μ_{ς_i} and standard deviation σ_{ς_i}, such that $\varsigma_{i,n} = \mu_{\varsigma_i} + \sigma_{\varsigma_i}\xi_{i,n}$, where $\xi_{i,n}$follows a standard normal distribution over respondents. The choice probability of the sequence of choices for individual *n* is then defined by (10):

$$P_{i,n}\left(Y_{i,n}|\ a^*{}_{i,n}, X_{i,n,t}, Z_n\ , \varsigma_n\right) = \int_{\varsigma_n}\prod_{t=1}^{T}\frac{e^{U_{i,n,t}}}{\sum_{j\in C_n}e^{U_{j,n,t}}}\ f\left(\varsigma_n|\mu_\varsigma, \sigma_\varsigma\right)d\varsigma_n \quad (10)$$

where $Y_{i,n}$is the vector of *stated choices*, C_n is the set of available alternatives, and t represents the sequence of observations.

Assuming that the first set of indicators (ordinal) is used, the final LL function for the proposed ICLV model is given by (11):

$$LL = \sum_{n=1}^{N} \ln\left[\left(\int_{a^*{}_{i,n}} \int_{\varsigma_n} \prod_{t=1}^{T} \left(P_{n,t}\left(Y_{n,t}|a^*{}_{i,n}, X_{n,t}, Z_n, \varsigma_n\right) P_{K_i,n}\left(I_{K_i,n}|\alpha_{i,n}\right)\right) \mathrm{f}\left(\varsigma_n|\mu_\varsigma, \sigma_\varsigma\right) \mathrm{g}\left(\alpha_{i,n}\middle|Z_{Ci,n}\right) d\varsigma_n da^*{}_{i,n}\right)\right] \quad (11)$$

The repeated choice nature of the data is taken into account through the use of a panel MMNL and the estimation of robust standard errors (cf. *36*). The models are all estimated using maximum simulated likelihood and 500 Modified Latin Hypercube Sampling draws (*37*).

RESULTS AND DISCUSSION

We account for *latent consideration* for the public transport alternative in the case of airport access mode choice for Bari airport. We assume that this alternative is not 'fully' considered by our sample of air travellers. This might be due to possible negative judgements about its reliability, safety concerns, lack of convenience (with respect to the departure location), or comfort, since it involves at least one change. Other modes are assumed to be fully considered.

The choices from the revealed (i.e. the access mode used by the respondents during their last trip to the airport) and stated preference data have been jointly estimated. Table 2 presents the results for five alternative model specifications. Model 1 is a MMNL model where all alternatives are fully considered, representing standard practice in the mode choice literature. In the following columns we report the estimation results for the proposed ICLV models, where the indicators vary across models. We first use responses to perception statements and a preference-based ranking of the alternatives (Model 2), followed by an inferred travel time threshold (Model 3), and finally stated consideration (Model 4) as indicators for latent consideration, respectively. Model 5 is a reduced-form MMNL model of the ICLV models in which we do not make use of any indicators. This latter model still includes the discounting factor (unlike Model 1), which is defined as a function of the same observed explanatory variable used in the structural equation for *latent consideration* in Models 2-4. The estimation of this reduced-form model is consistent with the discussion on the role of latent variables in Vij and Walker (*30*), and it aims at unveiling the actual benefits of using the indicators.

TABLE 2 Estimation results

	Model 1		Model 2		Model 3		Model 4[a]		Model 5	
STRUCTURAL MODEL	Est.	t-stat(0)	Est.	t-stat(0)	Est.	t-stat(0)	Est.	t-stat(0)	Est.	t-stat(0)
γ Student			0.204	3.95	0.213	3.13	*(0.217)*	*(3.40)*	0.368	2.33
MEASUREMENT MODEL										
Preference Ranking										
ζ Latent Consideration PT			1.909	5.55						
μ1 Threshold Ranking			-1.125	-6.84						
μ2 Threshold Ranking			1.419	7.84						
μ3 Threshold Ranking			3.030	9.51						
Perception Statement Frequency										
ζ Latent Consideration PT			1.094	8.28						
μ1 Threshold Statement Frequency			-1.773	-13.61						
μ2 Threshold Statement Frequency			-0.261	-2.84						
μ3 Threshold Statement Frequency			0.990	9.71						
μ4 Threshold Statement Frequency			3.665	16.02						
Perception Statement Reliability										
ζ Latent Consideration PT			0.191	2.19						
μ1 Threshold Statement Reliability			-3.662	-15.83						
μ2 Threshold Statement Reliability			-2.037	-17.85						
μ3 Threshold Statement Reliability			-1.180	-13.71						
μ4 Threshold Statement Reliability			0.817	10.06						
Travel Time Threshold										
ζ Latent Consideration PT					3.018	7.42				
σ Travel Time Threshold					4.952	15.24				
Stated Consideration										
ζ Latent Consideration PT							*(2.795)*	*(11.63)*		
θ Stated Cconsideration PT							*(0.787)*	*(4.19)*		
CHOICE MODEL										
ASC PT	-2.096	-5.57	-0.887	-2.99	-0.858	-2.98	-1.142	-3.60	-1.221	-3.76
ASC Direct Bus	-1.146	-3.08	-0.681	-2.03	-0.721	-2.17	-0.758	-2.25	-0.734	-2.18
ASC Car Driver	-1.168	-3.73	-0.845	-2.97	-0.890	-3.12	-0.938	-3.27	-0.921	-3.27
ASC Taxi	-1.758	-3.41	-1.340	-2.90	-1.272	-2.84	-1.334	-2.97	-1.346	-2.95
ASC PT, sd	0.822	10.33	0.602	8.61	0.566	8.40	0.637	8.55	0.662	8.90
ASC Direct Bus, sd	0.977	9.50	-0.900	-9.16	-0.888	-9.01	-0.904	-9.23	-0.905	-9.07
ASC Car Driver, sd	-1.150	-11.33	-1.013	-10.82	-1.022	-10.77	-1.037	-10.97	-1.022	-11.02
ASC Taxi, sd	-1.455	-7.63	1.287	7.38	1.316	7.52	1.310	7.84	-1.276	-8.74
β In-Vehicle Travel Time PT	-0.011	-5.17	-0.009	-4.48	-0.009	-4.53	-0.009	-4.51	-0.009	-4.52
β In-Vehicle Travel Time Direct Bus	-0.018	-3.51	-0.016	-3.49	-0.015	-3.46	-0.016	-3.61	-0.017	-3.64
β In-Vehicle Travel Time Car Driver	-0.017	-4.15	-0.013	-3.57	-0.013	-3.48	-0.014	-3.65	-0.014	-3.75
β In-Vehicle Travel Time Car Passenger	-0.033	-7.12	-0.025	-6.11	-0.025	-6.25	-0.026	-6.37	-0.026	-6.40

β In-Vehicle Travel Time Taxi	-0.037	-4.12	-0.030	-3.78	-0.033	-3.93	-0.034	-4.11	-0.033	-3.97
β Out-Vehicle Travel Time PT	-0.017	-5.94	-0.014	-5.24	-0.014	-5.22	-0.015	-5.29	-0.015	-5.35
β Headway time	-0.009	-8.71	-0.008	-8.12	-0.008	-8.10	-0.008	-8.17	-0.008	-8.16
β Travel Cost, income yes	-0.080	-11.25	-0.074	-11.39	-0.074	-11.25	-0.074	-11.35	-0.073	-11.31
β Travel Cost, income na	-0.090	-7.95	-0.081	-7.98	-0.083	-7.82	-0.082	-7.86	-0.081	-8.14
β Income Elasticity (Travel Cost)	-0.077	-2.97	-0.063	-2.51	-0.057	-2.23	-0.064	-2.56	-0.062	-2.36
β Travel cost paid employer (multiplier)	0.765	1.49[b]	0.753	-1.78[b]	0.776	-1.61[b]	0.766	-1.64[b]	0.772	-1.64[b]
scale SP	2.152	10.78[b]	2.422	10.24[b]	2.411	10.01[b]	2.399	10.29[b]	2.428	10.42[b]
β Female (Car Driver)	-0.526	-4.42	-0.467	-4.30	-0.456	-4.16	-0.473	-4.26	-0.467	-4.35
β Change Ruvo	0.595	4.89	0.389	3.71	0.605	5.03	0.518	4.65	0.498	4.56
β Business Trip (PT)	-0.211	-1.84	-0.093	-0.94	-0.105	-0.93	-0.142	-1.33	-0.124	-1.22
τ Latent Consideration PT			2.235	8.53	2.483	8.47	1.811	5.76	1.575	4.64
LL(0)	-6630.290		-10070.35		-24969.170		-6630.290 *(-1063.288)*		-6630.290	
LL(final, complete model)	-4676.765		-7595.827		-7003.418		-4660.365 *(-791.121)*		-4662.519	
LL(final, choice model only)	-4676.765		-4662.557		-4663.984		-4660.365 *(-791.121)*		-4662.519	

Note: a) The structural and measurement models in Model 4 have been estimated separately from the choice model, on a sub-sample of 307 respondents. The estimated parameters and the LL values for these models are in parenthesis; the γ parameter in the structural model has been fixed in the choice model, which has been estimated on the full sample of 746 respondents; b) t-stat against 1.

In Model 1, the estimates for the normally distributed alternative-specific constants (ASCs) reveal a strong preference for the car passenger alternative (chosen as reference alternative) over all other alternatives, particularly public transport. Standard deviations, which reflect the degree of heterogeneity for the ASCs, are all significant.

Alternative-specific in-vehicle travel time coefficients show the right (negative) sign and are all statistically significant. Similarly, parameters for the out-of-vehicle travel time (which only refers to the public transport alternative) and for the headway time (which refers to both the public transport and the private direct bus alternatives) also show the right (negative) sign and are statistically significant.

Travel cost has been interacted with income in a non-linear way, and we estimated the respective income elasticity. Not all respondents disclosed their income; therefore, we estimated two coefficients for travel cost, one for those who reported this information ('*Travel cost, income yes'*), and one for those who did not ('*Travel cost, income na'*). Both travel cost coefficients have the expected (negative) sign and are statistically significant, where the negative, and significant value for the income elasticity implies that the (absolute) sensitivity to travel cost decreases with increases in income. Respondents whose trip was paid by the employer show a lower sensitivity to travel cost, although the '*Travel cost paid employer*' coefficient - estimated as a multiplier of the overall travel cost coefficient - is not statically different from unity in this model.

Travellers on a business trip are less likely to choose public transport, while female respondents show a negative preference for the car driver alternative. '*Change Ruvo*' accounts for fact that public transport trips to/from Corato (i.e. one of the four cities under investigation) requested a more convenient transfer in Ruvo railway station rather than in Bari Central railway station.

Finally, given that we employed both RP and SP data, we also estimated a scale parameter for the SP observations to allow for difference in the variance of the error terms between SP and RP. The utility function can be re-written as (12):

$$U_{i,n,t}{}^{*} = \left(RP_{dummy} + scale_{SP} * \left(1 - RP_{dummy}\right)\right) * U_{i,n,t} \qquad (12)$$

Where RP_{dummy} equals 1 for RP observations, and 0 otherwise (i.e. for SP observations). As expected, the scale parameter for SP is greater and statically different from one (which is the RP case).

We now move towards the discussion of the results of Models 2-4, where *latent consideration* for public transport has been included in the utility. These are all ICLV models which differ by the indicators used to measure consideration. As discussed in Section 3, three separate components can be identified in an ICLV model, the structural, the measurement, and the choice sub-models. The three components have been estimated simultaneously in Models 2 and 3, and sequentially in Model 4, since the indicators for stated consideration were available only for approximately 40% of respondents.

In the structural sub-models for Models 2-4, we parametrised the *latent consideration* as a function of a dummy variable taking the value of one if the respondent was a student, and zero otherwise. Consistent with our expectation, the γ parameters (see Equation 1) indicates that the *latent consideration* for the public transport alternative is higher for students.

In Model 2, three distinct measurement sub-models have been estimated, given that three indicators have been used, namely the preference-based ranking, and answers to two perception statements related to frequency and reliability for public transport. Preference ranking was re-scaled on a 4-points scale, since the direct private bus alternative was not available for all routes. Therefore, for this indicators, we only estimated three thresholds (see Equation 2). In Model 4, the positive θ parameter (see Equation 6) reflects the fact that the stated consideration rates for public transport were larger than 50% in the sub-sample. The response-order for the preference ranking has been shifted, such that the general

assumption in all cases is that more positive responses to the indicators are observed when *latent consideration* increases. As expected, the ζ parameters are all positive.

In the choice sub-models for Models 2-4, the τ parameters measure the marginal impact of *latent consideration* on the utility for the public transport alternative, which is found in all cases to be statistically significant. This implies that a value for the *latent consideration* closer to unity (zero) would lead to higher (lower) utility for this alternative. We also observe that the parameters accounting for the likelihood of choosing public transport for respondents on a business trip is no longer significant. This might indicate a possible (negative) correlation with the γ parameters in the structural models, since students are less likely to travel for business purposes.

Model 5 is the reduced-form MMNL model of Models 2-4. In this model we do not estimate any measurement models since we do not make use of any indicators. The latent construct now only explains choices, and, as a result of this, we observe a larger standard error for the γ parameter (structural model) compared to Models 2-4, i.e. there is an efficiency loss.

Interestingly, all parameters in Models 2-5 (except for '*scale SP*') are reduced in size with respect to Model 1 (where we do not introduce the log-discounting factor). The estimated Value of Travel Time (VTT) indicators are also lower than - although not statistically different from - those obtained for Model 1 (Table 3).

TABLE 3 VTT (€/hour)

	Model 1	**Model 2**		**Model 3**		**Model 4**		**Model 5**	
	Est.	*Est.*	*Change (%)*	*Est.*	*Change (%)*	*Est.*	*Change (%)*	*Est.*	*Change (%)*
Public Transport	8.6	7.2	-16%	7.1	-17%	7.3	-15%	7.4	-14%
Direct Private Bus	13.2	12.8	-3%	12.5	-5%	13.3	1%	13.7	4%
Car Driver	12.8	10.9	-15%	10.5	-18%	11.2	-13%	11.4	-11%
Car Passenger	24.4	20.0	-18%	20.0	-18%	21.3	-13%	21.4	-12%
Taxi	27.5	24.8	-10%	26.6	-4%	27.4	-1%	26.6	-3%

Note: VTT indicators for an individual whose trip was not paid by employer.

Forecasted aggregate market shares are represented in Figure 2. In line with our expectations, in a *status quo* scenario (i.e. applying the model to the attribute levels faced by the respondents) models 2-5 predict a slightly lower market share for public transport with respect to Model 1. However, those differences appear negligible. More pronounced differences in forecasts between Model 1 and Models 2-5 can be observed when instead looking at the effect of a reduction in headway time by 30% for the public transport alternative (Scenario 1). For example, Model 1 predicts a larger increase over the *status quo* for the public transport alternative (+18.2%) and a larger decrease for the other alternatives (e.g. -8.2% for *Car passenger*) with respect to Models 2 (+7.5% and -3.2%, respectively). A similar pattern is observed when we reduce travel time for the public transport by 30% (Scenario 2). This means that a more traditional MMNL model - which assumes that public transport is considered by everyone in the sample - might overestimate the gains of policy actions aimed at improving modal share for this alternative.

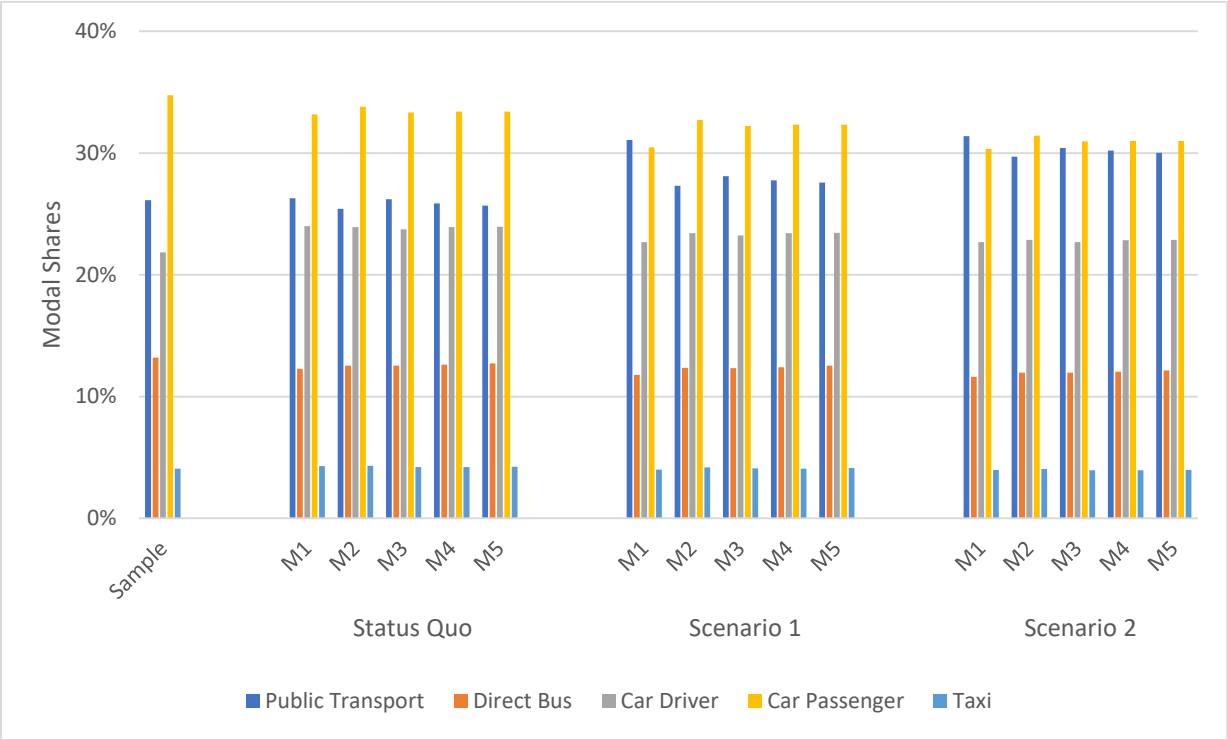

FIGURE 2 Forecasted aggregate market shares

Turning our attention to model fit, we acknowledge that the final Log-Likelihood across Models 1-5 cannot be compared, given that in Models 2 and 3 we actually estimate a joint Likelihood function for the (revealed and stated) choices and for the indicators. It is however possible to derive final Log-Likelihood measures for the choice model components separately from the other components. A comparison of these measures reveals that Models 2-4 outperform Model 1, i.e. the more conventional approach where all alternatives are assumed to be 'fully' considered. However, as suggested by Vij and Walker (30) such improvement in fit cannot be completely ascribed to the use of the indicators, given that it could be also attained by a properly specified reduced-form MMNL model (Model 5).

VALIDATION EXERCISE

Model validation on a different sample allows for a more rigorous comparison with respect to final Log-Likelihood measures, ensuring that the estimation results are not due to overfitting. As previously mentioned, we decided to estimate the models using the data collected in 2017 (richer in terms of supplementary information used to measure consideration) and to keep the data collected in 2016 for validation purposes. Indeed, the use of the ICLV approach allows for latent consideration to be directly predicted from the structural equation without relying on the availability of the indicators in the validation sample.

TABLE 4 Probability For The Chosen Alternative In The Validation Sample

	Model 1	Model 2		Model 3		Model 4		Model 5	
RP+SP	25.2%	25.6%	+0.4	25.7%	+0.5	25.6%	+0.4	25.5%	+0.3
Only RP	25.8%	27.6%	+1.8	28.0%	+2.2	27.5%	+1.7	27.0%	+1.2

The average probability for the chosen alternative is used as measure of fit on the validation sample. As we can see from Table 4, the ICLV models (Models 2-4) produce slightly better predictions with respect to both their reduced-form MMNL (Model 5) and the more traditional MMNL model (Model 1) form. Such an improvement is however almost negligible when using both RP and SP observations, meaning that *latent consideration* brings little additional correlation when multiple observations for each respondent are available. Nevertheless, when only RP observations are used we observe a more substantial increase in the probability for the chosen alternative up to 2.2 percentage points.

CONCLUSION

The challenge with consideration of alternatives is that this aspect of an individual's decision-making process is unobservable. When the only information available is that on the final outcome of the process, i.e. the choices individuals make, it is impossible to separately identify what drives 'consideration' and what drives 'choice'.

Supplementary information on aspects related to consideration can be collected during SC experiments; however, the direct use of such indicators as error-free explanatory variables in the estimation of discrete choice models is highly discouraged due to potential measurement errors (given that these are only indirect measures of consideration), endogeneity bias (since the answers could be correlated with factors included in the random part of utility of the choice model), and unsuitability of the resulting model for forecasting.

In this paper we overcome these drawbacks by treating indicators for consideration as dependent rather than independent variables, and modelling these together with choice within an ICLV framework. *Latent consideration*, rather than the indicators, enters the utility of an alternative through a 'discounting' factor, which effectively accounts for consideration lowering the utility, and therefore choice probability of that alternative.

The proposed approach is tested in the context of airport access mode decisions for journeys to Bari International Airport, in Italy, using data from a SC experiment on a sample of air travellers resident within the catchment area of the airport. For those travellers, a public transport alternative is always available; however, differently from the other available alternatives which are all direct, public transport involves at least one change, the timetables for the connecting services are not coordinated, and services have, in general, limited frequency. For these reasons, we here assume that this alternative might not be always considered as a 'feasible'. Three sets of supplementary information directly or indirectly related to consideration of public transport have been collected during the SC experiment, which are tested as potential indicators for *latent consideration* of this alternative.

Our results suggest that *latent consideration* has a significant (and positive) marginal effect on the overall utility of public transport; this means that the utility for those respondents with predicted lower levels of *latent consideration* gets highly discounted, and their choice probability for this alternative approaches zero. However, since we also use revealed preferences data in the estimation, it is possible that, for those observations, a share of what we identify as the effect of *latent consideration* might also capture unawareness or unavailability effects.

We additionally observe a decrease in the size of the estimates for key parameters (travel time, travel cost, headway time) relative to a more traditional MMNL model which assumes that all alternatives are considered; in turn, this affects willingness-to-pay indicators and most importantly forecasts for aggregate market shares. Emblematic is the case of headway time. If this is reduced by 30% for public transport, a traditional MMNL would predict an increase in the modal share for this mode by 18.2%, while the proposed models accounting for consideration would still predict an increase, but only by 7.5%. This result would suggest that not accounting for consideration of the alternatives might have serious implications in predicting the effect of planned or expected changes in the airport ground transportation system such as the introduction or removal of a key access mode, or a change in the quality of its services. Of course, given that the true data generating process is unknown, it is impossible to identify the size and direction of a 'possible' bias. All that we can observe is the difference with a more traditional MMNL model.

In general, accounting for consideration of public transport seems to provide a more realistic representation of airport access mode decisions with respect to a more traditional MMNL model, where all alternatives are assumed to be considered: this is shown through an improvement in model fit which also holds on a separate validation sample. However, consistent with the discussion in Vij and Walker (*30*), we acknowledge that this improvement cannot be completely ascribed to the use of the indicators, since a properly specified reduced-form MMNL model is able to attain very similar results. Nevertheless, the availability of indicators - similar to those used in this paper, which can be easily included when designing an air passenger survey - allows us to identify the structural drivers of consideration, in this particular case that students are more likely to consider public transport as a feasible access mode.

As with any paper, there are many areas for future research. This includes testing whether the consideration for public transport alternatives varies by time of day (for example becoming less likely in the early mornings and late evenings) as well as better understanding the drivers of consideration in general, e.g. for example as a result of luggage, who people were travelling with, etc.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Capurso, M., Dekker, T., Hess, S.; data collection: Bergantino, A.S., Capurso, M.; analysis and interpretation of results: Capurso, M, Dekker, T., Hess, S.; draft manuscript preparation: Capurso, M., Dekker, T., Hess, S. All authors reviewed the results and approved the final version of the manuscript.

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