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Accounting for attitudes and perceptions influencing users' willingness to purchase Electric Vehicles through a Hybrid Choice Modeling approach based on Analytic Hierarchy Process

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Abstract

Depending on the context, several factors may affect users' choices. In this paper, the main focus refers to modeling users' willingness to purchase a new/innovative technology. This is a crucial task in order to increase the attractiveness of strategies that may be employed to achieve sustainable transportation. In particular this paper aims to investigate the different attributes/determinants that may influence the decision on choosing an Electric Vehicle. As a matter of fact, psychological factors, may play a significant role which should be modeled. Indeed, it is widely recognized that traditional approaches used to interpret and model users' choice behavior may lead to neglect the numerous non-quantitative factors that may affect users' behaviors. In particular, the role of attitudes and perception towards EVs advantages/barriers were investigated through the specification of a Hybrid Choice Model where the utility function was specified in accordance with the consolidated Random utility modeling but an alternative approach, based on the Analytic Hierarchy Process, was adopted for attitudes and perceptions representation. The purposes of the paper rely on (i) the survey data collection, (ii) data analysis, (iii) purchase behavior modeling. In particular, the main contribution of the paper is in the preliminary investigation of the combination between HCM and AHP method.

Keywords: Hybrid Choice Models; Latent Variables; Analityc Hierarchy Process; Stated Preference

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1. Introduction and motivation

The gradual penetration of new transport modes and/or new technologies (advanced information systems, automotive technologies, etc...) requires effective theoretical paradigms able to interpret and model transportation system users' propensity to purchase and use them. Along with the traditional approaches mainly based on Random Utility Theory (RUT), it is a common opinion that numerous non-quantitative variables (such as psychological factors, attitudes, perceptions etc.) may affect users' behaviors. Indeed, RUT formulations usually focus on observable quantities and neglect the role of not directly observable psychological determinants (such as, for example, emotions, attitudes or perceptions). For these reasons, some recent research developments have focused on the detection of non-observable quantities and on their representation within utility functions. To this aim several contributions in the literature focused on the advanced development of Hybrid Choice Models (HCMs) in which non-observable factors are analytically represented in terms of Latent Variables (LVs) and then incorporated in the utility function, Walker (2001). However, a further analyst's effort is required in order to grasp users' preferences useful for LVs' specification and estimation. Indeed, HCMs are based on three main equations: 1) the utility function which is specified through socioeconomic attributes, level of service attributes and LVs; 2) the structural equations representing the LVs specifications and described through socioeconomic attributes and some specific variables which are the perception indicators; 3) the measurement equations able to represent the perception indicators which are specified trough LVs. It can be observed that each LV may be specified through several perception indicators. Regarding perception indicators these are based on some specific statements consistently with the psychological approach; therefore each LV may be described through a set of some statements indirectly able to grasp non-observable behaviors of users. In general users' preferences with respect to perception indicators may be collected through the Likert scale. In this case with respect to each statement the user may express an absolute judgement measured through an ordinal scale. In this context the main research contribution is to estimate LVs through indicators that do not result directly from an absolute judgement expressed by users, but rather from a measurement process as in case of Analytic Hierarchy Process methodology (AHP). Indeed, AHP approach is based on pair comparisons from which some weights may be obtained; these weights may be adopted as preferences suitable for the measurement equations calibration. The paper motivation is twofold: the first one is related to the interpretation of choice process the second one is operational. Regarding the interpretative aspect, it is necessary to investigate if the observations collected through the AHP survey can lead to better represent the users' latent behavior actually affecting the final choice. On the other hand, the operative aspect of the modeling is linked to the nature of the indicators used to estimate latent variables. It is worth noting, in particular, that surveys designed using Likert scales lead to the collection of discrete measurements, which can be modeled either with regressive models or more appropriately with ordered models; however, since the estimation of the latter is more complex, it is therefore more advisable to adopt models of the regressive type. The innovative contribution of this work is related to the fact that the regressive models would be compatible with the use of weights, obtained from the analysis of pair comparisons as proposed by the AHP method, as measurement indicators. The reminder of the paper is organized as follows: a brief description of the methodological framework is provided in section 2, an overview of the case study and preliminary estimations results is shown in section 3, finally conclusions and main remarks are summarized in section 4.

2. Methodological framework

2.1. Introduction

This work aims to combine two approaches: the HCM based on LVs and the AHP methodology. This section provides a detailed description of each of the two methods.

2.2. Hybrid choice models: Latent variables approach

In the case of HCM it is assumed that preferences are influenced not only by measurable attributes, but also by psychological factors such as perceptions and attitudes, which, in turn, are non-observable. However, in order to estimate these latent influences in a mathematical model, it is necessary to have their measures. In particular to detect these latent psychological factors, the "psychometric indicators" represented through psychological statements are introduced. In general, it may be argued that a specific survey is required. As previously anticipated in the introduction an HCM consists of two parts: a Discrete Choice Model and a Latent Variable Model (LVM), each of which includes one or more structural equations, which provide the relationship between the latent variable and the measurable factors (explanatory variables), and one or more measurement equations that link non-observable determinants to its observable indicators. By simultaneously integrating discrete choice and latent variable models, the latent variables can be treated as explanatory variables in the utility functions of choice alternatives. Structural equations link latent variables to directly observable explanatory variables, while measurement equations link latent variables to some observable indicators. The utility choice function in the hybrid choice model is based on the assumption that each individual is faced with a set of alternatives i, and each alternative expressed as a function of a vector of observed instrumental attributes, Xi, the users' attributes, $X_{i,SE}$, a vector of latent variables, LV_i, and the error term ε_i, by deLuca et al. (2018):

$$U^i = \beta_x X^i + \beta_{SE} X^i_{SE} + \beta_{LV} LV^i + \varepsilon^i \tag{1}$$

With reference to the LV^i vector, two equations have to be specified: the structural and the measurement equations. The structural equations are introduced in order to specify the latent variables, whilst the measurement equations are introduced in order to specify the perception indicators. In particular, if p is the generic latent variable, the structural equation for each latent variable may be expressed as follows:

$$LV^i_p = \gamma_p + \sum\nolimits_j \beta_{SE,j} X^i_{SE,j} + \omega^i_p \tag{2}$$

where: γ_p, is the intersect, $X^i_{SE,j}$ is the vector of the users' characteristics attributes, $\beta_{SE,j}$ is the vector of the coefficients associated with the users' characteristics (to be estimated), ω^i_p is the error term which is usually normally distributed with zero mean and $\sigma_{\omega,p}$ standard deviation. Furthermore, let I^i_n be a vector of perceptions indicators associated to each latent variable. Each perception indicator (i.e. vector component) may be specified by a measurement equation as follows:

$$I^i_{p,k} = \alpha_{p,k} + \lambda_{p,k} LV^i_p + \nu^i_{p,k} \tag{3}$$

where $\alpha_{p,k}$ is the intersect, $\lambda_{p,k}$ is the coefficient associated with the latent variable (to be estimated), $\nu^i_{p,k}$ is the error terms usually assumed normally distributed with zero mean and σ_{vpk} standard deviation of the error term. The psychometric indicators that reveal the latent variables may be coded using a Likert scale. These indicators can be considered to be a linear continuous expression of the LVs or an ordered discrete variable. The first approach has been historically chosen because simpler and more practical with a lower computational cost. However, assuming these indicators as continuous variables is in contrast with the real nature of the Likert scale, (the Likert scale is a discrete measure) such an approach may introduce some biases in the parameters' estimation. In recent years, several studies have treated them as discrete variables, but with a higher computational cost. In particular, if the measurement is represented by an ordered discrete variable J taking the values $j_1, j_2, \dots, j_M$, we have, by Bierlaire (2016) :

$$J = \{ j_1 \quad if\ I < \tau_1;\ j_2 \quad if\ \tau_1 \le I < \tau_2\ ;\ j_i \quad if\ \tau_{i-1} \le I < \tau_i;\ j_M \quad if\ \tau_{M-1} \le I \quad \}$$

Where I is defined by the measurement equation (2), and $\tau_1, \dots, \tau_{M-1}$ are parameters to be estimated, such that

$$\tau_1 \le \tau_2 \le \dots \le \tau_i \le \dots \le \tau_{M-1} \tag{4}$$

If the measurements use a Likert scale with M= 5 levels, 4 parameters τ_i are needed. But, in order to account for the symmetry of the indicators, two positive parameters δ_1 and δ_2 are specified instead, in order to define:

$$\tau_1 = -\delta_1 - \delta_2; \tau_2 = -\delta_1; \tau_3 = \delta_1; \tau_4 = \delta_1 + \delta_2 \tag{5}$$

Then, the probability of a given response j_i is given by the ordered Probit model. Now, let us focus again on the measurement equations that relate the generic indicator, $I^i_{p,k}$, to the latent variables. In particular, if the indicators are continuous, their representation through a regressive equation would not introduce any kind of bias in the parameters estimation; consequently, rather than introducing approximations to simplify a computational problem, we may think of achieving such a solution by changing the nature of the adopted indicators, from discrete to continuous. The main research contribution is about the use of continuous indicators, not yet investigated, to the author knowledge in the literature. This indicator may be represented through a regressive expression, as already discussed above (2). Therefore, this indicator is given by the weight attributed by each user to different criteria analyzed, in accordance with what is proposed by AHP approach. When continuous indicators are used, the probability of observing them depends on their density function, f_2, which in turn results, by Bolduc et al. (2008):

$$f(I_r) = \frac{1}{\theta_\epsilon}\phi\left(\frac{I_r - \overline{I_r} - Z_i}{\theta_\epsilon}\right) \tag{6}$$

where ϕ is the probability density function of a standard normal.

2.3. Analytic Hierarchy Process

The AHP is a multi-criteria decision support technique developed by Saaty (1970) suitable in case of decisional contexts. In general the problem may be subdivided in sub-problems starting from the bottom of the hierarchy aiming to identify: i) the alternatives; ii) the criteria and sub-criteria; iii) the goal to be achieved. The decision-maker identifies a set of criteria and sub-criteria to be used in the evaluation of competing alternatives, then he assigns a percentage weight to each criterion, followed by a score, which is the impact of the criterion on the decision. The score of each alternative is computed as the weighted average of each criterion's scores on the decision times the weight assigned to each criterion. AHP allows us to measure intangible elements through expert judgment, using indicators of preference, and this is why the outcome depends on the decision maker and on the goals that are intended to be pursued. To apply the methodology correctly, it is structured into five successive steps: i) the construction of the top-down hierarchical structure including the intermediate criteria; ii) the construction of a series of pair comparison arrays; iii) the calculation of the weights for all the criteria of the same group and definition of the relative priority vector; this operation must be repeated for all the groups; iv) the analysis of the consistency; v) the determination of global weights and a global priority vector. Following the AHP approach, the main steps to be considered are from 1 to 3. Specifically, the first and second phases are already taken into account when formulating an AHP approach survey, identifying several criteria that influence users' decisions, with particular reference to the topic under investigation, as well as several sub-criteria that influence the criterion itself. In order to assign the relative weight to each sub-criterion, it is necessary to compare in pairs the sub-criteria belonging to the same criterion. Therefore, in the survey, these elements are compared and it is asked which of them is the most important and in which measure with regard to the criterion they depend on; These pair comparisons lead to the realization of as many pairwise comparison matrices as there are criteria. In detail, each pair comparison identifies an element of the matrix, which is called "judgment of dominance". In fact, the element a_{ij} of the matrix identifies how much criterion *i* is dominant over criterion *j*. In order to obtain the a_{ij} values, in the survey the respondent is asked to refer to the "Saaty's semantic scale", which allows transforming qualitative judgments into quantitative and objective numerical judgments. This scale compares the first nine numbers with an equivalent number of judgments expressing, in qualitative terms, the possible results of the comparison (Ji and Jiang, 2003). The coefficients generally used are odd ones; intermediate values are rarely allowed when a compromise is required. The smallest element is the unit, so through semantics of the Saaty scale, we evaluate how many times an element is more or less dominant, compared to the unit. It is worth noting that often in AHP surveys, respondents are asked to define a dominance coefficient giving them the possibility that both positive and negative values can be assigned; this allows a more compact realization of the survey. Since neither Saaty's Semantic Scale nor the procedure for weight calculation include these negative values, they must be converted into a positive reference value (for example, if in survey it results i vs j = -5 we are saying that the evaluation is strongly in favor of element j respect to element i; according to Saaty' s semantic scale, therefore the obtained results will be codified in a_{ij}=1/5 and in a_{ji}=5). The third phase of our interest consists in estimating the weights to be associated with each sub-criterion. Once as many pairwise comparison matrices as there are criteria have been constructed, weights are calculated in a simple way by operating on the single lines of the pairwise comparison matrix (in size n x n) in question. For each row (each of which corresponds to a sub-criterion) the weight of the relative element is obtained by multiplying the values present on the row and evaluating the n^{th} root of that product; the weights are therefore nothing more than the result of the geometric average of the values on the examined row. The same procedure is applied to all the other rows of the matrix. It is finally assumed that the sum of the sub-criteria constituting the criterion is equal to 1, for this reason, each value is normalized with respect to the sum of the weights.

3. Experiment design and preliminary estimation results

3.1. Experimental framework

In order to analyze the contribution of AHP approach in HCMs, the choice of purchasing an EV vehicle was investigated through an SP experiment (see de Luca et al., 2018). It was designed and distributed within the university campus of Fisciano. The survey resulted 318 responses. Each respondent was randomly faced with five scenarios therefore in all the number of collected observations was 1462 in the Italian survey. Even though the minimum size required for the survey was estimated around 510[†] all collected (and reliable) observations were still considered in the estimation procedure.

Table 1. Socioeconomic user's characteristics and features of the respondent's car

SOCIOECONOMIC CHARACTERISTICS	***FEATURES OF THE RESPONDENT'S CAR***
Gender	Type of fuel
Age	Brand
Municipality of residence	Annual kilometers driven
Employment status	Main use of the vehicle
Number of people in the household	Car purchased by the respondent
Quantity of cars in possess in the household	

The survey was structured in six different sections aiming to collect: (i) The users' socioeconomic characteristics and the characteristics of the household vehicle; (ii) The users' attitudes when evaluating the general characteristics of vehicles that may influence the willingness to purchase an electric vehicle; (iii) The users' attitudes when evaluating the technical features; (iv) The users' perceptions, referred to some disadvantages of electric cars that may affect in terms of importance their behaviors in purchasing new vehicles; (v) The users' perceptions, referred to some of the advantages of electric cars; (vi) The users' propensity to buy a new electric car compared to a conventional one. The first section of the survey aims to know the directly observable variables that can be included both in the specification of the utility function and in the specification of the latent variables. The ii-v sections, whereas, are aimed to grasp respondents' perceptions and attitudes. The AHP approach is therefore pursued in these sections; in fact, each of these sections identifies a criterion that influences users when purchasing an electric car and for each of these criteria several sub-criteria are identified, according to the hierarchical approach typical of the method. The criteria and their sub-criteria are shown in the table below. In the same sections, the respondents were asked to express both absolute judgments of importance attributed to each sub-criterion and preferential judgments,

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[†] The minimum sample size was preliminarily defined as in accordance with the literature (e.g. Louviere[†], et al., 2000; Hensher[†], et al., 2005;) by using following analytical expression: $n \geq \frac{q}{pa^2}\left[\Phi^{-1}\left(\frac{1+\alpha}{2}\right)\right]^2$ where p is the true proportion, q = 1-p; α, is the level of confidence (0.95); a, is the accuracy (10%); $\Phi^{-1}(.)$ is the inverse cumulative normal distribution function.

comparing in pairs all the sub-criteria. For sake of brevity the results of collected absolute and relative judgments are not shown as well as the construction of the pairwise comparison matrix and the relative calculation of weights are not shown.

Table 2. Criteria and sub-criteria covered by the survey

Criteria	**Main characteristics when buying a car**	**Technical features**	**Disadvantages of EV**	**Advantages of EV**
Sub-criteria	c_1 = Price c_2= Technical features c_3 = Pollution c_4 = Consumption c_5 = Design	sc_1=Power sc_2=Top speed sc_3= Acceleration sc_4= Fuel range	b_1= High purchase price b_2= Lack of charging points b_3= Less performance b_4= Reduced battery range	v_1= Reduction of emissions v_2= Reduced acoustic pollution v_3= Greater energy efficiency v_4= Less moving parts

The last section is structured in the form of an SP survey. In this case each respondent was faced with different scenarios set-up starting from the monthly cost of a conventional vehicle. For each scenario different monthly costs of an electric vehicle with respect to the conventional one were considered.

Table 3. Importance ranking of sub-criteria for each criterion based on absolute and preference judgments

Criterion	Sub-criteria	Average value of importance	AHP weights	Absolute judgments ranking	Preference judgments ranking
Main characteristics when buying a car	c_1 = Price	7.19	0.41	2	1
	c_2= Technical features	6.36	0.23	4	2
	c_3 = Pollution	5.23	0.13	5	4
	c_4 = Consumption	7.64	0.17	1	3
	c_5 = Design	6.42	0.06	3	5
Technical features	sc_1=Power	6.00	0.38	2	1
	sc_2=Top speed	4.93	0.18	4	3
	sc_3= Acceleration	5.23	0.15	3	4
	sc_4= Fuel range	8.05	0.28	1	2
Disadvantages of EV	b_1= High purchase price	7.35	0.42	2	1
	b_2= Lack of charging points	7.42	0.32	1	2
	b_3= Less performance	5.48	0.12	4	4
	b_4= Reduced battery range	7.08	0.15	3	3
Advantages of EV	v_1= Reduction of emissions	7.21	0.55	1	1
	v_2= Reduced acoustic pollution	6.22	0.18	2	3
	v_3= Greater energy efficiency	5.79	0.19	3	2
	v_4= Less moving parts	4.92	0.08	4	4

Therefore, five scenarios are obtained in all (i.e. equal monthly cost, +10%, +20%, +30% and +40%). In order to minimize the influence of brand, size, and even color of the vehicle on the choosing and purchasing decision, the comparison was made between both cars from the same car maker: Renault. This brand was selected because is in the top 5 in sales, moreover it offers an affordable electric vehicle, the Zoe. The alternatives were a Renault Clio and Renault Zoe. The alternatives were presented to the respondents (and compared) in terms of power, top speed, acceleration, consumption, size of the fuel deposit/batteries, and maximum driving range. A travel scenario was fixed (urban and 40 kilometers/day) and it was hypothesized that the interviewee had a sufficient budget to purchase both cars. After this survey, the results were analyzed. Particular interest was given to the results of the ii-v sections of the questionnaire. More specifically, by referring to aggregate values, it was possible to compare the ranking given to the various criteria by referring to absolute judgments and the ranking given to them by referring to preference judgments. The first importance ranking has been defined by considering the average importance attributed to each sub-criterion by all users, while the second importance ranking is nothing more than the decreasing ranking of the weights calculated for each sub-criterion in accordance with the AHP methodology. The results obtained are summarized in the table above. In particular, also in this case for sake of brevity, the weights obtained for each sub-criterion using the AHP analysis are summarized in the fourth column. It is clear that these weights are quite different one from the another, even when the absolute relevance of the judgments is very similar. It is worth noting that the same weights are the continuous values associated with each indicator in the measurement equations. On the base of displayed results it may be argued that, the importance ranking given to the sub-criteria differs according to the information available to the analyst. Although these aggregated values are not used for the practical calibration of the choice models, this analysis is a useful starting point for a reflection: it often happens that a respondent assigns the same value of importance to two or more of the examined attributes, but actually he is able to express a preference between them. In following section, the estimation results of the preliminary investigation, aiming to verify the suitability of preferential judgments rather than absolute ones, are reported.

3.2. Estimation results of a preliminary investigation

This consideration has therefore increased interest in the innovative character of this work. For this reason, we specified, calibrated and validated a HCM in which each latent variable was specified through perception indicators represented not by the absolute judgments attributed to each sub-criterion, but rather by the weight attributed to each of them. Results are shown in Table 4.

Table 4. Model results

	Choice Utility Function		
Attributes	***Description***	***Attributes Coeff. (betas)***	
		Buy	***Not buy***
ASC	*[alternative specific constant]*	*+ 3.86 (+5.58)*	
b_Gender	*[Interviewee's Gender, 0 = female; 1 = male]*		
b_Delta_age	*[Age of the respondent, values 1 to 7]*		
b_Nveh_NComp	*[Ratio between the number of vehicles and the number of people in the household]*		
b_no_comp	*[Number of people in the household]*		
b_no_familycar	*[Quantity of cars in possess in the household]*		
b_CarYes	*[Car purchased by the respondent, 1 if yes; 0 otherwise]*		*+ 0.654 (+1.59)*
b_Fuel	*[Type of fuel : 1 if the car is fueled with petrol, 0 otherwise]*		*+ 0.399 (+1.40)*
b_Diesel	*[Type of fuel : 1 if the car is fueled with diesel, 0 otherwise]*		*+ 0.647 (+2.63)*
b_TripsKind	*[Use of the vehicle: if most of the trips made are urban, 0 otherwise]*	*+ 0.274 (+1.50)*	
b_deltaCost	*[Monthly change in cost between an electric and a conventional car]*		*+ 0.114 (+18.04)*

		Structural equation		
L.V	***significant attributes***	***Description***	***Attributes coefficients***	
			buy	***Not buy***
b_Z1	Pollution Consumption	*[Latent variable representing environment attitude]*	+ 20.7 *(+ 2.83)*	
b_Z3	Less performance Reduced battery range	*[Latent variable representing perception of EV's disadvantages]*		+7.30 *(+1.43)*

STATISTICS	
Number of observations	*1462*
Rho-square	*0.61*

**in parenthesis the t – tests values*

A hybrid binomial logit model has been specified with two alternatives: "buy the electric car" (*Buy*) and "do not buy the electric car" (*Not Buy*). We considered each section of the survey representative of a certain latent variable. The identification of each of these was immediate for sections iii, iv and v of the survey because all questions were representative of the same category. Less immediate was the identification for section ii. In this case, a preliminary distinction was made between indicators that would have had a positive impact on the choice of the alternative "buy the electric car " and those that would have had a negative impact. As a result, 4 latent variables were identified, each of which is representative of a section of the survey: Z1 = Attitude towards the environment; Z2 = Passion for technical characteristics; Z3 = Perception of the disadvantages of the electric vehicle; Z4 = Perception of the advantages of the electric vehicle. Furthermore, the structural equation of each latent variable is composed by: an intercept: b_meanZ1, b_meanZ2, b_meanZ3, b_meanZ4; the error term: b_sigma_1, b_sigma_2, b_sigma_3, b_sigma_4; the explanatory variables: to this end, the socioeconomic attributes have been studied as explanatory variables. The contribution of these latent variables to discrete choice models was first studied individually, i.e. considering the HCM consisting of one LV at time, and only then the combination of several latent variables was taken into consideration. The solutions obtained were verified by performing both a sequential and a simultaneous estimation. By combining several latent variables, the statistically significant solution involved the use of only two latent variables: Z1 and Z3. Finally, it may be observed that the two latent variables contribute positively and negatively respectively to the definition of the utility function of the alternative Buy.

4. Conclusions and main remarks

The analyses carried highlighted several issues. Surely, as already mentioned, the introduction of the AHP approach allows to obtain a model simplification without any compromise; in fact, as the indicators are represented by a continuous measurement, it is possible to use a regressive specification, reducing the computing time required in the calibration step. In addition, the AHP approach, as shown, allows obtaining more accurate information about the investigated attributes than the traditional approach. At the same time with these strengths, this application has highlighted the impossibility to identify the latent variables following the traditional rigorous approach of factor analysis. However, its application can be made possible by simply appropriately introducing a section in the survey in which respondents are asked to make their judgments among the criteria investigated. This, in fact, in accordance with the AHP method itself, would make it possible to define the overall weights of the different sub-criteria with respect to the alternatives and therefore would make them all comparable, not constraining the results of the factor analysis. Despite this critical point, the calibration results of the model obtained are good enough to suggest the positive contribution that an AHP approach could make for modeling choice behavior. Further perspectives will be about a more appropriate experiment design in order to consolidate the estimation results.

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