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Chapter

Approaches for Modelling User's Acceptance of Innovative Transportation Technologies and Systems

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Abstract

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, it is a common opinion that numerous nonquantitative variables (such as psychological factors, attitudes, perceptions, etc.) may affect users' behaviors. Different traditional approaches and more advanced ones (e.g. hybrid choice model (HCM) with latent variables, theory of planned behaviour, regret theory, prospect theory, etc.) may be identified and properly applied in the literature. In particular, the chapter will focus on the hybrid choice modeling with latent variables, aiming to incorporate users' perceptions, attitudes and concerns in order to model the user's propensity to use and the willingness to buy a new technology. The methodology overview and the results of the application at real data are discussed.

Keywords: transportation technologies, transportation systems, intelligent transportation systems, user's acceptance, choice modeling

1. Introduction

The diffusion and market penetration of new technologies are becoming a crucial point for transport system analysts and decision-makers. The main issues are regarding a correct understanding of the phenomena and the simulation of different possible operational scenarios.

Among the several new technologies aiming to let the transportation system be more efficient and sustainable, two main issues continue to be challenging tasks: (a) interpreting and modeling users' behaviour towards these new technologies and (b) assessing the potential environmental impacts.

Both issues are highly correlated as, without an effective interpretation of users' behaviour, no reliable estimation of the market penetration, and/or the corresponding impacts could ever be obtained.

Within the cited context, the consumer choice theory based on the random utility theory (RUT) may be considered the more effective and practical approach

to model and forecast user's behaviour, but it is a common opinion that consolidated random utility model (RUM) formulations may lead to neglect the numerous nonquantitative factors that may affect users' perceptions and behaviors. As a matter of fact, psychological factors, such as attitudes, concerns and perceptions, may play a significant role which should be explicitly modeled. On the other hand, collecting psychological factors could be a time- and cost-consuming activity. Furthermore, real-world applications must rely on theoretical paradigms easily implementable in order to allow the estimation of users' choices in different technological scenarios.

As clearly stated in the current literature, the propensity to adopt a new technology, and, in particular, an alternative fuel vehicle (AFV), is mainly affected not only by instrumental attributes of the technology of interest (alternative) and of the competing technologies (other alternatives) and by personal attitudes (attitudes) of the consumer (user) not depending on the alternatives but also on the consumer personal feelings and on the socioeconomic context in which he/she lives. Several recent analyses have pointed out the necessity to take into account attributes considering the perceptions and the attitudes of the users. For example, see [1]. The main issues of the literature refer to:

1. How to better collect information about users' attitudes, concerns and/or perceptions; an "ad-hoc" survey aiming to "collect" attitudes/perception needs to be designed.

2. The assessment of the methodology to be pursued in accordance with the RUT [2–5], which is the richest and by far the most widely used theoretical paradigm for modeling transport-related choices and, more generally, with discrete choice modeling (i.e. models representing choices made among discrete alternatives).

Indeed, even though RUMs models usually adopted in demand modeling are suitable for the representation of the choice process, these are not applicable to represent the perceptions and attitudes [6]. The issue was addressed in the literature through the hybrid choice models (HCM) [7–11] based on attitude investigations trying to infer the role of psychological factors with latent variables within a discrete choice modeling framework.

In particular, several studies aiming to overstep the boundary of RUMs have been conducted by Ortúzar and Hutt [12] and by McFadden [13], which around the 1980s investigated the possibility to include subjective variables in a discrete choice modeling. Starting from the approach proposed by Jöreskog [14] focusing on the investigation between latent variables and the measurement of the perception indicators, several researchers contributed to the assessment of the methodological framework of hybrid choice models (e.g. see [15–17]).

The book chapter is organized as follows: Section 2 focuses on modeling overview, while Section 3 focuses on survey design; the quantitative preliminary analyses and the model specification are, respectively, discussed in Sections 4 and 5. The corresponding results of two case studies are displayed and discussed in Sections 2 to 5.

2. Conceptual overview

The HCM based on RUT is a discrete choice model which integrates and simultaneously estimates different types of sub-models into a unique structure. If the

HCM includes a latent variable model, it is possible to take into account the effects of users' latent attitudes, perceptions and concerns (i.e. integrated choice and latent variable (ICLV) model).

Adopting the standardized notation for path analysis, **Figure 1** introduces the general structure of an ICLV and allows to comprehend the different sub-models that define an ICLV: the latent variable model and the discrete choice model. In particular, the ellipses represent the unobservable (latent) variables, the rectangles represent the observable variables, and the circles represent the error variance or disturbance terms.

Since the latent variables (attitudes, perceptions and concerns) cannot be directly observed and measured from a revealed choice or a stated preference experiment [18], they have to be modeled and then indirectly identified starting from a set of indicators. The latent variable model allows to identify and measure these unobservable variables as a function of the indicators, in order to include them in a choice model.

Mathematically, a latent variable is treated as a random variable; the latent variable is specified through a *structural equation* formalizing it as a function of several parameters and a random error term. With regard to the relationship between indicators and latent variables, it can be formalized through a *measurement equation*, in which each observed psychological indicator is a function of a latent variable and a random error term. In general, each latent variable may be part of more than one measurement equation.

Finally, in accordance with the RUT, the utility U_j^i that an individual i associates with an alternative j is considered as a function of explanatory variables. The latent variables are included in the utility function of the alternatives as explanatory variables.

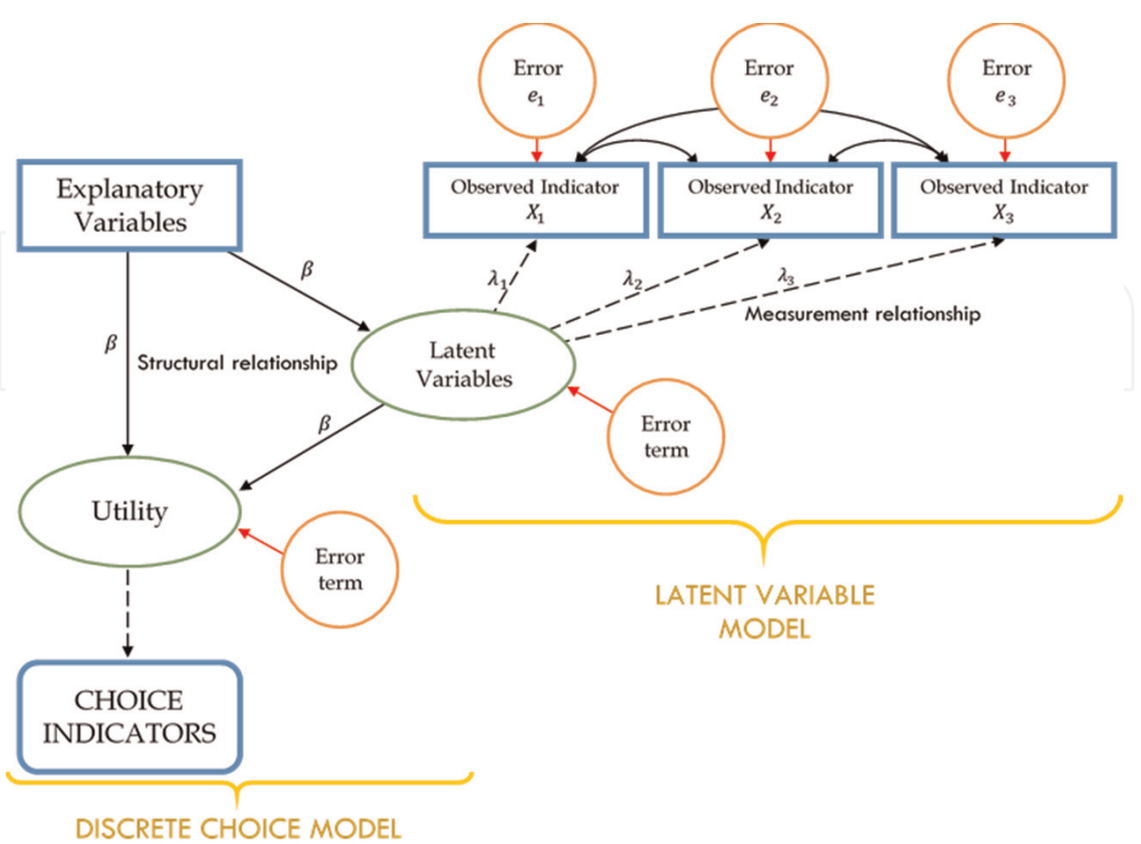

Figure 1.
Scheme of a hybrid choice model (HCM).

3. Survey design issues

One of the main issues in the specification of an ICLV model consists of the observation and the measurement of the attitudes/concerns/perceptions. The survey design is a crucial part since it should allow to characterize the respondents, to come up with respondents' attitudes/concerns/perceptions and to measure them.

Usually, a survey is structured in different subsections aiming to collect various information from the respondents. First, (a) socioeconomic and (b) household characteristics have to be inquired; then specific sections aimed to capture users' attitudes, concerns and perceptions should be specifically designed, for instance, (c) the users' attitudes and concerns that may influence the willingness to adopt/use/purchase a new technology and (d) the users' perceptions with regard to the advantages and disadvantages of the technology under investigation. Finally, it is necessary to collect (e) the users' propensity to adopt/use/purchase a new technology. In this case, different scenarios (usually not real but realistic) should be carefully designed in order to cover the possible range of the involved decisional variables.

Even though the literature is consolidated on survey design with respect to Sections (a), (b) and (e), Sections (c) and (d) need to be specifically discussed.

As introduced before, one of the main issues related to the specification and estimation of an HCM relies on how to collect users' attitudes (to observe and quantify them). Since attitudes are entities constructed to represent certain underlying response tendencies, they cannot be measured directly, but they could be inferred by studying behaviour which, in turn, might be reasonably assumed to indicate the attitudes themselves.

The behaviour may be one that occurs in a natural setting or in a simulated situation. In general, different approaches to measure attitudes may be pursued:

- *Direct observation*: this approach is based on either observing the actual behaviour of people or directly asking to state their feelings regarding the issue being studied. If the aim of the study requires the collection of information from a large number of individuals, this approach is not very practical. Moreover, the observation of peoples' behaviour may reveal the direction of the underlying attitude (i.e. whether it is positive or negative), but it cannot as easily indicate the magnitude or strength of the attitude itself, even when the behaviour is the outcome of the attitude being studied.

- *Direct questioning*: this approach consists of asking to a set of individuals what their feelings are, as a self-report technique. It serves only for a limited purpose of classifying respondents as *favorable*, *unfavorable* or *indifferent* towards a psychological object. An underlying issue with this technique is the fact that the individuals may possess certain attitudes and behave accordingly to them but may not be consciously aware of them, providing involuntary false statements to the direct questionings.

This method has two approaches to question the individuals: *direct* question on the investigated attitude (e.g. how important is the environment) and *indirect* question (e.g. do you normally buy…).

In general, direct questioning is the most pursued approach since it allows to control the investigated context and requires smaller times and costs. The method application requires the scale of measurement definition. Although the literature has proposed different scales as Thurstone, Likert and Bogardus, the Likert scale [19] has the most flexible, robust and easy to implement scale of measurement.

Latent variables may be classified as attitudes [20, 21], perceptions [22] and concerns [23]:

- *Attitudes* refer to the users' characteristics and to their approach in real-life society and can be related to the alternatives (alternative-related attitudes) or not (non-alternative-related attitudes). They can be collected through direct or indirect questioning, but indirect questioning seems the most appropriate approach [24, 25].

- *Perceptions* are usually interpreted as alternative-related and refer to the users' interpretation and reaction to a stimulus [21]. They can be gathered through direct questioning only.

- *Concerns* may be related to a specific problem/issue. They may depend on the choice context (e.g. the concern towards the environment may depend on the specific problem/activity carried out). They can be collected through direct questioning only.

Within the aforementioned conceptual framework, it is suggested to design a direct questioning survey considering two different types of questions to be submitted to the respondents: direct and indirect questions. An overview of two examples of survey design is provided in the following.

3.1 Example 1: the HySolarKit case study

A first example refers to the HySolarKit [26] case study. The questionnaire described in this section was designed [24] to investigate the role of latent factors in the choice of a new automotive technology which aims to electrify/hybridize existing vehicles through an aftermarket kit which can be recharged by the grid but also by solar power (the HySolarKit). The experiment was applied to the case study of the Salerno municipality which is the capital city of Salerno province (region of Campania, southern Italy).

The first section of the questionnaire aimed to collect users' socioeconomic, activity-related attributes and household-vehicle characteristic information; therefore, respondents were provided with direct and indirect questions.

In particular, direct questions were about fuel consumption, vehicle reliability, vehicle design and the environmental impact; indirect questions were about three main latent behaviors: the fuel consumption, the vehicle design and the environmental impact. A detailed description is displayed in **Tables 1** and **2**.

The questionnaire was completed through a second section based on installation cost scenarios. In particular, each respondent was faced with two scenarios based on different installation costs (ranging from 500 to 4000 €).

Respondents were provided with a brief description of the technology and its main characteristics: how it works, how it is installed, the different performances (e.g. power, acceleration, speed), the environmental and fuel consumption benefits that can be achieved and the operating time. A brief overview is displayed in more detail in **Table 3** [27].

3.2 Example 2: the electric vehicle case study

The second example was about electric vehicle (EV) market penetration [28]. The questionnaire was designed with the aim to investigate the different attributes/determinants that may influence the decision to purchase an electric vehicle.

Indicator	Statement
Q_{cons}	The vehicle fuel consumption significantly influences my choice in purchasing a new car
Q_{rel}	The vehicle reliability significantly influences my choice in purchasing a new car
Q_{design}	The vehicle design significantly influences my choice in purchasing a new car
Q_{env}	The evaluation of the environmental impact significantly influences my choice in purchasing a new car
Q_{price}	The price significantly influences my choice in purchasing a new car

Table 1.
Psychological statements—Direct questions.

Attitude towards fuel consumption	
Indicator	**Statement**
$I_{cons}1$	The consumption and the energy class significantly influence my choice in purchasing an appliance
I_{cons} 2	I am usually attentive to the special offers of electric operators
I_{cons} 3	My home bulbs are energy efficient
I_{cons} 4	I usually evaluate the car efficiency with respect to the car cost mileage
I_{cons} 5	I normally compare the fuel prices among different petrol stations
I_{cons} 6	When driving I am not willing to behave to reduce the environmental impacts (my driving behaviour is normally aggressive)
Attitude towards vehicle design	
Indicator	Statement
$I_{design}1$	When parking I am usually careful to avoid having my car damaged
$I_{design}2$	I often read journals of design
$I_{design}3$	When furnishing I am willing to buy pieces with modern design features and original details
$I_{design}4$	I am willing to go to the body shop mechanic not only for major damages
$I_{design}5$	I am willing to install not standard equipment (such as antitheft block shaft) on my own car
Attitude towards environmental impacts	
Indicator	Statement
$I_{env}1$	I often control the exhaust/emission system of my car
$I_{env}2$	In consciously make the separate waste collection
$I_{env}3$	I really enjoy spending my free time in parks and green areas to breathe clean area
$I_{env}4$	How much do you agree with following sentence: We must act and make decisions to reduce emissions of greenhouse gases
$I_{env}5$	How much do you agree with following sentence: The government should invest in low energy impact
$I_{env}6$	I am not willing to use the car during weekend to protect the environment and then reduce air pollution

Table 2.
Psychological statements—Indirect questions.

The first section of the questionnaire aims to gather information about the users' socioeconomic characteristics, the characteristics of the owned household vehicles and the psychometric indicators of the latent variables. Particularly, two types of

Your owned car (internal combustion engine, ICEV)	**Your owned car with the HSK**

Brief description of the HSK

The hybridizing equipment (see figure above) consists of:

- In-wheel electric engine
- Auxiliary lithium-ion battery pack
- Additional control system that interacts with existing vehicle components and optimizes energy flows
- Flexible photovoltaic panels installed on vehicle roof and hood

A mild parallel hybrid structure is obtained by substituting/integrating the rear wheels with in-wheel motors. In this way, the vehicle can operate in pure electric mode (when ICEV is switched off or disconnected by the front wheels) or in hybrid mode (when the ICEV drives the front wheels and the rear in-wheel motors operate in traction mode or in generation mode)
The battery can be recharged by:

- Rear wheels, when operating in generation mode
- Photovoltaic panels
- A regular electric power outlet, when the vehicle is connected to the grid power in plug-in mode

Technological features (averages)*

	ICEV	ICEV + HSK
Power	P	P + (30%) × P
$Speed_{max}$	V	V or 40 km/h in pure electric mode
Acceleration (acceleration time from 0 to 100 km/h)	A	A−(25%) × A
Consumptions	C	C−(20%) × C
Emissions	E	E−(20%) × E
Operating time	T	T or 15 m in pure electric mode

Table 3.
Overview of the two alternatives in the choice context.

attitudes and two types of perceptions were inquired. The investigated attitudes were towards the environment and about the vehicle's technical features, while the investigated perceptions referred to the advantages and disadvantages of electric vehicles that may affect users' willingness to purchase them. To this end, several direct/indirect questions were specifically designed adopting a five-point Likert scale (ranging from strongly disagree to strongly agree). The psychological statements used as indicators of those unobservable latent variables are detailed in **Table 4**.

The second section of the questionnaire contains the users' choice behaviour in buying a new car. To this end, a Renault Zoe as the electric alternative and a diesel-fuelled Renault Clio are considered as conventional vehicles (CV).

Attitudes towards the environment	
Indicator	**Statement**
F_cons	The vehicle fuel consumption significantly influences my choice in purchasing a new car
F_poll	I care about the amount of pollution generated by a car when it's being used
Attitudes about technical features	
Indicator	Statement
F_tech_fea	The vehicle technical features significantly influence my choice in purchasing a new car
TF_power	I prefer driving a car with a powerful engine
TF_top_speed	When I am choosing a car, I find myself spending a lot of time checking out differences in terms of top speed (km/h)
TF_accel	The immediate acceleration increases my driving pleasure
TF_range	The vehicle range is very significant with respect to my mobility needs in everyday life
Advantages	
Indicator	Statement
AD_{Red_CO2}	I am interested in EV to contribute to the emissions reduction
$AD_{Efficiency}$	Compared to a normal car, EV are superior in terms of energy efficiency
AD_{Red_poll}	I believe using EV can significantly reduce the acoustic pollution in cities
AD_{Less_parts}	I prefer having a car with less moving parts
Disadvantages	
Indicator	Statement
DIS_{infr}	When driving an EV, I would always be worried about the lack of charging points
DIS_{red_fea}	Compared to a normal car, EV are inferior in terms of performances
DIS_{batt_range}	The low range of the battery is a real disadvantage

Table 4.
Psychological statements of the survey.

These two alternatives were compared in terms of their technical features and then hypothesized that the interviewee has a budget enough to buy a new car to be used in urban areas. The monthly cost of buying and fuelling the conventional vehicle is calculated, considering 8-year monthly payments to buy it and an estimated fuel cost to drive it for 10,000 km per year. This results in a total cost of 192 € per month (**Table 5**).

After the comparison, each respondent was faced with five monthly cost scenario setup for the electric vehicle. They started from the same value calculated for the diesel vehicle (i.e. 192 €/month), and then it was considered that the EV would have cost 10, 20, 30 and 40% more (€211, €230, €250 and €270 per month, respectively).

4. Preliminary analyses

In the case of HCM, descriptive and statistical analyses of the collected answers regarding the perception indicators are necessary for two main reasons: firstly, they allow supporting the soundness of the experimental design setup; secondly, they allow deriving first correlations between observed behaviour, collected attributes

Vehicle A—Electric **Renault ZOE Life R90**	**Vehicle B—Diesel** **Renault Clio 1.5 dCi Life**

Technical features (averages)*		
	Electric	*Gasoline*
Power	92 CV	75 CV
Top speed	135 km/h	168 km/h
Acceleration (0–100 km/h)	13.4 s	14.3 s
Consumption	10.9 km/kWh	30.3 km/l
CO_2 emissions	0 g/km	85 g/km
Range	240 km	1364 km

Table 5.
Comparison of the two alternatives in the choice context.

and investigated attitudes/perceptions/concerns. Therefore, results from preliminary analyses may give important insights on the survey robustness and a useful guidance for the model specification. In general, the analyses may be divided in basic preliminary analyses based on the analysis of *Cronbach's alpha* which focuses on the evaluation of the internal consistency of the answers and the evaluation of *mean and standard deviations* and other advanced analysis, as the *factor analysis* which aims to identify the latent variables. A further and more detailed explanation of the methods is provided below.

4.1 Cronbach's alpha

The Cronbach's alpha, α (or coefficient alpha), is a measure of the internal consistency (or reliability) of the responses to multiple questions that are meant to measure a specific latent variable in a survey using a Likert scale. This indicator aims to tell whether the survey was accurately designed, and the questions were not answered randomly.

For each latent variable, it is necessary to have at least two indirect questions. The higher the number of questions, the better the latent variable would be measured. These questions, if possible, should be a mix of "+keyed" and "-keyed", depending if each one is positively correlated to the latent variable or negatively (**Table 6**).

When a survey intends to measure more than one latent variable, it is recommended to alternate their questions. This strategy combined to the mix of "+ keyed" and "− keyed" is employed in order to encourage respondents to be more aware of each item and the response provided and, therefore, increases the probability of gathering valid responding. If not, respondents may realize which latent

Scoring	Very inaccurate	Moderately inaccurate	Neither inaccurate nor accurate	Moderately accurate	Very accurate
+ keyed	1	2	3	4	5
− keyed	5	4	3	2	1

Table 6.
Scores for a five-point Likert scale.

variable is being measured, and they might tend to answer with the same response if the questions are all equally keyed. In this case, the total variance will be lower, and the relation with other variables in the study will be underestimated.

The Cronbach's alpha is calculated for each group of questions that measure a specific latent variable. Given $X = Y_1 + Y_2 + ... + Y_K$ the sum of the scores of the K questions for each respondent, Cronbach's alpha is obtained as

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K}\sigma_{Y_i}^2}{\sigma_X^2}\right) \tag{1}$$

where:
K is the number of items (questions).
σ_X^2 is the variance of the observed total scores.
$\sigma_{Y_i}^2$ is the variance of the scores of each item i.

A rule commonly accepted to interpret the values of Cronbach's alpha when used with a Likert scale is (**Table 7**):

4.2 Mean and standard deviation

An easy quantitative/qualitative analysis to perform on the data collected consists of calculating the mean value and the standard deviation of the responses to the Likert scale for each question and then evaluating whether the responses are consistent (they have a low deviation) or if the mean value corresponds to the one expected.

4.3 Factor analysis

Given Y_i is an observable random variable, with mean μ_i, with $i = 1, ..., p$ where p is the number of observed variables (the number of indirect questions), the factor analysis is a statistical method to investigate if each observed variable can be reduced to a linear combination of k unobservable factors (i.e. F_k, latent variables,

Cronbach's alpha	Internal consistency
$0.9 \leq \alpha$	Excellent
$0.8 \leq \alpha < 0.9$	Good
$0.7 \leq \alpha < 0.8$	Acceptable
$0.6 \leq \alpha < 0.7$	Questionable
$0.5 \leq \alpha < 0.6$	Poor
$\alpha < 0.5$	Unacceptable

Table 7.
Scales of values for the Cronbach's alpha.

considered independent from each other) and error terms (i.e. ε_i). Mathematically, that can be expressed as

$$Y_i - \mu_i = l_{i1}F_1 + \ldots + l_{ik}F_k + \varepsilon_i \tag{2}$$

In matrix terms

$$Y - \mu = L\,F + \varepsilon \tag{3}$$

$$\begin{bmatrix} Y_1 \\ \vdots \\ Y_i \\ \vdots \\ Y_p \end{bmatrix} - \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_i \\ \vdots \\ \mu_p \end{bmatrix} = \begin{bmatrix} l_{11} & \cdots & l_{1j} & \cdots & l_{1k} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ l_{i1} & \cdots & l_{ij} & \cdots & l_{ik} \\ \vdots & \cdots & \vdots & \ddots & \vdots \\ l_{p1} & \cdots & l_{pj} & \cdots & l_{pk} \end{bmatrix} \begin{bmatrix} F_1 \\ \vdots \\ F_j \\ \vdots \\ F_k \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_i \\ \vdots \\ \varepsilon_p \end{bmatrix} \tag{4}$$

where

$Y = \left[Y_1, \ldots, Y_i, \ldots, Y_p\right]^T$ is the vector of p observable random variables.

$\mu = \left[\mu_1, \ldots, \mu_i, \ldots, \mu_p\right]^T$ is the vector of the mean values of Y.

$F = \left[F_1, \ldots, F_j, \ldots, F_k\right]^T$ is a vector of k unobserved random variables, called "common factors" as they influence all the observed Y_i.

$L = \begin{bmatrix} l_{11} & \cdots & l_{1j} & \cdots & l_{1k} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ l_{i1} & \cdots & l_{ij} & \cdots & l_{ik} \\ \vdots & \cdots & \vdots & \ddots & \vdots \\ l_{p1} & \cdots & l_{pj} & \cdots & l_{pk} \end{bmatrix}$ is a matrix of unknown constants, called "loadings" that have to be calculated.

$\varepsilon = \left[\varepsilon_1, \ldots, \varepsilon_i, \ldots, \varepsilon_p\right]^T$ is a vector of unobserved stochastic error terms, with zero mean and finite variance, that can assume different values for each i.

Assuming that:

- ε_i are independent from one another, and $E(\varepsilon_i) = 0$ and $Var(\varepsilon_i) = \sigma_i^2$.
- F are independent from one another, as there is no relationship between factors, and are also independent from the error terms. They are also standardized to $E(F_j) = 0$ and $Var(F_j) = 1$.
- $Cov(F) = I$ so the factors are uncorrelated.
- $k \leq p$: the number of observed variables Y_i is larger or equal to the number of common factors F_j.

Any solution for the unknown values l_{ij} of Eq. (2) or (3) with the constraints for F is defined as factors, and L is the loading matrix.

With these assumptions, the variance of Y_i in (2) can be calculated as

$$\begin{gathered} Var(Y_i) = {l_{i1}}^2 Var(F_1) + \ldots + {l_{ik}}^2 Var(F_k) + 1^2 Var(\varepsilon_i) \\ Var(Y_i) = {l_{i1}}^2 + \ldots + {l_{ik}}^2 + \sigma_i^2 \end{gathered} \tag{5}$$

where ${l_{i1}}^2 + \ldots + {l_{ik}}^2$ is the *communality* of the variance: the part that is explained by the common factors $F_1, \ldots, F_j, \ldots, F_k$ and shared with other variables.

σ_i^2 is the *specific* variance: the part of the variance of Y_i that is not considered in the common factors. This value would be equal to 0 if the common factors were perfect predictors of the observed variables.

Given two variables, Y_m and Y_n,

$$\begin{aligned} Y_m &= \mu_m + l_{m1}F_1 + \ldots + l_{mk}F_k + \varepsilon_m \\ Y_n &= \mu_n + l_{n1}F_1 + \ldots + l_{nk}F_k + \varepsilon_n \end{aligned} \tag{6}$$

The covariances can be calculated as

$$\begin{aligned} Cov(Y_m, Y_n) &= l_{m1}l_{n1}Var(F_1) + \ldots + l_{mk}l_{nk}Var(F_k) + (1)(0)\varepsilon_m + (0)(1)\varepsilon_n \\ Cov(Y_m, Y_n) &= l_{m1}l_{n1} + \ldots + l_{mk}l_{nk} \end{aligned} \tag{7}$$

This shows that the covariance of two variables is equal to the scalar product of their loadings.

With the expressions in Eqs. (5) and (7), it is possible to construct a *theoretical variance–covariance matrix*, implied by the model's assumptions. Then, with the data collected in the survey, an *observed variance and covariance matrix* can be calculated and constructed. If the model's assumptions are correct, it is possible to estimate the loadings l_{ij} in order to obtain a theoretical matrix closer to the observed one.

To extract the first set of loadings and factors from the observed variables, there are different methods. However, principal component analysis (PCA) and common factor analysis (CFA) are the most preferred and most used:

- *Principal component method*, or component factor analysis, determines the loadings l_{ij} that allows a close estimation of the total communality to the sum of the observed variances, while ignoring the covariances. The principal components are chosen by extracting the maximum variance and putting it in the first factor, gathering as much of the variation in the data as possible. Then, the variance explained by the first factor is removed and then extracts the maximum variance for the second factor; repeating the process until the last factor.

This model can be written as

$$C_1 = l_{11}Y_1 + l_{21}Y_2 + l_{31}Y_3 \tag{8}$$

- *Common factor analysis*: the factors are linear combinations that maximize the common portion of the variance and put them into factors, underlying *latent constructs*. This method does not include the specific part of the variance to determine the factor, and it is used for structural equation modeling.

This model can be set up as

$$\begin{aligned} Y_1 &= l_{11}F_1 + \varepsilon_1 \\ Y_2 &= l_{21}F_1 + \varepsilon_2 \\ Y_3 &= l_{31}F_1 + \varepsilon_3 \end{aligned} \tag{9}$$

Once the factors are extracted, their eigenvalues (or characteristic roots) provides the amount of variance explained by every factor out of the total variance. Then, the number of factors is reduced by retaining only those which have an eigenvalue larger than 1, according to Kaiser's criterion [29].

The factor loadings obtained represent the amount of variance explained by the variable on every factor. In structural equation modeling, a value of 0.7 or higher represents that the factor extracts sufficient variance from that particular variable.

The loading values may be hard to interpret at a first glance. So, in a second step of the analysis, the loadings obtained can be "rotated" in order to arrive at another set of loadings, which renders the values more understandable, while fitting the observed variances and covariances equally. The effect of rotating the factors produces that each variable loads more strongly only on one of the factors and weakly on the other factors, producing the eigenvalues to vary.

There are several rotation methods that provide different solutions, arising to different interpretation. The interpretation of each factor and the number of factors needed are very subjective, and the researcher has the task to identify what is the meaning of each factor (i.e. which is the unknown latent variable hidden in the indicators).

From a general point of view, the rotation methods can be subdivided in orthogonal (when the factors cannot correlate) or oblique (the factors are allowed to correlate). The most common methods within each one of two groups are listed below:

- Orthogonal methods
    - *Varimax*: it aims to minimize the complexity of each factor by relating them to few variables while discouraging the detection of factors that influence all the variables. It produces the increase of the strongest loading values while decreasing the weaker ones in each factor.
    - *Quartimax*: it aims to find a general factor (or a reduced amount of them), on which most variables are loaded to, while minimizing the number of factors needed to explain each variable. This is done by increasing the strongest loading values while decreasing the weaker ones in each variable. This factor structure is usually not helpful to the research purpose.
    - *Equimax*: it is a method that attempts to simplify both factors and variables.
- Oblique methods
    - *Direct oblimin* is the standard method when the factors are allowed to be correlated, resulting in higher eigenvalues, but the interpretability of the factors may be reduced.
    - *Promax* is an alternative to the previous one, used for large dataset as it is computationally more efficient.

4.4 Example 1: the electric vehicle case study

An overview of the preliminary statistical analysis for the electric vehicle case study[1] introduced in Section 3.2 is provided. The proposed example includes analysis of Cronbach's alpha, mean and standard deviations, factor analysis with principal components as the extraction method and rotated component matrix using the Varimax method.

First of all, it may be observed that Cronbach's alpha is not consistent for all answers; therefore, the survey reliability is confirmed only in the case of

[1] For the sake of brevity only, the results which are related to one case study, the electric vehicle case study, are displayed.

psychological statements referred to the environment, the technical features and the EV's advantages (i.e. Cronbach's alpha is higher than 0.5). Among them, a further analysis is provided in terms of mean and standard deviations: with respect to the attitude about the environment, for both statements the mean is higher than 3, and the standard deviation is lower than 1; regarding the attitude about technical features, higher values of mean (higher than 3) and lower values (lower than 1) of standard deviations are observed for the following statements (refer to Section 3.2 for the meaning of the following variables): <*F_tech_fea*>, <*TF_power* > and < *TF_range*>. Finally, the perceptions of EV's advantages show mean values higher than 3 and standard deviations lower than 1 only for the following statements: <AD_{Red_CO2}>, <$AD_{Efficiency}$ > and < AD_{Red_poll}>. However, even though the Cronbach's alpha is not satisfying for the perceptions of disadvantages of EVs, the mean values and the standard deviations for all statements (<DIS_{infr}>, <DIS_{red_fea}>, <DIS_{batt_range}>) highlight their relevance on users' behaviour. All significant results are in bold in **Table 8**.

Attitudes about environment		
Cronbach's alpha = 0.551		
	mean	*SD*
F_cons	**4.32**	**0.71**
F_poll	**3.13**	**0.98**
Attitudes about technical features		
*Cronbach's alpha = **0.656***		
	mean	SD
F_tech_fea	**3.68**	**0.85**
TF_power	**3.51**	**0.84**
TF_top_speed	2.98	0.85
TF_accel	**3.14**	**1.00**
TF_range	**4.53**	**0.73**
Perceptions of advantages of EVs		
*Cronbach's alpha = **0.549***		
	Mean	*SD*
AD_{Red_CO2}	**4.11**	**0.82**
$AD_{Efficiency}$	**3.42**	**1.08**
AD_{Red_poll}	**3.62**	**0.97**
AD_{Less_parts}	3.01	1.14
Perceptions of disadvantages of EVs		
Cronbach's alpha = 0.364		
	Mean	SD
DIS_{infr}	4.21	0.82
DIS_{red_fea}	3.25	0.94
DIS_{batt_range}	4.05	0.87

Table 8.
Mean and standard deviations of the responses in the EV study.

Factor analysis				
Variables	***Components***		***Rotated components***	
	1	**2**	**1**	**2**
AD_red_CO_2	**0.721**	−0.306	**0.773**	0.125
AD_red_poll	**0.601**	−0.018	**0.751**	−0.156
AD_efficiency	**0.553**	−0.532	**0.519**	0.305
F_consumption	0.548	**0.518**	−0.068	**0.768**
F_pollution	0.352	**0.686**	0.188	**0.731**

Table 9.
Factor analysis of the EV study.

The factor analysis carried out through the principal component analysis extraction method, allowed to identify the latent factors correlated to the psychological statements. The components extracted were also rotated using the Varimax method.

The results (significant values are highlighted in bold in **Table 9**) underline the correlations among the following statements referred to the advantage perceptions $<AD_{Red_CO}>$, $<AD_{Efficiency}>$ and $< AD_{Red_poll} >$ and all statements regarding the environmental attitude, $<F_consumption>$ and $< F_pollution >$.

5. Mathematical formulation

5.1 Choice function and structural and measurement equations

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 $\varepsilon_{i:}$

$$U^i = \beta_x X^i + \beta_{SE} X^i_{SE} + \beta_{LV} LV^i + \varepsilon^i \tag{10}$$

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, while 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:

$$LV^i_p = \gamma_p + \sum_j \beta_{SE,j} X^i_{SE,j} + \omega^i_p \tag{11}$$

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 $\sigma_{\omega,p}$ is the 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:

$$I^i_{p,k} = \alpha_{p,k} + \lambda_{p,k} LV^i_p + \nu^i_{p,k} \tag{12}$$

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 $\sigma_{\nu pk}$ is the standard deviation of the error term.

The psychometric indicators that reveal the latent variables may be coded using a Likert scale [19]. These indicators can be considered to be a linear continuous expression of the LV's or an ordered discrete variable. The first approach has been historically chosen because simpler and more practical with lower computational cost. However, assuming these indicators as continuous variables are in contrast with the real nature of the Likert scale (the Likert scale is a discrete measure) [30], 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 [31]. In particular, if the measurement is represented by an ordered discrete variable J taking the values $j_1, j_2, \ldots, j_M$, we have

$$\mathrm{J} = \begin{cases} j_1 & \text{if } \mathrm{I} < \tau_1 \\ j_2 & \text{if } \tau_1 \le \mathrm{I} < \tau_2 \\ \vdots & \\ j_i & \text{if } \tau_{i-1} \le \mathrm{I} < \tau_i \\ \vdots & \\ j_M & \text{if } \tau_{M-1} \le \mathrm{I} \end{cases} \tag{13}$$

where I is defined by Eq. (12) and $\tau_1, \ldots, \tau_{M-1}$ are parameters to be estimated, such that

$$\tau_1 \le \tau_2 \le \ldots \le \tau_i \le \ldots \le \tau_{M-1}$$

If the measurements use a Likert scale with M = 5 levels, four 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

$$\begin{aligned} \tau_1 &= -\delta_1 - \delta_2 \\ \tau_2 &= -\delta_1 \\ \tau_3 &= \delta_1 \\ \tau_4 &= \delta_1 + \delta_2 \end{aligned} \tag{14}$$

Then, the probability of a given response j_i is given by the ordered probit model [5].

For completeness, in the following section, the estimation results related to the HySolarKit and the electric vehicle case study are shown.

In this research report, the model parameters were estimated in accordance with the maximum simulated likelihood statistical approach.

5.2 Example: the HySolarKit case study

The first results shown in this section refer to the HySolarKit case study. As already anticipated in Section 3.1, the choice set was composed of two alternatives: "install" and "not-install". In the following the estimation results are presented, distinguishing the choice utility function, the structural equations and the measurement equations.

5.2.1 Parameters of the choice utility function

The utility choice functions were analytically specified in accordance with the following equation:

$$U^i = \beta_x X^i + \beta_{SE} X^i_{SE} + \beta_{LV} LV^i + \varepsilon^i \tag{15}$$

The results are shown in **Table 10**. In particular, the estimation results underline the following latent variables as statistically significant: attitudes towards fuel consumption (LV1), towards the vehicle design (LV2) and towards the environment (LV3).

The coefficients related to the parameters in the measurement equation for an ordinal specification are estimated in the considered model. As the measurements are using a Likert scale with seven levels, six parameters τ_i are needed

Attributes	***Attributes coefficients (betas)***	
	Install	***Not-install***
Age *[def: age of the respondent]*	+0.160 *(+0.960)*	
Master's degree *[def: 1 for users achieved this educational attainment]*	+ 0.156 *(+1.16)*	
ZonRes *[def: 0 for users living to the historical centre, 1 if in the outskirts]*	+0.0761 *(+0.960)*	
CarAge *[def: age of the owned car on which the respondent would install the kit]*	+0.0272 *(+1.55)*	
by Car-Shopping *[def: mode choice "Car" and trip purpose "Shopping"]*	+0.669 *(+1.490)*	
by Car-Personal Services *[def: mode choice "Car" and trip purpose "Personal Services"]*	+0.192 *(+0.53)*	
Δ_{cost} *[def: In order to compare the scenarios with and without the kit, the financial gain was expressed in terms of weekly costs, rather than yearly costs or life costs based on the year of the vehicle owned by the respondent]*		+0.0638 *(+8.16)*
LV_1 *[def: latent variable representing consumption attitude]*	+0.548 *(+2.55)*	
LV_2 *[def: latent variable representing design attitude]*		+0.0682 *(+0.46)*
LV_3 *[def: latent variable representing environment attitude]*	+0.104 *(+0.98)*	
Statistics		
Number of respondents	1364	
Number of observations	1364	
Init-log-likelihood[1]	−944.760	
Final log-likelihood	−779.81	
Rho-square	0.212	

**in parenthesis the t-test values.*
[1]Only the log-likelihood associated with the discrete choice component is considered.

Table 10.
Attribute coefficients of the choice model. HySolarKit case study.

$DELTA_1$	+ 1.46 *(+ 38.90)*
$DELTA_2$	+ 1.34 *(+ 43.85)*
$DELTA_3$	+ 1.52 *(+ 46.11)*

**in parenthesis the t-test values.*

Table 11.
Delta values of the calibrated measurement equations. HySolarKit case study.

(see Section 5.1). However, in order to account for the symmetry of the indicators, three positive parameters δ_1, δ_2 and δ_3 are actually required (**Table 11**).

5.2.2 Parameters of the structural model

The coefficients in the structural model are analytically represented by the following equation:

$$LV_p^i = \gamma_p + \sum_j \beta_{SE,j} X_{SE,j}^i + \omega_p^i \tag{16}$$

This equation shows that each latent variable is a function of an intercept value γ_p of beta-coefficients $\beta_{SE,j}$ for each of the socioeconomic attributes $X_{SE,j}^i$ of the respondents that influence the latent variable and contains an error term ω_p^i normally distributed with zero mean and $\sigma_{\omega p}$ standard deviations.

The estimation results displayed in below refers to the significant latent variables of the model, representing the attitude towards the fuel consumption (LV_1), the vehicle design (LV_2) and the environment (LV_3) (**Table 12**).

5.2.3 Parameters of the measurement model

Finally, with regard to the measurement model depending on the perception indicators, they are analytically represented by the following equation:

$$I_{p,k}^i = \alpha_{p,k} + \lambda_{p,k} LV_p^i + \nu_{p,k}^i \tag{17}$$

where each perception indicator is a function of an intercept value $\alpha_{p,k}$, a coefficient $\lambda_{p,k}$ associated with the latent variable and an error term $\nu_{p,k}^i$ assumed normally distributed with zero mean and $\sigma_{\nu pk}$ standard deviation.

Table 13 shows the coefficients for each perception indicator, which were specified in accordance with the preliminary analyses (not shown for the sake of brevity). In particular, the first latent variable about fuel consumption (LV_1) is described by two indicators $<I_{cons0}>$ and $< I_{cons2}>$. The second latent variable, about vehicle design (LV_2), is described by four perception indicators, $<I_{design0}>$, $<I_{design1}>$, $<I_{design3}>$ and $< I_{design4}>$. Finally, the last latent variable representing the attitudes towards the environment (LV_3) is described by four indicators $< I_{env0}>$, $< I_{env3}>$, $< I_{env4}>$ and $< I_{env6}>$.

In general, the estimation results underline the necessity to introduce two different kinds of questions: direct and indirect questions.

Structural model	
Attributes	***Attribute coefficients (betas)***
LV_1: Attitude towards fuel consumption	
γ_1	−2.32 *(−29.80)*
ω_1	+0.787 *(+16.37)*
by car-shopping *[def: mode choice "Car" and trip purpose "Shopping"]*	−0.448 *(−2.52)*
by car-personal services *[def: mode choice "Car" and trip purpose "Personal Services"]*	+0.550 *(+3.88)*
Master's degree *[def: 1 for users achieved this educational attainment]*	+0.128 *(+2.22)*
LV_2: Attitude towards design issues	
γ_2	−3.39 *(−42.17)*
ω_2	+0.299 *(+6.96)*
Age *[def: age of the respondent]*	−0.0955 *(−2.37)*
SE_male *[def: respondent's gender (0 = female; 1 = male)]*	−0.278 *(−6.65)*
LV_3: Attitude towards environment	
γ_3	—
ω_3	+1.34 *(+27.18)*
Age *[def: age of the respondent]*	−1.06 *(−15.60)*
SE_male *[def: respondent's gender (0 = female; 1 = male)]*	−1.12 *(−16.74)*

**in parenthesis the t-test values.*

Table 12.
Coefficients of the calibrated structural model. HySolarKit case study.

5.3 Example 2: the electric vehicle case study

As described in Section 3.2, the considered choice set is composed of two alternatives: the alternative A representing the respondent's willingness to buy an electric vehicle and the alternative B corresponding to the willingness of buying a conventional (diesel) vehicle. The provided results are referred to an ordered model specification.

In the following the estimation results are presented, distinguishing the choice of utility function, the structural equations and the measurement equations.

5.3.1 Parameters of the choice utility function

The attribute coefficients in the utility choice function are analytically specified by the following equation:

$$U^i = \beta_x X^i + \beta_{SE} X^i_{SE} + \beta_{LV} LV^i + \varepsilon^i \tag{18}$$

Measurement model					
Fuel consumption		***Vehicle design***		***Environment***	
I_{cons0} *[def: The vehicle fuel consumption significantly influences my choice in purchasing a new car]*		$I_{design0}$ *[def: The vehicle design significantly influences my choice in purchasing a new car]*		I_{env0} *[def: The evaluation of the environmental impact significantly influences my choice in purchasing a new car]*	
α_{10}	+0.567 *(+3.46)*	α_{20}	−1.79 *(−2.77)*	α_{30}	−1.89 *(−24.48)*
λ_{10}	+0.725 *(+11.40)*	λ_{20}	+0.148 *(+0.85)*	λ_{30}	+0.495 *(+14.12)*
ν_{10}	+0.787 *(+16.37)*	ν_{20}	+1.38 *(+33.16)*	ν_{30}	+1.18 *(+31.06)*
I_{cons2} *[def: I am usually attentive to the special offers of electric operators]*		$I_{design1}$ *[def: When parking I am usually careful to avoid having my car damaged]*		I_{env3} *[def: I really enjoy spending my free time in parks and green areas to breathe clean area]*	
α_{12}	0	α_{21}	0	α_{33}	−1.36 *(−19.03)*
λ_{12}	1	λ_{21}	1	λ_{33}	+0.729 *(+20.82)*
ν_{12}	1	ν_{21}	1	ν_{33}	+0.983 *(+25.99)*
		$I_{design3}$ *[def: When furnishing I am willing to buy pieces with modern design features and original details]*		I_{env4} *[def: How much do you agree with following sentence: We must act and make decisions to reduce emissions of greenhouse gases]*	
		α_{23}	+2.79 *(+2.72)*	α_{34}	0
		λ_{23}	+1.60 *(+5.72)*	λ_{34}	1
		ν_{23}	+1.43 *(+31.24)*	ν_{34}	1
		$I_{design4}$ *[def: I am willing to go to the body shop mechanic not only for major damages]*		I_{env6} *[def: I am not willing to use the car during weekend to protect the environment and then reduce air pollution]*	
		α_{24}	+2.79 *(+2.69)*	α_{36}	−1.95 *(−26.15)*
		λ_{24}	+1.84 *(+6.52)*	λ_{36}	+0.396 *(+12.18)*
		ν_{24}	+1.65 *(+28.17)*	ν_{36}	+1.13 *(+31.68)*

**in parenthesis the t-test values.*

Table 13.
Coefficients of the calibrated measurement model. HySolarKit case study.

The results are shown in **Table 14**. In particular, the following attitudes were statistically significant: the attitudes towards the environment (LV_1) and the perception of the advantages of EVs (LV_2).

Attributes	***Attribute coefficients (betas)***	
	BUY - EV	***BUY - CV***
VAR_monthly_cost_abs *[def: Variation in monthly cost [EUR] between an electric car and a conventional one]*		**+0.118** *(+17.65)*
SE_AutoSI *[def: 1 if the respondent has at least 1 car in the household]*		**+0.865** *(+2.02)*
F_tech_fea [5] *[def: The vehicle technical features significantly influence my choice in purchasing a new car (5 = strongly agree)]*		**+0.451** *(+1.67)*
DIS_red_fea [5] *[def: Compared to a normal car, EV are inferior in terms of performances (5 = strongly agree)]*		**+0.778** *(+2.25)*
LV_1	**+2.10** *(+11.86)*	
LV_2	**+0.435** *(+1.57)*	
Statistics		
Number of respondents	*1462*	
Number of observations	*1462*	
Init-log-likelihood[1]	*−1013.38*	
Final log-likelihood	*−385.55*	
Rho-square	*0.620*	

**in parenthesis the t-test values.*
[1]Only the log-likelihood associated with the discrete choice component is considered

Table 14.
Attribute coefficients of the choice model. EV case study.

$DELTA_1$	0.531 *(+30.25)*
$DELTA_2$	1.27 *(+38.94)*

**in parenthesis the t-test values.*

Table 15.
Delta values of the calibrated measurement equations. EV case study.

The coefficients related to the parameters in the measurement equation for an ordinal specification are estimated in the considered model. As the measurements are using a Likert scale with five levels, four parameters τ_i are needed. However, in order to account for the symmetry of the indicators, two positive parameters δ_1 and δ_2 are actually required (**Table 15**).

5.3.2 Parameters of the structural model

The coefficients in the structural model are analytically represented by the following equation:

Structural model	
Attributes	***Attribute coefficients (betas)***
LV_1: Attitude towards the environment	
γ_1	+1.83
	(+33.70)
ω_1	+0.119
	(+3.84)
SE_male *[def: Interviewee's gender (0 = female; 1 = male)]*	−0.242
	(−5.41)
LV_2: Perception of EV's advantages	
γ_2	+0.857
	(+11.57)
ω_2	+0.584
	(+9.86)
SE_male *[def: Interviewee's gender (0 = female; 1 = male)]*	−0.0445
	(−1.01)
SE_delta_age *[def: Age class of individuals (0 = 19 years; 1 = 20 years; 2 = 21 years; 3 = 22 years; 4 = 23 years; 5 = 24 years; 6 = 25 years; 7 = 26 years)]*	−0.0246
	(−1.39)
**in parenthesis the t-test values.*	

Table 16.
Coefficients of the calibrated structural model. EV case study.

$$LV_p^i = \gamma_p + \sum_j \beta_{SE,j} X_{SE,j}^i + \omega_p^i \tag{19}$$

The estimation results displayed in **Table 16** refer only to the two significant latent variables of the model, standing for the attitudes towards the environment (LV_1) and the perception of the advantages of EVs (LV_2). In particular, for each latent variable, the table displays the results of the intercept value γ_p, the beta-coefficients $\beta_{SE,j}$ of the socioeconomic attributes $X_{SE,j}^i$ of the respondents that influence the latent variable and the error terms ω_p^i normally distributed with zero mean and $\sigma_{\omega p}$ standard deviations of the error term.

5.3.3 Parameters of the measurement model

Finally, the measurement model depending on the perception indicators is analytically represented by the following equation:

$$I_{p,k}^i = \alpha_{p,k} + \lambda_{p,k} LV_p^i + \nu_{p,k}^i \tag{20}$$

These parameters were specified in accordance with the preliminary analyses. In particular, the first latent variable about the environment (LV_1) is described by two indicators, $<F_cons>$ and $<F_poll>$, while the second latent variable, perception of EV's advantages (LV_2), is described by three perception indicators $<AD_{Red_CO2}>$, $<AD_{Efficiency}>$ and $<AD_{Red_poll}>$. In **Table 17**, the intercept value $\alpha_{p,k}$, the

Measurement model			
LV 1: Environment		***LV 2: Perception of EV's advantages***	
F_cons *[def: The vehicle fuel consumption significantly influences my choice in purchasing a new car]*		***AD_{Red_CO2}*** *[def: I am interested in EV to contribute to the emissions reduction]*	
α_{10}	−4.62 *(−4.92)*	α_{20}	+0.391 *(+2.96)*
λ_{10}	+2.85 *(+5.23)*	λ_{20}	+1.32 *(+8.40)*
ν_{10}	+1.03 *(+30.15)*	ν_{20}	+0.742 *(+11.55)*
F_poll *[def: I care about the amount of pollution generated by a car when it's being used]*		*$AD_{Efficiency}$* *[def: Compared to a normal car, EV are superior in terms of energy efficiency]*	
α_{11}	0	α_{21}	−0.143 *(−1.37)*
λ_{11}	1	λ_{21}	+0.881 *(+7.27)*
ν_{11}	1	ν_{21}	+1.22 *(+27.41)*
		AD_{Red_poll} *[def: I believe using EV can significantly reduce the acoustic pollution in cities]*	
		α_{22}	0
		λ_{22}	1
		ν_{22}	1

**in parenthesis the t-test values.*

Table 17.
Coefficients of the calibrated measurement model. EV case study.

coefficient $\lambda_{p,k}$ associated with the latent variable and the error terms $\nu^{i}_{p,k}$ assumed normally distributed with zero mean and $\sigma_{\nu pk}$ standard deviation are displayed for each perception indicator.

6. Conclusions

Depending on the context, several factors may affect users' choices. In this chapter, the main focus refers to modeling users' propensity to choose/adopt 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, two related main issues are still open in the literature: (a) interpreting and modeling users' behaviour towards these new technologies and (b) assessing the potential environmental impacts. It is widely recognized that traditional approaches used to interpret and model users' choice behaviour may lead to neglect the numerous nonquantitative factors that may affect users' behaviors. Indeed, users' choices may be influenced by social and psychological factors, symbolic and affective factors, habits and the conflict between collective and individual interests (e.g. car use as a commons dilemma). These imply that changes in transportation modes may be achieved either by influencing individual motivations and perceptions (*psychological*

strategies) or by changing the context in which decisions are made (*structural strategies*).

The book chapter provides an overview of the methodology to be adopted in order to support psychological-based strategies. In fact, psychological factors, such as attitudes, concerns and perceptions, may play a significant role which should be explicitly modeled.

Although several approaches may be identified in the literature able to address the above-mentioned issue, the hybrid choice modeling approach based on RUT can be considered a proper solution to explicitly consider the perceptions, attitudes and concerns in the modeling of the choice behaviour. The specification of such models requires a careful survey design, rigorous preliminary descriptive analyses and the model parameter estimation. The present chapter deals with all the cited issues, first introducing the main criticalities in modeling choice behaviour in new technological contexts, then proposing a methodological framework and finally introducing different explanatory examples on real case studies. In particular, Section 3 focuses the attention on the different approaches to collect users' attitudes/perceptions and concludes the need for a mixed approach based on both direct and indirect questioning. Section 4 introduces the methodology to properly evaluate the consistency of the dataset and the latent variables identification. It evidences the need for basic analysis, such as the estimation of the mean and standard deviations, and the importance of the Cronbach's alpha test and the principal components and the rotate component matrices for the identification of the latent variables. Section 5 deals with the model's specification issues, pointing out the most robust approach for the specification and calibration of a hybrid choice model with latent variable. All the introduced sections are supported by real experimental results [24, 25] for explanatory and guideline purposes.

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Conflict of interest

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