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Testing for saliency-led choice behavior in discrete choice modelling: an application in the context of preferences towards nuclear energy in Italy

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Abstract

This work proposes a discrete choice model that jointly accounts for heterogeneity in preferences and in decision making procedures adopted by respondents, as well as for non-linearities in the utility function, allowing for the potential effect of salient attributes in choice experiments. We present an innovative application in the context of preferences towards nuclear energy, with data obtained from a nationwide online survey conducted in Italy. Results show that most of the variation in the choice data is indeed due to heterogeneity in the decision process, where the saliency heuristic plays an important role. Furthermore, the proposed model provides more conservative monetary valuations as opposed to standard models, potentially leading to substantial differences in cost-benefit analysis. Implications for choice modeling practitioners are discussed, emphasizing the need to account for saliency effects when modelling the choice data.

Keywords Discrete choice; heuristics; LC-RPL model; nuclear energy

1. Introduction

Stated preferences surveys based on choice experiments are extensively employed in transport, health, and environmental economics to value attributes of non-market goods. Research towards improving validity and reliability of results has received widespread attention. Particular focus has been directed at modeling different attribute processing strategies, allowing practitioners to venture beyond the assumption that individuals conform to a fully compensatory decision process all the time, thereby reducing the risk of biased policy implications caused by misspecification of the decision processing strategies (Balbontin et al. 2019; Campbell et al. 2014, 2015; Hensher et al. 2005; Hess et al. 2010, 2012, 2013; Hole 2011).

In this work, we focus on the analysis of choice experiment data relative to the potential implementation of nuclear energy in Italy. Whilst it may contribute to curb climate change, this energy source is generally identified as intrinsically divisive and problematic (Lock et al. 2014). In Italy, public opinion towards nuclear energy has been particularly negative overall (Bersano et al. 2020). In this country there are currently no nuclear plants in operation, but there were until the Chernobyl's accident. Italians rejected further nuclear energy projects via referendum twice, first in 1987 and then in 2011, following the Fukushima's accident. Remarkably, Italy still lacks a complete nuclear waste management program: location of nuclear waste management sites is an unsettled issue between national and local authorities, regardless of economic benefits being offered (La Repubblica 2021). In such a context, it appears important to consider potential decision processing strategies at play when respondents make their choices regarding new nuclear projects. The proposed options may trigger emotions which in turn could affect choice behavior (Araña and León 2008; Araña et al. 2008). People may display non-compensatory choice patterns which may be explained by strategic behavior. If some individuals are radically against nuclear energy, they may completely disregard the attributes presented in the choice experiment. As discussed by Hess et al. (2010) in a different context, "*respondents may be so opposed to the principle of road tolls that they will never choose a tolled alternative in [a Stated Choice] experiment, no* *matter how large the time savings may be*" (Hess et al. 2010, p.406). So, it may happen that some respondents strongly opposed to nuclear plants may just refuse to move from a 'No Nuclear option' (if available). In other cases, apparent non-trading behavior may be caused by different levels of importance attached to specific attributes by some respondents. For example, respondents may always choose the alternative with the better level of one attribute: this behavior is referred to as "attribute dominance" (Johnson et al. 2019). Attribute dominance can be explained by respondents valuing an attribute very highly, with the range of variation in other attributes being too narrow to offer sufficient compensation for moving away from the better level of the preferred attribute (Johnson et al. 2019). Thus, some respondents may accept a trading, but only if some conditions regarding their preferred attributes are satisfied. For example, respondents may not in principle be opposed to nuclear energy, provided that the facility is not developed in their local area: this is often referred to as NIMBY effect, associated with free riding (Carley et al., 2020). Ample literature has shown that acceptance of hazardous facilities is actually influenced by many factors, such as trust in institutions (Bronfman and Vázquez 2011; Siegrist et al. 2005; Poortinga and Pidgeon 2003), place attachment (Devine-Wright 2011; Van Veelen and Haggett 2017), benefit and risk perception (de Groot et al. 2020, Strazzera et al. 2022), which cannot be simply interpreted as free-riding; yet, as suggested by Uji et al. (2021), these perceptions may trigger a NIMBY attitude, so that in the choice exercises respondents may overly focus on the distance attribute and choose the project option only if this attribute attains a certain level. It may as well happen that other attributes are considered irrelevant, and hence completely ignored in the decision process.

These choice behaviors could be problematic if modelled with standard choice models, e.g. a random utility maximization (RUM) model (Manski 1977), under the assumption that all individuals follow the same utility maximization process. As advocated by Johnston et al. (2017), data analysts should evaluate *"whether response anomalies merely add random noise to value estimates or whether they have systematic effects that can distort these estimates"* (Johnston et al. 2017, p.362). Allowing for deviations from rational consumer theory, it can be hypothesized that respondents apply a variety of heuristics (Kahneman 2003), which may have a systematic impact on the estimates resulting from the choice model. Decision heuristics recognize that when humans make decisions, some information is ignored in order to make decisions "*more quickly, frugally, and/or accurately than more complex methods*" (Gigerenzer and Gaismaier 2011, p.454). Drawing on research on lexicographic preferences and non-trading (Hess et al. 2010), attribute non-attendance (Scarpa et al. 2010), attribute importance (Balcombe et al. 2014), we allow for decision process heterogeneity employing a finite mixture model. A Latent Class model is fitted to the data, estimating the probability that a respondent uses a specific decision process characterized by attribute saliency, possible attribute non-attendance, and alternative-specific effects, allowing for possible combinations of decision making procedures. Moreover, since individuals who differ in their decision strategies may also have different preferences for the characteristics of the alternatives (Hess et al. 2013), we employ a Latent Class Random Parameters Model (Greene and Hensher 2013), specifying randomly distributed preference parameters over the latent classes. Such a modelling strategy should allow to control for the risk of confounding heterogeneity of taste and decision making (Hess et al. 2012, 2013). Our paper contributes to the literature in showing that accounting for process heterogeneity, jointly with taste heterogeneity, improves goodness of fit; furthermore, in our application, the resulting estimates are more efficient for most parameters of interest, and the point estimates of the compensatory monetary measures are more conservative than those obtained when multiple heuristics are not taken into account. Choice experiment data was collected by means of an online survey aimed at estimating willingness to accept (WTA) measures for the hypothetical building of new nuclear plants in Italy. We opted to run a choice experiment in this context to value changes which are multidimensional, and to infer monetary valuations implicitly (Hanley et al. 2001; Bateman et al. 2002).

The rest of the paper presents the literature review in Section 2, the econometrics of the model in Section 3; Section 4 presents the specific case study; Section 5 describes the results and Section 6 concludes.

2. Literature review

2.1 Heuristics in choice modeling

A substantial body of research has investigated reasons why individuals employ heuristics in decision making, including simplification of the decision process (Heiner 1983; Payne 1976; Payne et al. 1993) and limited cognitive capabilities or information overload (Simon 1955; Miller 1956). In economic valuations conducted via choice experiments, individuals are presented with a number of choice situations in which they are asked to compare options, which are characterized by specific attributes and levels. Mounting evidence has been indicating that respondents might indeed not conduct a full comparison of the levels, attributes, and options proposed in each choice task, and that they might even use multiple heuristics when making their choices (Balbontin et al. 2019). Decision heuristics include status quo bias (individuals tend to remain at the status quo because of inertia effects), and lexicography (individuals make decisions by only evaluating aspects of each alternative) (Tversky 1969).

Attribute dominance occurs when respondents choose the alternative *“…with the better level of one attribute in all or nearly all the choice questions”* (Johnson et al. 2019, p.158). The concept of attribute’s dominance has been discussed in reference to attributes that might have a *“…too large impact on decisions*”, e.g. regarding health (Helter and Boehler 216, p.665). Authors caution practitioners to conduct a careful attribute selection so as to avoid, if possible, dominant attributes, or at the very least to conduct internal validity tests to identify cases of attribute dominance alongside straight-lining and failure of preference stability and transitivity (Johnson et al. 2019).

A largely investigated heuristic is the attribute non-attendance (ANA) process, according to which respondents evaluate only a subset of the attributes presented in each choice task, whilst failing to evaluate one or more of the attributes presented (Hensher et al. 2005; Lagarde 2013; Rose et al. 2013; Sandorf et al. 2017; Mariel et al. 2021). Research has also highlighted that non-attendance might concern particular levels of the attributes (Caputo et al. 2016). This heuristic is related to the concept of lexicographic preferences, according to which respondents choose repeatedly the option containing the best level of a particular attribute (Hess et al. 2010; Scarpa et al. 2013). In the latter case, the attention is on what respondents focus on, rather than on what they do not consider in the choice. More recently, the terms ‘elimination-by-aspect’ and ‘selection-by-aspect’ have been employed, referring to situations where respondents may systematically exclude some alternatives, or make choices based on specific attributes (Erdem et al. 2014; Daniel et al. 2018). Besides attributes, respondents might ignore, or pay little attention, to entire alternatives (Campbell and Erdem 2018). This heuristic draws from the work of Tversky (1972a, 1972b). Additionally, according to what has been termed as majority of confirming dimensions heuristic (Mariel et al. 2021), some respondents might fail to compare all the alternatives simultaneously and rather compare a pair of options at a time.

It has also been suggested that attributes and/or levels considered may be affected by thresholds and cut-offs (Swait 2001; Cantillo et al. 2006; Cantillo and Ortúzar 2006). Individuals' choices can be also influenced by reference points (Hensher and Collins 2011; Hess et al. 2012); that is, their decision process in successive choice tasks might be affected by what was presented in earlier comparisons. As in choice experiments respondents engage in a series of choice tasks, some respondents might discover their preferences on the go, thereby failing to display preference stability. In other words, according to this heuristic referred to as value learning, preferences are endogenous, depending on the options shown in the experiment (Balbontin et al. 2019).

The guidelines elaborated by Johnston et al. (2017) for stated preference studies recommend that *"surveys should be designed to investigate anomalous responses and analysis should use the information to investigate the effects"* (p.362). So, the questionnaire *"should include debriefing questions to allow the effect on value estimates to be evaluated during data analysis and ameliorated if possible"* (p.363). In the current paper we use information regarding the relative importance of the attributes as stated by each respondent after the choice exercises, to model possible non-compensatory behavior associated with saliency effects and specific alternative effects. Our work is related to Balcombe et al. (2014), who also employ a stated ranking of attribute importance from the respondents, although our modelling approach is different. Evidence has shown the necessity to test a simultaneous modeling of preference heterogeneity and decision process heterogeneity to minimize confounding effects and biased estimates (Leong and Hensher 2012; Hess et al. 2013). This can be done by employing a Latent Class Random Parameter model (Greene and Hensher, 2013), with different latent classes mapped to specific decision processes, and random taste parameters to allow for preference heterogeneity within each segment.

2.2 Preferences towards nuclear energy

In spite of this extensive methodological research, applications as part of choice experiment studies in the field of energy preferences remain rather scant. In Table 1 below, we list relevant choice experiment studies related to the valuation of preferences towards nuclear energy[1]. The study of Cicia et al. (2012) was conducted in Italy prior to the Fukushima accident. The results of this work pointed towards lack of support towards nuclear energy and, instead, ample acceptability of renewable energy sources. Lack of support towards nuclear energy was found in studies that included different energy mixes as attributes (Murakami et al. 2015; Kim et al. 2018), as well as when different energy sources were associated to different alternatives either labelled (Motz 2021; Rijnsoever et al. 2015) and unlabeled (Byun and Lee 2017). Contu et al (2016) evaluated preferences towards nuclear energy in Italy after the Fukushima accident; this study found evidence of substantial opposition towards nuclear energy projects with one latent segment-amounting to 33% of the respondents-apparently not willing to accept any monetary compensations (in correspondence

[1] A number of studies had investigated preferences for nuclear energy using the contingent valuation method (e.g. Liao et al 2010; Jun et al. 2010; Woo et al. 2014; Sun and Zhu 2014). These works, with the exception of Jun et al. 2010, seem to indicate a preference for limiting the building of new nuclear plants.

of this class it was found a non-significant preference coefficient associated to bill reduction and a high positive value for the coefficient associated to the alternative specific constant of the 'no-project' option). Distance from the nuclear plants and nuclear waste reductions emerged as the most important attributes both in the valuation estimates and in a ranking exercise where respondents were asked to grade the relevance of the proposed attributes when making their choices. The same set of attributes was also considered by Contu and Mourato (2020), in an application to the UK. Whilst in this instance there was no evidence of opposition towards nuclear to the extent observed in Contu et al. (2016), again the attributes distance and waste reduction appeared to outweigh the other project components. Choice experiments studies that focus on WTA for new nuclear plants found distance to be a crucial attribute with stronger opposition towards potential new plants built closer to the area of residence of the respondents (Contu and Mourato 2020; Huh et al. 2019), even when overall opposition towards nuclear energy project is much milder (Contu et al. 2020).

Table 1: Relevant choice experiments studies concerning the evaluation of preferences towards nuclear energy

Reference	Method	Energy Source(s)	Object of the study	Attributes	Geography
Motz (2021)	Discrete choice experiment with hybrid choice modeling	Nuclear, Hydro, Solar, Wind	WTP for different energy sources & optimal energy mix	Electricity source, price of electricity, frequency of short blackouts, frequency of long blackouts	Switzerland
Contu and Mourato (2020)	Discrete choice experiment with standard RPL and latent class modeling	Nuclear energy	WTA for new nuclear plants	Distance from the nuclear plants, atmospheric emission reduction, electricity bill reduction, building of new hospitals and land recovery measures	UK
Contu et al. (2020)	Discrete choice experiment with standard RPL and latent class modeling	Nuclear energy	WTA for new nuclear plants	Distance from the nuclear plants, atmospheric emission reduction, electricity bill reduction, building of new parks	UAE
Huh et al. (2019)	Discrete choice experiment with standard RPL modeling	Nuclear energy	WTA for new nuclear plants	Reduced electricity bill, construction of new public facilities, job creation, residents' participation, installation of solar panels, distance from the nuclear plants	South Korea
Kim et al. (2018)	Discrete choice experiment with hierarchical Bayesian logit model accounting for reference-dependent preferences	Nuclear, fossil fuels, renewable	WTP for different energy sources & optimal energy mix	Share of energy sources, Smart meter, n. of blackouts per year, duration of each blackout, active social contribution, additional electricity bill	South Korea
Byun and Lee (2017)	Discrete choice experiment with hierarchical Bayesian logit model	Coal, natural gas, petroleum, nuclear, renewable	WTP for different energy sources & optimal energy mix	Danger posed, GHG emissions, Instability, Energy dependence on imports, power generation costs	South Korea
Contu et al. (2016)	Discrete choice experiment with standard RPL and latent class modeling, structural equation modeling	Nuclear energy	WTA for new nuclear plants	Distance from the nuclear plants, atmospheric emission reduction, electricity bill reduction, building of new hospitals and land recovery measures	Italy
Murakami et al. (2015)	Discrete choice experiment with standard RPL modeling	Nuclear, Renewable, Fossil fuels	WTP for nuclear and renewable electricity	Monthly bill, Air emissions, Energy mix	US and Japan
Rijnsoever et al. (2015)	Discrete choice experiment with standard RPL and latent class modeling	Nuclear, Solar, Wind, Biomass, Coal, Natural Gas	WTP for different energy sources and impact of labels	Long term problems, Security of supply, Private costs and discomfort, Spatial impact, Price per KWh	Netherlands
Cicia et al. (2012)	Discrete choice experiment with standard latent class modeling	Nuclear, Fossil fuels, Wind, Solar, Biomass	WTP for different energy sources	Energy sources, Change in electricity bill	Italy

0

Previous choice experiments studies dealing with acceptance of nuclear projects have not focused on the potential role of heuristics in affecting choice and, in turn, monetary valuations derived from the exercise. The current paper aims to address the issue of identifying and modeling non-compensatory behavior in this field of application. By further analyzing the data used in Contu et al. (2016), we intend to verify the hypothesis that multiple heuristics, including saliency, may have been used by the respondents when making their choices, and to analyze the potential impact on the estimates.

2.3 Modelling saliency

Respondents may overly focus on attributes that they particularly like or dislike. Some respondents might fail to compare all the attributes across the options presented because one attribute is particularly worrying or attractive for them, captures their attention and influences their choice. These attributes or levels that receive a higher attention are likely to be salient in subsequent choices made by the respondents. For instance, respondents afraid of the risks of accidents in nuclear plants might put a higher weight to the option with the furthest nuclear plant; or people who are worried about radioactive waste could lean toward the option with the highest reduction of waste, with lesser consideration of the levels of the remaining attributes.

By using complementary information obtained from the respondents at the end of the series of choice tasks, we identify whether, in each choice task, an alternative contains the salient attribute for a given respondent. Then, a saliency alternative constant is included in the model, to take into account possible alternative effects generated by the presence of the salient attribute. Our modelling approach accounts for the possibility that saliency fully drives the choice behavior, or only to some extent. Whilst this heuristic brings to mind a decision process affected by lexicographic preferences or attribute dominance, it differs from that as it does not postulate that respondents will always, choose the alternative containing specific levels of a given attribute. Rather, as in the ANA framework, a Latent Class model is specified, which probabilistically assigns each respondent to a decision making process class. The model can accommodate for multiple decision processes, and may include the possibility that some attributes are ignored.

In addition, the model proposed in the current paper takes into account general alternative specific effects, not associated with the salient attribute, which may occur when respondents tend to select a specific alternative regardless of the levels of the attributes presented in the other alternatives (Campbell and Erdem 2018). For example, in our application some respondents tend to repeatedly choose the opt out option: this could happen, for instance, among respondents who are strongly opposed to nuclear energy regardless of the compensatory measures presented.

The model proposed accounts for special cases of elimination or selection by aspect, thresholds or cut-off effects; while we do not account for heuristics such as value learning. In Table 2, we summarize the decision processing strategies we have taken into account in this work. Our primary goal is to establish whether evidence can be found with regards to the impact of attributes' saliency on choice. We assess this by simultaneously allowing for taste heterogeneity and, as discussed above, by also allowing for a certain degree of decision process heterogeneity. The econometric modelling strategy used in the current work is presented in the next section

Table 2: List of major Non-RUM choice heuristic and links to the modeling strategy proposed

Non-RUM choice heuristic	References	Displayed by…	Fields of application	Taken into account in this work?
Attribute dominance	Johnson et al. (2019)	Respondents who tend to choose the option containing the best level of a given attribute in all or nearly all choice tasks	Health	Yes. Attribute dominance can be inferred in our model from choices driven by saliency across all or nearly all choice tasks (where saliency might only partially influence choice).
Lexicographic choice behavior	Hess et al (2010); Rose et al (2013)	Respondents who choose the option always based on specific levels of a given attribute	Transportation	Yes. When introducing preference heterogeneity across parameters, lexicographic behavior is also taken into account as the saliency behavior is then allowed to become quasi-lexicographic for some of the respondents
Non trading behavior	Hess et al (2010); Campbell and Erdem (2018)	Respondents who always choose the same option	Transportation, Health,	Yes. Our model includes latent classes where choice behavior is influenced by the option 'none'.
Attribute non attendance	Hensher et al (2005); Scarpa et al (2009); Scarpa et al (2010); Scarpa et al (2013); Lagarde (2013); Sandorf et al (2017); Rose et al (2013); Mariel et al (2021)	Respondents who do not consider some of the attributes when comparing the options	Transportation, Health, Environmental Economics, Food choice	Partially. Our model includes latent classes where the coefficients associated to the attributes are set equal to 0.
Attribute importance	Balcombe et al (2014)	Respondents who attach different levels of importance to different attributes, not necessarily ignoring them fully	Food choice	Partially. We consider the most and second most important attributes rather than a full ranking.
Elimination by aspect	Erdem et al (2014), Daniel et al (2018)	Respondents who do not consider some of the options presented	Health, Environmental Economics	Partially. Attribute saliency might induce elimination by aspect choice behavior.
Selection by aspect	Erdem et al (2014)	Respondents who focus on particular options presented	Health	Partially. Attribute saliency might induce selection by aspect choice behavior.
Thresholds & cut-off effects	Swait (2001); Cantillo and Ortúzar (2006)	Respondents who tend to choose the option containing attributes that present levels above certain minimum thresholds	Transportation	Partially. Attribute saliency might induce thresholds effects in choice behavior.
Value learning	Balbontin et al (2019)	Respondents whose choices at choice task t are related to the choice at choice task t-1	Transportation	No

3. Econometrics

3.1 The utility function & the variable 'SAI'

We build from the random utility maximization approach, albeit we caution practitioners that more frameworks[2] can be considered depending on the data at hand and the hypotheses being tested. All models were estimated in R with Apollo (Hess and Palma 2019a; Hess and Palma 2019b). We model the deterministic component of the utility function V_{nit} of a given respondent 'n', for the option 'i', choice task 't', as follows:

$$V_{nit} = \alpha^c AS_{nit} + \beta_x^c X_{nit} + \beta_m^c M_{nit} + \gamma^c SAI_{nit} \quad (1)$$

where the superscript 'c' indexes a given class, α is the coefficient associated to an alternative specific dummy (AS), associated to the alternative 'none of the two options'[3]; β is the effect associated to the attributes, distinguishing by the effect (β_m^c) attached to the monetary attribute included in the vector M_{nit} and the effect (β_x^c) associated with the non-monetary attributes included in the matrix X_{nit}, presented in the choice experiment; while γ is the effect associated to the alternative specific variable, defined as SAI (stated attribute importance), that captures the effect of the stated most or second most important attribute in a given choice task. The second most important attribute is considered in choice situations where the most important one appears at the same level in the two project alternatives. This information was obtained by means of a ranking exercise at the end of the choice experiment exercise, namely after completion of all the choice tasks.

[2] Such as random regret minimization (Chorus et al 2008).
[3] Failure to take into account status-quo effects might lead to substantial bias in the estimated coefficients (Scarpa et al. 2005). There were three options presented in these discrete choice experiment: option A, B, or none. An anonymous referee suggested to include an effect for all J-1 alternatives, hence one more alternative specific constant associated to either option A or B. We have tried to include such additional effect but its associated coefficient was not significant, and hence we did not consider it in subsequent modeling. This is as expected since the options A and B are unlabeled as discussed in the results section.

The SAI variable is an alternative specific dummy which takes the value 1 if the attribute ranked first is highest in that alternative. The effect of this variable in the utility function is strictly linked to the levels of the attributes shown in the option that the respondent chooses. If the level of the attribute ranked first is the same across alternatives, then the attribute ranked second is considered for identification of the SAI variable. If also the attribute ranked second is overlapping across alternatives, then we assume that no saliency emerges in the choice task, and the SAI variable takes the value zero. Other behavioral hypotheses may be more restrictive, i.e. only the first ranked attribute is considered for the saliency definition; or looser, for example considering the third ranked attribute if both the first and second overlap across alternatives.

Let $x_n^R, R \in [1, K]$ be the rank of attribute *k* stated by individual *n*, with 1 denoting the first ranked attribute, 2 the second, and K the last attribute. For each alternative $i \in [1, J]$ and choice situation $t \in [1, T]$, we define

$$SAI_{nit} = \begin{cases} 1 \;\; if \; x_{nit}^1 > x_{njt}^1 \\ 1 \; if \; x_{nit}^1 = x_{njt}^1 \; and \; x_{nit}^2 > x_{njt}^2 \\ 0 \; otherwise \end{cases} \qquad (2)$$

The use of only a subset of the ranking data is one of the important differences as opposed to Balcombe et al (2014). The specification (2) does not use the full set of information potentially available from the full ranking data due to the specific heuristic being tested: we hypothesize that attributes ranked third or below do not have a saliency effect. However, the information regarding low ranked attributes might be useful to estimate other types of heuristics, e.g. ANA effects (Hess and Hensher 2013, Chalak et al. 2016).

If saliency is relevant for decision makers, we expect to obtain a positive and significant γ, indicating that respondents are more likely to choose the option containing the better level of the salient attribute. When modeling saliency, we aim to test situations in which respondents place a greater emphasis on certain attributes, without necessarily choosing only based on the salient attribute, in which case the preference would tend to be lexicographic. In addition, it should be noticed that saliency is an effect produced by non-compensatory behavior, which adds to the preference weights of the utility function: it is fundamental to model simultaneously preference and decision process heterogeneity to minimize the risk of wrongly attributing excessive preference weights.

It must be noticed that the inclusion of a stated SAI variable raises the potential issue of endogeneity and measurement error. Some authors have addressed this issue in modelling stated ANA by resorting to a hybrid modelling approach (Hess and Hensher 2013). In the current paper the saliency effect is modelled as a random variate in a finite mixture probabilistic framework, as discussed in the following subsection.

3.2 Description of the latent classes

The hypothesis we aim to test is that saliency of a particular attribute might drive the respondent to choose a particular option. Different decision process strategies are envisaged. For some respondents, a purely compensatory behavior could be a fair approximation, i.e. when their choices are driven uniquely by their preferences for the attributes of the project included in the scenarios; some may select a specific alternative (in this application the 'No Choice' option, represented by the variable AS), disregarding any of the attributes of the alternative options; others may choose the option that contains the salient characteristic as described above; finally, other individuals may be characterized by a mix of compensatory and heuristics driven behavior.

We employ a Latent Class specification to model these different decision process strategies. This is a further difference compared to Balcombe et al. (2014), where stated attribute importance information was included within a mixed logit model. The approach we follow has been previously described as constrained latent class approach (Scarpa et al. 2009) or probabilistic decision process (Hensher et al. 2013) as the classes are employed to probabilistically determine different decision-making strategies, in a confirmatory fashion.

The model proposed in this paper involves different decision making processes: compensatory behavior (CB), driven by utility parameters beta; a status quo effect, captured by the parameter alpha; the saliency effect driven by the SAI parameter gamma. Table 3 reports the specification used for each class in our constrained latent class model.

Table 3: List of constraints to determine classes

Class	Constraint	Decision process
Class 1	$\alpha^{c=1} \neq 0, \beta^{c=1} \neq 0, \gamma^{c=1} \neq 0$	CB, SAI and AS
Class 2	$\alpha^{c=2} \neq 0, \beta^{c=2} \neq 0, \gamma^{c=2} = 0$	CB and AS
Class 3	$\alpha^{c=3} = 0, \beta^{c=3} \neq 0, \gamma^{c=3} \neq 0$	CB and SAI
Class 4	$\alpha^{c=4} = 0, \beta^{c=4} \neq 0, \gamma^{c=4} = 0$	CB
Class 5	$\alpha^{c=5} \neq 0, \beta^{c=5} = 0, \gamma^{c=5} = 0$	AS
Class 6	$\alpha^{c=6} = 0, \beta^{c=6} = 0, \gamma^{c=6} \neq 0$	SAI
Class 7	$\alpha^{c=7} \neq 0, \beta^{c=7} = 0, \gamma^{c=7} \neq 0$	AS and SAI
Class 8	$\alpha^{c=8} = 0, \beta^{c=8} = 0, \gamma^{c=8} = 0$	Full non attendance

β^c *includes both* β_x^c *and* β_m^c.

The decision makers may be characterized by only one of these strategies (Classes 4, 5 and 6); or different approaches may be combined in driving the final choice (Classes 1, 2, 3, 7). Finally, we allow for a fully inconsistent behavior, modelling a class where all parameters are set to zero.

Individuals in Class 1, 2, 3 and 4 use a compensatory behavior (CB), either in combination with other strategies, or alone. Class 1 models the decision process by individuals who are characterized by compensatory behavior (CB), but who are also influenced by a status quo effect (AS), allowing for the potential impact of salient attributes (SAI) as well. The latter effect is not relevant for individuals in Class 2, while in Class 3 we introduce once again the potential role of saliency in choice, this time postulating that no status quo effect is present. In Class 4 respondents follow a fully compensatory behavior. Individuals in Classes 5, 6, 7 and 8 are characterized by non-compensatory behavior: Class 5 deals with respondents who are strongly against the proposed projects, resulting in a tendency to choose none of them. In class 6 we again introduce the potential impact of salient attributes, yet assuming a much stronger influence as opposed to class 1, since we postulate here that saliency is the sole driver of choice (which can be interpreted as a lexicographic behavior). Class 7 deals with respondents who sometimes choose lexicographically, and in other occasions choose the status quo. This may occur when in some choice situations the respondent, who otherwise would choose only based on the salient attribute, is not satisfied by its levels, hence resorting to choose none of the options; whilst possible, this could be expected to be a rare occurrence. Finally, Class 8 implies that the respondent's choice was completely random (this was dubbed as "complete ignorance" by Araña et al. 2008).

3.3 Econometric models

The probability of observing a sequence of choices y_n over T_n choice situations with j alternatives is expressed as follows:

$$\Pr(y_n|\alpha,\beta,\gamma,AS,X_n,M_n,SAI,\tau,C)=\sum_c^C \tau_c \prod_t^T\left(\frac{\exp\left(\alpha^c AS_{nit}+\beta_x^c X_{nit}+\beta_m^c M_{nit}+\gamma^c SAI_{nit}\right)}{\sum_j^J \exp\left(\alpha^c AS_{njt}+\beta_x^c X_{njt}+\beta_m^c M_{njt}+\gamma^c SAI_{njt}\right)}\right) \quad (3)$$

where τ_c, with $0 \leq \tau_c \leq 1$, represents the probability associated with a given class c. Class membership probability can be computed by means of a multinomial logit:

$$\tau_c=\frac{\exp\left(\mu_c\right)}{\sum_{c=1}^C \exp\left(\mu_c\right)} \quad (4)$$

(4) does not include covariates. When coefficients are set to be the same across classes, with no preference heterogeneity, we obtain a multinomial logit model that incorporates saliency (referred to LC_MNL_SAI hereafter). Further, within classes, we set α, β_x and γ to follow normal distributions with parameters' vectors ζ, θ, and φ, respectively, whereas β_m, associated to the monetary attribute, is assumed to follow a log-normal distribution with parameter vector ω:

$$\Pr(y_n|\alpha,\beta_x,\beta_m,\gamma,\zeta,\theta,\omega,\varphi,AS,X_n,M_n,SAI)=$$

$$\int \prod_t^T\left(\frac{\exp(\alpha^c AS_{nit}+\beta_x^c X_{nit}+\beta_m^c M_{nit}+\gamma^c SAI_{nit})}{\sum_j^J \exp(\alpha^c AS_{njt}+\beta_x^c X_{njt}+\beta_m^c M_{njt}+\gamma^c SAI_{njt})}\right) f(\alpha,\beta_x,\beta_m,\gamma|\,\zeta,\theta,\omega,\varphi)d(\alpha,\beta_x,\beta_m,\gamma) \quad (5)$$

Means and standard deviations associated with each attribute were set equal across classes, so that class allocation is driven by heterogeneity in decision process. We refer to this model as LC_RPL_SAI.

For comparison purposes, we also estimate standard multinominal logit (MNL) and random parameters logit (RPL) models. The MNL assumes both preference and decision process homogeneity, whereas the RPL introduces preference heterogeneity whilst maintaining decision process homogeneity. In the RPL model we assumed all parameters of non-monetary attributes to be normally distributed, while β_m is assumed to follow a lognormal distribution. We also offer the comparison with analogous RPL models where β_m is constrained to be fixed.

In order to compute the monetary valuations, we estimated the models in WTA space, using the following specification:

$$V_{nit} = \alpha^c AS_{nit} + \beta_m^c M_{nit} + \beta_m^c WTA_n X_{nit} + \gamma^c SAI_{nit} \qquad (6)$$

where WTA_n is a vector of willingness to accept estimates associated with the non-monetary attributes (Hess and Train 2017). As we employ continues mixtures within latent classes, we will report (unconditional) means and standard deviations for each monetary valuation. It must be noticed that this model postulates classes where beta coefficients are constrained to be equal to zero; hence, when computing weighted WTA estimates where the weights are the average class membership probabilities, monetary valuations are going to be affected downwards depending on the size of the non-compensatory classes.

4. Research design

4.1 Selection of attributes

Attributes and levels were selected based on the analysis of the literature review and pilots[4]. The pilots were conducted with a total of 75 students from the University of Cagliari (Italy). This helped fine tune the description of the attribute and levels, as well as to test the randomization of the choice tasks. Since during normal operation a nuclear plant poses potential environmental threat (Beheshti 2011) and risks for human health (Fairlie 2013), and those living nearby are more likely to suffer from negative effects (Munro 2013; Schneider and Zweifel 2013; Steinhauser et al. 2014), we selected 'Distance from the nuclear plant' as a further attribute. In Italy there are no nuclear plants in operation and we would expect a project including a nuclear plant further away

[4] Further details regarding the survey can be found in Contu et al. (2016).

to be preferred, all else equal. Based on Italian laws concerning compensation measures in case of the building of nuclear plants, a minimum level of 20 Km from the town of residence of the respondent was chosen (Iaccarino 2010).

An additional attribute selected was 'atmospheric emission reduction' as nuclear energy seems to be associated to zero, or close to zero, atmospheric emissions at least during the operation phase (Apergis et al. 2010; Hayashi and Hughes 2013; Samseth 2013; Van der Zwaan 2013; Wang et al. 2013). Following the pilots, we kept the description of this attribute general, without specifying exactly CO_2 or Green House Gas emissions in order to minimize confusion and chances of information overload. The production of nuclear waste appeared to be an additional key attribute of nuclear energy projects, and found in previous research to be an important factor shaping attitudes towards perceived risks of nuclear energy (Truelove 2012). We selected the attribute 'Nuclear waste reduction' with respect to current nuclear technology. The levels were set according to current information and discussions with experts from Enel (a major Italian company, manufacturer and distributor of gas and electricity).

We also included attributes related to public benefits in line with suggestions from previous research (Mansfield et al. 2002; Strazzera et al 2012) that pointed towards the need of complementing private compensations with measures to compensate public risks, such as medical services (Gregory et al. 1991; Yamane et al. 2011). We specifically introduced land recovery measures and the building of hospitals following our initial pilots. We had also initially considered an attribute linked with the creation of new jobs, but it appeared as the piloted respondents did not see this as realistic, so it was discarded.

Finally, the electricity bill reduction compared to the previous year, essential to compute the monetary valuations (as it can be seen in Table 1, this is the payment vehicle usually used in the relevant literature). The average monthly electricity bill was asked in order to obtain a monetary equivalent associated to the levels of the bill reduction attribute. From the average monthly electricity bill, we derived the sample average for a 10%, 20% and 30% reduction, amounting to ≈67, 135 and 203€ respectively. This implies an annual average of around ≈670€ for electricity, in line with ISTAT estimates indicating a total annual average household expenditure for electricity and gas combined equal to 1635€ (La Repubblica 2014).

The final attributes and associated levels chosen for the study are as shown in Table 4. The attributes are the distance from the hypothetical nuclear plant, the potential annual atmospheric emission reduction compared to the previous year, the potential nuclear waste reduction of a IV generation technology[5] nuclear plant as opposed to standard technology, the building of new hospitals, the undertaking of land recovery measures and electricity bill reduction.

Table 4. Attributes and levels of the choice experiment

Attributes	**Levels**
Distance from the nuclear plant (Distance)	20, 50, 100, or 200 Km from the city of residence
Nuclear waste reduction (Waste)	30%, 20%, 10% or 0%
Atmospheric emissions reduction (Emission)	20%, 10% or 0%
Electricity bill reduction (Bill reduction)	30%, 20%, 10% or 0%
Construction of hospitals (Hospitals)	Yes or No
Land recovery measures (Land recovery)	Yes or No

[5] IV generation nuclear energy is a technology to generate electricity from nuclear energy currently under research and development, which aims to reduce risks and increase benefits of the currently available technology (Zohuri 2020).

4.2 Experimental design & sample characteristics

Respondents were presented with a block of eight choice tasks, each of them offering three options (generic option A, generic option B, or none of the two), followed by the ranking exercise. The experimental design was prepared following a Bayesian efficient approach (Ferrini and Scarpa 2007) whose priors were derived from an initial stage where an orthogonal design had been employed. The Bayesian efficient design had a total of 5 blocks for a total of 40 choice tasks and it is available upon request from the corresponding author. A total of 765 individuals completed the tasks. The survey was conducted in 2014. The respondents' average age was 43.2, 46% men, with an average household size of 3 individuals, 54% completed high school and 18% had at least one university degree.

After completion of the choice exercises the respondents were asked to give a ranking of the attributes in terms of perceived importance when they made their choices (similarly to Hess and Hensher 2013). Figure 1 presents information on the stated attribute importance. The attribute 'Distance' was most frequently indicated as the most important one (33%), followed by the reduction of nuclear waste (21%). Less than 8%, instead, indicated the construction of hospitals as the most important attribute, and only 9% selected 'Land recovery measures'. Conversely, the attributes 'Bill reduction' and 'hospital' were most frequently as the least important, specifically by one quarter of the sampled respondents. The attribute 'Emissions' takes an intermediate position, being ranked as the most important by the 17% of respondents, while it is the least important one for only 7.1%.

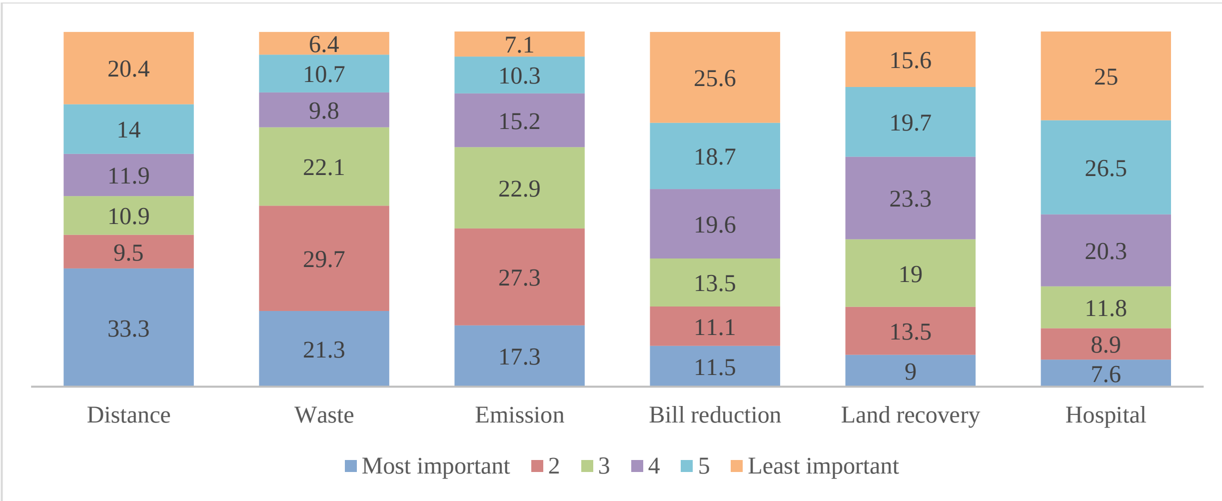

Figure 1: Stated attribute importance by attribute (% reported)

5. Model estimation and results

We begin our analysis starting with the simplest specification that assumes a pure compensatory behavior, namely excluding potential AS and SAI effects. Significant non-linear effects were detected for the attributes ‘Distance’ and ‘Waste’, which are therefore specified as dummy variables associated with different levels of the attribute; while no such effects were found for the attribute ‘Emissions’, which is included in the model as a continuous variable. The model (MNL CB) is reported in column two of Table 5. The β coefficients are significant and signs are in line with expectations. Namely, individuals prefer nuclear plants away (significantly valuing more a distance of 200Km over 100 and 50Km), positively value emission and nuclear waste reductions, land recovery measures, the building of new hospitals; they also positively value reductions in the electricity bill. When adding the status quo effect (MNL CB-AS), the model fit improves, as it can be seen from the AIC and BIC statistics; the AS coefficient is positive, indicating that CB is not sufficient to explain the respondents' choices, and that overall respondents showed some tendency to choose the status quo. An additional improvement in model fit is found when adding the effect associated to the variable SAI (model MNL CB-AS-SAI): its associated coefficient is positive and significant, indicating that among respondents there is some tendency to opt for the options containing the best level of their salient attribute.

Table 5: MNL models

Attributes/Constants	MNL (CB)		MNL (CB, AS)		MNL (CB, AS, SAI)	
	Coefficient	(s.e.)	Coefficient	(s.e.)	Coefficient	(s.e.)
SAI	/	/	/	/	0.29***	0.05
AS (status quo)	/	/	2.29***	0.11	2.27***	0.11
Distance: 200 Km	0.87***	0.06	0.72***	0.06	0.71***	0.06
1Distance: 100 Km	0.54***	0.07	0.56***	0.07	0.58***	0.07
Distance: 50 Km	0.31***	0.05	0.38***	0.06	0.38***	0.06
Emission reduction	0.24***	0.02	0.27***	0.02	0.23***	0.02
Waste reduction: 30%	0.61***	0.04	0.75***	0.06	0.65***	0.06
Waste reduction: 20%	0.54***	0.05	0.67***	0.06	0.61***	0.06
Waste reduction: 10%	0.16***	0.05	0.4***	0.06	0.34***	0.06
Hospital	0.23***	0.05	0.31***	0.05	0.31***	0.05
Land recovery	0.46***	0.04	0.55***	0.04	0.51***	0.04
Bill reduction	0.0002***	0.00	0.001***	0.00	0.001***	0.00
LL	-6225.11		-6174.44		-6149.71	
AIC	12470.22		12370.88		12323.42	
BIC	12537.41		12444.79		12404.05	
Adjusted R^2	0.07		0.08		0.08	

Level of significance:*** 1%; LL: Log-likelihood.

We then proceed to gradually increase the complexity of the models considered, introducing further decision making classes, while maintaining at this stage the assumption of non-random parameters within classes (LC_MNL_SAI specification). We report in Table 6 the resulting AIC and BIC values, alongside with the description of the constraints employed in each model, in alignment with the labels and numbering of classes mentioned earlier in Table 3. To avoid overburdening of the paper we do not report the detail of the estimated coefficients, but they are available upon request from the corresponding author. It can be observed that adding one class (i.e. the class CB and AS) to the MNL (CB-AS-SAI) model allows to obtain a better fit, as can be seen comparing the AIC and BIC measures of the latter with those of the Latent Class model with 2 classes model reported in Table 6. However, more remarkable is the improvement when moving to the Latent Class model with 3 classes where we include a third class with individuals characterized by CB, and SAI. The improvement can be easily seen from the plunge in the AIC and BIC statistics, while the Adjusted R^2 jumps from 0.07 to 0.30. When adding more classes the overall goodness of fit continues to improve marginally reaching the best value in correspondence of the Latent class model with 8 classes-which includes all classes that were presented in Table 3; we notice though that the Latent class model with 7 classes -which adds the class AS and SAI- does not improve the fit with respect to the Latent Class model with 6 classes.

Table 6. AIC and BIC of LC models

Class/Model	LC 2 classes	LC 3 classes	LC 4 classes	LC 5 classes	LC 6 classes	LC 7 classes	LC 8 classes	Decision process
Class 1	•	•	•	•	•	•	•	CB, SAI and AS
Class 2	•	•	•	•	•	•	•	CB and AS
Class 3		•	•	•	•	•	•	CB and SAI
Class 4			•	•	•	•	•	CB
Class 5				•	•	•	•	AS
Class 6					•	•	•	SAI
Class 7						•	•	AS and SAI
Class 8							•	Full non attendance
LL	-6000.11	-4642.52	-4063.38	-4580.19	-4554.37	-4554.37	-4543.88	
AIC	12026.22	9313.06	9236.75	9192.37	9142.74	9144.77	9125.75	
BIC	12113.58	9407.13	9337.54	9299.88	9256.97	9265.72	9253.42	
Adjusted R^2	0.07	0.30	0.31	0.31	0.32	0.32	0.32	

Note: Across the models presented above, all parameters were set to be fixed, with estimated parameters constrained to be equal across classes.

Next, we included random parameters within classes. Across all models we performed Maximum simulated likelihood estimation with 1000 Modified Latin Hypercube Sampling (MLHS) draws[6]. Furthermore, in order to control for convergence to local optima, we have conducted a starting value search with 100 candidates drawn from initial model estimations, using the function 'apollo_searchStart' available within the software Apollo (Hess and Palma 2019b).

We started from the model with 8 classes which was the best fitting among the LC_MNL_SAI models reported in Table 7. Under the LC_RPL_SAI specification with 8 classes, the probability of class membership probability shrinks to zero for class 2 (CB and AS), class 3 (CB and SAI), class 7 (AS and SAI) and class 8 (Full non-attendance). We iteratively removed each one of these classes, reaching to a model specification with four classes, where none of the class membership probabilities is zero or close to zero, and the goodness of fit is the best across all the models considered so far (Table 7).

[6] We avoided Halton draws due to correlation patterns that can arise because of the number of parameters considered, as previously documented in the literature (Hess et al. 2006).

Table 7. AIC and BIC of LC_RPL_SAI models

Classes	LC_RPL_SAI 8 classes	LC_RPL_SAI 7 classes	LC_RPL_SAI 6 classes	LC_RPL_SAI 5 classes	LC_RPL_SAI 4 classes	Decision process
Class 1	•	•	•	•	•	CB, SAI and AS
Class 2	•	•	•			CB and AS
Class 3	•	•	•	•		CB and SAI
Class 4	•	•	•	•	•	CB
Class 5	•	•	•	•	•	AS
Class 6	•	•	•	•	•	SAI
Class 7	•					AS and SAI
Class 8	•	•				Full non attendance
LL	-4474.94	-4474.94	-4479.65	-4479.24	-4474.64	
AIC	9011.29	9009.29	9007.29	9005.29	9003.29	
BIC	9219.59	9210.87	9202.15	9193.43	9184.71	
Adjusted R^2	0.33	0.33	0.33	0.33	0.33	

Note: Across the models presented above, all parameters were set to be randomly distributed following a normal distribution, with the exception of the attribute 'bill reduction' assumed (positive) log-normal.

We also estimated the LC_RPL_SAI with 4 classes allowing for correlations between all parameters. However, whilst the class membership probabilities and coefficients' magnitudes were not found to be significantly different, we found few significant correlation effects, and a worsening of the BIC statistic (BIC=9573.48 as opposed to 9184.71 without correlations), due to the substantial increase in the number of parameters. Hence, we proceeded with the models without correlations. Table 8 reports results from the estimation of a RPL_LC_SAI model with 4 classes and the bill coefficient either randomly distributed as a log-normal, or estimated as a non-random parameter. These models are compared with standard RPL models with analogous specifications for the bill parameter. Estimated standard deviations are reported in Appendix, Table A1.

Table 8: LC_RPL_SAI and RPL models

Attributes/Constants	LC_RPL_SAI (a) (bill log-normal)		LC_RPL_SAI (b) (bill fixed)		RPL (a) (bill log-normal)		RPL (b) (bill fixed)	
	Coefficient	(s.e.)	Coefficient	(s.e.)	Coefficient	(s.e.)	Coefficient	(s.e.)
SAI	0.61***	0.10	0.61***	0.10	/	/	/	/
AS (status quo)	3.28***	0.38	3.32***	0.30	3.01***	0.22	2.95***	0.52
Distance: 200 Km	1.35***	0.16	1.35***	0.16	0.97***	0.09	0.95***	0.24
Distance: 100 Km	1.12***	0.15	1.10***	0.17	0.79***	0.10	0.76***	0.16
Distance: 50 Km	0.58***	0.11	0.56***	0.11	0.45***	0.08	0.43***	0.15
Emission reduction	0.41***	0.04	0.39***	0.04	0.37***	0.03	0.36***	0.04
Waste red.: 30%	1.03***	0.11	1.02***	0.10	0.93***	0.08	0.89***	0.11
Waste red.: 20%	0.99***	0.10	0.99***	0.19	0.88***	0.07	0.85***	0.09
Waste red.: 10%	0.49***	0.10	0.49***	0.10	0.43***	0.08	0.43***	0.09
Hospital	0.59***	0.08	0.58***	0.08	0.46***	0.06	0.45***	0.07
Land recovery	0.96***	0.08	0.96***	0.09	0.75***	0.06	0.72***	0.08
Bill reduction	-1.78***[a,b]	0.33	0.003***	0.000	-1.97*** [a,c]	0.28	0.002***	0.000
Class 1 (CB, SAI, AS)	50%		50.2%		/		/	
Class 2 (CB)	24%		23.9%		/		/	
Class 3 (AS)	20.5%		20%		/		/	
Class 4 (SAI)	5.5%		5.8%		/		/	
LL	-4474.64		-4476.98		-4541.42		-4548.19	
AIC	9003.29		9005.97		9126.85		9138.38	
BIC	9184.71		9180.67		9274.67		9279.48	
Adjusted R^2	0.33		0.33		0.32		0.32	

Level of significance:*** 1%; LL: Log-likelihood. [a]Bill reduction was assumed to follow a log-normal distribution. The estimated parameters represent the mean of the natural logarithm of the coefficient (Train 2003).
[b]mean=exp(-1.78+((-1.16)^2)/2)/100= 0.0033; [c]mean=exp(-1.97+((-1.23)^2)/2)/100=0.0030.

It can be observed that the largest segment is the one that allows for compensatory behavior, jointly with saliency and status quo effects: this class accounts for 50% of the respondents. An additional 24% is probabilistically allocated to the class of respondents who behave in a purely compensatory manner. A slightly lower percentage (20%) of respondents will tend to choose the status quo, not making any trade-off between attribute levels. Finally, about 5% of the sampled respondents are allocated to the class where choices seem to be mainly driven by saliency, i.e. a lexicographic behavior. Hence, on average, 74% of the sampled respondents have displayed some form of compensatory behavior: the beta parameters displayed in Table 8 are associated with these respondents. The presence of a group of respondents who seem to be mainly driven by willingness to refuse any project of new nuclear plants confirms the results obtained in Contu et al. (2016); these respondents can be thought of as giving a zero (or non-positive) valuation of the project.

Monetary valuations are reported in Table 9 and in Figure 2. We initially attempted the willingness to accept space estimation with all parameters randomly distributed following a normal distribution, with the exception of the bill attribute, (positively) log-normally distributed. However, the estimates obtained would lead to substantially different class membership allocation and much poorer goodness of fit. This is despite setting even larger numbers of simulated draws (2000) and starting values iterations (200). We therefore proceed to present monetary valuations obtained from the model where the bill coefficient is assumed to be fixed. It must be noticed, however, that a fixed cost parameter implies assuming that all respondents have the same marginal utility towards money and, in turn, that differences in monetary valuations are only driven by different preferences for changes in the non-cost attributes. This model presents an analogous class allocation distribution as opposed to the model with the bill coefficient log-normally distributed, besides a very similar goodness of fit with just a few units differences in the AIC and BIC measures.

Table 9: Monetary valuations, Euro per household per year (95% confidence intervals)

	MNL (CB & AS)	RPL (b)	LC_RPL_SAI (b)
Distance: 200 Km	421.8 (298.5-585.2)	341.7 (257-443.7)	324.1 (252.5-397.9)
Distance: 100 Km	331.8 (249.1-470.4)	273.2 (216.8-350.7)	264.2 (216.2-351)
Distance: 50 Km	226.3 (152.1-342.1)	157.4 (119.9-208.3)	135.9 (101.7-178.3)
Emission reduction	162.7 (114.2-245.5)	130.1 (92.9-159.2)	94.6 (63.5-120.9)
Waste red.: 30%	440.9 (308.7-607.5)	322.3 (228.8-422)	238.1 (151.2-315.8)
Waste red.: 20%	394.9 (273.1-523.1)	308.6 (230.1-418.6)	237.1 (167.7-302.9)
Waste red.: 10%	236.4 (171.7-338.9)	154.7 (115.4-224)	117.5 (72.7-188.1)
Hospital	185.1 (141.7-295.5)	165.0 (136.2-213.8)	141 (112.4-193.8)
Land recovery	322.7 (236-452.3)	261.3 (212.8-328.4)	229.4 (190-279)

95% confidence intervals in parenthesis (lower bound – upper bound), computed via bootstrapping (100 repetitions). Values also reported in Fig. 2 for RPL and LC_RPL_SAI models. Monetary valuations associated with the LC_RPL_SAI (b) are obtained applying class membership probabilities as weights to take into account the classes where the betas are equal to zero (class 3 and 4).

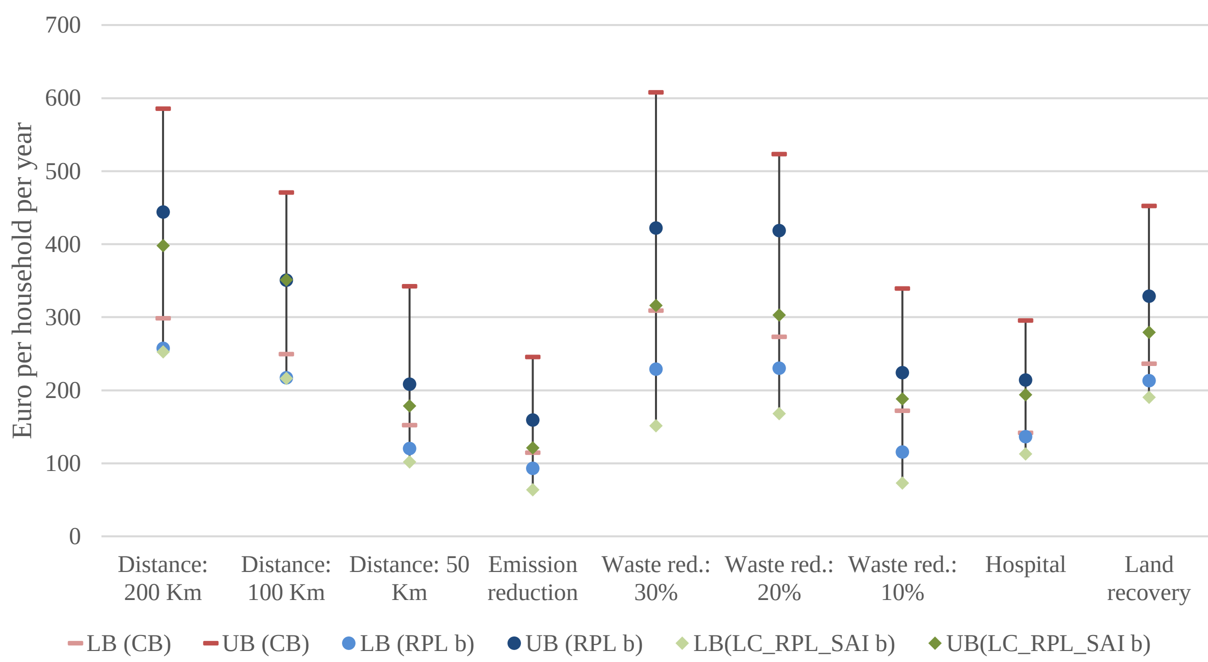

Figure 2: Monetary valuations. LB: lower bound; UP: upper bound (Models RPL b & LC_RPL_SAI b)

It can be observed that the MNL model presents the largest monetary valuations across all attributes considered. These decrease considerably when moving to the LC_RPL_SAI model with four classes. This is especially the case for the valuations associated with the nuclear waste reductions: 84 Euro per year per household less on average for a 30% waste reduction according to the LC_RPL_SAI vis a vis the RPL model. Important differences are also found when comparing average monetary valuations associated to the attributes hospitals (24 Euro per year per household less on average), and land recovery measures (32 Euro per year per household less on average). Less pronounced is the reduction in average WTA when comparing distance levels (especially for the level 100 Km, where confidence intervals of RPL and LC_RPL_SAI overlap) and emissions reductions.

6. Conclusions

This work provides a modeling framework for eliciting preferences towards energy sources that a considerable share of individuals is expected to perceive as problematic, such as nuclear energy (Visschers and Siegrist 2014). It has applied a model that simultaneously includes preference heterogeneity, the role of saliency in choice, as well as respondents' potential inclination to reject any of the projects proposed, in the context of preferences towards nuclear energy.

Findings show the substantial role played by the saliency heuristic in driving choices in the context of preferences towards nuclear energy. In line with previous literature, it appears crucial to jointly model taste and decision process heterogeneity to minimize confounding preferences' attribution (Hess et al. 2013). The proposed model, LC_RPL_SAI, accounting for heterogeneity both in decision making process and in tastes, outperforms the others in terms of goodness of fit measures such as AIC and BIC. Differences in monetary valuations are also observed: the LC_RPL_SAI model in this application produces WTA which appear more conservative as opposed to the standard RPL and MNL models.

It is important to acknowledge a limitation of this work that could potentially be addressed as part of future research. We employed stated information obtained from the respondents to build the variable used in turn to measure the effect of saliency in choice. Using reported information as error-free explanatory variables may induce some measurement error and endogeneity issues (Hess and Hensher 2013). Future work can address the issue by adopting the hybrid modelling approach proposed by Hess and Hensher (2013), possibly by using multiple measurement items. Different questions could be used, or the question could be asked after each choice task, rather than just at the end of the whole choice experiment. In addition, ways to infer saliency could be explored, for instance by means of eye tracking (Van Loo et al 2018; Segovia and Palma 2021). Despite this limitation, we believe this work is of interest for the choice modelling practitioners given the novelty of the heuristic being modelled, the findings produced and potential applications across more fields besides nuclear energy.

Whilst this study focused on preferences towards nuclear energy, more fields of application can be envisaged. It could be assumed that the saliency-led choice behavior could be an important heuristic in health-related choice experiments, where previous research had focused on attributes' dominance. As suggested by Johnson et al. (2017, p. 362) "*surveys should be designed to investigate anomalous responses and analyses should use the information to investigate the effects*". Checks for saliency effects could be conducted at the piloting stage, adopting the modelling approach suggested in this paper to the preliminary data. If saliency effects are detected, the experimental design of the choice experiment could be modified. However, in many cases inclusion of potentially dominant attributes in choice experiments may be unavoidable. In such situations we suggest to carefully test for saliency and model choice data accordingly –according to the lines suggested in this work- so as to increase the chances of a better model specification and potentially more accurate monetary valuations.

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Appendix

Table A1: LC_RPL and RPL models-standard deviations

Attributes/Constants	LC_RPL_SAI (a) (bill log-normal)		LC_RPL_SAI (b) (bill fixed)		RPL (a) (bill log-normal)		RPL (b) (bill fixed)	
	Coefficient	(s.e.)	Coefficient	(s.e.)	Coefficient	(s.e.)	Coefficient	(s.e.)
SAI	0.59***	0.16	0.66***	0.15	/	/	/	/
AS (status quo)	4.63***	0.39	4.85***	0.43	3.85***	0.18	3.83***	0.37
Distance: 200 Km	0.69***	0.11	0.68***	0.14	0.60***	0.13	0.57***	0.13
Distance: 100 Km	0.48***	0.16	0.42	0.27	0.35	0.27	0.34	0.23
Distance: 50 Km	0.02	0.04	0.08	0.11	0.04	0.11	0.11	0.09
Emission reduction	0.12	0.13	0.20***	0.07	0.15	0.10	0.08	0.9
Waste red.: 30%	0.31	0.55	0.36**	0.19	0.35***	0.12	0.31***	0.10
Waste red.: 20%	0.15	0.42	0.27***	0.13	0.09	0.21	0.15	0.8
Waste red.: 10%	0.46***	0.18	0.47***	0.21	0.46***	0.14	0.36*	0.20
Hospital	0.41***	0.14	0.42***	0.14	0.45***	0.18	0.38*	0.20
Land recovery	0.42***	0.16	0.44***	0.17	0.59***	0.11	0.56***	0.18
Bill reduction	-1.16***[a]	0.22			-1.23*** [a]	0.14		
Class 1 (CB, SAI, AS)	50%		50.2%		/		/	
Class 2 (CB)	24%		23.9%		/		/	
Class 3 (AS)	20.5%		20%		/		/	
Class 4 (SAI)	5.5%		5.8%		/		/	
LL	-4474.64		-4476.98		-4541.42		-4548.19	
AIC	9003.29		9005.97		9126.85		9138.38	
BIC	9184.71		9180.67		9274.67		9279.48	
Adjusted R^2	0.33		0.33		0.32		0.32	

Level of significance:*** 1%, **5%, * 10%; LL: Log-likelihood. [a]Bill reduction was assumed to be associated to a log-normal distribution. The estimated parameters represent the standard deviation of the natural logarithm of the coefficients (Train 2003).