On the Use of Alternative-Specific Designs in Choice-Based Conjoint Analysis

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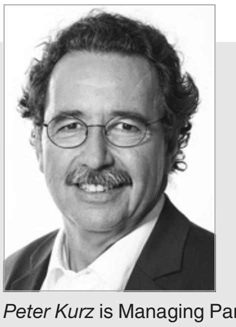
In this paper, we'd like to draw the attention of marketing academics and marketing practitioners to the use of alternative-specific designs (ASD) for choice-based conjoint (CBC) studies in marketing research. As opposed to transportation research, where the ASD approach for discrete choice experiments (DCE) or discrete choice modeling in general originated from and is still widely used, this design method rather tends to lead a shadowy existence in marketing research despite its obvious superiority for generating more realistic choice situations for respondents compared to the application of the generic designs. The latter are commonly employed in conjoint experiments in a marketing context, for example for product design and related market simulations and optimizations. We discuss why and when it is recommendable to use an ASD, propose a typology for characterizing different types of ASD structures, and work out the particularities of interpreting the estimation results of an ASD-CBC model and calculating related willingness-to-pay quantities. For illustration, we use an empirical example based on an ASD-CBC study on consumer preferences for electric vehicles in the UK. We further point to advanced modeling options for enriching or extending ASD-CBC models, including alternative-specific hybrid choice models and nonlinear utility specifications. Finally, we discuss the state-of-the-art how artificial intelligence (AI) is already influencing the domain of conjoint analysis and DCE.

1. Introduction

Nowadays, the most widely used approach to collect and quantify consumer preferences is the discrete choice experiment (DCE) or choice-based conjoint (CBC). CBC as a term is typically attributed to consumer research in marketing, whereas the term DCE originated from transportation research and is still widely applied there as well as in other fields such as urban planning, environmental economics, or health economics. However, it is worth mentioning that although it is common in many research areas, including marketing, to refer to the estimation of choice models based on stated choice data as choice-based conjoint analysis, this can be misleading. This concerns primarily the term "conjoint analysis" in its traditional understanding. Here, ranking or rating data from respondents is collected and a statistical model is fitted



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in a first step, before choice probabilities are calculated in a second independent step based on the previously estimated part-worth preferences/utilities (for more details, see Louviere et al., 2010, p. 69). Balderjahn et al. (2021) also recently clarified the terminology by emphasizing that, "strictly speaking, CBC is a discrete choice analysis (DCA) applied to a conjoint design" (Balderjahn et al. 2021, p. 186; cited according to Cohen 1997). Louviere and Woodworth (1983) connected the concept of conjoint analysis with discrete choice theory by estimating parameters of conjoint-type functions from discrete choice data, which Green et al. (2001) later referred to as choice-based conjoint analysis (CBC). In this groundbreaking work by Louviere and Woodworth (1983), the application of random utility theory to aggregate consumer choice (and allocation) data was demonstrated for a variety of empirical examples, among them a study for vacation destination choice with *destination-specific* air travel costs. The paper demonstrated the power of the proposed new approach in managing strategic pricing and product design problems, making CBC subsequently one of the most popular marketing tools for the measurement of consumer preferences.

Typically, choice designs used for CBC studies in the academic marketing community and also in marketing research practice (see Kurz 2024) are constructed in a way that relevant attributes are common to all alternatives, which is also referred to as a generic design. From a practical perspective, this is oftentimes not realistic, as Louviere and Woodworth (1983) have already suggested in their example with alternative-specific air travel costs depending on the different destination alternatives. Therefore, more flexible but also more complex choice designs, where not all attributes apply to all alternatives, but instead are specific to each alternative (transportation mode, brand, or technology) seem justified. This was only recently highlighted in an interview with Bryan Orme (2022), where Jordan Louviere noted, "*... the overwhelming majority of papers that I see ... use generic designs when they should be using alternative-specific designs".* One may explicitly prohibit particular attributes or attribute levels from appearing with others when using generic designs, however, in most cases, this can lead to serious problems with the design efficiency (Chrzan and Orme 2000). The solution to this issue can be the application of an alternative-specific design (ASD) where interactions are *implicitly* taken into account.

In the ASD, the attributes have their own terminology. The ***primary attribute***, also known as alternative-specific constant (ASC), is an attribute whose levels appear in every alternative and upon which conditional attributes depend. ***Conditional attributes*** (alternative-specific attributes) are attributes that are only displayed with a certain level or several levels of the primary attribute. Additionally, attributes that will be shown with all levels of the primary attributes across the alternatives, called ***common attributes***, can be specified as well (Sawtooth Software 2008, p. 7). However, the ASCs are not always primary attributes. Some studies include only fixed ASCs with no conditional attributes attached to them (e.g. brand constants, which as a very special case of an ASD are also widespread in marketing applications). The most famous example of an ASD stems from transportation research on the commute mode, where walking or riding a bicycle are alternatives on their own with no further modifying attributes (e.g., Anderson et al. 1992, Swait and Ben-Akiva 1987).

The different alternatives (levels of the primary attribute) however can also belong to the same product category, such as electric vehicle brands offered by different car manufacturers but at very different price levels; which makes it reasonable to specify vehicle-specific price attributes instead of only one generic price attribute with all levels common to all alternatives. *Fig. 1* below illus-

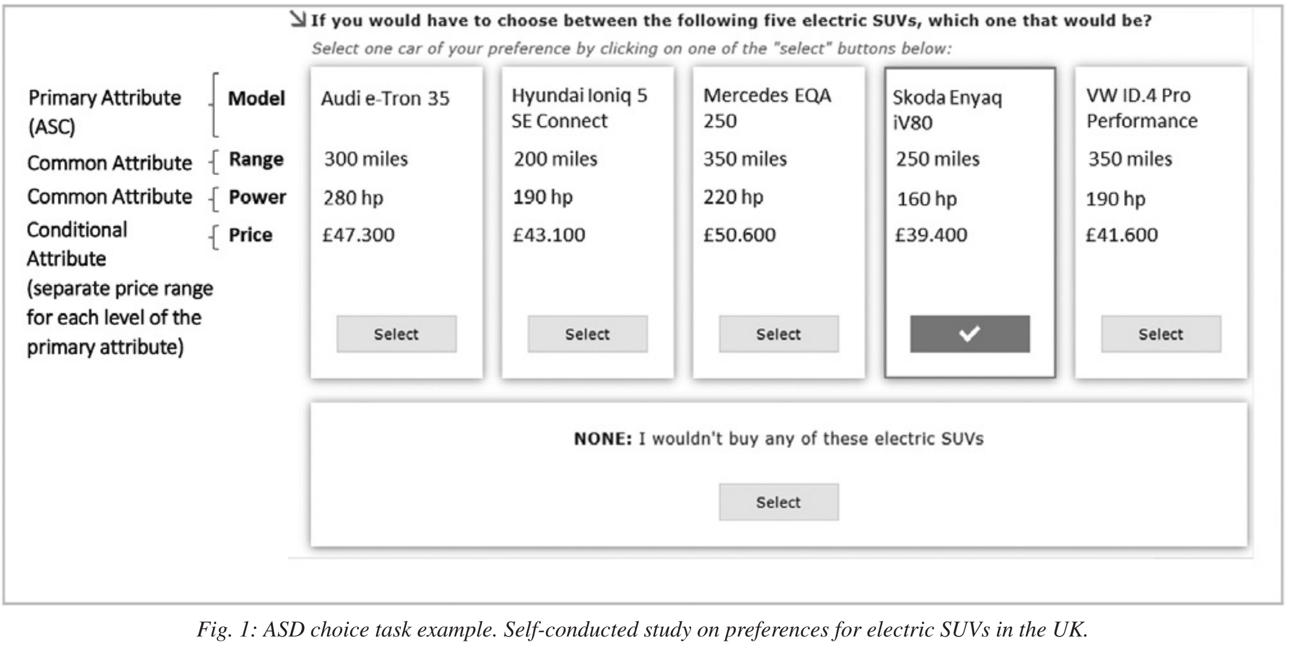

Fig. 1: ASD choice task example. Self-conducted study on preferences for electric SUVs in the UK.

trates this situation. Including a brand name or more precisely the car manufacturer and model here (denoted by the primary attribute "model) allows estimating its value via the alternative-specific constant and further creates a primary attribute-conditional attribute interaction, which is incorporated into the model (Rao, 2014, p. 133). By creating brand-specific price attributes (the conditional attributes), a researcher can accommodate that the impact of the price depends on the brand it is assigned to. Therefore, a price effect can be estimated separately for each brand, i.e. brand-specifically (Zwerina et al., 1996, p. 274). In contrast, driving range and horsepower for the different electric vehicles represent common attributes since each brand can take on all levels of these two attributes. We elaborate on this example in more detail later in section 4.

Further examples of this and different types of ASDs will be shown in the following section, where we develop a corresponding ASD typology. Sometimes, alternative-specific designs are also referred to as labeled choice experiments (Rose and Bliemer 2009).

As outlined above, alternative-specific designs have been well-established in transportation research and other disciplines such as urban planning, environmental economics, or health economics, yet they have been only rarely used or explicitly mentioned in marketing research despite their obvious conceptual advantage for consumer studies. One of the rare exceptions in the (German) marketing literature is the work of Balderjahn et al. (2021), who illustrated this approach in an empirical CBC study for chocolate bars and provided the basics of interpreting the estimation results for alternative-specific effects. We elaborate on their work and extend it by providing a typology for building alternative-specific designs for CBC studies and details on the construction of alternative-specific choice designs, by further deepening the interpretation of estimation results, and in particular by focusing on the calculation of related willingness-to-pay quantities which is more tricky compared to designs with a generic price attribute.

The construction of designs for alternative-specific choice experiments is more challenging from a theoretical point of view, however, it promises to provide respondents with much more realistic choice situations when this is justified, without imposing harmful prohibitions for the design efficiency. For example, product concepts of electric vehicle manufacturers with a higher (lower) brand value will not be shown with an unrealistically low (high) price level, if vehicle-specific prices are used. The ASD is, therefore, a design method, where a researcher can specify which characteristics (attributes and levels) are allowed to appear with which alternative offered to respondents for evaluation in a choice set, without endangering the statistical design efficiency. Instead, the consideration of alternative-specific effects permits a much wider range of choice situations compared to the typically used generic main-effects designs where all profiles share the same attributes and levels (Chrzan and Orme 2000, p. 8).

From our perspective, more attention to the practical implications of alternative-specific choice designs for CBC studies is required in the marketing literature and can be helpful to facilitate a wider use of this design technique in marketing research in general. Hence, with the present paper, we aim to provide readers with a better understanding of the application of the ASD framework in choice-based conjoint studies and to show the particularities of this approach for interpreting the estimation results and when willingness-to-pay calculations as related quantities are of particular interest. For an illustration in a marketing research context, we use an empirical example based on a self-conducted CBC study on consumer preferences for electric vehicles. We describe the methodology in section 2 and propose a typology for characterizing different types of ASDs in section 3. Section 4 contains the empirical case study for demonstration. In section 5, we point to various newer approaches for extending ASD-CBC models (hybrid choice models, nonlinear utility specifications), which can be seen as advanced options to further improve CBC studies. Here, we also discuss the state-of-the-art how artificial intelligence (AI) is already influencing the domain of conjoint analysis and DCE. Section 6 concludes the paper with a summary and a discussion of limitations.

2. Methodology

McFadden (1974) applied logit analysis in choice-based modeling (also called discrete choice) to forecast commuters' travel demand for the San Francisco Bay Area Rapid Transit (BART). Four existing transportation modes plus two new BART modes were used in the study. Each transportation mode (alternative) was described by its own set of characteristics (attributes). Consequently, each alternative was represented by an alternative-specific constant (ASC) and the characteristics of these constants could be described as modifying (conditional) attributes. Part-worth utilities were estimated for the ASCs and the parameters for the modifying attributes were estimated with respect to the ASC. The ASC for each alternative incorporates similarly to a regression model the average effect on the utility of all factors not included in the model, which means that the unobserved portion of the utility of respondent i for alternative j has zero mean (Train 2009, p. 25).

Based on random utility theory (McFadden 1974), the deterministic component of the utility function for an alternative (product concept) that includes both alternative-specific and generic (common) attributes can be stated as follows:

$$V_{ij} = \sum_{h \in H_a} \beta_{(i)jh} \cdot x_{jh} + \sum_{h \in H_g} \beta_{(i)h} \cdot x_{jh}, \tag{1}$$

where i denotes the respondent, j denotes the alternative, h denotes the attribute, $\beta_{(i)(j)h}$ is the utility parameter for attribute h (of alternative j) and x_{jh} is the value of attribute h in alternative j. H_a is the set of attributes specific to alternative j, and H_g is the set of generic (common) attributes. The respondent index on the right-hand side of equation (1) is set in parentheses to indicate that utility parameters in early applications of discrete choice models were often estimated at the aggregate consumer level only.

Based on random utility theory and the assumption of independent and identical Gumbel distributed error terms for the random component, the choice probability of respondent i for alternative j can be represented by the multinomial logit (MNL) model (McFadden 1974):

$$P_{ij} = \frac{\exp(\sum_{h \in H_a} \beta_{(i)jh} \cdot x_{jh} + \sum_{h \in H_g} \beta_{(i)h} \cdot x_{jh})}{\sum_{k \varepsilon C_i} \exp(\sum_{h \in H_a} \beta_{(i)kh} \cdot x_{kh} + \sum_{h \in H_g} \beta_{(i)h} \cdot x_{kh})}, \quad (2)$$

where C_i is the choice set of respondent i.

The log-likelihood as a function of the parameters is given by

$$LL(\beta) = \sum_{i=1}^{I} \sum_{j=1}^{J} y_{ij} \cdot lnP_{ij}, \quad (3)$$

where β is a vector containing the parameters of the model, y_{ij} is a binary variable that takes on the value of 1 if respondent i has chosen alternative j from choice set C_i, and 0 otherwise.

The development of Hierarchical Bayesian (HB) estimation techniques made it further possible to estimate individual-level parameters from choice data, including the ASD-CBC coding (Allenby, Arora, and Ginter 1995; Allenby and Ginter 1995; Lenk et al. 1996). The HB-MNL model with the multivariate normal distribution as a probability distribution, also called the HB mixed logit model (see Train 2009, Ch. 12), became the standard estimation approach for the representation of random taste variation on the individual respondent level, also due to the availability of commercial software for computation (e.g., Sawtooth Software 2022). Although Sawtooth Software is widespread in market research practice for conducting choice-based conjoint analyses, with renowned market research institutes using its ASD module, ASD-CBC studies are rarely found in the academic marketing literature (Orme 2022) as well as applied by only a minority of users of the software (Kurz 2024, p. 364).

3. Typology for Alternative-Specific Designs Based on Empirical Evidence

ASDs can be classified into the following types:

3.1. Alternative-specific constants (ASC) for fixed alternatives (such as transportation mode or brand)

Louviere and Woodworth (1983) in their soft-drink choice study example analyzed choices among eleven major brands of soft drinks (Coca-Cola, Pepsi, RC, Sprite, 7-Up, Fresca, Mountain Dew, Hires, Dr. Pepper, Mr. Pibb, and Orange Crush), where each soft drink was treated as an ASC. No additional, characterizing attributes were included in the study. This is the simplest form of an ASD.

3.2. Alternative-specific designs with an equal number of attributes for all alternatives.

(a) One price attribute for each ASC with an equal number of price levels and the same price points.

In Balderjahn et al. (2021), an empirical CBC study on the choice between chocolate bars included three alternatives represented by chocolate brands with five price levels each. Price levels (points) were the same for each chocolate brand. However, prices (conditional attributes) were each modeled as chocolate-specific variables (brand as a primary attribute), since the price had a different effect for each brand despite the same price points (see *Tab. 1* below).

In a study on choices between jeans reported by Louviere et al. (2000), prices were also brand-specific and had the same four price levels (points). The effect of price similarly differed between jeans brands.

(b) One price attribute for each ASC with an equal number of price levels but different price points.

In a choice experiment on alternative fuel vehicle (AFV) preferences for private car owners in the Netherlands, Hoen and Koetse (2014) created price attributes (conditional attributes) specific to each type of the AFV (car type as a primary attribute: hybrid, plug-in hybrid, fuel cell, electric, and flexi-fuel) by adding a technology-specific mark-up to the price of the current technology. This led to five alternative-specific attributes with three levels each (see *Tab. 2*).

Brand	*Price levels*
Milka	0.59 €, 0.79 €, 0.99 €, 1.19 €, 1.39 €
Alpia	0.59 €, 0.79 €, 0.99 €, 1.19 €, 1.39 €
Sarotti	0.59 €, 0.79 €, 0.99 €, 1.19 €, 1.39 €

Tab. 1: An example of an equal number of price levels with the same price points in the ASD-CBC study adapted from Balderjahn et al. (2021), p. 194.

Car Type	*The mark-up for price levels*
Hybrid	0 €, 2,000 €, 6,000 €
Plug-in hybrid	0 €, 2,000 €, 7,000 €
Fuel-cell	1,000 €, 3,000 €, 10,000 €
Electric	1,000 € x (driving range/140), 3,000 € x (driving range/140), 10,000 € x (driving range/140)
Flexi-fuel	500 €, 1,200 €, 3,000 €

Tab. 2: Example for an equal number of price levels but different price points for the conditional attributes in the ASD-CBC study adapted from Hoen and Koetse (2014), p. 201.

(c) One price attribute for each ASC with a different number of levels and different price points.

An equal number of price levels is not always justified in empirical ASD-CBC studies. As an example, we shall consider a CBC study for vehicles of different brands. Car manufacturers often hire market research institutes to carry out conjoint studies for pricing or designing new car models. However, the results of such studies are usually for internal use only and are treated as top secret. Yet, based on own experience in the automotive industry, there are situations, where some car alternatives do not only require different price points, but also a different number of price levels. Even though the car models as a rule considered belonging to the same car segment, each brand may have its own price range. Depending on the starting "sticker" price, the number of trim levels (different versions of the same car model), and the number of selectable additional features, this range might be wider or narrower for a particular car model. To demonstrate this, we take two electric SUV models, the BMW iX3 and Volkswagen ID.4, which belong to the same car class. The BMW iX3 is a more expensive model than the Volkswagen ID.4. Its price starts at £ 60,970 in the UK (BMW 2022) and this model has only two trim levels, whereas, Volkswagen ID.4 has four trims in the UK and its price starts at £ 36,560 (Volkswagen 2022). However, to allow price-elasticity calculations for potential price changes and to achieve more variation, additional price levels with a few steps below and/or higher than the current market price are usually added. Furthermore, it is advisable to have price levels with equally large price intervals within the price attribute or brand. Additionally, to avoid possible psychological effects from 0 and 9-ending prices (Baumgartner and Steiner 2007; Levy et al. 2020), it is reasonable to exclude such price endings. Hence, possible price attributes for this example could look as follows (see *Tab. 3*).

Alternative	*Price levels*
BMW iX3	£ 57,970, £ 60,970, £ 63,970, £ 66,970
Volkswagen ID.4	£ 33,560, £ 36,560, £ 39,560, £ 42,560, £ 45,560, £ 48,560, £ 51,560, £ 54,560

Tab. 3: A theoretical but realistic example of one price attribute (conditional attribute) for each ASC (primary attribute) with a different number of levels and different price points.

Vehicle	*Driving Range*
Plug-in-hybrid	16 km, 32 km, 64 km
Electric	120 km, 160 km, 200 km, 240 km

Tab. 4: Example of a vehicle-specific driving range attribute with different numbers of levels and different driving range points adapted from Axsen et al. (2015), p.194.

Some studies applied a different number of levels with differing points for attributes other than price. Axsen et al. (2015) in their study on preference and lifestyle heterogeneity among potential electric vehicle buyers had different numbers of driving range levels with different points for plug-in-hybrid and electric vehicle alternatives (see *Tab. 4*).

In principle, cases (b) and (c) could also be addressed with "prohibitions" when using a generic design, thereby restricting certain levels of one attribute from appearing in combination with specific levels of other attributes. However, this makes it challenging to achieve two-way level balance, i.e. that each level of one attribute appears equally often with each level of another attribute. If the levels of one attribute cannot be displayed alongside a level of another attribute, achieving two-way level balance becomes impossible. In contrast, an alternative-specific design does not employ prohibitions, but instead utilizes conditional attributes, which are controlled by the levels of the primary attribute. This approach ensures, similarly to using prohibitions, that certain attributes and their levels are only displayed when a specific level of the primary attribute is shown. However, by adopting this methodology, D-efficient choice designs can be generated that are nearly orthogonal and level-balanced.

3.3. Different attributes per alternative

A simple modal-choice problem (bus versus car) from Louviere and Hensher (1982) can serve as an example of this type of ASD. Each travel mode is an alternative and is represented by three different attributes with two levels each (see *Tab. 5*).

In the example from *Tab. 5*, the number of attributes per alternative and the number of levels are identical, however, they could also vary as in the study of Anderson et al. (1992) (see *Tab. 6* below).

3.4. Primary (ASC level 1) and sub-primary attributes (ASC level 2) (nested structures)

In the previous example of Anderson et al. (1992) starting in *Tab. 6*, some attribute levels (e.g. for the attributes

Alternative	*No. of Attribute and Levels*
Car	4 attributes, 3 levels each
Train	7 attributes, 6 with 3 levels, 1 with 2
Carpooling	6 attributes, 3 levels each
Bus	7 attributes, 6 with 3 levels, 1 with 2

Tab. 6. Example of different number of (conditional) attributes per alternative (primary attribute) from Anderson et al., (1992), p. 52.

Bus		***Car***	
Attribute	*Levels*	*Attribute*	*Levels*
Fare	0.25 €, 0.50 €	Gasoline cost	1.35 €, 1.75 €
Travel time	15 min, 40 min	Travel time	10 min, 20 min
Walking distance	1 block, 5 blocks	Parking cost per hour	0.20 €, 0.50 €

Tab. 5: Example of different conditional attributes per alternative (primary attribute) from Louviere and Hensher (1982), p. 14.

Car		
ASC Level 1	*ASC Level 2 (Distance)*	*Conditional Attribute Levels*
Travel time	8 km	7.5 min, 10.0 min, 12.5 min
	16 km	15.0 min, 20.0 min, 25.0 min
	24 km	20.0 min, 30.0 min, 40.0 min
Costs	8 km	2.00 €, 3.00 €, 4.00 €
	16 km	3.00 €, 5.10 €, 7.20 €
	24 km	4.40 €, 7.00 €, 9.60 €

Tab. 7. Example of primary and sub-primary alternative-specific attributes from Anderson et al., (1992), p. 53.

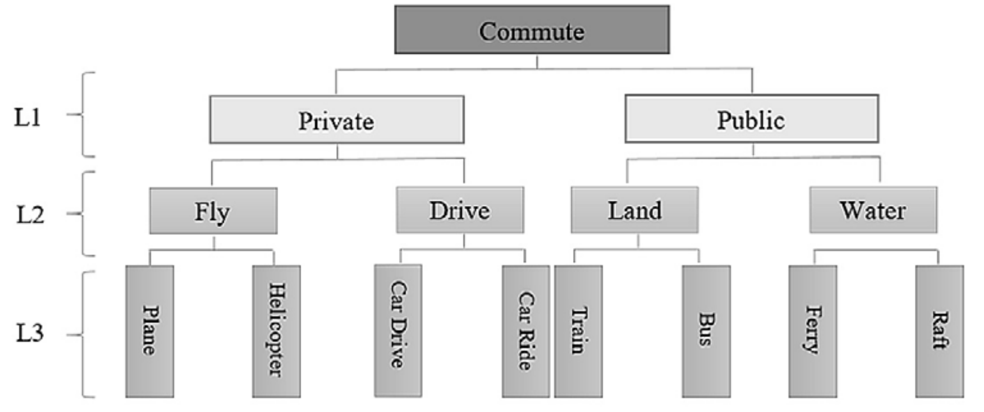

Fig. 2: Three-level nested choice structure. Source: Greene, 2009, p. 63.

travel time and fare/costs) were additionally made specific to the distance to the destination in order to design more realistic profiles, creating a second level of alternative-specific attributes (sub-primary attributes). *Tab. 7* provides an example of the primary and sub-primary attributes of the car alternative in Anderson et al. (1992).

3.5. Two or more sets of primary attributes (ASC level 3) (complex nested structures).

An example of this type of ASD is represented by a "tree structure" in *Fig. 2*, following Greene (2009). Two choices of commuting modes can be presented to the respondents, private and public. Both the private and public commute modes consist of two choices each: flying or driving by car in case of the private commute, and going by land or water in case of the public commute. However, each of these choices is represented by further two options, creating a third level of primary attributes, which can additionally be described by further modifying (conditional) attributes.

4. Empirical case study

In this section, we would like to demonstrate in more detail how to create and interpret results of an alternative-specific CBC study, using a self-conducted study on preferences for electric vehicles for illustration. We assume that the reader is familiar with the estimation of the standard and (HB) mixed MNL model and with the standard interpretation of estimation results (e.g. part-worth structures, statistical performance measures such as likelihood ratio tests or odd ratios), and therefore refer the interested reader to Elshiewy et al. (2019), Balderjahn et al. (2021), and Goeken et al. (2021). Instead, we'd like to focus on the particularities of ASD models regarding the interpretation of attribute importances and the derivation of willingness-to-pay quantities, which is more complex and different from the standard CBC approach (i.e. when using a generic main-effects design).

The data for our empirical study was collected in the United Kingdom in September 2021, comprising a total of 509 interviews and a final effective sample size of 494 respondents after data cleaning. Only respondents that were e-mobility intenders and indicated to buy a new electric SUV were admitted to participate in the study. The alternatives offered to the respondents in the choice task were electric SUVs, and the primary attribute was represented by the brand (car manufacturer) and a car model (e.g. Hyundai as the brand, Ioniq 5 Premium as the car type). Each level of the primary attribute (i.e. each electric SUV) had its own price range (conditional attributes). Driving range and engine power were specified as common attributes since each of the SUV alternatives could be equipped with a driving range between 200 miles and 400 miles and a power between 160 hp and 280 hp. The full list of attributes and levels of the UK electric SUV study can be found in *Tab. 8*.

We used the Sawtooth Software module for CBC analysis to create the ASD design and to estimate the HB-MNL model. The suggested design method for generating alternative-specific designs is the complete enumeration algorithm (Sawtooth Software 2008, Sawtooth Software Lighthouse Studio n.d.). In general, *Complete Enumeration (CE)* considers all possible concepts (except prohibited ones) and is aimed at providing a design with both one- and two-way level balance for the entire choice

Attribute	*Type of attribute*	*No. of levels*	*Levels*
Car Model (brand / type of car)	Primary attribute	10	VW ID.4 Pure Performance, VW ID.4 Pro Performance, Skoda Enyaq iV60, Skoda Enyaq iV80, Audi Q4 e-tron 35, Audi Q4 e-tron 40, BMW iX3 Premier Edition, Mercedes EQA 250, Hyundai Ioniq 5 SE Connect, Hyundai Ioniq 5 Premium
Driving Range	Common attribute	5	200 miles, 250 miles, 300 miles, 350 miles, 400 miles
Power	Common attribute	5	160 hp, 190 hp, 220 hp, 250 hp, 280 hp
Price VW ID.4 Pure Performance	Conditional attribute	5	£ 36,600, £ 39,600, £ 42,600, £ 45,600, £ 48,600
Price VW ID.4 Pro Performance	Conditional attribute	5	£ 38,600, £ 41,600, £ 44,600, £ 47,600, £ 50,600
Price Skoda Enyaq iV60	Conditional attribute	5	£ 31,400, £ 34,400, £ 37,400, £ 40,400, £ 43,400
Price Skoda Enyaq iV80	Conditional attribute	5	£ 36,400, £ 39,400, £ 42,400, £ 45,400, £ 48,400
Price Audi Q4 e-tron 35	Conditional attribute	5	£ 38,300, £ 41,300, £ 44,300, £ 47,300, £ 50,300
Price Audi Q4 e-tron 40	Conditional attribute	5	£ 41,300, £ 44,300, £ 47,300, £ 50,300, £ 53,300
Price BMW iX3 Premier Edition	Conditional attribute	5	£ 55,800, £ 58,800, £ 61,800, £ 64,800, £ 67,800
Price Mercedes EQA 250	Conditional attribute	5	£ 41,600, £ 44,600, £ 47,600, £ 50,600, £ 53,600
Price Hyundai Ioniq 5 SE Connect	Conditional attribute	5	£ 34,100, £ 37,100, £ 40,100, £ 43,100, £ 46,100
Price Hyundai Ioniq 5 Premium	Conditional attribute	5	£ 39,100, £ 42,100, £ 45,100, £ 48,100, £ 51,100

Tab. 8: Attributes and levels in the electric SUV ASD-CBC study in the UK.

task (i.e. across respondents) and at creating concepts (stimuli) that are nearly orthogonal within respondents with respect to main effects (Chrzan and Orme 2000). Level Balance implies that CE tries to consider any attribute levels not shown to one respondent in the choice task of the next respondent (i.e., in some more complex studies one cannot show one respondent everything due to a large number of attributes and/or levels). In other words, CE tries all possible permutations for the next concept and chooses the best one in terms of one- and two-way frequencies to balance the entire design well and thus to better realize orthogonality.

CE further strives for minimal overlap within each choice set, which seems, at first glance, not beneficial for estimating interaction effects (like one wants to do with the primary-conditional attribute interactions in ASD-CBC models). Moreover, if an attribute has as many or more levels than the number of alternatives offered in a choice task, it is almost impossible for an attribute level to appear more than once within the same choice task using CE. However, in an ASD-model, the primary-conditional attribute interactions are implicitly incorporated into the design, which makes CE applicable. CE does not explicitly differentiate between ASD and generic designs. However, due to the fact that CE does not generate any overlap, it is easy to create one- and two-way level balance if there is a conditional attribute (e.g. price) with the same number of levels for each level of the primary attribute. Otherwise, the algorithm can of course also create almost perfect designs by trying to distribute a different number of levels of the conditional attributes in the same way as generally in case of differences in the number of levels of attributes in generic designs. In sum, it is recommendable to use CE for alternative-specific designs. Research has shown that generating fewer design versions while using this algorithm is generally more beneficial than employing a simpler algorithm [1]. By doing so, CE maximizes the statistical design efficiency while ensuring orthogonality and minimal overlap [2].

However, to meet all these conditions for CE at the individual respondent level, a large number of possible concepts must be tested and then used to construct the choice tasks. This process pushes the computational limits of even modern computers for larger problem settings [3] (Sawtooth Software, 2011, p. 328). Therefore, CE can become computationally too expensive in these situations and the *shortcut algorithm (SC)* could be used instead. Unlike CE, SC optimizes the design only in terms of one-way level balance at the individual respondent level (i.e. there is no association between respondents here in generating the design). Technically, SC always starts over with a new design seed for the next respondent to generate the choice sets for her/him [2], and therefore chooses randomly among the currently least represented levels in the design. Consequently, the two-way frequencies suffer for the whole design, and thus only loose orthogonality can be attained, which results in correlations between attribute levels. For very complex ASD designs, even the shortcut algorithm can become problematic in terms of computing time, leaving the *Random* algorithm as another option for constructing ASD designs. In this case, it seems recommendable to switch to other packages for generating alternative-specific designs (e.g., SAS or Ngene). Furthermore, if *balanced overlap* (the fourth algorithm available in the Sawtooth software) were used, an overlap would be created between the conditional attributes, which is exactly what one would like to exclude in an ASD.

Alternative-specific designs for choice experiments are more complex and require defining which conditional attributes will appear beneath the levels of the primary attribute [4]. All levels of one conditional attribute may not be shown with another level of the primary attribute. Typically, each level of the primary attribute is available in each choice set. To achieve this, the number of concepts in a choice task should be equal to the number of the levels of the primary attribute (Sawtooth Software 2008, p. 8). However, if the number of the levels of the primary attribute is too high, which would make the choice between this many alternatives for respondents too burdensome, it is advisable to choose the number of choice sets for each respondent in such a manner that all levels of the alternative-specific (conditional) attributes are shown at least once across all choice sets per respondent to avoid missing preference information completely for these levels and to achieve level balance in the design.

Our ASD-CBC design was generated with the CE algorithm multiple times with varying numbers of versions and from different starting points (design seeds). The resulting design has been tested each time by applying the advanced test in Sawtooth Software for the expected number of respondents participating in the study to achieve the best possible design in terms of standard errors and D-efficiency. The advanced test in the Sawtooth Software generates random data and uses the MNL model to estimate the effects (Sawtooth Software 2008). Standard errors of the estimated utility parameters should all be approximately of the same order of magnitude (Kuhfeld 2010, p. 316). Please note that the size of the standard errors for the effects of the conditional attributes will be greater than for the common attributes, but nevertheless should not exceed 0.1 (Sawtooth Software, 2008). Further, estimated utility parameters from the advanced test that deviate more strongly from zero indicate a not well-balanced design, inducing from scratch a bias for parameter estimation when based on real respondent data later (Kuhfeld 2010, p. 316). In addition to the standard statistical performance measures for model fit, such as Log-Likelihood, Root Likelihood, Chi-Square, and t statistics, the measure of D-efficiency became part of the advanced design test output in the Sawtooth Software. However, the software does not compute the D-value of the optimal design given the number of attributes, attribute levels, choice sets per respondent, and number of alternatives in a choice set, which is why one can only compare several generated designs against each other and choose the one with the best D-value.

Our final design for the UK electric SUV study consisted of 10 versions and included 10 random choice tasks (per respondent) plus 2 fixed choice tasks (across respondents) with 5 alternatives plus the "None" option in each choice set. Five alternatives per choice set were chosen to more easily enable level balance (remember that all attributes were chosen to have five levels). Hence, all SUV alternatives were shown once already after two choice sets, implying that they were shown each respondent 5 times across the 10 choice sets. Accordingly, the levels of the common attributes driving range and engine power were shown each respondent 10 times across the 10 choice sets.

The coding of ASDs differs from generic main-effects CBC designs. Considering the example of one choice set from the UK electric SUV ASD-CBC study, where price attributes were specific to each of the 10 electric SUVs, the design matrix looks as displayed in *Tab. 9*. For instance, the alternative *Mercedes EQA 250* was coded as the eighth of ten levels of the SUV primary attribute, leading to the coding '3' for its conditional attribute *Price SUV8* (representing the third price level) and 0 for all other conditional price attributes that do not apply to this particular SUV model. The same logic holds for the other SUV alternatives with their alternative-specific price attributes. The common attributes of Range and Power had five levels each as well, thus the number in the respective columns varies from 1 to 5 indicating the present level of these common attributes, independent of the primary attribute (SUV alternative).

To estimate the alternative-specific price effects, we decided to also use the part-worth utility model due to its higher flexibility to account for possibly nonlinear patterns in price response. Therefore, the estimated MNL model included 58 parameters (i.e. 9 for the primary attribute, 4 for each of the ten conditional price attributes and the two common attributes, and 1 for the none option) [5]. Alternatively, the conditional price effects could have been modeled linearly as well. We further applied monotonicity constraints on the parameter esti-

Alternative/ Attributes	Car Model	Driving Range	Power	Price SUV1	Price SUV2	Price SUV3	Price SUV4	Price SUV5	Price SUV6	Price SUV7	Price SUV8	Price SUV9	Price SUV10
Mercedes EQA 250	8	2	3	0	0	0	0	0	0	0	3	0	0
Skoda Enyaq iV60	3	1	1	0	0	2	0	0	0	0	0	0	0
Audi Q4 e-tron 40	6	5	5	0	0	0	0	0	5	0	0	0	0
VW ID. Pro	2	4	2	0	3	0	0	0	0	0	0	0	0
VW ID. 4 Pure	1	3	4	4	0	0	0	0	0	0	0	0	0
NONE	0	0	0	0	0	0	0	0	0	0	0	0	0

Tab. 9: Design matrix of the self-conducted study on preferences for electric SUVs in the UK.

Make and Car Model	***Driving Range***	***Power***	***Price***
VW ID.4 Pure Performance	**35.3%** (3.6-81.7%)	**30.8%** (4.8-72.9%)	**33.9%** (0.1-82.5%)
VW ID.4 Pro Performance	**29.6%** (2.6-77.6%)	**25.9%** (3.2-67.7%)	**44.5%** (0.1-88.6%)
Skoda Enyaq iV60	**34.6%** (3.0-86.7%)	**30.0%** (4.3-76.3%)	**35.4%** (0.5-84.7%)
Skoda Enyaq iV80	**31.9%** (2.6-78.6%)	**27.9%** (3.8-69.7%)	**40.2%** (0.2-86.9%)
Audi Q4 e-tron 35	**32.6%** (2.9-80.8%)	**28.2%** (4.8-73.2%)	**39.2%** (0.4-84.6%)
Audi Q4 e-tron 40	**29.4%** (3.8-65.8%)	**25.6%** (25.2-65.5%)	**45.0%** (3.2-79.3%)
BMW iX3 Premier Edition	**38.2%** (6.5-80.1%)	**32.3%** (6.0-72.1%)	**29.5%** (3.9-74.1%)
Mercedes EQA 250	**29.2%** (3.2-70.1%)	**25.4%** (4.8-70.3%)	**45.5%** (0.3-83.1%)
Hyundai Ioniq 5 SE Connect	**35.7%** (3.4-85.9%)	**31.1%** (4.3-74.2%)	**33.2%** (0.1-88.2%)
Hyundai Ioniq 5 Premium	**31.9%** (4.3-75.8%)	**27.8%** (5.0-71.9%)	**40.3%** (0.1-87.2%)

Tab. 10: Average attribute importances (across respondents) per SUV model in the ASD-HB-MNL model (range of individual attribute importances in parentheses). N=494.

mates of the price attributes to guarantee economically plausible price utility curves. Especially when respondents are confronted with totally realistic prices for a respective SUV alternative, as is the case with the employed ASD (but not necessarily with standard CBC models based on generic designs), it can be assumed that higher price levels are associated with lower utilities. Furthermore, it is well known that imposing monotonicity on price effects can improve the predictive model performance (e.g. Brezger and Steiner 2008). Estimation of the HB-MNL model was carried out by the Monte Carlo Markov Chain (MCMC) procedure implemented in the Sawtooth software, and we eventually used a total of 1,000 draws for each respondent from the converged MCMC chain for parameter estimation [6].

As mentioned above, we further used two holdout choice tasks to assess the predictive validity of the ASD model, resulting in out-of-sample hit rates of .472 and .516. With six alternatives in the choice task (including the none option), hit rates in both holdouts are about three times higher than the chance probability of 0.167.

In the following, we elaborate on the particularities of ASD-CBC models regarding the computation and interpretation of attribute importances and the calculation of related willingness-to-pay quantities. It is not possible to isolate the relative importance of each attribute in an ASD-CBC study, which is standard in CBC studies that are based on generic main-effects designs. The computation of importance scores requires the independence of attributes. However, the ASD implicitly comprises interactions between primary and conditional attributes. In case of our study, prices were specified to be conditional attributes upon the electric SUV models. Hence, the effects of the primary attribute (SUV model) and the alternative-specific prices cannot be evaluated independently from each other. It is only possible to determine the attribute importance of the price per specific electric SUV, i.e. conditional upon each level of the primary attribute (see *Tab. 10*).

Driving range is the most important attribute of the BMW iX3 Premier Edition, which is by far the most expensive SUV alternative. For the VW ID.4 Pure Performance, the Skoda Enyaq iV60, and the Hyundai Ioniq 5 SE Connect, all three attributes (range, power, price) turn out to be roughly equally important. Furthermore, the attribute importance of price is substantially higher for the more expensive trim levels of the car manufacturers offering two SUV alternatives (i.e. VW, Skoda, Audi, and Hyundai). For these SUVs, price is clearly the most important attribute. Since VW, Skoda, and Hyundai were the brands with the lowest prices in the UK market for electric vehicles at the time the data were collected, it seems to be plausible that consumers who choose these brands might be more price-sensitive, when considering a more expensive trim level of these car manufacturers. Finally, price is also the most important attribute of the Mercedes EQA 250. Because of the limited interpretability of attribute importances in ASD-CBC models, choice simulations are all the more important for these type of CBC models.

If a researcher would like to calculate willingness-to-pay (WTP) quantities based on the results of an ASD-CBC study, it is strongly recommended to consider the following. For changes in the levels of the primary attribute, the corresponding WTP values can be determined as usual in conjoint studies by means of choice simulations, but only as far as the ranges of levels of the conditional prices overlap or at least have one joint price point. Transferred to our empirical SUV example, this means that a consumer's willingness to pay for switching from e.g. the VW ID.4 Pro Performance to the Audi Q4 e-tron 40 can only be calculated if an overlap between the two electric SUVs conditional price ranges or at least one common anchor price point (price ranges border one another) was included in the design. If no overlap between the ranges of the conditional price attributes would exist, no comparable WTP quantities can be calculated. Of course, the specification of the conditional price ranges should be realistic and be based on the current market situation. As can be seen from *Tab. 8*, WTP calculations could be performed for each two SUV alternatives except BMW (i.e. for 9 out of 10 SUV models), since the ranges of the conditional price attributes for these 9 alternatives pairwise overlap. No WTP calculations can be made for the BMW iX3 Premier Edition, whose lowest price level is still higher than the upper bound price point of the price ranges of each of the other 9 SUV alternatives. Moreover, in our example, it is possible to define one single joint price point for all these 9 SUV alternatives, so that WTP values can become still more comparable between the different SUVs (i.e. between all levels of the primary attribute except BMW).

WTP quantities (e.g. for switching from one to another SUV model in our study) from conjoint studies can generally be determined by employing choice simulations based on the estimated individual-level part-worth utilities of the respondents. For this, a specific product configuration with two product concepts equivalent in all attribute levels including the price except the one attribute of interest (for which the WTP is to be determined) has to be defined as a starting point. Continuing our example for the VW ID.4 Pro Performance and the Audi Q4 e-tron 40 from our UK ASD-CBC study, both SUVs would have to be firstly configured to have the same range, power, and price. Subsequently, WTP could be determined by searching for the price of the Audi Q4 e-tron 40 (VW ID.4 Pro Performance) that leads to equal choice shares (50 %) for the two alternatives. That means, apart from the need to have a joint starting price point for two alternatives, there is no difference in WTP simulations compared to standard main-effects CBC studies. Note, however, that different price parameter estimates obtained for the different conditional price attributes (depending on the SUV alternatives considered) enter the market simulation here. Usually, the basic price for simulations to calculate the WTP for the change in the attribute level is the average price in the design, the average market price or the price of the main competitor. To illustrate the calculation of WTP quantities, we have selected the price of £ 42,000 as a joint anchor point to be able to compare the WTP for the primary attribute *car model* (compare *Tab. 8*) between three SUVs as example alternatives, the *Volkswagen ID.4 Pro Performance*, the *Skoda Enyaq iV80*, and the *Audi Q4 e-tron 40*. Actual prices of the three SUVs at the time the study was conducted in the UK were £ 40,130 for the *Skoda Enyaq iV80,* £ 42,520 for the *Volkswagen ID.4 Pro Performance,* and £ 46,065 for the *Audi Q4 e-tron 40.* Therefore, the selected joint anchor price of £ 42,000 roughly corresponds to the average price between the three SUVs and thus follows the suggestion for the selection of the basic price for the WTP calculations quite well. Also note that respondents' price utilities for the price of £ 42,000 are determined for each model by linear interpolation between the adjacent price levels, respectively. *Fig. 3* shows that, assuming each time equally equipped cars regarding driving range and engine power were presented, respondents in the UK would be willing to pay a £ 6,420 price premium for the Volkswagen ID.4 Pro Performance compared to the Skoda Enyaq iV80. However, when the Volkswagen ID.4 Pro Performance is compared to the Audi Q4 e-tron 40, respondents would be willing to pay £ 6,144 extra for the same electric SUV from Audi. The obtained WTP values for the three SUV car models (primary attribute) are a bit more symmetrical compared to the actual price differentials, however the price premiums turn out about two times higher. Obviously, the respondents were willing to pay more than the actual price differences. This demonstrates the necessity to collect a CBC study for supporting pricing decisions, the more when the product category is relatively new on the market and preference structures of customers are probably not yet fully developed.

For common attributes, WTP calculations are only possible conditional on a particular level of the primary attri-

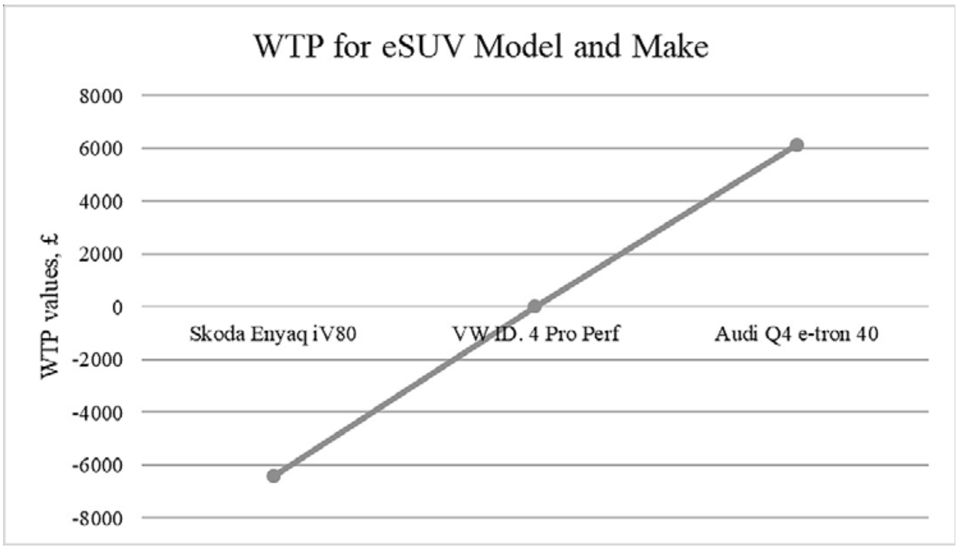

Fig. 3: WTP of UK respondents for three selected electric SUV alternatives.

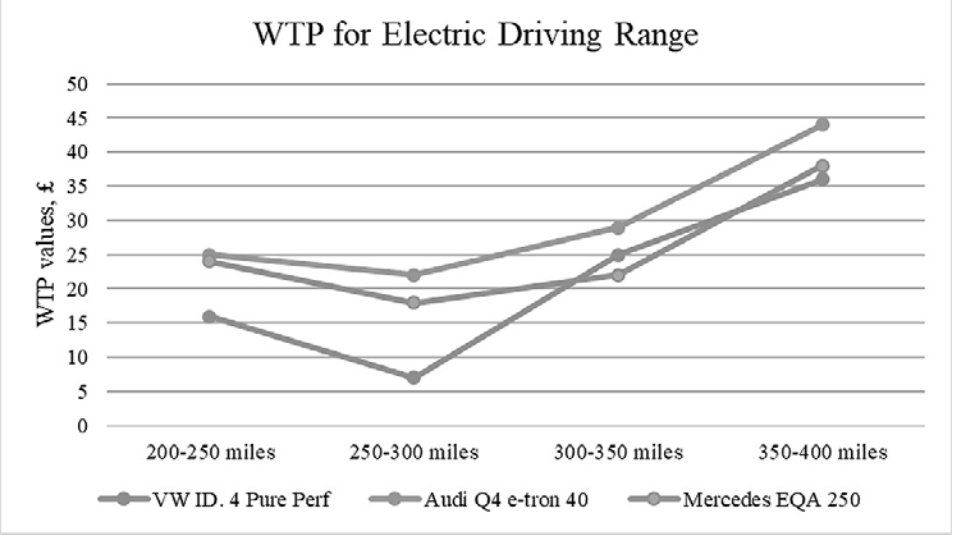

Fig. 4: WTP for 1 mile of additional electric driving range for selected electric SUVs in the UK.

bute. Transferred to our example, WTP for an upgrade in the driving range or horsepower can only be determined for a particular SUV alternative and not independently across the board for all SUVs. Seemingly a limitation at first glance, it can make perfect sense that the price response for changes in the driving range and horsepower can be very different for more versus less expensive cars. In other words, the possibility to compute an alternative-specific WTP for common attributes can be seen as an additional advantage of an ASD. In addition, opposed to WTP calculations for the levels of the primary attribute, overlaps between the alternative-specific price ranges are not absolutely necessary for common attributes. However, a joint price point in the brand-specific price ranges additionally enables the comparison of WTP values between the different alternatives. To illustrate the latter, we have chosen three electric SUVs (VW ID.4 Pure Performance, Audi Q4 e-tron 40, and Mercedes EQA250) from our ASD-CBC study and calculated WTP quantities for the common attribute of driving range (see *Fig. 4*). We have once more selected the price of £ 42,000 as joint anchor point to be able to compare the WTP for an additional mile of driving range between all three SUV alternatives (one could perform this exercise at this particular price point for all other SUVs alternatives except the BMW iX3). The SUV-specific price utilities for £ 42,000 (per respondent) were as before obtained by linear interpolation between the adjacent price levels for which part-worth utilities were estimated based on the ASD (per SUV alternative, e.g. by linear interpolation between £ 39,600 and £ 42,600 for the VW ID.4 Pure Performance, see *Tab. 8*).

The quantities shown in *Fig. 4* represent the WTP values for one additional mile of driving range depending on the assumed current driving range level. For example, if the VW ID.4 Pure Performance is equipped with a driving range of 200 miles, respondents would be willing to pay £ 16 for each additional mile in the interval between 200 and 250 miles. Note that WTP values differ both depending on the particular electric SUV everything else being equal and for different starting points of driving range.

The former is accomplished due to the use of alternative-specific price attributes. The latter is due to the part-worth model used for estimating price utilities (as well as for the utilities of the common attributes) and enables uncovering non-linearities in price response and related WTP values for a different current equipment in driving range. Using a linear model for price response would imply that the WTP for an additional mile of driving range is independent from the driving range of an SUV alternative (hence equal for different starting points of driving range), which seems unrealistic. We see that for all three SUVs, WTP is lowest in the interval between 250 and 300 miles and highest for changes in the driving range in the interval from 350 to 400 miles. As we can see, there is no monotonic increase in WTP for an increasing driving range. Note that monotonicity constraints were only imposed to the price attributes but not to the common attributes, which otherwise would have distorted the clearly non-monotonic true preference structures of the respondents regarding driving range.

Overall, respondents in the UK are willing to pay more for an additional driving range of an Audi Q4 e-tron 40 than of a VW ID.4 Pure Performance or a Mercedes EQA250, all else (price and engine power) being equal.

5. Advanced Modeling Options for ASD-CBC Models

At this place, it is important to point to novel and/or more advanced approaches for improving CBC models. Such developments include hybrid choice models, more flexible (nonparametric or learning) choice models to accommodate nonlinear utility specifications, as well as AI-based applications in different phases of conjoint studies. All these approaches can be adapted to further expand an ASD-CBC model, as proposed in this manuscript.

5.1. Hybrid choice models

The idea of hybrid choice models is to additionally include latent psychological factors in a choice model in order to explain parts of the unobserved heterogeneity of respondents (Ben-Akiva et al. 2002). Since psychological factors, like perceptions, attitudes, beliefs, motives, social network influences, etc., are not directly observable, they need to be measured via indicator variables using additional survey questions within a CBC study. Formally, a hybrid choice model integrates a discrete choice model and a latent variable model into a single estimation framework, allowing the latent psychological variables to be treated as additional predictors in the respondents' utility functions for the choice alternatives (Kim et al. 2014). Examples of psychological factors used in hybrid choice models in the context of travel mode/vehicle type choice in general, or (electric) car choice in particular, comprise perceptions of comfort and convenience (Walker and Ben-Akiva 2002), attitudes toward the environment (e.g. Daziano and Bolduc 2013), or the attitude towards leasing of an electric car (Glerum et al. 2013). Importantly, Bahamonde-Birke et al. (2017) emphasized that attitudes, values, or personality traits are individual-specific latent predictors, while perceptions additionally depend on the alternative (cited according to Pickens 2005), which opts for an alternative-specific hybrid choice model even if the manifest product attributes were all generic. Mariel (2024), however, has recently warned against a too careless application of the much more complex hybrid choice models in case of the typically small sample sizes and/or unvalidated scales for the latent variables. Finally, as a preliminary result of an empirical study, Mariel and Meyerhoff (2016) suggest preferring a hybrid choice model if the focus lies on "disentangling preference heterogeneity", while a standard choice model (like the mixed logit model) if predictive performance is more important. An alternative but much less complex approach to consider psychological factors of decision-makers would be to reparametrize estimated individual part-worth utilities as a function of these covariates in the upper level of a hierarchical choice model or in a second independent step subsequent to the estimation of the choice model.

5.2. Nonlinear utility functions

A different possibility to expand an ASD-CBC model is to relax the assumption of linear utility that is predominant in discrete choice modelling. Note that nonlinearities for non-categorical attributes (such as price) can already be accommodated in standard discrete choice models with a linear utility function in terms of piecewise linear functions along the support points generated via the predefined levels of an attribute, provided a part-worth utility function is estimated for these attributes. In order to address more complex nonlinearities, that are hard to capture even by parametric non-linear functions (i.e. intrinsically non-linear or irregular utility shapes caused for example by distinct threshold and/or saturation effects), more flexible estimation techniques, like splines or artificial neural networks (ANNs) have been developed. Kim et al. (2007) proposed splines of the truncated power basis for capturing individual latent utilities in choice models. Schindler et al. (2007) employed linear splines and bivariate tensor products of splines to represent piecewise linear functions for price effects. Hruschka et al. (2002, 2004, 2007) developed ANN based choice models by replacing the linear utility function by a multilayer perceptron, respectively. Still earlier, Bentz and Merunka (2000) had also used a neural net extended choice model, and Abe (1999) embedded GAM into their choice model to capture nonlinear utilities. From all the mentioned approaches, only Kim et al. (2007) applied their nonlinear modelling framework to CBC data, while all other researchers demonstrated the power of the more flexible techniques to improve the predictive model performance in the context of household panel data. From our perspective, one reason for this might be that panel data provide a larger number of different support points (e.g. more different price levels), which makes the application of nonparametric estimation technique more promising.

Opposed to the early neural net approaches in this field, the terminology for these kinds of models has moved towards the terms "deep choice models" or "learning choice models". Recently, Su et al. (2022) went one step further and introduced an alternative-specific deep choice model for transit route choice analysis. They also used a multilayer perceptron to approximate nonlinear utility functions, but they relaxed the assumption that all alternatives must share the same (common) attributes. More formally, connection weights of the network architecture were now specific to alternatives. Han et al. (2022) proposed to separate the utility into two parts: a flexible one where interactions between (alternative-specific) attributes and individual respondents' characteristics can be captured via a neural net, and the usual parametric part of a choice model. As such, coefficients of (some) attributes were nonlinearly reparametrized as functions of individual background covariates in the flexible part, while keeping the parametric part preserves model interpretability. However, the approach of Han et al. (2022) doesn't capture nonlinearity in attributes.

5.3. Artificial Intelligence

As in all research fields, discussions on AI and its impact on methodologies are also emerging in the domain of conjoint analysis and discrete choice models. Still, it is essential to differentiate between the various phases of conjoint studies in which AI could be applied. AI can certainly assist in the creation of stimuli for conjoint studies. Often, only a subset of stimuli is available as images (or real products), and AI can be useful in generating and preparing missing product combinations. There are already successful applications in this area, and it is expected that AI will soon be used more frequently (Dotson 2024). However, in the present empirical electric car study of this paper, all stimuli were physically available.

Regarding the construction of experimental designs, AI-based ANNs could, in principle, generate experimental designs that surpass existing approaches, provided that sufficient training data is available. A key challenge here lies in generating candidate sets suitable for training universal ANNs capable of handling all aspects of design generation. To date, research has mainly focused on specific design challenges (Kurz & Binner, 2020). The primary limitation is the high computational power required to train such networks, making implementation costly. It remains to be seen whether large language models (LLMs) such as ChatGPT, DeepSeek, or Claude will be able to address these challenges in the future. Nonetheless, this area certainly holds potential. The experimental design used in this study, which follows the complete enumeration approach, is already statistically efficient, making significant improvements unlikely.

AI as a tool for conducting surveys faces challenges, particularly in conjoint analysis, where simulations often involve future products not yet on the market. Since AI models rely on historical training data, they frequently lack information relevant to new product launches. However, AI already shows promise as a support tool for designing studies and conducting preliminary assessments of market potential. In the present study, which focuses on electromobility – a product category that was, at the time of investigation, a new market introduction – using AI would not have been appropriate.

AI can already estimate part-worth utilities from survey data with valid results. Existing routines enable multinomial logit (MNL) estimations and allow for the analysis of both aggregate and individual-level utility values (Belyakov 2018). However, AI-based approaches have not yet demonstrated superior accuracy compared to established methods such as bayesm, Mlogit, or Latent Gold (Alwosheel et. al. 2017). Consequently, the choice of technique remains at the discretion of the researcher. Given that traditional methods can typically be run on standard workstations, cost considerations may often discourage the use of AI.

6. Summary, Limitations, and Outlook

This paper dealt with the use of alternative-specific designs (ASD) in choice-based conjoint (CBC) studies. There is clearly not enough attention paid to the use of ASDs both in the academic marketing literature and in marketing research practice, as opposed to transportation research and applications in other fields such as urban planning, environmental economics, and health economics. We wanted to shed more light on this topic by working out that an ASD is always reasonable to determine consumer preferences (a) if alternatives (products) share the same attributes but customer responses to changes in at least one of these attributes depend on the specific alternative and/or (b) if the range of feasible attribute levels is different for different alternatives. In the latter case, using a generic instead of an alternative-specific response modeling would additionally lead to unrealistic product configurations consumers were confronted with when choosing from alternatives and as a consequence most likely to biases in estimated parameters and prediction biases in subsequent market simulations. Furthermore, we intended to develop a typology of ASDs to sensitize readers regarding the different possible options of specifying an ASD structure in CBC studies. To illustrate the advantages of ASDs and to especially work out the particularities of interpreting attribute importances from an ASD-CBC study and calculating willingness-to-pay quantities for different types of attributes of ASDs (primary versus common attributes), we used a self-conducted empirical ASD-CBC study on preferences for electric SUVs in the UK. We also discussed promising conceptual and methodological advancements proposed in the academic literature to further enrich ASD-CBC models and improve their performance. In particular, we focused on hybrid choice models as well as nonlinear specifications of utility to increase the functional flexibility for parameter estimation. Not least, we added a discussion on the state-of-the-art how AI is already influencing the field of conjoint analysis and DCE.

From a theoretical or conceptual perspective, ASDs are much more flexible to uncover the true preferences of consumers correctly. Nevertheless, some disadvantages or limitations of ASDs are noteworthy. Since ASD or "labeled" experiments usually involve the estimation of both alternative-specific and generic parameters (Rose et al. 2008, p. 398), an ASD-CBC model comprises a higher number of parameters to be estimated compared to a standard generic or main-effects CBC model. A larger number of parameters generates more flexibility and is expected to lead to less bias for parameter estimates, yet at the same time reduces the available individual respondent information per parameters und thus increases the variance (statistical uncertainty) in the model (Wittink 2000, p. 229). In other words, even if an ASD might produce more realistic product configurations to be evaluated by respondents, the bias-variance trade-off eventually determines the quality of predictions for new data or, like illustrated in this contribution, of WTP calculations. Therefore, the specification of alternative-specific attributes and levels must be done with great care and with regard to the individual market conditions. For example, it might be reasonable to estimate only one linear price effect per level of the primary attribute instead of one part-worth utility for each discrete price point (like in our SUV example), if nonlinearities in price response were known to play only a minor role in the considered market. This would lead to a largely reduced number of alternative-specific price parameters in the ASD model. One could also think about estimating price effects at the tier-level by defining the same price points for similar levels of the primary attribute (e.g. if similarly priced premium, national, or private label brands exist) and grouping conditional price attributes for estimation.

Another approach to improving outcomes in ASD models with a high number of parameters is the use of monotonicity constraints for vector attributes, such as the price attribute in our SUV study. The application of monotonicity constraints can be particularly helpful when nonlinear alternative-specific effects are expected (e.g., threshold effects in price sensitivity) and the researcher does not wish to reduce the number of parameters by assuming linear effects in the model (as this would obscure existing nonlinearities). In this case, introducing monotonicity constraints is advisable, as this not only stabilizes parameter estimates (lower variance) but also produces economically plausible results. Without the use of constraints, reversals might frequently occur, since in complex ASD models the number of observations at the individual level is relatively low compared to the number of parameters to be estimated. A number of options how monotonicity constraints can be employed in ASD-CBC models are discussed in the appendix to this paper.

In our opinion, much more attention to the practical implications of alternative-specific designs for CBC studies is required in the marketing literature. More academic research is needed to assess the trade-off between the clear conceptual advantage of ASDs over generic choice designs for data collection and the resulting higher model complexity from a statistical perspective (parameter estimation and model validation).

Notes

[1] The number of versions represents the number of different choice tasks (composition of choice sets) on the respondent level. For example, with 100 respondents and 10 versions, every 10th respondent gets the same choice task. The number of versions have also an impact on the statistical efficiency of a design.

[2] Based on the expert opinion of Peter Kurz, one of the leading market researchers worldwide for choice-based conjoint analysis and currently managing partner at bms marketing research+strategy, https://bms-net.de/

[3] We ran our empirical study on a Core i7 Laptop (11th generation) with 4 cores and 32GB RAM. The generation of the design for our ASD model with 58 parameters (among them only 9 parameters for the two common attributes and the none option, and the rest for the primary and conditional attributes) took about 60 minutes. All else being equal, doubling the levels of the primary attribute (i.e. 20 instead of 10 SUV models) would increase the computing time by about a factor of 4. Note that multiple runs with different random seeds and other modifications are oftentimes necessary for complex designs (as occurring in studies for frequently purchased consumer goods with many SKUs).

[4] As noted before, imposing prohibitions on generic main-effects designs often significantly decreases the statistical efficiency of a design. This does not apply to alternative-specific designs where interactions are implicitly incorporated.

[5] Note that, in the part-worth utility model, one level of each attribute has to be defined to constitute the reference category with a fixed part-worth utility of either 0 (in the case of dummy-coding) or the negative sum of estimated part-worth utilities for the other levels of this attribute (in case of effects-coding).

[6] More details about model estimation as well as all results regarding parameter estimates and model performance statistics are available from the authors upon request.

Appendix: Implementation of Monotonicity Constraints

Monotonicity constraints can be implemented through various techniques. The most widely used technique is "Simultaneous Tying" which discards an entire draw when a reversal occurs (Sawtooth Software, 2016). However, if many draws need to be discarded, this can negatively impact the convergence of the HB sampler. Additionally, in the case of a monotonically decreasing arrangement of part-worths, the commonly used multiple normal distributions tend to draw frequently from the positive region of the distributions, which increases the number of part-worths that are reversals. Therefore, a second often proposed technique is the use of a truncated normal distribution, which avoids positive part-worths due to the fact that only the negative part of the distribution is used (Pachali et al., 2020). Another approach to solving this issue is the logarithmic transformation of the price parameters, which also prevents reversals during the drawing of samples. However, this technique requires a back-transformation of the price part-worths after estimation is completed to ensure comparability with the non-transformed part-worths (Allenby et al., 2014). A relatively simple and practical method was suggested by Rich Johnson, which he termed tie-draws. In this method, all draws are initially used, and after the model converges, a large number of draws are saved. From these saved draws, any that show reversals are eliminated, leaving only the draws without reversals at the end of the estimation process. The advantage of this approach is that, unlike the first method, it does not interfere with the estimation process itself, and therefore has no negative impact on model convergence (Sawtooth Software, 2016).

References

Abe, M. (1999). A Generalized Additive Model for Discrete-Choice Data. *Journal of Business & Economic Statistics*, 17(3), 271–284. https://doi.org/10.1080/07350015.1999.10524817

Allenby, G.M., Arora, N., & Ginter, J.L. (1995). Incorporating prior knowledge into the analysis of conjoint studies. *Journal of Marketing Research* 32(2), 52–162.

Allenby, G.M. & Ginter, J.L. (1995) Using extremes to design products and segment markets. *Journal of Marketing Research* 32(4), 392–403.

Allenby, G.M., Brazell, J.D., Howell, J.R., & Rossi, P.E. (2014). Economic valuation of product features. *Quantitative Marketing and Economics* 12, 421–456.

Alwosheel, A., van Cranenburgh, S., Chorus, C. (2017): Artificial neural networks as a means to accommodate decision rules in choice models. *International Choice Modelling Conference 2017*.

Anderson, D., Borgers, A., Ettema, D., & Timmermans, H. (1992). Estimating availability effects in travel choice modeling: A stated choice approach. *Transportation Research Record*, 1357, 51–65.

Axsen, J., Bailey, J., & Castro, M. A. (2015). Preference and lifestyle heterogeneity among potential plug-in electric vehicle buyers. *Energy Economics, 50*, 190–201. https://doi.org/10.1016/j.eneco.2015.05.003

Bahamonde-Birke, F. J., Kunert, U., Link, H., & Ortúzar, J. D. D. (2017). About attitudes and perceptions: Finding the proper way to consider latent variables in discrete choice models. *Transportation* 44, 475–493. https://doi.org/10.1007/s11116-015-9663-5

Balderjahn, I., Hedergott, D., Appenfeller, D., & Peyer, M. (2021). Choice-Based Conjointanalyse. In: *Conjointanalyse: Methoden – Anwendungen – Praxisbeispiele*, 185–203, Springer Gabler.

Baumgartner, B., & Steiner, W. J. (2007). Are consumers heterogeneous in their preferences for odd and even prices? Findings from a choice-based conjoint study. *International Journal of Research in Marketing*, 24(4), 312–323.

Belyakov, D. (2017, June). *KNNLogit Ensembles for CBC Studies* [Paper presentation]. AMA ART Forum, Seattle, United States.

Belyakov, D. (2018, April). *Applying machine learning to CBC data* [Paper presentation]. SKIM/Sawtooth Software European Conference, Paris, France.

Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., & Munizaga, M. A. (2002). Hybrid choice models: Progress and challenges. *Marketing Letters, 13,* 163–175. https://doi.org/10.1023/A:1020254301302

Bentz, Y., & Merunka, D. (2000). Neural networks and the multinomial logit for brand choice modelling: A hybrid approach. *Journal of Forecasting, 19*(3), 177–200. https://doi.org/10.1002/(SICI)1099-131X(200004)19:3<177::AID-FOR738>3.0.CO;2–6

Brezger A., & Steiner, W. J. (2008). Monotonic regression based on bayesian p-splines: An application to estimating price response functions from store-level scanner data. *Journal of Business and Economic Statistics, 26(1),* 90–104. https://doi.org/10.1198/073500107000000223

BMW. (2022). X-Models. Retrieved December 16, 2022, from https://www.bmw.co.uk/en/all-models/x-models/iX3/2021/bmw-ix3-highlights.html

Chrzan, K., & Orme, B. (2000). An overview and comparison of design strategies for choice-based conjoint analysis. *Sawtooth Software Research Paper Series*, Sequim, WA 98382.

Cohen, S. H. (1997). Perfect union. *Marketing Research*, *9*(1), 12–17.

Daziano, R. A., & Bolduc, D. (2013). Incorporating pro-environmental preferences towards green automobile technologies through a Bayesian hybrid choice model. *Transportmetrica A: Transport Science, 9*(1), 74–106. https://doi.org/10.1080/18128602.2010.524173

Dotson, J. (2024). *Complex Generative AI Stimuli in Conjoint Measurement* [Paper presentation]. Sawtooth Software Conference, Provo, United States.

Elshiewy, O., Guhl, D., & Boztug, Y. (2017). Multinomial Logit Models in Marketing – From Fundamentals to State-of-the-Art. *Marketing ZFP, 39*(3), 32–49. https://doi.org/10.15358/0344-1369–2017–3-32

Glerum, A., Stankovikj, L., Thémans, M., & Bierlaire, M. (2014). Forecasting the demand for electric vehicles: Accounting for attitudes and perceptions. *Transportation Science, 48*(4), 483–499. https://doi.org/10.1287/trsc.2013.0487

Goeken, N., Kurz, P., Steiner, W.J. (2021). Hierarchical Bayes conjoint choice models – Model framework, Bayesian inference, model selection, and interpretation of estimation results. *Marketing ZFP, 43(3)*, 2021, 49–66. https://doi.org/10.15358/0344-1369–2021–3-49

Green, P. E., Krieger, A.M., & Wind, Y. (2001). Thirty years of conjoint analysis: Reflections and prospects. In: *Marketing research and modeling: Progress and prospects* (pp. 117–139). Springer. https://doi.org/10.1287/inte.31.3s.56.9676

Greene, W. (2009). Discrete choice modeling. In: *Palgrave Handbook of Econometrics: Volume 2: Applied Econometrics* (pp. 473–556). Palgrave Macmillan. https://doi.org/10.1057/9780230244405_11

Han, Y., Pereira, F. C., Ben-Akiva, M. & Zegras, C. (2022). A neural-embedded discrete choice model: Learning taste representation with strengthened interpretability. *Transportation Research, Part B: Methodological, 163*, 166–186. https://doi.org/10.1016/j.trb.2022.07.001

Hoen, A., & Koetse, M. J. (2014). A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands. *Transportation Research Part A: Policy and Practice, 61,* 199–215. https://doi.org/10.1016/j.tra.2014.01.008

Hruschka, H., Fettes, W., Probst, M., & Mies, C. (2002). A flexible brand choice model based on neural net methodology: A comparison to the linear utility multinomial logit model and its latent class extension. *OR Spectrum, 24,* 127–143. https://doi.org/10.1007/s00291-002-0095-1

Hruschka, H., Fettes, W., & Probst, M. (2004). An empirical comparison of the validity of a neural net based multinomial logit choice model to alternative model specifications. *European*

Journal of Operational Research, 159(1), 166–180. https://doi.org/10.1016/S0377-2217(03)00410–7
Hruschka, H. (2007). Using a heterogeneous multinomial probit model with a neural net extension to model brand choice. *Journal of Forecasting, 26(*2), 113–127. https://doi.org/10.1002/for.1013
Kim, J. G., Menzefricke, U., & Feinberg, F. M. (2007). Capturing flexible heterogeneous utility curves: A Bayesian spline approach. *Management Science, 53*(2), 340–354. https://doi.org/10.1287/mnsc.1060.0616
Kim, J., Rasouli, S., & Timmermans, H. (2014). Hybrid choice models: Principles and recent progress incorporating social influence and nonlinear utility functions. *Procedia Environmental Sciences, 22*, 20–34. https://doi.org/10.1016/j.proenv.2014.11.003
Kuhfeld, W. F. (2010). *Marketing Research Methods in SAS. SAS 9.2 Edition*. SAS Institute, Inc.
Kurz, P. (2024). 60 years of conjoint: Where we come from and where we are. *Proceedings of the Analytics & Insights Summit, 357*–382. https://sawtoothsoftware.com/resources/technical-papers/conferences/sawtooth-software-conference-2019
Kurz, P., Binner, S. (2020). Conjoint meets AI. *Proceedings of the 2020 Sawtooth Conference*, 165–184. https://sawtoothsoftware.com/resources/technical-papers/conferences/sawtooth-software-conference-2019
Lenk, P.J., DeSarbo, W.S., Green, P.E., & Young, M.R. (1996). Hierarchical Bayes conjoint analysis: Recovery of partworth heterogeneity from reduced experimental designs. *Marketing Science 15(2)*, 173–191.
Levy, D., Snir, A., Gotler, A., & Chen, H. A. (2020). Not all price endings are created equal: price points and asymmetric price rigidity. *Journal of Monetary Economics, 110*, 33–49. https://doi.org/10.1016/j.jmoneco.2019.01.005
Louviere, J. J., & Hensher, D. A. (1982). On the design and analysis of simulated choice or allocation experiments in travel choice modelling. *Transportation Research Record, 890(1)*, 11–17.
Louviere, J. J., & Woodworth, G. (1983). Design and analysis of simulated consumer choice or allocation experiments: an approach based on aggregate data. *Journal of Marketing Research, 20(4),* 350–367. https://doi.org/10.2307/3151440
Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: Analysis and applications.* Cambridge University Press.
Louviere, J. J., Flynn, T. N., & Carson, R. T. (2010). Discrete choice experiments are not conjoint analysis. *Journal of Choice Modelling*, 3(3), 57–72. https://doi.org/10.1016/S1755-5345(13)70014–9
McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics, 3(4),* 303–328. https://doi.org/10.1016/0047-2727(74)90003–6
Ma, Y., Zhang, Z., & Ihler, A. (2020). A Deep Choice Model for Hiring Outcome Prediction in Online Labor Markets. *International Journal of Computers, Communications & Control, 15*(2). https://doi.org/10.15837/ijccc.2020.2.3760
Mariel, P., & Meyerhoff, J. (2016). Hybrid discrete choice models: Gained insights versus increasing effort. *Science of the Total Environment, 568*, 433–443. https://doi.org/10.1016/j.scitotenv.2016.06.019
Mariel, P., Artabe, A., Liebe, U., & Meyerhoff, J. (2024). An assessment of the current use of hybrid choice models in environmental economics, and considerations for future applications. *Journal of Choice Modelling, 53,* 100520. https://doi.org/10.1016/j.jocm.2024.100520
Orme, B. (2022). A dinner conversation with legends in choice research. Published on LinkedIn, May 7th 2022.
Pachali, M.J., Kurz, P., & Otter, T. (2020). How to generalize from a hierarchical model? *Quantitative Marketing and Economics 18*, 343–380.
Pickens, J. (2005). Attitudes and perceptions. *Organizational behavior in health care, 4*(7), 43–76.
Rao, V. R. (2014). *Applied conjoint analysis*. Springer. https://doi.org/10.1007/978-3-540–87753-0
Rose, J. M., Bliemer, M. C., Hensher, D. A., & Collins, A. T. (2008). Designing efficient stated choice experiments in the presence of reference alternatives. *Transportation Research Part B: Methodological, 42(4),* 395–406. https://doi.org/10.1016/j.trb.2007.09.002
Rose, J. M., & Bliemer, M. C. (2009). Constructing efficient stated choice experimental designs. *Transport Reviews, 29(5),* 587–617. https://doi.org/10.1080/01441640902827623
Sawtooth Software (2008). The CBC advanced design module. *Technical Paper Series*. Sawtooth Software, Inc., Sequim (WA).
Sawtooth Software (2016). CBC/HB v5, *Software for Hierarchical Bayes estimation for CBC data*, Technical Paper Series, Sawtooth Software, Inc., Sequim (WA).
Sawtooth Software (2011). SSI/WEB v7, *Software for web interviewing and conjoint analysis,* Sawtooth Software, Inc., Sequim (WA).
Sawtooth Software (n.d.). Lighthouse studio. Online manual. Available at https://sawtoothsoftware.com/help/lighthouse-studio/manual/index.html
Schindler, M., Baumgartner, B., & Hruschka, H. (2007). Nonlinear effects in brand choice models: Comparing heterogeneous latent class to homogeneous nonlinear models. *Schmalenbach Business Review, 59,* 118–137. https://doi.org/10.5283/epub.377
Su, P., Liu, Y., & Zhao, L. (2022). General Deep Multinomial Logit Model. *Computing and Informatics, 41*(5), 1240–1259. https://doi.org/10.31577/cai_2022_5_1240
Swait, J., & Ben-Akiva, M. (1987). Empirical test of a constrained choice discrete model: Mode choice in Sao Paulo, Brazil. *Transportation Research Part B: Methodological, 21(2),* 103–115. https://doi.org/10.1016/0191-2615(87)90010–5
Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge University Press.
Volkswagen. (2022). ID.4. Build, compare and see pricing. Retrieved December 18, 2022, from https://www.volkswagen.co.uk/en/electric-and-hybrid/electric-cars/id4.html#MOFA
Walker, J., & Ben-Akiva, M. (2002). Generalized random utility model. *Mathematical Social Sciences, 43(3)*, 303–343. https://doi.org/10.1016/S0165-4896(02)00023–9
Wittink, D. R., (2000). "Predictive Validity of Conjoint Analysis." *Sawtooth Software Conference Proceedings*, 221- 237. Sequim: Sawtooth Software.
Zwerina, K., Huber, J., & Kuhfeld, W. F. (1996). A general method for constructing efficient choice designs. Fuqua School of Business, Duke University.

Keywords

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