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The Difficulties in Measuring Individual Utilities of Product Attributes: A Choice Based Experiment

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ABSTRACT

The study combines different theoretical approaches in the field of conjoint analysis to estimate the importance of product related attributes. This is of major importance in food marketing, where we still try to find a valid answer, in particular, how to measure the real willingness to pay (WTP) for specific product specifications. Based on a comprehensive literature analysis, a common method was used to approximate the importance of several product attributes. As usually suggested in literature, we used discrete choice modeling and developed a choice based experimental design considering selected product attributes. The study object was frozen pizza, a convenience good frequently bought by most households.
Up to this point, there is nothing special about the choice based experiment in comparison to direct measurement of the importance of product attributes. However, one of the core problems of discrete choice modeling – the approximation of individual utility functions – was then addressed by *transforming the choices of consumers into scores*. With these scores traditional conjoint measurement can be used to approximate individual utilities even in choice based experiments. The individual part-worth utilities will be compared with a usual but very complex approach to approximate individual part-worth utilities, the hierarchical Bayes method. Our approach addresses methodological considerations concerning the restrictions of discrete choice modeling, namely the complexity of approximating individual utilities which is of huge importance in particular for market segmentation.

Keywords: *discrete choice modeling, choice based conjoint analysis, estimation of utilities, consumer survey*

1 Introduction: Convenience foods

In general, convenience foods are described “as all commercially pre-prepared foodstuffs in which part of the work, knowledge, culinary skills and time needed to prepare food […] is transferred from the home-kitchen to the food industry and other food distributors” (Daniels and Glorieux, 2015). By that, convenience foods are helping households to prepare meals and save time and efforts (Brunner et al., 2010). Convenience foods can be considered to be one of the major trends in food marketing, the market for convenience foods has been steadily growing during the last decades (Brunner et al., 2010). Some authors identified specific correlations between socio-demographic variables like age, sex, income, or social class and the usage of convenience foods (e.g. Daniels and Glorieux, 2015; Swoboda and Morschett, 2001). Others identified different convenience foods consumer segments where lifestyles influence the extent to which convenience foods are used (Buckley et al., 2007). Apart from these findings, it can be assumed that all parts of the population are meanwhile using convenience foods in their daily diet, even though the extent of usage might differ from one consumer segment to another. Therefore, we used a commonly bought convenience product, frozen pizza, for our research as we

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intended to approximate the importance of the price attribute when buying convenience foods. Further, the individual willingness to pay (WTP) shall be approximated to identify consumer segments.
The main reason for buying convenience products is saving time (Brunner et al., 2010); technological innovations like microwave ovens further boosted the development and marketing launch of convenience foods. Higher rates of female employment and consequently less time for housekeeping led to a further rise of convenience foods as well (Darian und Klein, 1989). And due to globalization and the rise of fast food consumers get used to convenience foods as well. This was shown by Barbut (2012) on the example of chicken wings (convenience breaded poultry meat), which gained significant importance during the last decades.
Convenience foods is usually considered to be less healthy; e.g., fast food chains recently started to offer more healthy convenience food like salads, wraps, or even oat flakes (Hanks et al., 2012). Altogether, these considerations lead to the first research question of this study: *How important are specific product attributes and attribute levels of convenience foods?*

2 The importance of the price attribute – willingness to pay for convenience foods

There are different methods available to approximate the willingness to pay (WTP) for food products. Several authors developed bidding procedures to approximate WTP for specific products, like Vickrey auctions[1]. By use of appropriate experimental designs these methods can deliver valid approximations of applicable price levels of foods. Direct questioning of consumers is another possibility; however, quite often interviewees overestimate their WTP in situations where they don't have any real expenditures in connection with food purchases (like in surveys). Therefore, other approaches use market monitoring to analyze prices (e.g. by using revealed preference data form scanner tills; Ben-Akiva et al., 1994). However, in this case it is not possible to estimate maximum price levels, which consumers would be willing to accept, but only to analyze existing prices and consumers' acceptance of these. Experimental designs might lead to more valid approximations; usual ways of doing so are all forms of conjoint analysis (CA). Historically, CA application goes back to the early 1960ies; the significant improvements led to enormous applications during the last decades (Moskowitz and Silcher, 2006).

3 Choice Based Conjoint Analysis (CBCA)

Conjoint Analysis is a conventional method of marketing research (Green and Srinivasan, 1990), which is widely used mainly because there are simple and easy-to-use software systems available (Halme and Kallio, 2011). The software systems help to approximate part-worth utilities even on an individual level. "In particular, conjoint measurement allows the estimation of the impact of individual attribute levels on the overall utility of a product" (Annunziata and Vecchio, 2013). In its conventional form, the Traditional Conjoint Analysis (TCA), respondents are asked to rank a limited amount of product alternatives from best to worst. The product alternatives are realistic combinations of a small number of attributes and attribute levels representing the most important attributes ideally responsible for consumers' product purchase decisions. By use of these methods, it is possible to estimate part-worth utility for attribute levels even on an individual level (same can be said of rating based methods; Moore, 2004; de Andrade et al., 2016; Endrizzi et al., 2011). E.g., Cranfield et al. (2009) used CA ranking method to estimate the importance of different product attributes of apples including pesticide testing, region of origin, and price.
However, from the respondents point of view, the easiest and probably most trustworthy way of assessing data is to use simple product choices. Choice based approaches are easier to perform, external validity is expected to be higher as choices are similar to market behavior, and are therefore, from a cognitive point of view, less demanding than other forms of CA (Asioli et al., 2016). Respondents then are not forced to compare product alternatives and rank or rate them (Moore, 2004; for a comparison between ranking and rating methods see Almli et al., 2015). They only have to select the most adequate product alternative out of a limited set of product choices (often including a no choice option if no alternative meets the demands of the respondents, making evaluations more realistic; Vermeulen et al., 2008). Even though CBCA only provides binary data, it is nowadays possible to approximate individual part-worth utilities by use of the HB method (Lenk et al., 1996; Halme and Kallio, 2011; Gensler et al., 2012; Andrews et al., 2002). The approximation of individual part-worth

[1] Vickrey auctions are going back to Vickrey (1961) who proposed a bidding auction where the winner with the highest bid will only have to pay the second highest bid. Therefore, bidders cannot immediately influence selling prices and WTP can be approximated accordingly.

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utilities is, however, an iterative, very complex task and cannot be done without computer assistance. This leads to the second and main research question of this study: *Is it possible to approximate part-worth utilities out of a CBCA design based on a more simplistic, easy to understand way?* In the following section, we will describe a method of deriving scores out of binary choice data in order to approximate individual part-worth utilities and will compare these results with the outcomes based on the HB method. We will do so by using experimental choice data from a survey where consumers assessed different alternatives of frozen pizza, a commonly bought convenience good.

4 Experimental design

The research object of the study is frozen pizza. The product attributes (attribute levels) are: brand (A, B, C), variant (Mozzarella, Prosciutto, Salami), price (€1.29, €2.39, €3.75), and nutrient content (i.e. coverage of average calorie requirement per day: 35%, 45%). The partial design consisted of 8 product profiles (Table 1). In total, the respondents had to make 8 choices; each choice task consisted of 3 choices plus one no-choice option (Table 2). The choice sets were developed by means of a conventional CBCA software package.

Table 1: Product alternatives – attributes and attribute levels

Product alternative a_j	Brand	Variant	Price	Nutrient content
a_1	B	Mozzarella	€1.29	35%
a_2	B	Prosciutto	€2.39	45%
a_3	A	Prosciutto	€3.75	35%
a_4	A	Salami	€1.29	45%
a_5	C	Salami	€2.39	35%
a_6	A	Mozzarella	€2.39	35%
a_7	C	Prosciutto	€1.29	45%
a_8	C	Mozzarella	€3.75	45%

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Table 2: Choice tasks

Choice-Task No.	Choice 1	Choice 2	Choice 3	Choice 4:
1	a_2: Brand B Prosciutto €2.39; 45%	a_4: Brand A Salami €1.29; 45%	a_1: Brand B Mozzarella €1.29; 35%	No-choice
2	a_6: Brand A Mozzarella €2.39; 35%	a_8: Brand C Mozzarella €3.75; 45%	a_5: Brand C Salami €2.39; 35%	No-choice
3	a_3: Brand A Prosciutto €3.75; 35%	a_5: Brand C Salami €2.39; 35%	a_2: Brand B Prosciutto €2.39; 45%	No-choice
4	a_7: Brand C Prosciutto €1.29; 45%	a_1: Brand B Mozzarella €1.29; 35%	a_6: Brand A Mozzarella €2.39; 35%	No-choice
5	a_4: Brand A Salami €1.29; 45%	a_6: Brand A Mozzarella €2.39; 35%	a_3: Brand A Prosciutto €3.75; 35%	No-choice
6	a_8: Brand C Mozzarella €3.75; 45%	a_2: Brand B Prosciutto €2.39; 45%	a_7: Brand C Prosciutto €1.29; 45%	No-choice
7	a_5: Brand C Salami €2.39; 35%	a_7: Brand C Prosciutto €1.29; 45%	a_4: Brand A Salami €1.29; 45%	No-choice
8	a_1: Brand B Mozzarella €1.29; 35%	a_3: Brand A Prosciutto €3.75; 35%	a_8: Brand C Mozzarella €3.75; 45%	No-choice

The profiles were presented using a visual stimulus (standardized photograph of a frozen pizza, clearly indicating the variants Mozzarella, Prosciutto, and Salami) and textual description of the product alternatives. In addition, several other information like socio-demographics and the reasons for buying frozen pizza was acquired.

5 Transformation of CBCA data into scores

As mentioned above, a usual method of approximating individual part-worth utilities out of the limited information provided within a CBCA experiment is the HB method. We will use the HB method, too, in order to compare these results with another, much more simplified approach to approximate individual utilities. In general, a CBCA provides a limited number of binary data out of the selection decision of respondents. In general, they select one (or none – in case that a no-choice option is provided) product alternative out of a small number of possible choices. In our case, respondents had to choose between 3 product alternatives and the no-choice option. In the end, we can simply calculate the frequency each alternative a_j was selected (with j = 1 to 8 in our study; see Table 1). In our case, the maximum frequency amounts to 3 (as each alternative is presented 3 times in the choice sets 1 to 8; see Table 2), the minimum possible frequency is 0. An important precondition, which has to be fulfilled for this approach, is that all a_j are presented with equal frequency (3 in our case). In the following section, we will interpret the frequencies as scores s_j with whom we can solve the commonly used TCA additive model

$$u_j = \mu + \sum_{k=1}^{K} \sum_{l=1}^{L} \beta_{kl} \cdot x_{jkl}$$

with

u_j : estimated total utility of alternative a_j

μ : mean part worth over all stimuli

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β_{kl} : part-worth of attribute level l (l = 1 … L) of attribute k (k = 1 … K)
x_{jkl} : dummy variable with x_{jkl} = 1 if attribute level l of attribute k at stimulus j exists, else x_{jkl} = 0

For example, one respondent of the sample delivered the following binary data out of the choice experiment:

Table 3: Example data: Choices 1-8 of respondent

	Choice1	Choice2	Choice3	Choice4	Choice5	Choice6	Choice7	Choice8
Choice no.	2	3	1	1	3	4	1	2
a_j	a_4: Brand A Salami €1.29; 45%	a_5: Brand C Salami €2.39; 35%	a_3: Brand A Prosciutto €3.75; 35%	a_7: Brand C Prosciutto €1.29; 45%	a_3: Brand A Prosciutto €3.75; 35%	no-choice	a_5: Brand C Salami €2.39; 35%	a_3: Brand A Prosciutto €3.75; 35%

The frequencies = scores s_j of the chosen product alternatives a_j amount to:

Table 4: Product alternatives – scores s_j

Product alternatives a_j	s_j
a_1: Brand B, Mozzarella, €1.29; 35%	0
a_2: Brand B, Prosciutto, €2.39; 45%	0
a_3: Brand A, Prosciutto, €3.75; 35%	3
a_4: Brand A, Salami, €1.29; 45%	1
a_5: Brand C, Salami, €2.39; 35%	2
a_6: Brand A, Mozzarella, €2.39; 35%	0
a_7: Brand C, Prosciutto, €1.29; 45%	1
a_8: Brand C, Mozzarella, €3.75; 45%	0

Consequently, we can now approximate part-worth utilities for all attribute levels l (l = 1 … L) and attributes k (k = 1 … K) by means of TCA and compare these individual results with the approximation by means of HB method. The results out of this comparison are part of the next chapter.

6 Results

In total, 122 respondents took part in the experiment. The study was conducted in Vienna, the largest urban region in Austria, and in a small village in Burgenland to be able to estimate the influence of urban/rural place of residence, as well. In view of the small sample size, the outcomes of the survey are far from being representative for the Austrian population (which is not crucial for the aim of this study as we focus on a methodological discussion about CA). Further, there are important differences between the sample and the Austrian average (Table 5).

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Table 5: Socio-demographic variables of the sample (n = 122)

		n	total %	valid %	Austria % (2014)[a]
Place of residence	urban	60		49.2%	n.a.
	rural	62		50.8%	n.a.
Gender	female	85		69.7%	48.90%
	male	37		30.3%	51.10%
Age	up to 15	0		0.0%	14.30%
	15 - 29 years	41		33.6%	18.40%
	30 - 49 years	45		36.9%	28.60%
	50 and older	36		29.5%	38.70%
Persons in household	1 person	17		13.9%	37.0%
	2 persons	43		35.2%	29.8%
	3 persons	31		25.4%	15.1%
	4 persons	17		13.9%	11.8%
	5 or more persons	14		11.5%	6.4%
Children in household	no children	74		60.7%	39.6%
	1 kid	27		22.1%	31.8%
	2 kids	18		14.8%	21.3%
	3 kids or more	3		2.5%	7.2%
Income	no information	22	18.0%		
	less than €1500 / month	21	17.2%	21.0%	n.c.
	€1500 - €2500 / month	37	30.3%	37.0%	n.c.
	€2501 - €3500 / month	19	15.6%	19.0%	n.c.
	€3501 - €4500 / month	16	13.1%	16.0%	n.c.
	more than €4500 / month	7	5.7%	7.0%	n.c.
Education	compulsory school	13		10.7%	27.2%
	apprenticeship	12		9.8%	31.7%
	vocational school	26		21.3%	22.7%
	grammer school	39		32.0%	6.1%
	university degree	32		26.2%	12.3%
Total		122	100.0%	100.0%	100.0%

[a] Source: http://www.statistik.at; n.a. … not available; n.c. … not comparable

Female respondents are more prevalent within the sample, respondents are younger, and better educated. However, this will not influence the quality of our analysis as the main goal of the study is to compare outcomes using different approximation methods for individual part-worth utilities. Table 6 contains the distribution, mean, and standard deviation of scores 0-3 of all alternatives a_j. Obviously, the respondents evaluated the different alternatives quite differently. To cope with this heterogeneity, it is wise to approximate individual part-worth utility. We did that for the whole sample and estimated part-worth utilities using the additive TCA model from above.

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Table 6: Distribution, mean and standard deviation of s_j

Product alternatives a_j	Scores s_j 0	1	2	3	Mean	Std. dev.
a_1: Brand B, Mozzarella, €1.29; 35%	54	22	23	23	1.123	1.175
a_2: Brand B, Prosciutto, €2.39; 45%	48	30	25	19	1.123	1.103
a_3: Brand A, Prosciutto, €3.75; 35%	81	18	15	8	0.590	0.943
a_4: Brand A, Salami, €1.29; 45%	57	24	20	21	1.041	1.153
a_5: Brand C, Salami, €2.39; 35%	86	16	18	2	0.475	0.805
a_6: Brand A, Mozzarella, €2.39; 35%	48	38	30	6	0.951	0.917
a_7: Brand C, Prosciutto, €1.29; 45%	67	27	15	13	0.787	1.030
a_8: Brand C, Mozzarella, €3.75; 45%	96	17	8	1	0.295	0.626

Table 7: Part-worth utilities TCA and CBCA (HB)

		Utility estimate TCA		Importance TCA		Utility estimate CBCA		Importance CBCA	
		Attribute level β_{kl}	Std. dev.	Attribute β_k	Std. dev.	Attribute level β_{kl}	Std. dev.	Attribute β_k	Std. dev.
Brand	A	0.106	0.547	0.304	0.152	0.613	1.235	0.295	0.136
	B	0.178	0.689			0.591	1.478		
	C	-0.284	0.532			-1.204	1.205		
Variant	Mozzarella	0.032	0.630	0.328	0.154	0.362	2.137	0.374	0.141
	Prosciutto	0.046	0.612			0.123	1.510		
	Salami	-0.078	0.799			-0.485	2.284		
Price	€1.29	0.204	0.509	0.251	0.123	0.878	1.286	0.250	0.134
	€2.39	0.095	0.459			0.508	0.496		
	€3.75	-0.299	0.577			-1.385	1.482		
Nut. cont.	35%	-0.047	0.321	0.117	0.086	-0.332	0.458	0.081	0.056
	45%	0.047	0.321			0.332	0.458		
(Constant)		0.815	0.266						
(Zero)						-0.302	2.975		

Table 7 presents the results of both approximation algorithms, first our simplistic one using scores s_j that were calculated on the basis of the respondents' choice data and TCA; second the results based on HB method using conventional CBCA software (iterative approximation with 30431 iterations, convergence = 0.001, random start of iterations). As we can see from that, the average importance of the attributes is more or less comparable between the two approximation methods. It is estimated to be at about 0.3 for attribute "Brand", 0.33-0.36 for attribute "Variant", 0.25 for "Price", and 0.08-0.12 for "Nutrient content". The metric size of the approximated utilities for the attribute levels cannot be immediately compared, as the basic calculation is dependent on the relevant algorithms and empirical design (no. of presented product choices, total number of product profiles). But as we can see from Table 7, the estimation delivers mostly comparable information. E.g., in both cases brand C is evaluated worst, price evaluation is linear decreasing; evaluation of nutrition content delivers largely the same results, etc. However, there are some differences like the average evaluation of Brand A and B or of variant Mozzarella and Prosciutto. Therefore, we compared both approximations on an individual level using conventional correlation analysis.

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Figure 1: Correlations part-worth utilities attribute “Brand” / Importance (Imp.)

	Brand A (CBCA)	Brand B (CBCA)	Brand C (CBCA)
Brand A (TCA)	**0.927**	-0.577	-0.242
Sig.	0.000	0.000	0.009
n	116	116	116
Brand B (TCA)	-0.563	**0.909**	-0.538
Sig.	0.000	0.000	0.000
n	116	116	116
Brand C (TCA)	-0.223	-0.584	**0.944**
Sig.	0.016	0.000	0.000
n	116	116	116

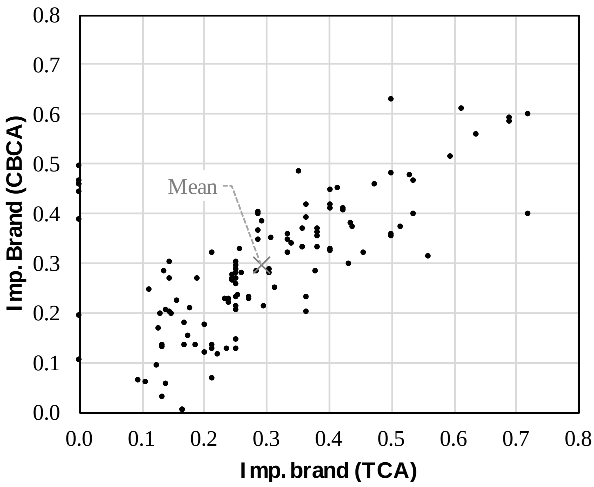

Figure 1 clearly shows that the individual part-worth utilities are highly correlated; Pearson’s correlations usually amount to more than 0.9 (also for all other attribute levels within our choice experiment; Figure 1 only shows the results for attribute “Brand”). This is a clear evidence that the simplified approximation method delivered similar results. Further, in case that respondents did not choose any of the presented product alternatives (they always selected the no-choice option), the data were not used to approximate utilities using s_j because these respondents are showing no preferences (i.e. missing values; in the graph these cases are shown only for presentation purposes with $\beta_{kl} = 0$). Due to methodological fundamentals in the HB method (the distribution within the total sample is taken to iteratively approximate individual part-worth utilities), even in these cases utilities are estimated (points on vertical axis, left part of graph in Figure 1). This approximation is rather wrong and might be an immanent error of the HB method.

One important goal of approximating individual part-worth utilities is to analyze the sample in view of heterogeneity. For this purpose, a usual approach is to cluster the sample taking individual part-worth utilities as clustering variables. In our case, 4 clusters can be identified (hierarchical cluster analysis, Ward’s method, elbow criterion).

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Tabelle 1: Cluster analysis

Cluster	1	2	3	4	Total	ANOVA	
	Mean	Mean	Mean	Mean	Mean	F	Sig.
Brand A	-0.243	0.120	0.211	0.970	0.106	37.746	0.000
Brand B	0.787	-0.347	-0.011	-0.511	0.178	54.061	0.000
Brand C	-0.544	0.227	-0.200	-0.459	-0.284	16.774	0.000
Variant Mozzarella	0.317	0.120	-0.733	0.526	0.032	46.299	0.000
Variant Prosciutto	-0.189	0.866	-0.078	-0.281	0.046	34.783	0.000
Variant Salami	-0.128	-0.986	0.811	-0.244	-0.078	55.972	0.000
Price €1.29	0.180	0.588	-0.044	0.163	0.204	8.334	0.000
Price €2.39	0.104	0.245	-0.167	0.348	0.095	6.419	0.000
Price €3.75	-0.284	-0.833	0.211	-0.511	-0.299	24.948	0.000
Nutrition content 35%	-0.014	-0.049	0.000	-0.244	-0.047	2.344	0.077
Nutrition content 45%	0.014	0.049	0.000	0.244	0.047	2.344	0.077
Importance Brand	0,383	0,191	0,235	0,375	0,304	16,637	0,000
Importance Variante	0,243	0,397	0,435	0,272	0,328	16,698	0,000
Importance Price	0,239	0,331	0,217	0,228	0,251	4,97	0,003
Importance Nutrition	0,135	0,081	0,113	0,126	0,117	2,196	0,093
N	47	24	30	15	116		

Cluster 1 clearly prefers Brand B, variant Mozzarella, at a medium price level. In contrast, cluster 4 prefers Brand A at the lowest possible price level. Cluster 2 can be considered to be most price sensitive, the importance of the variant is of special interest for Cluster 3. Nutrition content is not quite important for all clusters (despite Cluster 4); the group differences are not significant (see Anova). As our example shows, any CA may provide additional information at a sub-group level, which might be of huge interest for practitioners. This can be seen to be the core advantage of approximating individual utilities. In our case, we used the part-worth utilities approximated on the basis of s_j. However, the cluster analysis based on HB values would deliver comparable results.

7 Conclusions and discussion

Independent of the relevant approximation approaches, we can now answer the first research question of this study: *How important are specific product attributes and attribute levels of convenience foods?* As to frozen pizza, the most important attribute is the variant, followed by attribute "Brand". Therefore, the price attribute is not as important as we assumed. WTP seems to decrease with higher prices. This result however has to be considered in the shed light of fragmented markets: a general conclusion will have limited validity as consumers' demands are differing. Therefore, it is advisable to analyze individual preferences, which can be done by approximating individual utilities and grouping homogenous consumers to clusters.

Both approximation methods delivered largely the same results. The empirical example is, of course, no mathematical proof of our method. Further methodological research has to be done to evaluate this approach also within the framework of CA theory. We tested the approach with another choice based experiment (evaluation of drinking milk; n =117) to test the robustness with different sample data; the results are the same; correlations between HB approximation and our scoring method are in most cases beyond 0.9. The approximated importance values for the included attributes are more or less the same (on an individual level as well as on an aggregated level). This helps us to get an answer on our second, main research question of this study: *Is it possible to approximate part-worth utilities out of a CBCA design based on a more simplistic, easy to understand way?* The question can be clearly answered positively: with our approach it seems to be possible to get valid estimations of part-worth utilities based on choice based experiments. The method is easy to be understood also by users which are probably less familiar with HB method and comparable approaches. For those users the latter may be a black box. Finally, HB produces questionable results in cases where respondents don't want to

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purchase any of the presented product profiles (which is not completely unrealistic), simply because the HB estimates are using the whole sample distribution to iteratively estimate part-worth utilities on an individual level. Overall, the results of this study are promising. However, as mentioned above, more research has to be done also in view of methodological considerations.

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