

## CONJOINT ANALYSIS FOR MARKETING RESEARCH IN BRAZIL

### ABSTRACT

This article offers a review from 1971 to the present, methods of conjoint analysis approaches that are data collection based on stated preferences or choices by consumers. Thousands of studies have been performed using conjoint analysis, since the introduction of the method in the early 70's. This set of methods allows market researchers to study trade-off between the attributes of new products, and is useful for various decisions marketing to product design, pricing and market segmentation. The current set of options conjoint analysis is made by the traditional approach stated preference, the discrete choices techniques (or CBCA choice based conjoint analysis) which are based on choices declared by self-explanatory approach which uses direct elicitation of importance attributes and evaluation levels of the attributes and the adaptive approach (ACA or adaptive conjoint analysis) that involves data collection in stages and adaptive. This article summarizes these methods and their recent developments and presents an application in the Brazilian Market. Given the versatility of the method, there is huge potential for marketing research in Brazil. Essentially, this methodology is alive and growing.

**Keywords:** Conjoint Analysis; Measurement of Trade-Offs; Multi-Attribute Preference Models; Sets Stated Preference Methods; Sets of Methods Declared Choice; Adaptive Methods of Conjoint Analysis Applications.

## CONJOINT ANALYSIS PARA PESQUISA DE MARKETING NO BRASIL

### RESUMO

Este artigo oferece uma revisão, de 1971 até a atualidade, dos métodos de conjoint analysis que são abordagens de coleta de dados baseadas em preferências ou escolhas declaradas pelos consumidores. Milhares de estudos foram realizados com o uso de conjoint analysis, desde a introdução do método no início da década de 70. Este conjunto de métodos permite que os pesquisadores de mercado estudem trade-off entre os atributos de novos produtos, sendo útil para várias decisões de marketing com design de produto, apereçamento e segmentação de mercado. O conjunto atual de opções de conjoint analysis é composto pela abordagem tradicional de preferência declarada, pelas técnicas de escolhas discretas (CBCA ou choice based conjoint analysis) que se baseiam em escolhas declaradas, pela abordagem autoexplicativa que usa elicitação direta de importância de atributos e avaliação dos níveis dos atributos e pela abordagem adaptativa (ACA ou adaptive conjoint analysis) que implica em coleta de dados por etapas e adaptativa. Este artigo resume estes métodos e seus desenvolvimentos recentes e apresenta uma aplicação no Mercado brasileiro. Dada a versatilidade do método, existe um enorme potencial para a pesquisa de marketing no Brasil. Essencialmente, esta metodologia está viva e crescendo.

**Palavras-chave:** Conjoint Analysis; Mensuração de Trade-Offs; Modelos de Preferência Multiatributo; Métodos Conjuntos de Preferência Declarada; Métodos Conjuntos de Escolha Declarada; Métodos Adaptativos; Aplicações de Conjoint Analysis.

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## 1 INTRODUCTION

Marketing strategy for a brand (of a product or service) involves several interdependent decisions such as product design and positioning as well as its communication, distribution, and pricing to chosen segments of targeted customers. In order to be successful, these decisions need to take account of changing environment and uncertain competitive reactions. Naturally, the decision maker must have a clear understanding of how customers will choose among (and react to) various competing alternatives. One important aspect of choice is the way consumers typically make trade-offs among the attributes of a product or service. Conjoint analysis is a set of techniques ideally suited to studying customers' choice processes and determining tradeoffs.

Conjoint analysis is probably the most significant development in marketing research methodology over the last forty-five years or so. The method has been applied in several thousand applied marketing research projects since its introduction to the marketing researchers in 1971 (Green and Rao, 1971) and has been applied successfully for tackling

several marketing decisions as shown in Table 1. Some high profile applications of these techniques include the development of Courtyard Hotels by Marriott (Wind et al., 1989) and the design of the E-Z Pass Electronic Toll Collection System in New Jersey and neighboring States in the US (Green, Krieger, and Vavra, 1997). One reason for popularity is the ability to answer various "what if" questions using market simulators based on the results from a conjoint study for hypothetical and real choice alternatives<sup>3</sup>.

Against this brief background, this paper will be organized as follows. The next (second) section, will describe principal types of conjoint analysis that are in vogue in marketing research. The third section will briefly describe of the process for conducting a conjoint study; this section will also include a discussion of various data collection formats and designs for developing stimuli (or profiles) for a conjoint research problem. The fourth section will describe the basics of conjoint models and estimation. An application of this methodology in the Brazilian context is described in the fifth section. Some recent developments and future directions are described with limited elaboration in the final section.

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<sup>3</sup> It will be useful to review some terms used in conjoint analysis. Attributes are (mainly) physical characteristics that describe a product; levels are the number of different values an attribute takes; profile is a combination of attributes, each

attribute at a particular level, presented to a respondent for an evaluation (or stated preference); choice set is a pre-specified number of profiles presented to a respondent to make a pseudo-choice (stated choice).

**Table 1** - A Selection of Domain Areas of Past Applications

APPLICATION DOMAIN	PRODUCTS (OR GOODS)	SERVICES
Product Design	Electric Car Carpet Cleaners Personal computers	Hotels (Courtyard by Marriott) Electronic Toll Systems (E-Z Pass) Consumer discount cards
Market Segmentation	Copying machines	Car rental agencies
Product Positioning	Ethical drugs	Banking services
Competitive Analysis	Ethical drugs	Transcontinental airlines
Pricing	Gasoline pricing	Telephone services pricing Health insurance policies
Sales/Distribution	Auto retailing facilities	Branch banking services

Five different features of conjoint analysis have contributed to its versatility for tackling marketing managerial problems: (i) Quantifying buyer tradeoffs and values; (ii) Ability to predict buyers' likely reactions to new products/services; (iii) Identifying groups of buyers who share similar tradeoffs/values (or segments); (iv) Assessing new product service ideas in a competitive environment using simulation; and (v) Optimizing for best product/service profiles that maximize share/return (Green, Krieger and Wind, 2003).

## 2 PRINCIPAL TYPES OF CONJOINT ANALYSIS

Over the past several years, various researchers have contributed the general methodology of conjoint analysis. The reader is referred to Green and Srinivasan (1978; 1990) for excellent reviews of the field of conjoint analysis; other reviews are available in Hauser and Rao (2004), Rao (2008); a recently published book by Rao (2014) provides a comprehensive discussion of these methods. Essentially, there are four types of conjoint methods; traditional method (CA) that uses stated preference ratings; choice-based conjoint analysis (CBCA) that uses stated choices; adaptive conjoint analysis (ACA) developed in part to handle the issue of large number of attributes, and self-explicated conjoint analysis, which is a bottom-up method. The first three of these can be called decompositional methods because the

stated preference or stated choice data are decomposed to obtain part-worth functions. The fourth one is called compositional method because it composes a preference score from ratings of scores on attribute levels and relative importances of attributes. The traditional conjoint analysis (CA) collects preferences (judgments) for profiles of hypothetical products each described on the entire set of attributes selected for the conjoint study. These profiles are called full profiles. However, when one concatenates levels of all attributes, the complete set of full profiles (or full factorial design) will in general be very large. A respondent will be unduly burdened when asked to provide preference judgments on all profiles. Typically, a smaller set of full profiles (selected according to an experimental design) are used in a conjoint study. An individual's overall stated preferences are decomposed into separate and compatible utility values corresponding to each attribute typically using regression-based methods. These separate functions are called attribute-specific part-worth functions. In most cases, the preference functions can be estimated at the individual level. This estimated preference function can be deemed as an indirect utility function.

In contrast to collecting preferential data on full product profiles, several new data collection formats have emerged over the years. A significant development is the use of data on stated choices elicited under hypothetical scenarios that mimic the marketplace and estimating part-worth functions from such data using primarily multinomial logit methods;

these methods are labeled choice-conjoint methods (CBCA or CBC) and have become popular in the early 1990s and are probably the most widely used method today. They are based on the behavioral theory of random utility maximization (McFadden, 1974); the origin of this approach is the law of comparative judgment development by Thurstone (1927). This approach decomposes an individual's random utility for an object into two parts: deterministic utility and random part. Depending on the distributional assumptions for the error part, a number of alternative models are developed to describe the probability of choice of an object. The most popular one is the multinomial logit model that uses the extreme value distribution for the error term. An excellent volume that elaborates on these stated choice methods is by Louviere, Hensher, and Swait (2000); see also Ben-Akiva and Lerman (1991).

Researchers have also developed adaptive conjoint methods, which is called adaptive conjoint analysis (ACA) (Johnson, 1987). This method involves first a self-explicated task (i.e., eliciting data on attribute importances and attribute level desirabilities using ranking and subsequent rating) followed by preference ratings for a set of partial profiles descriptions, two at a time using a graded, paired comparison scale. The partial profile descriptions are tailored to each respondent based on the data collected in the self-explicated task. Both the tasks are administered by computer. This method is a type of hybrid<sup>4</sup> model approach.

In contrast, the compositional approach based on the multi-attribute attitude models (see Wilkie and Pessemier, 1973) estimates preferences from judged values of the components (importances and desirabilities) that contribute to preference. In this approach (called "self-explicated method") respondents are asked to evaluate the desirability of each level of all the attributes as well as the relative importances assigned to the attributes. Then, the preference for any product concept is estimated as a weighted sum of the desirabilities for the specific levels of attributes describing that concept; the weights are the relative importances (see Green and Srinivasan, 1978 for more details). Studies have shown that the self-explicated method is surprisingly quite robust (Srinivasan and Park, 1997).

<sup>4</sup> Hybrid models involve a combination of several tasks aimed to increase the "efficiency" of data collection in conjoint studies usually for large number of attributes. See Green (1984) for a review of these methods; see also Green

### 3 PROCESS OF CONDUCTING A CONJOINT STUDY

The problem of determining the steady-state demand for a new product will provide a good context for describing a conjoint study. In a conjoint study, a sample of  $n$  consumers is drawn randomly from a total of  $N$  customers in the target market for the product. Let  $q_i$  denote the quantity of product bought by  $i$ -th customer in the sample;  $i = 1, 2, \dots, n$  (generally measured in the survey) and let  $p_i$  denote the probability that the  $i$ -th customer will purchase the new product in a steady state (conditional on his/her consideration set of alternative items including the new product). Then, the demand forecast for the new product is given by the model:

$$D = \left( \frac{N}{n} \right) \sum_{i=1}^n q_i p_i$$

The problem then is to estimate the probability of purchase  $p_i$  for the new product for the members of the sample. There are at least two solutions for this problem.

One solution is to employ the traditional conjoint analysis (CA) and estimate the utility a customer derives for a new product relative to other items considered and transform the utility into probabilities of purchase. Several methods exist for this transformation; see Green and Krieger (1988). The second solution is the choice-based conjoint analysis method (CBC) which directly estimates the probabilities using a multinomial logit (MNL) model. This backdrop is good to describe, the process of designing conjoint studies for the two solutions.

A typical conjoint analysis project for collecting and analyzing stated preference or stated choice data<sup>5</sup> consists of four main steps: (i) development of stimuli based on a number of salient attributes (hypothetical profiles or choice sets); (ii) presentation of stimuli to an appropriate sample of respondents; (iii) estimation of part-worth functions for the attributes as well as any heterogeneity among the respondents; and use of the estimates in tackling any managerial problems (e.g., forecasting, pricing, or product design). Figure 1 shows the steps schematically.

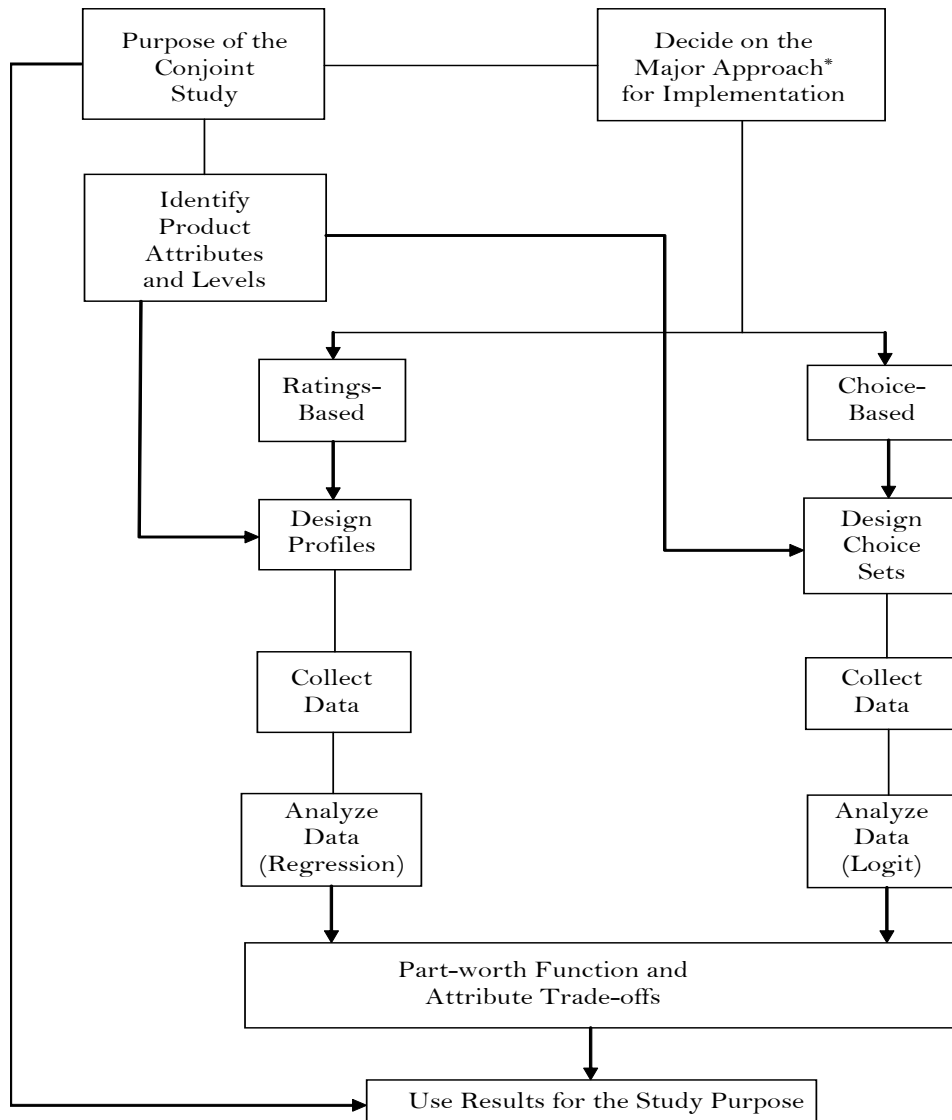
One major step is the design of stimuli (either profiles or choice sets). To illustrate profiles and choice sets, consider a simple conjoint problem with three attributes, A, B, and C each described at 3 levels.

and Krieger (1996). We will not delve much into these methods due to space limitations.

<sup>5</sup> For the sake of ease in exposition, we will restrict to these two types of data and will not delve into methods that involve variations such as the hybrid methods.

Levels described as a1, a2, a3 etc. An example profile is (a2, b3, c1) and an example choice set is {(a1, b2, c3); (a2, b1, c4); (a3, b3, c2); (No choice)} with some times “no choice” not included. Stated preference for a profile is measured as a rating or a rank relative to

other profiles while stated choice is the choice made by the respondent among the alternatives in a choice set.



\* Several alternatives exist here; two are highlighted.  
 Source: Rao, V. R. "Developments in Conjoint Analysis" in B. Wierenga (ed.) *Handbook of Marketing Decision Models*, New York: Springer Science + Business Media, LLC, 2008.

**Figure 1 - Major steps in a conjoint study**

The aspect of designing stimuli (profiles or choice sets) has received considerable attention since the beginning of conjoint analysis; it draws much from the theory of experimental design, where procedures for constructing subsets of combinations of all attribute levels are developed. Conjoint analysis for ratings-based studies makes extensive use of orthogonal arrays (Addelman, 1962; Green, 1974).

The process for designing choice sets for collecting stated choice data is a lot more complicated; after developing a number of profiles (usually a subset of all possible profiles), subsets of profiles (4 or 5) are used as choice sets. Researchers can use the OPTEX procedures in the SAS system (2002-2003) for designing profiles or choice sets; see also Kuhfeld (2005).

In the ratings-based conjoint approach, the researcher provides the respondents a number of profiles of product concepts; each described on the attributes under study, to elicit his/her preference for each profile on a rating scale (e.g., 10 points or 100 points). These preference data are analyzed using multiple regression methods (typically a dummy variable OLS regression) to estimate a utility function for each respondent (or for a subgroup of respondents). Typically, additive utility functions are used although utility functions with interaction terms are possible depending on the experimental designs used for constructing profiles.

The attributes in a conjoint study are either categorical or continuous (or interval-scaled) with only a few selected values. A categorical attribute (such as low, medium, or high) is usually converted into a number of dummy variables (one less than the number of levels). A continuous attribute (such as price of a product) can be used directly or can also be converted into dummy variables; if used directly, only a linear term or both linear and quadratic terms to account for any nonlinear effects can be included in the utility function. With suitable redefinitions of variables, the utility function for the ratings-methods can be written as  $y = X\beta + \varepsilon$ ; where  $\varepsilon$  is the random error of the model assumed to be normally distributed with zero mean and variance of  $\sigma^2$ ,  $y$  is the rating on given profile, and  $X$  is the corresponding set of  $p$  dummy (or other) variables. The model is estimated using regression methods (usually ordinary least squares method). The  $\beta$  is a  $p \times 1$  vector of regression coefficients associated with the dummy variables or continuous variables included in the model. The part-worth values for each attribute can be derived from these regression coefficients.

In the choice-conjoint methods, the respondent is given a number of choice sets, each choice set consisting of a small number (typically 4 or 5) profiles and is asked to indicate which profile will be chosen. A multinomial logit model (MNL) is used for estimating the deterministic component of the random utility using maximum likelihood methods. A variety of extensions and alternatives exist for analyzing stated choice data. The MNL model for the choice-conjoint data will be: probability of choosing profile  $j$  in choice set  $C = \exp(v_j) / \sum \exp(v_k)$  where the summation is taken over all the profiles in the choice set  $C$  and  $v_j$  is the deterministic component of the utility for the profile  $j$ . The deterministic utility function  $v$  is specified analogous a linear combination to the function for  $y$  in the ratings methods. The

estimated coefficients will be used in computing the part-worth values for the attributes in the study.

Current approaches for implementing a conjoint analysis project differ in terms of several features; some main features are: stimulus representation, formats of data collection, nature of data collection, and estimation methods. Several alternatives are in vogue for these features. For example, conjoint stimuli (e.g. profiles or choice sets) can be represented as verbal descriptions, pictures, prototypes, videos or combinations of these. As noted above, data can be collected as stated preferences or stated choices or as self-explicated measurements. The use of product configurators is also becoming common. Depending on the objective of the research, data can be collected multiple times or just only at one time. However, there is no clear agreement as to which data collection format is the best; see Hauser and Rao (2004) and Rao (2008).

While the estimation methods of least squares regression and multinomial logit are common, one notable development is the use of hierarchical Bayesian estimation methods which enable an analyst to incorporate prior knowledge in the part-worth values as monotonic or other types of order constraints in the estimation process (Allenby, Arora and Ginter, 1995); see also Lenk et al. (1996). Further, part-worth functions are estimated at the aggregate (or subgroup) level or at an individual level. Researchers have also used finite mixture methods (DeSarbo et al., 1992) to “uncover” segments of respondents based on the preference or choice data collected in conjoint studies; see also Andrews, Ansari, and Currim (2002). The variety of recently developed techniques for estimation of part-worth functions is very impressive and is beyond the scope of this chapter. For a recent discussion of conjoint methods see Hauser and Rao (2004), Rao (2008), and Rao (2014).

#### 4 BASICS OF CONJOINT MODELS

Conjoint methods are intended to “uncover” the underlying preference function of a product in terms of its attributes<sup>6</sup>. A general product profile defined on  $r$  attributes can be written as  $(x_{j1}, x_{j2}, \dots, x_{jr})$  where  $x_{jt}$  is the level for the  $j$ -th profile on the  $t$ -th attribute in a product profile. Researchers usually start with an additive conjoint model; but, the theory extends to models with interactions as well. The preference score<sup>7</sup> for the  $j$ -th product profile,  $y_j$  for one respondent additive conjoint model is:

same can apply to the  $v$ -function in the choice-based conjoint analysis.

<sup>6</sup> For an introduction to conjoint analysis, see Orme (2006).

<sup>7</sup> For exposition purposes, we are considering a ratings-based conjoint analysis where respondents provide preference ratings for a number of product profiles. The

$$y_j = U_1(x_{j1}) + U_2(x_{j2}) + \dots + U_r(x_{jr})$$

where  $U_t(\bullet)$  is the component utility function specific to the  $t$ -th attribute (also called part-utility function or part-worth function). No constant term is specified, but it could be included in any one of the  $U$ -functions or assumed to be zero (without any loss of generality.) The specification of the  $U$ -function for any attribute will depend upon its type (categorical and quantitative). In practice, a conjoint study may contain both types of attributes.

Brand names or verbal descriptions such as high, medium or low are examples of a categorical attribute; here the levels of the attribute are described by words. A quantitative attribute is one measured by either an interval scale or ratio scale; numbers describe the “levels” of such an attribute; examples are the weight of a laptop and speed of the processor.

The levels of a categorical attribute can be recoded into a set of dummy variables (one less various than the number of levels) and a part-worth function is specified as a piecewise linear function in the dummy variables. In this case, the component-utility function for a categorical attribute ( $t$ -th for example) will be:

$$U_t(x_{jt}) = U_{t1}D_{t1} + U_{t2}D_{t2} + \dots + U_{tr}D_{tr}$$

where  $r_t$  is the number of discrete levels for the  $t$ -th attribute (resulting from the construction of the profiles or created ex post);  $D_{tk}$  is a dummy variable taking the value 1 if the value  $x_{jt}$  is equivalent to the  $k$ -th discrete level of  $x_t$  and 0 otherwise; and  $U_{tk}$  is the component of the part-worth function for the  $k$ -th discrete level of  $x_t$ . In practice, only  $(r_t - 1)$ —one less the number of discrete levels of the attribute—dummy variables are necessary for estimation.

A quantitative attribute can be used in a manner similar to a categorical attribute by coding its values into categories or used directly in the specification of the part-worth function for the attribute. In the latter case, the function can be specified as linear (vector model) or nonlinear; one example of a nonlinear function is the ideal point model. Mathematically, the component-utility function can be specified as:

$$U_t(x_{jt}) = \begin{cases} w_t x_{jt} & \text{for the vector model; and} \\ w_t (x_{jt} - x_{0t})^2 & \text{for the ideal point model;} \end{cases}$$

where  $w_t$  is a weight (positive or negative); and  $x_{0t}$  is the ideal point.

A linear function is appropriate for an attribute deemed to be desirable (e.g., speed of a laptop computer) or undesirable (e.g., weight of a laptop computer); such a function is called a vector model for which the utility increases (or decreases) linearly with the numerical value of the attribute.

As mentioned above, with suitable redefinitions of variables, the preference function can be written as  $y = X\beta + \epsilon$ ; where  $\epsilon$  is the random error of the model assume to be normally distributed with zero mean and variance of  $\sigma^2$  and  $y$  is the rating on a given profile and  $X$  is the corresponding set of  $p$  dummy (or other) variables. The  $\beta$  is a  $p \times 1$  vector of partworths among the levels of attributes.

At this point, it will be useful to indicate the software available for designing and implementing conjoint studies. These are:

- Sawtooth Software (ACA, CBC, etc.; probably the most complete solution)
- SPSS (useful for preference –based approach)
- SAS (OPTEX for design and several other programs for analysis)
- LIMDEP (useful for analyzing data of various types; Greene (2003))
- Bayesm package in R (developed by Rossi, Allenby, and McCulloch (2005))
- MATLAB (one needs to develop specific program code)

## 5 AN ILLUSTRATION OF CHOICE-BASED CONJOINT ANALYSIS IN BRAZIL

To illustrate the technique deployment, we will present the results from a choice based conjoint analysis conducted in Sao Palo, Brazil. The product studied was television and the attributes used to generate the profiles were brand (7 levels), screen size (5 levels), screen technology (3 levels) and price (5 levels). The attribute levels are detailed in Table 2. It is interesting to notice that the levels for price are contingent to screen size attribute. One set of price levels (R\$899 to R\$3.799) is used for 32”, 37” or 40” screen sizes and a different set (R\$1.599 to R\$7.179) is used for 46” or 50” screen sizes.

**Table 2 - Attributes and attribute levels for choice based conjoint analysis**

BRAND	SCREEN SIZE	SCREEN TECHNOLOGY	PRICE
CCE LG Panasonic Philips Samsung Semp Sony	32 inches 37 inches 40 inches 46 inches 50 inches	LCD LED Plasma	<u>Screen size: 32" / 37" / 40"</u> R\$899 / R\$1.289 / R\$1.849 / R\$2.649 / R\$3.799 <u>Screen size: 46" / 50"</u> R\$1.699 / R\$2.429 / R\$3.489 / R\$4.999 / R\$7.179

However, such differences in prices are only for exhibit the stimuli for respondents. For the experimental design, there are five price levels and, therefore, four parameters (utilities) to be estimated for this attribute.

There were seventeen choice tasks experimentally generated using the CBC/WEB,

version 7.0, from Sawtooth Software, and three additional tasks used as holdouts for validation purposes. A choice task example is portrayed in figure 2.



**Figure 2 - Example of a Choice Set for the Television Study**

One important feature of this stimulus is that the respondent chooses, firstly, the most preferred option after he/she decides whether the option would really be purchased. The option of not purchasing is a feature in any real market place, and this is the reason to have it represented in our experimental design. However, each time the no-choice option is selected, the participant offers no information about preferences. The two step approach deployed in this study overcomes this issue and allows a more precise parameter estimative (Brazzel et al., 2006).

The data was collected from 20 to 28 of March 2012. A total of 111 consumers were screened from Livra Panels and invited to answer a computer aided web interview. The eligibility criteria defined for the study established that the respondents must be 18 years old or more and live in a household classified in segments ABC following Criterio Brasil.

The first step of the analysis was the utility estimation at individual level, using the hierarchical Bayes method. The estimation was implemented through CBC-HB v5.0, from Sawtooth Software. The utility estimates are reported in Table 3.



**Table 3 - Average utilities for choice based conjoint analysis**

BRAND		SCREEN SIZE		SCREEN TECHNOLOGY		PRICE	
Level	Utility	Level	Utility	Level	Utility	Level	Utility
CCE	-42.22						
LG	12.70	32 inches	-9.78			Level 1	49.49
Panasonic	-10.42	37 inches	9.67	LCD	12.42	Level 2	29.58
Philips	12.03	40 inches	18.59	LED	18.82	Level 3	1.59
Samsung	22.01	46 inches	-14.45	Plasma	-31.24	Level 4	-24.51
Semp	5.70	50 inches	-4.03			Level 5	-56.16
Sony	0.21						
No choice				-18.21			

The part-utilities in Table 3 are numerical representations of consumers' preference, and the higher the utility, the higher the preference. Hence, we can infer that Samsung is the most preferred brand among these respondents, followed by LG and Philips. CCE would be the least preferred brand. These affirmations are valid when we consider that the remaining attributes (screen size, screen technology and price) are the same for all considered brands.

The other way to look into this information is that, since this is a compensatory model, for CCE to overcome the disadvantage posed by the weak brand preference, it would need to build some advantage in the other attributes.

Moreover, it is worth to notice the preference pattern in the screen size attribute. The utility increase as screen size rises from 32" to 40". However, it decreases when screen size increases from 40" to 46" and increase again when screen sizes changes from 46" to 50".

This outline is explained by the conditional price structure. The studied price range is the same for screen sizes from 32" to 40" and preference is higher for the largest screens. The price range is also the same for screen sizes from 46" to 50", and the largest screen is the preferred one. Yet, prices for screen sizes from 46" to 50" are higher than those for 32" to 40" and the latest is preferred in comparison to the former. Nevertheless, given the price differences, we must assume that the preference for screen sizes from 32" to 40" holds only at the different average prices studied.

The interpretation for screen technology is straightforward, with LED and LCD being preferred to Plasma. The same occurs with the finding for price, with preference decreasing as price increases.

The utility for no choice is also estimated and, under the linear additive models, it provides a threshold that any option must overcome in order to be chosen.

Attribute importance's can also be inferred from the utility estimates, and the clue for such understanding is within attribute amplitude at individual level. Therefore, the importance of each attribute is given by:

$$I_{it} = \frac{Max(U_{it}) - Min(U_{it})}{\sum_{t=1}^j [Max(U_{it}) - Min(U_{it})]}$$

Where  $I_{it}$  is the importance of attribute  $t$  for individual  $i$ ,  $Max(U_{it})$  is the utility value for the most preferred attribute level of attribute  $t$  and  $Min(U_{it})$  is the utility value for the least preferred level of attribute  $t$ . The sample importance for any attribute is the average of the individuals attribute importance.

**Table 4 – Sample attributes' importance**

ATTRIBUTE	IMPORTANCE
Brand	26%
Screen size	19%
Screen technology	23%
Price	32%

The attributes' importance of the study on focus is presented on Table 4. We can observe some balance in the attributes' importance, with price being the most important attribute for this application, followed by brand and screen technology. The least important attribute is screen size.

One should notice that the importance is dependent on the attribute range (or amplitude), which is defined by the researcher. For example, prices could have been studied within a narrow range or CCE could have been excluded from the brand attribute. If this was the case, the range of these utilities would be

smaller and, consequently, they would be less important. It means that attribute importance should be interpreted cautiously since it is contingent to the study design.

The analysis and learnings from the technique deployment can be extended further through simulations that allow us to predict share of preference. If a market place was configured as the one showed in figure 2, and based on the utilities estimates provided in Table 3, it would lead to the following prediction:

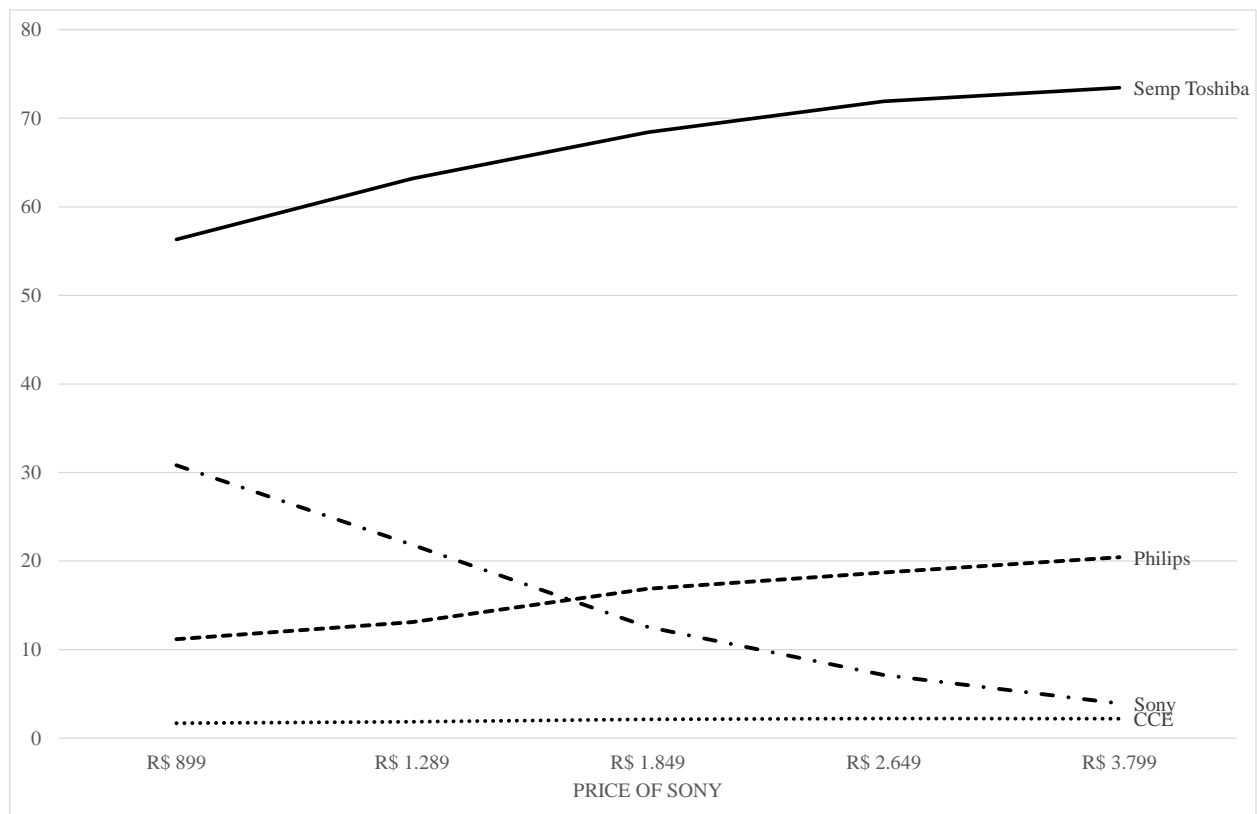
**Table 5 – Predicted share of preferences**

PRODUCT	SHARE OF PREFERENCE
Sony	21.85%
Semp Toshiba	63.18%
CCE	1.86%
Philips	13.12%

The same kind of simulation allows us to predict changes in shares of preference resulting from changing the product configuration in any of the scenario option. If we take Sony, as an example, and vary its prices across the entire studied price range, keeping the remaining options unchanged, we can observe what the resulting shares of preference will be. The results of such simulation are presented in Figure 3.

The prices for Sony Bravia are presented in horizontal axis and the share of preference for each brand is represented in the vertical axes. From this demand curve, it can be noticed that as Sony prices increase its share of preference decreases and the remaining brands capture higher shares of preference.

This pattern is consistent with demand theory, which states that, in a competitive marketplace, the increase in prices for any brand should lead to a decrease in the amount sold for the brand. And, as a consequence, the amount sold for competitive brands should be increased. For an introductory demonstration, see Pindyck and Rubinfeld (2009).



**Figure 3 - Demand curve for Sony**

The relationship between variation in price and volume sold for any product is expressed by the price elasticity of demand. This idea expresses the relative variation in a product demand that can be expected from a relative variation in its price. The easiest way to obtain a rough estimate to this relationship is through the arc elasticity given by:

$$E_p = \frac{\Delta Q}{\Delta P} \frac{(P_2 + P_1)/2}{(Q_2 + Q_1)/2} = \frac{Q_2 - Q_1}{P_2 - P_1} \frac{P_2 + P_1}{Q_2 + Q_1}$$

In this formula,  $P_2$  and  $P_1$  are the final and initial prices and  $Q_2$  and  $Q_1$  are final and initial quantities, always for product in focus.

From the use of this formula on the data supporting Figure 3, we can find  $E_p = -1,25$ . It means that for every 1% of variation in price, we can expect the demand to vary 1,25% in the opposite direction. The minus signal for  $E_p$  is consistent with demand theory and with the slope of the curve for Sony in figure 3.

Similarly, the relationship between variation in price for any product and volume sold for any competitive offer is given by the cross-price elasticity of demand, expressed as:

$$E_p = \frac{\Delta Q_b}{\Delta P_a} \frac{(P_{a,2} + P_{a,1})/2}{(Q_{b,2} + Q_{b,1})/2}$$

$$E_p = \frac{Q_{b,2} - Q_{b,1}}{P_{a,2} - P_{a,1}} \frac{P_{a,2} + P_{a,1}}{Q_{b,2} + Q_{b,1}}$$

This formula works in the same way that the previous, except that  $P_a$  is the price for the product that will have its price changed and  $Q_b$  is the quantity of the competitive offer.

The deployment of this formula leads to a cross elasticity of 0,21 between Sony and Semp Toshiba, meaning that a 1% variation in Sony's price will lead to a 0,21% variation in Semp Toshiba's quantity. Now, the signal is positive indicating that quantities for Toshiba will vary in the same direction of Sony price variation. Likewise the, the cross elasticity between Sony and CE is 0,21 and between Sony and Philips is 0,45. The cross elasticities pattern suggests that Phillips is the main competitor of Sony in the proposed competitive arena.

## 6 OPPORTUNITIES FOR BRAZILIAN MARKETING RESEARCH

Through the above application, we could demonstrate that conjoint analysis is a straightforward tool to understand consumers' preference and to

develop what if simulations that help the marketer to develop and implement efficient market strategies. Despite the focus of the analysis in the price variable, many other applications for the Brazilian market can well be deployed through conjoint analysis.

At the level of marketing strategy, segmentation can be developed using the individual utilities as base variables or through the latent variables models described earlier that can fit different set of utilities taking into account heterogeneity among respondents. So conjoint would help to identify and profile consumers segments that are price sensitive, brand loyal or that seek for different benefits,

At the marketing and product management, conjoint analysis can be used to study preference across distribution channels, to identify the most persuasive and promising communication concepts and to refine product development, designing the optimal set of attributes targeted to any specific segments. There is an enormous opportunity in Brazil to utilize conjoint analysis for a variety of marketing problems identified in Table 1. These methods can be employed for decisions in the public sector as well.

## 7 SOME RECENT DEVELOPMENTS

We have mentioned the development of hierarchical Bayesian methods and experimental design described earlier in the article. In addition, there have been developments on dealing with a positive part-function for price (Rao and Sattler, 2003), use of incentive-aligned methods for data collection (Ding, Grewal, and Liechty, 2005; Ding, 2007), a range of methods for handling large number of attributes (reviewed in Rao, Kartono, and Su, 2008), polyhedral methods aimed at reducing respondent burden (Toubia, Simester, Hauser, and Dahan, 2003; and Toubia, Hauser, and Simester, 2004), and modeling choices for bundles (Bradlow and Rao, 2000; Chung and Rao, 2003) and upgrading methods (Park, Ding, and Rao, 2008) based on the BDM method (Becker, DeGroot, and Marschak, 1964), barter conjoint methods (Ding, Park and Bradlow, 2009); conjoint poker methods (Toubia et al. 2012); experimental designs based on new criteria such as utility balance (Huber and Zwerina, 1996; and Hauser and Toubia, 2005; Street and Burgess 2004, 2007; Street, Burgess and Louviere 2005), continuous conjoint analysis (Wittink and Keil, 2003; and Su and Rao, 2006) adaptive self-explicated analysis (Netzer and Srinivasan, 2011), and measuring reservation prices for single products and bundles (Jedidi and Zhang, 2002; and Jedidi et al., 2003). These are but only a few examples of continuous developments in conjoint analysis research. The paper written from the 2007 Choice Symposium, Netzer, Toubia et al. (2008)

identifies several new directions in this methodology; see also Hauser and Rao (2004), Bradlow (2005), and Rao (2008; 2014) for ideas for future research in this area. In conclusion, one might say that conjoint analysis is alive and well!

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