Consumer preferences in food packaging: cub models and conjoint analysis

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Packaging features have been shown to be of great importance for the consumer final choice of fresh products (Connolly and Davidson, 1996; Silayoi and Speece, 2007). Packaging is an extrinsic attribute, which consumers tend to rely on, when relevant intrinsic attributes of the product are not available. Thus, packaging is constantly developing to meet changing and challenging consumer demands. In the current literature, studies on the influences of packaging features on consumer preferences are mainly related to classical preference evaluation methods like conjoint analysis (CA). Starting from a real case study in this field, along with Conjoint Analysis, we apply CUB models (Iannario and Piccolo, 2010) as a useful tool to evaluate preferences. CUB models can grasp some psychological characteristics of consumers related to the "feeling" towards packaging attributes and related to an inherently "uncertainty" that affects the consumers' choices. Both psychological characteristics "feeling" and "uncertainty" can be linked to relevant subject's information. The aim of our paper is twofold. At first we detect preferred packaging attributes of fresh food by means of CA, then we apply CUB models to some relevant attributes from the CA study. Results show that attributes like packaging material and size/shape of packaging are the most important attributes and that biodegradable packaging, reclosable trays/bags and long "best by" date are also valuable features for consumers.

Keywords: attributes, factorial designs, food packaging, mixed models.

Consumer behavior: preference analysis.

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Introduction

Within the framework of preference evaluation, stated and revealed preferences are widely used approaches by marketing operators. The present study is mainly based on stated preferences, in particular on the Conjoint Analysis (CA) method (Green & Srinivasan, 1978) and on an innovative statistical method called CUB (**C**ombination of **U**niform discrete and shifted **B**inomial distributions) model (Iannario & Piccolo, 2012). Both methods have been applied to study the consumer behavior in several fields.

The relevance of studying packaging can be derived from a simple observation: products are usually packaged when consumers buy them. The packaging is a sort of "silent vendor" and could make the difference in uncertain consumers (Connolly & Davidson, 1996). About those uncertain consumers, they could rely on some relevant packaging attributes for their purchase decisions (Silayoi & Speece, 2007).

The packaging has at least a logistic function and a marketing function: the former protects the product during transportation, the latter provides information about product attributes to consumers (Prendergast & Pitt, 1996). According to Silayoi and Speece (2007) there are two main categories of packaging elements influencing consumers: visual and informational elements. Visual elements are related to graphics and size/shape of packaging, informational elements are related to product information and information on the technologies used in the package.

The packaging features and quality judgments are somewhat related and if packaging features communicate high quality, those perceptions are transferred to the product itself. The color is the most well-studied attribute. Perception of an acceptable color is associated with the perception of flavor, nutrition and satisfaction levels. About the several packaging features, pictures on the package can provoke feels, tastes and other perceptions on consumers. Moreover, pictures attract consumers through vivid stimuli compared to words and they are a method of differentiation linking a particular product to the brand.

The segmentation is a fundamental part in a research when the aim is to study preferences. Those segments are indicative of the subjects' characteristics related to a particular configuration of preference. It is a relevant issue to collect information on how consumers perceive packaging and to integrate perceptions, needs, wants and past experiences into the packaging design process (Nancarrow *et al.*, 1998). Moreover, segmentation is a fundamental step that can help to identify specific needs and wants. Demographic variables, behaviors and lifestyles are among those variables that can be used to segment the market (Orth *et al.*, 2004).

Several Conjoint Analysis (Green & Srinivasan, 1978) studies have been conducted on food packaging. In a study on the influence of shape and color for dessert, Ares *et al*. (2010) show that the color of packaging and the pictures on it created sensorial expectations (e.g. taste). Those expectations could affect the consumer's perception of the food product. Moreover, for healthy food products, the color of packaging and pictures on it seemed to be relevant to the intention to buy.

A choice experiment on innovation technology for food packaging (Chen *et al.*, 2013) shows that risk perception and food safety concerns are the main factors that prevent consumers from buying vacuum packaging of fresh beef. They underline the importance to inform consumers on the safety of the innovative food packaging technology.

Koutsimanis *et al.* (2012) in a study on some food packaging attributes (price, packaging material, size, shelf life, etc.) showed that price, shelf life, the packaging material and a biodegradable packaging were the attributes affecting purchase decisions. A longer shelf life was evaluated as more convenient while the packaging material was perceived to influence the food product quality. Williams *et al.* (2008) show that the consumer satisfaction for food product is linked to specific packaging designs that are able to protect the content from leakage/disruption and extend the shelf life. A study on yogurt packaging (Rokka & Uusitalo, 2008) revealed that a recyclable packaging, a low-medium price and a re-closable packaging are among the more preferred attributes. Similar results have been shown in a study on food products in the first (at the store) and in the second (at home) moment of the truth (Lofgren *et al.*, 2008). Some quality attributes such as a recyclable packaging and a re-closable packaging are very attractive and influence the choice of purchasing and utilizing the product.

The packaging design has been suggested to be a relevant factor that gives a competitive advantage. Rundh (2009) shows the importance to interact with customers and suppliers in the packaging design process: suppliers can provide the best solutions in order to meet the customer requests.

CUB models (D'Elia & Piccolo, 2005; Iannario & Piccolo, 2012) are a class of mixture models that have been successfully applied to preference evaluation and customer satisfaction measurement for food products. In a study on smoked salmons, Piccolo and D'Elia (2008) analyzed a preference data set introducing subject's and object's variables in order to explain "feeling" and "uncertainty" consumer behaviors. An interesting application of CUB models along with a latent class logit model (Cicia *et al.*, 2010) reveals CUB models as a useful tool in order to identify segmentation variables.

The aim of the study is to present an integrate approach in the field of preference evaluation. The Conjoint Analysis methodology and the CUB models are applied to a preference data set on food packaging with the aim to show the contribution of CUB models on conjoint analysis results.

Methodology

Conjoint Analysis and CUB models are very different approaches both aimed at evaluating preferences. In a typical CA application, attribute levels are experimentally combined and an orthogonal plan is usually applied in order to lower the number of profiles. CA estimates the utilities of the levels and the relative importance of the attributes by appropriate estimate methods (Green & Srinivasan, 1978).

CUB models have been developed in order to explain the choice process of an item. "*Feeling*" and "*uncertainty*" are supposed to be latent variables involved in the choice process of an item (Iannario & Piccolo, 2012). D'Elia and Piccolo (2005) present the model as a valuable method for evaluating preferences, describing the probability structure of the model. Many years later, after several successful applications of CUB models, Iannario and Piccolo (2012) and Iannario (2014) present a detailed description of the CUB models along with the main extensions.

The random variable *Y* is fully explained by:

$$\Pr(Y = y) = \pi \left[\binom{m-1}{y-1} (1-\xi)^{y-1} \xi^{m-y} \right] + (1-\pi) \left[\frac{1}{m} \right], \quad y = 1, 2, ..., m.$$

A shifted binomial distribution is intended to mimic the choice behaviour of a rate *y* among *m* according to the *feeling* of respondents, while a discrete uniform distribution is aimed at describing the maximum expression of the *uncertainty* component surrounding any choices. The random variable *Y* is distributed as a mixture of shifted binomial and discrete uniform distributions with 1-π, $\pi \in (0,1]$, a direct measure of uncertainty and $\xi \in [0,1]$ a measure of feeling according to the measurement scale coding (Iannario, 2014). CUB model has been shown to be very flexible and parsimonious assuming very different shapes thanks to only two parameters π and ξ (Piccolo, 2003a; D'Elia & Piccolo, 2005). This flexibility allows CUB models explain different choice behaviours. We referred to D'Elia (2003) and Piccolo (2003b) for maximum likelihood parameter estimation by an E-M algorithm.

The feeling latent variable has been considered a psychological component involved in the choice process. The final choice is the result of psychological aspects like the

agreement/disagreement toward the item, socio-cultural aspects, the knowledge of the item, past experiences and so on. On the other side uncertainty takes into consideration the inherent indecision accompanying any human choice and it can be referred to a tendency to joke or fake, to have a confusing idea of the evaluated object, a bias involving questions/questionnaires, a way of collecting data and so on (Corduas *et al.*, 2009; Iannario & Piccolo, 2012; Iannario, 2014).

Among the several extensions that have been developed (Iannario, 2014), we are considering the introduction of covariates for explaining feeling and uncertainty parameters. A formal description of CUB model with covariates (D'Elia, 2003; Piccolo, 2003b) shows that thanks to the logistic functions

$$\pi_i = \frac{1}{1+e^{-\beta_0 - \beta_1 x_{i1} - \ldots - \beta_p x_{ip}}} = \frac{1}{1+e^{-\beta_0 - x_i \beta}}$$

and

$$\xi_i = \frac{1}{1+e^{-\gamma_0 - \gamma_1 w_{i1} - \ldots - \gamma_q w_{iq}}} = \frac{1}{1+e^{-\gamma_0 - w_i \gamma}},$$

parameters π_i and ξ_i can be fully explained by covariate vectors $x_i=(1,x_{i1},\ldots,x_{ip})$ and $w_i=(1,w_{i1},\ldots,w_{iq})$. In such a framework, the model extension

$$\Pr(Y_i = y_i) = \pi_i \left[\binom{m-1}{y_i-1} (1-\xi_i)^{y_i-1} \xi_i^{m-y_i} \right] + (1-\pi_i) \left[\frac{1}{m} \right], \quad y = 1, 2, \ldots, m$$

describes the probability distribution of the random variable *Y* for the *i-th* subject conditioned to relevant covariates. Piccolo and D'Elia (2008) show that subjects'/objects' covariates were relevant to describe different patterns of smoked salmon evaluations according to gender, age and country of origin of respondents and according to salt content, lightness and intensity of red of smoked salmons.

For the sake of completion, we briefly describe some important CUB model extensions. Iannario (2012) and Iannario (2014) introduce some CUB model extensions in order to catch specific choice behaviors. A *shelter choice* is considered an over-selected grade in order to simplify the evaluation task. Such a behavior can be responsible for an upward choice of a specific grade or rank and Iannario (2012) shows that a proper CUB model can capture the *shelter effect* and help to improve model fitting.

Iannario (2014) discusses about extra-variability that could be ascribed to an inter-personal way of selecting among grades that is a variability of personal feeling. A *Beta-binomial* random variable has been considered to be involved in the *overdispersion* effect and the

CUBE (convex **C**ombination of a **U**niform and a shifted **BE**ta-binomial random variable) model has been described by Iannario (2014).

Useful fitting measures for CUB models are based on estimated and observed probabilities and on log-likelihood. A dissimilarity index has been developed in order to measure the absolute distance between estimated and observed probabilities (Corduas *et al*., 2009; Iannario, 2009). The normalized dissimilarity index

$$Diss = 0.5\sum_{y=1}^{m}\left|f_y - p_y(\theta)\right|$$

represents the percentage of respondents that should change their choice in order to reach a perfect fitting. It can be considered a satisfactory fitting when Diss ≤ 0.1 (Iannario, 2009). The dissimilarity index approach cannot be extended to the CUB model with covariates and it should be noticed the application of Likelihood Ratio Test (LRT) in order to compare log-likelihoods of nested models (Piccolo, 2003b; Corduas *et al*., 2009; Iannario, 2009).

We are considering a CUB (0, 0) with the parameter vector $\theta'=(\pi, \xi)$ and a nested model CUB (*p*, *q*) with the parameter vector $\theta''=(\beta_i, \gamma_j)$, *i=1,...,p+1, j=1,...,q+1*. The log-likelihood deviance is derived as $LRT = -2\left(\ell(\theta') - \ell(\theta'')\right)$ and it is distributed as a χ^2 with degree of freedom equal to the difference of the parameter number (D'Elia & Piccolo, 2008; Iannario & Piccolo, 2009).

The basic idea of our proposal (figure 1) is to deepen the conjoint analysis results by applying CUB models to those product profiles described by attribute levels that have been evaluated as most relevant.
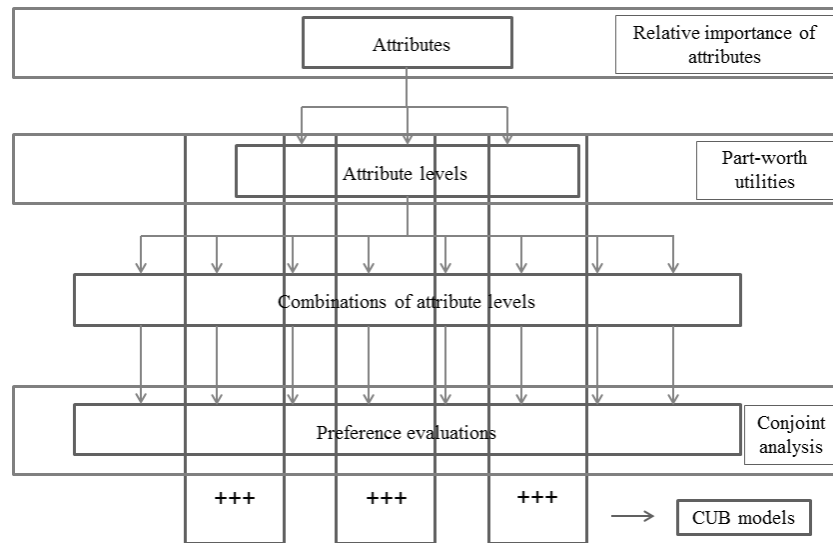

Figure 1 CUB models application to CA results.

We consider *x* attribute levels that have been estimated as with maximum utility so that we define *x* groups of profiles and each of those has undergone CUB models analysis.

Procedures

The case study involved a firm that produces the raw material for food packaging purposes. The main scope of the research was to collect consumer preferences for food packaging in order to carry out insightful analysis. Once defined attribute levels (table 1), two experimental designs were drawn. Each experimental design was drawn to define the product concepts on which the conjoint analysis study was based. Each conjoint analysis has considered product concepts that were described by four out of five attributes. We excluded "disposal" as an attribute in the conjoint analysis called "cook-able", the opposite occurred when we excluded "cook-able packaging" as attribute. A fractional factorial design using an orthogonal plan was adopted to reduce the number of level combinations.

	Disposal	Cook-able pkg	Size	Shape	Shelf life
1	Recyclable	Oven	Single pack	Vacuum packaging	Long
2	Not recyclable	Microwave	Split packs	Not reclosable bag	Short
3	Biodegradable	Steaming	Family pack	Reclosable bag by zip lock	
4		Not possible		Easy to peel tray with reclosable top	
5				Reclosable tray by cover	

Table 1 Attribute levels selected from previous customer satisfaction studies.

Considering four attributes, a complete full profile-Conjoint Analysis (CA)would have brought one to evaluate 90 concepts: such a number has been lowered to 25 by means of an orthogonal plan. Two out of 25 concepts were discharged because they were implausible. A total of 23 cards was drawn by mixing pictures and descriptions. Two versions of the conjoint analysis' questionnaire were developed. Two groups of consumers were identified and they were asked to provide demographic information and to express their preferences by selecting a grade from 1 to 10 (with 1 = "I would never buy it") for each profile card. The estimation method to derive utilities was based on Ordinary Least Squares (OLS) as described in Hauser and Rao (2004). After obtaining conjoint analysis results, some of those relevant results were elaborated by CUB models in order to estimate feeling and uncertainty parameters. We have considered, for each attribute, the cards with the highest part-worth utility. The four groups of cards were similar for at least one level attribute: the CUB models were applied to the four groups of cards.

Results

We collected a total of 205 CA questionnaires, 83 for "cook-able" version and 122 for "disposal" version. For the "cook-able" version we have 60 females and 22 males; 72 are Italian and 11 are Austrian. The age ranges from 18 to 80 (M=42; SD=16.8). For the "disposal" version we have 66 females and 56 males; 102 are Italian and 20 are Austrian. The age ranges from 18 to 83 (M=41; SD=15.7).

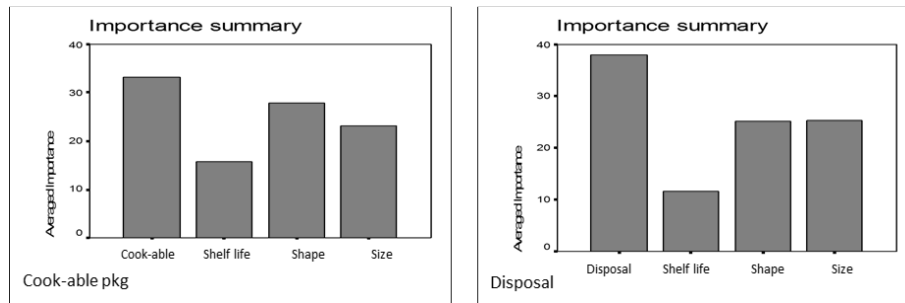Aggregated relative importance of attributes can be represented by bar plots.

Figure 2 Attribute importance of cook-able version (left panel) and disposal version (right panel).

Consumers gave more importance to both cook-able pkg and disposal than other attributes. We hypothesize that this trend could be a bias due to the interviewing procedures. In fact consumers were asked to state if they paid more attention to the possibility to cook food inside the packaging or if they paid more attention to the packaging material (recyclable or not). The shape and the size of packaging were also important attributes.

At the same time we describe a summary of the part-worth utilities for each version of the CA. Utilities are shown in bar plots in order to have an overview of the levels with the highest utility.
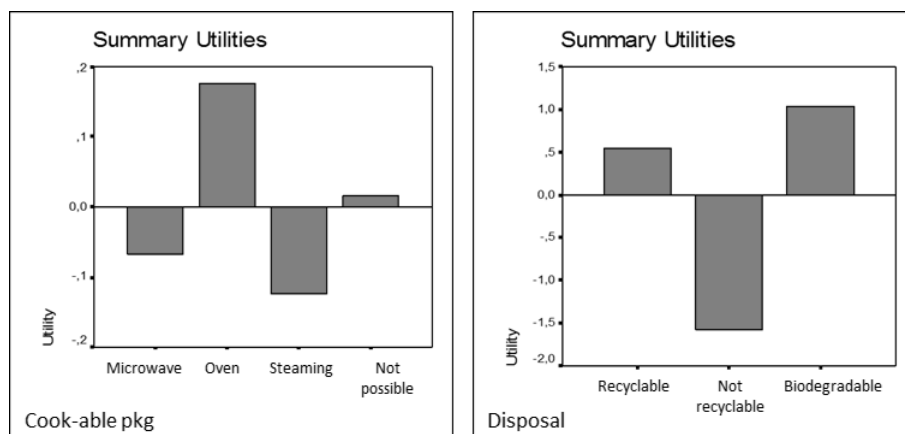

Figure 3 Level utilities for cook-able and disposal attributes.

Results show that the levels with the highest utility were the cook-able packaging by oven and the biodegradable packaging.
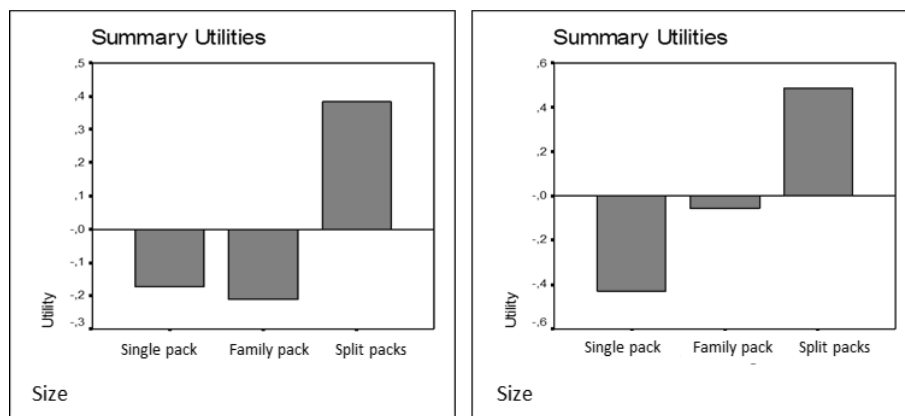
Figure 4 Level utilities for size attribute: cook-able and disposal versions in left and right panel respectively.

Split packs and long shelf life are the levels with the highest utility in both CA versions. Figure 4 shows that single pack and family pack have negative utilities while figure 5 shows that a long shelf life has very positive utility with respect to short shelf life. Long shelf life was defined to be two weeks while short shelf life was set at one week. Finally "shape" shows a slightly different pattern of level utilities.

Figure 5 Level utilities for shelf life attribute: cook-able and disposal versions in left and right panel respectively.

The levels for "shape" with the highest utility are cover-reclosable trays and zip lock-reclosable bags. The pattern shown in figure 6 stresses the importance of a bag or a tray that can be closed after that it has been opened.
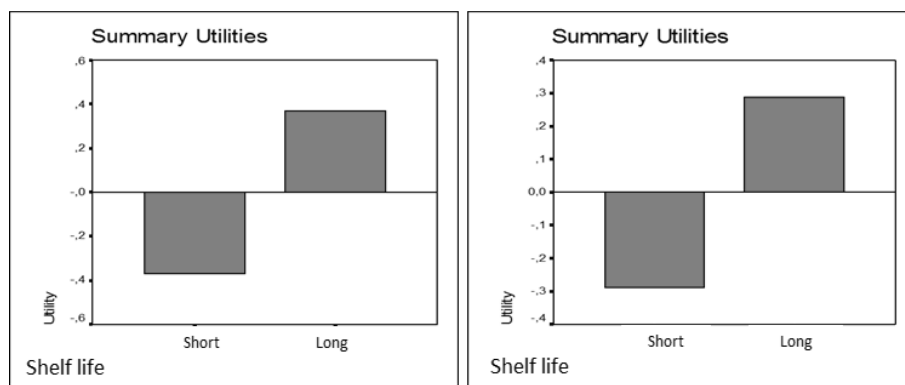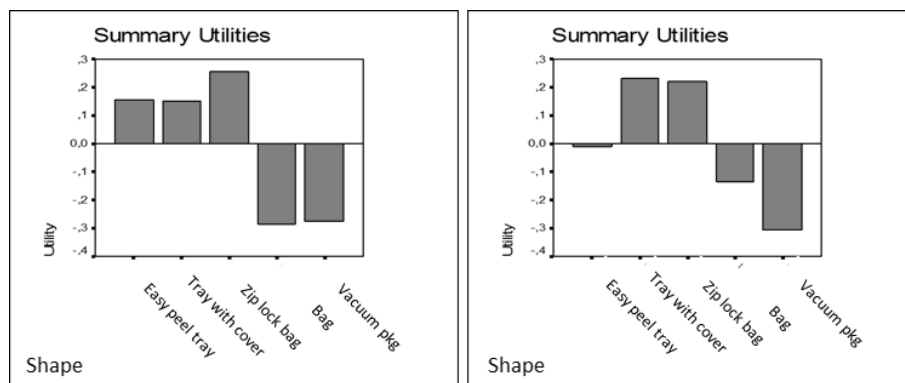

Figure 6 Level utilities for shape attribute: cook-able and disposal versions in left and right panel respectively.

Based on the levels with the highest utility, we have selected and grouped the profiles and we have run CUB models without and with covariates. Parameter π, parameter ξ and dissimilarity indexes are shown in tables 2 and 3 for both versions of CA. The variable "All" is representing all cards with at least one attribute level that has been estimated with the highest utility.

	Variable	π	ξ	Diss.	Log likelihood
1	Cook-able pkg: oven	0.576 (0.051)	0.342 (0.016)	0.0489	-792.351
3	Shelf life: long	0.451 (0.037)	0.257 (0.014)	0.0756	-1620.434
4	Shape: bag with zip lock	0.309 (0.052)	0.221 (0.028)	0.0619	-826.835
5	Size: split packs	0.546 (0.066)	0.121 (0.019)	0.0857	-301.8470
6	All	0.418 (0.031)	0.286 (0.013)	0.0533	-2448.948

Table 2 Pai and Csi estimates (standard error), dissimilarity indexes and log likelihood for cook-able version of CA.

	Variable	π	ξ	Diss.	Log likelihood
2	Disposal: biodegradable	0.527 (0.046)	0.141 (0.016)	0.1842	-1074.460
3	Shelf life: long	0.321 (0.034)	0.199 (0.019)	0.1179	-2065.394
4	Shape: tray with cover	0.232 (0.052)	0.310 (0.036)	0.1059	-930.4743
5	Size: split packs	0.373 (0.054)	0.120 (0.023)	0.1082	-668.8398
6	All	0.320 (0.027)	0.220 (0.015)	0.1141	-3446.425

Table 3 Pai and Csi estimates (standard error), dissimilarity indexes and log likelihood for disposal version of CA.

Observed relative frequency and fitted probability plots are reported (figure 7 and figure 8).
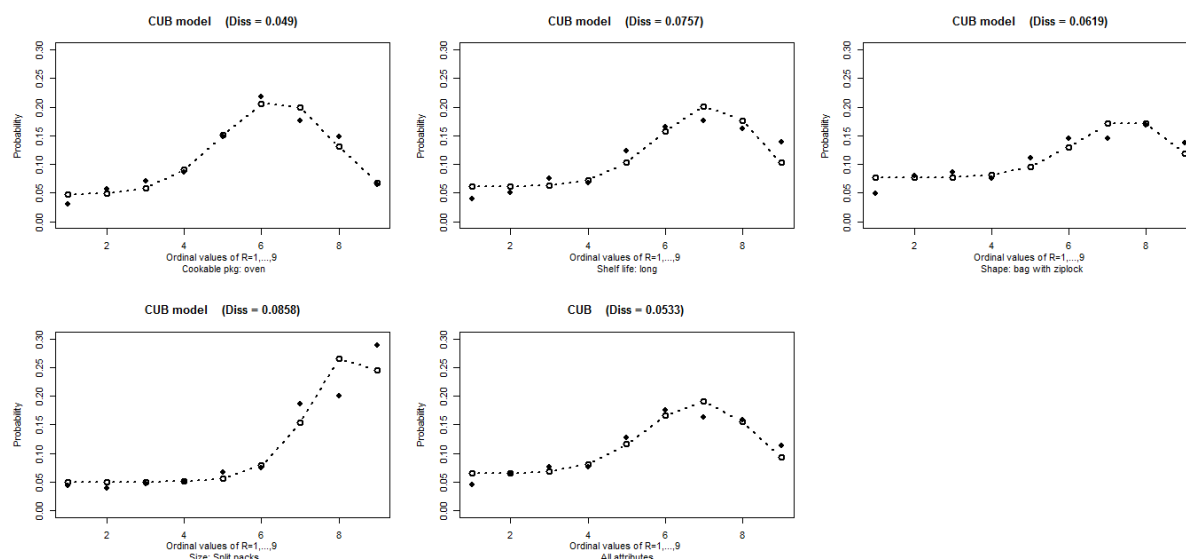
Figure 7 Observed relative frequencies (dots) and fitted probabilities (circles) of CUB models for cook-able version of CA.
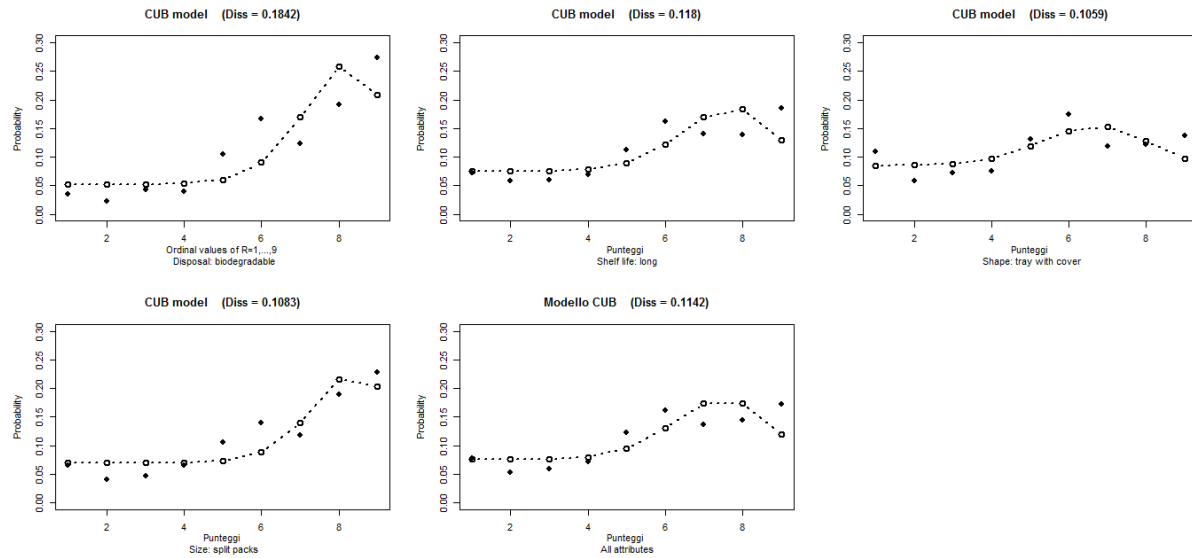
Figure 8 Observed relative frequencies (dots) and fitted probabilities (circles) of CUB models for disposal version of CA.

In order to have a comprehensive overview of the uncertainty and the feeling dimensions, we placed each of those attribute levels into space (figure 9). The CUB model gives two parameters for each attribute level so that we can determine points into a two-dimensional space.
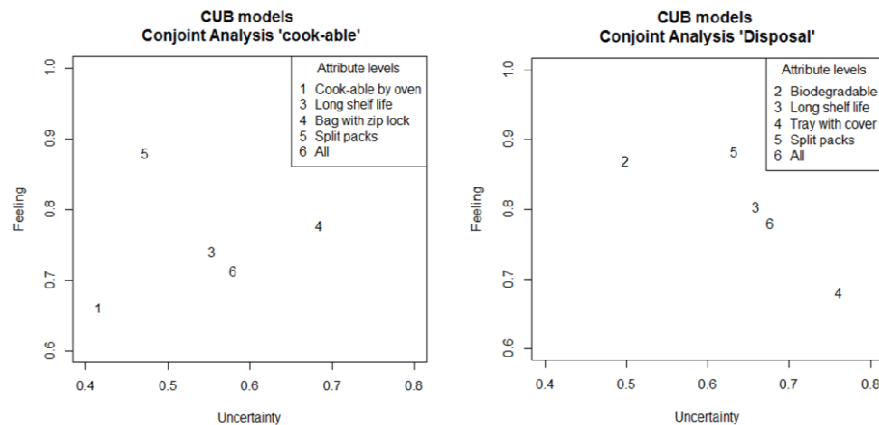
Figure 9 Feeling/Uncertainty dimensions of attribute levels: cook-able and disposal versions in left and right panel respectively.

The feeling for "split packs" is very high and also for "biodegradable". The attribute level with the higher uncertainty is the tray reclosable by cover. Then we have applied a CUB model with covariates for each group of cards.

Covariates	Coding
Gender	0= male;1= female
Nationality	0= Italy;1= Austria
Age	Continuous variable
Educational level	1= elementary; 2= intermediate; 3= high school; 4= graduate
Income (monthly in Euros)	1= <800; 2= 800-1700; 3= 1800-2900; 4= >2900

Table 4 Covariates for CUB model.

The covariates (table 4) have been introduced once at a time and useful descriptions (from tables 5 to table 8) show which of them and how they affect CUB-model parameters. In particular we reported π or ξ estimates, the effect estimates (β or γ) of covariates that we can use to estimate parameter π or ξ and we reported also the log-likelihood in order to have sufficient data to compare nested models.

Variable	π or β_0	π covariate	β_1	ξ or γ_0	ξ covariate	γ_1	Log likelihood
Shelf life: long	0.449 (0.037)	-	-	-0.861 (0.114)	Gender	-0.323 (0.149)	-1618.10
	0.466 (0.036)	-	-	-0.149 (0.212)	Educational level	-0.371 (0.083)	-1610.121
Shape: bag with zip lock	0.310 (0.051)	-	-	-0.833 (0.232)	Gender	-0.620 (0.302)	-824.8445
	-2.432 (0.971)	Income	0.933 (0.482)	0.220 (0.0260)	-	-	-824.5315
Size: split packs	0.566 (0.064)	-	-	-2.947 (0.499)	Age	0.024 (0.011)	-299.6697
	0.607 (0.067)	-	-	-0.146 (0.488)	Educational level	-0.635 (0.182)	-295.8138
	-2.354 (0.857)	Educational level	0.956 (0.296)	0.110 (0.017)	-	-	-295.5072
All	0.111 (0.220)	Gender	-0.627 (0.272)	0.292 (0.013)	-	-	-2446.353
	-1.168 (0.411)	Income	0.484 (0.215)	0.283 (0.013)	-	-	-2446.366
	0.417 (0.031)	-	-	-0.703 (0.091)	Gender	-0.359 (0.122)	-2444.622
	0.429 (0.031)	-	-	-0.286 (0.188)	Educational level	-0.250 (0.072)	-2442.787

Table 5 Parameter estimates (standard error) and log-likelihood of CUB models with covariates (cook-able version of CA).

Table 5 and table 7 show CUB (1, 0) with a significant covariate for π and CUB (0,1) with a significant covariate for ξ. Each line in table 5 and table 7 presents the CUB model with a significant covariate.

Each line in tables 6 and 8 show which covariates were significant for a CUB model with more than one covariate. The first line of table 8 presents results of a CUB (1, 1) for "disposal": nationality and age were significant for explaining parameters π and ξ respectively. The first line of table 6 shows a CUB (0, 2) for "long shelf life" (cook-able version of CA): gender and educational level were both significant for explaining parameter ξ. The LRT was also significant ($\chi_{31.618, 2}$, p-value < 0.000001).

Variable	π or β_0	π covariate	β_1	ξ or γ_0	ξ covariate	γ_1 and γ_2	Log likelihood
Shelf life: long	0.463 (0.036)	-	-	0.319 (0.255)	Gender	-0.484 (0.147)	-1604.625
					Educational level	-0.442 (0.087)	
Shape: bag with zip lock	-2.342 (0.915)	Income	0.896 (0.463)	-0.937 (0.209)	Gender	-0.556 (0.284)	-822.639
Size: split packs	-1.474 (0.878)	Educational level	0.702 (0.304)	-0.626 (0.570)	Educational level	-0.463 (0.190)	-292.9269
All	0.272 (0.213)	Gender	-0.803 (0.263)	0.195 (0.215)	Gender	-0.525 (0.123)	-2430.956
					Educational level	-0.329 (0.075)	

Table 6 Parameters (standard error) and log-likelihood of CUB models with more than one covariates applied to cook-able CA cards.

From table 6, considering all attribute levels (the variable called "All"), the parameter π of CUB model was significantly affected by gender and the parameter ξ was affected by gender and educational level.

Variable	π or β_0	π covariate	β_1	ξ or γ_0	ξ covariate	γ_1	Log likelihood
Disposal: biodegradable	0.372 (0.201)	Nationality	-1.599 (0.611)	0.146 (0.015)	-	-	-1068.66
	-1.491 (0.509)	Educational level	0.595 (0.174)	0.144 (0.015)	-	-	-1067.423
	0.515 (0.047)	-	-	-2.671 (0.383)	Age	0.019 (0.007)	-1069.814
	0.521 (0.045)	-	-	-0.705 (0.353)	Educational level	-0.403 (0.138)	-1069.253
Shelf life: long	-1.853 (0.488)	Educational level	0.395 (0.153)	0.199 (0.018)	-	-	-2061.719
	0.251 (0.488)	Income	-0.573 (0.282)	0.192 (0.019)	-	-	-2063.067
	0.319 (0.035)	-	-	-2.600 (0.398)	Age	0.026 (0.007)	-2056.569
	0.326 (0.034)	-	-	-2.059 (0.295)	Income	0.361 (0.129)	-2062.043
Shape: tray with cover	0.241 (0.050)	-	-	-0.699 (0.158)	Nationality	-2.301 (1.055)	-926.0493
Size: split packs	-1.948 (0.700)	Educational level	0.494 (0.216)	0.116 (0.022)	-	-	-665.8254
	0.364 (0.048)	-	-	-3.423 (0.598)	Age	0.030 (0.010)	-663.9665
	0.394 (0.052)	-	-	-0.311 (0.785)	Educational level	-0.558 (0.276)	-665.6478
All	-1.900 (0.411)	Educational level	0.411 (0.121)	0.222 (0.014)	-	-	-3439.968
	0.319 (0.027)	-	-	-2.076 (0.265)	Age	0.017 (0.005)	-3439.09
	0.320 (0.027)	-	-	-1.843 (0.245)	Income	0.298 (0.108)	-3443.031

Table 7 Parameter estimates (standard error) and log-likelihood of CUB models with covariates (disposal version of CA).

Variable	π or β_0	π covariate	β_1	ξ or γ_0	ξ covariate	γ_1 and γ_2	Log likelihood
Disposal: biodegradable	0.339 (0.207)	Nationality	-1.564 (0.590)	-2.541 (0.348)	Age	0.017 (0.006)	-1064.042
Shelf life: long	0.323 (0.035)	-	-	-2.936 (0.433)	Age	0.024 (0.007)	-2054.960
					Income	0.241 (0.129)	
All	-1.558 (0.366)	Educational level	0.299 (0.121)	-1.822 (0.244)	Age	0.013 (0.005)	-3435.976

Table 8. Parameters (standard error) and log-likelihood of CUB models with more than one covariates applied to disposal CA cards.

Tables 9 and 10 show directions of uncertainty (1-π) or feeling (1-ξ) when a significant covariate is introduced. This way of representing effect direction is aimed at giving a tool to easily discriminate patterns. Table 9 indicates that females have constantly higher feeling and uncertainty than males.

Variable	π covariate	(1-π) effect	ξ covariate	(1-ξ) effect
Shelf life: long	-	-	Gender	↑
			Educational level	↑
Shape: bag with zip lock	-	-	Gender	↑
Size: split packs	Educational level	↓	Age	↓
			Educational level	↑
All	Gender	↑	Gender	↑
	Income	↓	Educational level	↑

Table 9 Direction of the effect when covariates are introduced (cook-able version of CA).

Table 10 presents a slightly different pattern of covariates. Gender was not significant and educational level was an important covariate that seemed to affect the uncertainty component.

Variable	π covariate	(1-π) effect	ξ covariate	(1-ξ) effect
Disposal: biodegradable	Nationality	↑	Age	↓
	Educational level	↓	Educational level	↑
Shelf life: long	Educational level	↓	Age	↓
	Income	↑	Income	↓
Shape: tray with cover	-	-	Nationality	↑
Size: split packs	Educational level	↓	Age	↓
			Educational level	↑
All	Educational level	↓	Age	↓
			Income	↓

Table 10 Direction of the effect when covariates are introduced (disposal version of CA).

Discussion and conclusions

The results show what are the most relevant packaging characteristics after applying the conjoint analysis' estimation method to a preference evaluation dataset. The profiles have been experimentally designed to collect preferences on food packaging. Relevant information on subjects has also been collected in order to study how the characteristics of the subjects affect uncertainty and feeling toward the most preferred food packaging attributes.

Results have shown that biodegradable packaging and split packs have the highest feeling and that the cook-able food packaging has the lowest feeling and uncertainty. About the shape of packaging, consumers seem to appreciate reclosable bags by zip lock that have been estimated to have higher feeling and lower uncertainty with respect to reclosable tray by cover. Consumers seem to feel more comfortable with reclosable bags.

Dissimilarity indexes indicate that CUB models have very good fitting with respect to cook-able version of profiles. CUB models applied to the disposal version of CA show high dissimilarity indexes that suggested the need to run further analysis. In fact, when we introduce covariates CUB models improve a lot and LRTs can give a measure of those improvements.

About the cook-able version of CA, the most relevant covariates of the subjects introduced to explain feeling and uncertainty were gender and educational level, whereas about the disposal version, educational level and age have often resulted to be involved as significant covariates. Concerning the worst CUB model fitting of profiles related to biodegradable packaging, a CUB (1, 1) has been identified to be very useful in order to improve the model fitting. Italians seem to express lower uncertainty than Austrians and younger consumers have higher feeling that older consumers.

What we see is a different pattern of covariates for food packaging including the possibility to cook the product with the packaging itself: the gender and the level of education could affect in some way the final choice of evaluation and ultimately the purchase decision. A different pattern of behaviours is explaining the choice involving food products that are described by different characteristics like a biodegradable packaging and a reclosable tray: age and educational level were relevant in order to define different behaviours with respect to the feeling and the uncertainty. Younger consumers with a higher level of education seem to be more resolute with respect to their final choice selecting higher preference scores than older consumers with a lower level of education.

An in-depth analysis shows that, the approach identified specific characteristics of the subjects that seemed to be related to a specific attribute level. For example, the feeling and the uncertainty toward split-pack packaging were significantly affected by educational level and age and educational level respectively for both versions of CA. The split pack packaging has been estimated to be the most preferred with the highest feeling, especially among younger consumers with a high level of education.

Concerning the long-shelf life attribute level, CUB model results are more difficult to read: there is a very different pattern between the two versions of CA. Results indicate a more

heterogeneous groups of respondents for disposal version of CA so the suggestion is to apply the innovative approach "conjoint analysis and CUB models" not only on large and representative samples but also on comparable samples. The approach that we have presented could be very useful in order to drive the choice of a final product configuration specific to a market segment.

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