Element category importance in conjoint analysis: Evidence for segment differences

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Howard Moskowitz

is the President and founder of Moskowitz Jacobs Inc. His background includes a PhD in Experimental Psychology from Harvard University, and seven years as a senior scientist at the US Army Natick Laboratories. Widely published in the scientific press (11 books and over 200 scientific articles, he is known worldwide as the leading thinker and creator of advanced research technology in the area of new product and concept development. His extensive speaking engagements span both scientific and market research conferences, as well as guest lectures at leading business schools and food science schools. Moskowitz Jacobs Inc. has conducted thousands of ProductEngineer® studies on product formulation and IdeaMap® studies on the development and optimisation of product and positioning concepts for leading manufacturers worldwide.

Bert Krieger

is the Executive Vice-President at Moskowitz Jacobs Inc. in his 13 years at MJJ, Bert has consulted with a multitude of Fortune 500 food and beverage manufacturers and service industry providers. He brings a wealth of experience in strategic thinking and problem solving throughout the concept and product development process.

Samuel Rabino

is a professor in the Marketing Group at Northeastern University, a research associate in the Master Program in Technology Management at Scuola Superiore di Studi Universitari e di Perfezionamento S. Anna, Pisa, Italy, and lecturer at Harvard University. Rabino holds an MBA and PhD from New York University. The author of numerous articles on industrial marketing, international marketing, export incentive programmes, product planning and brand strategies and development, Rabino conducted workshops and has been a consultant to the US Government and a number of multinational organisations. Rabino's research is in the globalisation of the Italian industrial districts, the role of accountancy in the new product development process and a new global segmentation methodology.

Abstract Conjoint measurement is a popular research tool that uses experimentally designed combinations of concept elements (phrases, pictures), obtains consumer reactions to these combinations, and then employs statistical modelling (eg regression analysis) to understand the drivers of concept acceptance. The elements used in conjoint analysis can be classified into categories or buckets of like-minded statements, such as benefits, brands, heritages, mode of action, etc. This paper introduces the concept of the relative importance index (RII), for categories comprising different numbers of elements (verbal or visual descriptors of a concept). This index is the proportion of the total sum of squares of individual utilities attributable to each category. The RII value can be further normalised by dividing by the number of elements within the category to estimate the importance of each category normalised for the number of concept elements. Categories exhibit different importance. This study presents empirical analyses of 12 studies, each with more than ten categories, and more than 100 concept elements. Segmentation of respondents based upon the pattern of element impacts often shows dramatic segment differences in this RII index, suggesting different product development and communication strategies.

Howard Moskowitz
President, Moskowitz &
Jacobs Inc.
1025 Westchester Avenue,
White Plains, New York NY
10604, USA.

Tel: +1 914 428 9204;
Fax: +1 914 428 8364;
e-mail:
hrm@mji-designlab.com

INTRODUCTION: UNDERSTANDING THE CONSUMER MIND BY CONJOINT ANALYSIS

During the past three decades consumer marketers and market researchers have spent a great deal of time and effort trying to understand the mind of the consumer. One of the most important outcomes of these concerted efforts has been a suite of research procedures known as conjoint measurement.¹ Conjoint measurement at its most fundamental level is simply the application of experimental design principles to concepts. Experimental design consists of systematic variations of independent variables, which for concepts constitute the phrases and pictures in a concept. These are 'elements'. There may be many such elements in a conjoint analysis study. For bookkeeping purposes it is necessary to create some mechanism that ensures the meaningfulness and reality of a concept. One way is to put together elements of the 'same type' (eg benefits, names) into a group or category. A rule for creating a concept could be that only one element (eg one name or one benefit) could appear in any single concept. This will ensure that the concept is at least superficially meaningful, rather than comprising a set of elements strung together at random.

The raw material, or elements of the concepts, are mixed and matched in order to create a number of test concepts. Underneath these test concepts is a structure, so that the researcher knows what elements reside in each test concept. The consumer respondent, faced with these combinations, is instructed to rate the combination on some type of scale, such as purchase intent. The researcher then relates the presence/absence of the concept elements (developed in the

experimental design) to the ratings assigned by the respondents (known from the evaluation). The result is an equation, showing the number of rating points contributed by each concept element to the respondent's rating of interest or other dependent variable. An exceedingly straightforward technique, conjoint measurement has seen use in thousands of studies in both the academic and commercial realms.²

A quick glance through a search engine such as Google™ will reveal many different uses for conjoint measurement, spanning the range from product design to promotion analysis, to service concepts and the like. Conjoint measurement is a powerful tool because it enables the researcher to deconstruct a product, a message, or a promotion into components, and discover the importance of each of the components. At a simple practical level a conjoint measurement exercise provides the user with guidance about what to choose in order to increase product or service acceptance and sales. At a more profound level a conjoint measurement exercise reveals the importance of different factors to the consumer, and thus sheds light on the decision rules employed by various consumers in a variety of contexts.

THE IMPORTANCE OF A SINGLE ELEMENT VERSUS THE IMPORTANCE OF A CATEGORY OF ELEMENTS

When there are multiple categories of elements in the conjoint exercise (eg name, price and heritage), one of the first questions to arise is the relative importance of the category. Importance of a category is relevant when questions arise as to the way the consumer processes information. An unimportant category is one in which the consumer disregards the information. An important

category is one in which the consumer attends to the information.

Conjoint measurement works primarily at the element level not at the category level. The category is a basic unit of bookkeeping, to ensure that a concept only has one element in the category. Each element in the category generates its own impact, so it is technically more correct to ask about the importance of single elements. An individual element is important when its impact is either highly positive or highly negative. The impact or utility value for an element developed by the IdeaMap® method (the conjoint method discussed here),³ is defined as the conditional probability that a respondent will change the response to the concept from indifferent to interest if the concept element is present. A positive impact value means that the concept element adds to the probability, whereas a negative impact value means that the concept element subtracts from the probability.

A category comprises many related elements, and can be arbitrary in size, unless the specific conjoint procedure dictates, ahead of time, that all categories comprise the same number of elements. The importance of the category must be obtained from some combination of the impact or utility values of the elements within the category. Keep in mind that the method must take into account the differences in the sizes of the categories. In studies dealing with a very large number of elements (often 100+) there may be many elements in the category that show low impact values (near zero), and a few elements that show very high or very low impact values (eg +10 or higher). It is important to take this range of impact values into account when computing category importance.

Relative importance of categories needs an operational definition that can handle the large number and arbitrary

nature of elements. For this paper the operational definition of relative importance is the sum of squares of the element impacts *within a category* versus the total sum of squares of all element impacts across all categories. The squaring of the impact value removes the importance of sign. Thus, two elements, which have impacts of +10 and -10, would become +100 each, rather than cancelling each other out. Other operational definitions could be constructed for relative importance as well. The strategy of dealing with sums of squares parallels the statistical framework of analysis of variance.

SEGMENTATION, MIND-SET AND DIFFERENT LEVELS OF RELATIVE IMPORTANCE OF CATEGORIES

Marketing researchers segment consumers on the basis of their preferences in order to discover new groups of consumers who can be better targeted for marketing programmes. Improved understanding of customer needs leads to greater customer satisfaction through a cleaner focus for the firm's marketing strategies.⁴ By segmenting consumers, the marketer attempts to identify homogeneous groups of individuals, who presumably share similar preferences for goods and services, and who therefore can be satisfied by a more limited set of offerings that are better suited for their needs.

Segmentation is well accepted in the marketing community, but the key issue is how to segment. Wells suggested segmentation on the basis of psychological attitudes, and coined the term 'psychographics'.⁵ Others took up the approach, and have created batteries of questionnaires that divide consumers into homogeneous groups on the basis of their attitudes in general. One of the

better-known segmentation schemes of these is the VALS segmentation (values, attitudes, lifestyle segmentation).⁶ Some investigators have eschewed the more global segmentation and have looked into segmenting consumers on the basis of their responses to concepts.⁷ Over the past decade other forms of segmentation have emerged.⁸ In the main, these segments have tackled the same problem — how to identify consumers with similar ‘mind-sets’, in order to focus the advertising and direct mailing efforts.

SENSORY PREFERENCE SEGMENTATION – THE FORERUNNER OF CONCEPT RESPONSE SEGMENTATION

Moskowitz and his colleagues proposed a segmentation of consumers, based upon the pattern of sensory preferences.⁹ Using well-established methods from experimental psychology, they were able to create a segmentation procedure that was effectively independent of an individual’s degree of liking for a set of products, but rather depended upon the relation between an individual’s liking ratings and an underlying set of sensory attributes. Sensory preference segmentation was able to identify clusters of individuals who exhibited radically different, yet explainable, patterns in the acceptance ratings assigned to physical products. The word ‘explainable’ is important here, because the segmentation procedure transcended a simple data-analytic approach. The procedure actually created subgroups with clearly different, yet coherent patterns of preferences.

This segmentation was subsequently extended to concepts.^{10–12} What makes this segmentation important and the topic of this paper is that the segmentation provides both a data-analytic approach and at the same

time a clearer insight into the underlying mechanisms driving the segments. In contrast most conventional segmentation procedures search for statistically powerful ways to partition consumers, but do not search for underlying mechanisms that potentially can influence behaviour of respondents.

The organising principle for concept response segmentation is derived from the observation in food products that as a sensory attribute increases acceptance changes in a systematic fashion. In the prototypical relation liking first increases, peaks and then drops down.¹³ Figure 1 (top left) shows the organising principle behind sensory segmentation (top panel), and its straightforward extension to concepts (bottom panel). As an attribute increases (sensory for products; semantic scale for concept elements), acceptance increases, peaks and drops down. Individual curves can be analysed to produce clusters of similar responding individuals. When it comes to individuals, however, the single inverted U-shaped curve may not hold, as Figure 1 (top right) shows. Rather, the sensory-liking curve in its smoothed format may show a variety of different shaped curves.

EXTENDING THE ORGANISING PRINCIPLE TO CONCEPTS

The sensory segmentation approach is readily translated to the world of concept testing, if the following equivalencies are made:

- the liking assigned to a product is equivalent to either the acceptance of the full concept, or the part-worth impact of the concept element (from conjoint measurement)
- the sensory attribute assigned to the product is equivalent either to a communication attribute assigned to

Figure 1

the full concept, or to the location of the concept element on a semantic differential scale.

If these two equivalencies are made, then the same algorithm that was used for products can be used for concepts. The outcome of the equivalence is that one can plot concept interest (or element impact) against communication (or location on the semantic differential scale). The plot will result in a quadratic function, once the scattergram is smoothed. Figure 1 (bottom two panels) shows the equivalent set of patterns, this time for element impact versus location on the semantic differential scale 'male versus female'.

The concept response segmentation for conjoint measurement follows nine steps described in the algorithm for concept response segmentation below. This

algorithm is similar to the algorithm used for sensory segmentation.

- step 1: dimensionalise. For each element in the study, profile that element on a limited set of non-evaluative semantic differential scales. This is called dimensionalisation. Typically there will be four–eight attributes on which the concept elements are dimensionalised. Each element will be rated on the full set of attributes, with a nine–point scale. A small group of six–eight raters (matched in qualifications to the final sample) generates the rating of elements on the semantic profile scales
- step 2: arrange the data matrix for modelling. For each respondent, array that respondent's impacts (part worth coefficients) versus the semantic

- differential scale. Work on a respondent-by-respondent basis, a scale-by-scale basis, respectively
- step 3: create the quadratic function. On a respondent-by-respondent basis, and for each semantic scale, create a quadratic equation relating that respondent's part-worth coefficients to the semantic scale. If there are 100 people and 12 semantic differential scales, then a total of 1,200 quadratic functions will be estimated
 - step 4: optimise the quadratic function. For each quadratic function in step 3, find the value of the semantic scale (X -axis of the function) where that equation peaks. Limit the search for the optimum between the upper and lower range of the semantic scale as actually used in the dimensionalisation. Each respondent generates a vector of numbers corresponding to the optimum level on the semantic scales where that respondent's impacts (part-worth coefficients) maximise. Although each individual's impacts may not be easily compared, one can readily compare the locations on the semantic differential scales
 - step 5: create a full matrix of optimal levels for semantic scale x respondent. The data matrix comprises a rectangular matrix of semantic scales (columns) by respondents (rows). Each number in the body of the table corresponds to an optimum level for the respondent on the specific semantic differential scale
 - step 6: reduce redundancy in the matrix by factor analysis (principal components). The semantic scales may exhibit a great deal of redundancy. In order to reduce the redundancy, perform a principal components analysis on the columns. Save the factor scores of the rows (respondents). Typically two–five factors emerge from the principal components analysis
 - step 7: cluster the respondents by K-means clustering. Clustering will amalgamate individuals who have the same set of factor scores, and therefore show the same pattern of optimal semantic scale values
 - step 8: average the individuals within a cluster (segment). Average the part-worth coefficients of individuals in the same cluster (segment) in order to yield a set of part-worth impacts, one mean impact per concept element per cluster
 - step 9: compare the clusters (segments) on elements to interpret the meaning of the clusters. Assign a label to each cluster, based upon the pattern of elements most differentiating one cluster (segment) from the other(s), or based upon which elements are most positive versus most negative for the cluster.

CATEGORY IMPORTANCE AND CONCEPT RESPONSE SEGMENTS

Relative importance becomes interesting when comparing the responses of different groups. These groups see the same elements, and therefore the calculation of relative importance for each group is similar. When looking at the impact values of the total panel, often only modest-size impact numbers at best are seen, ranging between -5 and $+5$ in many cases. Quite often the small impacts values for the total panel can be shown to be the consequence of combining two or more opposing groups of consumers, with opposite impact values. One segment may love elements in a category, whereas the other segment may hate those very same elements. By comparing subgroups in the same study on relative importance as operationally

defined above, one can begin to see how the different segments have truly different value structures in what they find to be important.

The segments each generate a full set of impact values, one value for each element in each category. This similarity of data structures across key subgroups makes the computation of relative importance fairly straightforward, and allows for easy comparison across subgroups.

Two key indices show the differences between categories, and the importance of categories:

- the total sum of squares of the impact of elements within a single category. This number shows the degree to which the elements in a category drive interest in the concept. If one segment shows a total sum of squares (of impacts in a category) far greater than does the other segment, then it is concluded that the first segment ascribes greater importance to that category
- the proportion of the total sum of squares for a category versus the total sum of squares across all elements. Each segment generates a total sum of squares of the impacts of all elements, independent of category. The proportion ascribable to a category shows the percentage of total sum of squares accounted for by the particular category. The greater the proportion the more important the category as a driver for that segment.

METHOD

This paper summarises findings from 12 studies conducted using the IdeaMap® approach for conjoint analysis. Each study used many dozens, and in some cases, hundreds of concept elements. All elements in each study were used in the

concept response segmentation (see algorithm above). The studies were run over a five-year period, for different manufacturers and service organisations. Key phrasing for the concept elements are disguised to maintain confidentiality.

DEVELOPING THE CONCEPTS BY EXPERIMENTAL DESIGN AND TEST EXECUTION

The steps involved in concept design, execution and modelling are listed below. The objective of the sequence of steps is to provide data at the individual respondent level, showing the impact or utility of each concept element. By following the set of steps the researcher can ensure that the data will lend themselves to segmentation, with the full set of elements in the study comprising the raw material on which the segmentation analysis is performed.

- step 1: select the basic concept design. Each study uses variations of a single design (5 Level, Plackett Burman Screening Design).¹⁴ The experimental design is unsaturated, and allows the researcher to estimate the impact of every concept element. When multiple designs are used for the same respondent the researcher can estimate the impacts of 20N, where N is the number of designs
- step 2: create multiple concept stimuli from a set of experimental designs. In a given test session the respondent evaluates concepts created from at least two, or more generally, from four different experimental designs. Two designs comprise 40 elements embedded in 50 concepts. Four designs comprise 80 elements embedded in 100 concepts (*viz.*, 80 elements in 100 combinations). A typical respondent can go through four or five designs in a half-hour session

Table 1: Specifics for the 12 studies

Product or service	Total elements	Categories	Respondents participating	Number of segments
Credit card	349	19	388	5
Mid-sized car	300	14	125	3
Laundry product	278	9	200	4
Baby sanitary product	267	7	103	2
OTC regimen	246	18	150	2
Condiment	236	11	150	2
Frozen pastry snack	226	15	120	3
Luxury car	216	15	369	6
Carbonated soft drink	195	18	150	2
Car oil additive	180	11	100	2
Mexican condiment	168	14	105	2
Meat	160	20	120	3

- step 3: run the study with consumers. The experimental designs are interdigitated with each other in order to reduce any boredom or fatigue. The respondents are pre-recruited to participate, and paid for their time. Typical interviews last 20–40 minutes. The respondents evaluate the concepts, which are shown on a computer screen. The computer also acquires the data, and then processes the data to create the model
- step 4: create the additive model for each consumer respondent. By means of a dummy variable regression create a model relating the presence/absence of the elements tested to that respondent's ratings
- step 5: estimate the utility for untested elements on an individual basis by interpolating using the semantic space (smoothing). A smoothing algorithm estimates consumer's responses to elements not evaluated in the conjoint analysis. Each person is shown a unique set of elements, whose utilities could be estimated for that respondent. The complement of that set comprises elements whose utilities have to be estimated or imputed. The smoothing algorithm uses non-evaluative semantic differential scales to locate the concept elements in a geometrical

space. The impacts of untested elements are replaced by the average of the impacts of their eight closest neighbours in the space. The smoothing algorithm repeats on the data set until the maximum change in impact value of an untested element is less than 0.01 per cent. At this point the algorithm is considered to have reached stability¹⁵

- step 6: use each respondent's data as inputs for segmentation. The impact values from each respondent in the study are then used as input for the segmentation algorithm. Each respondent generates a full set of impact values, one per concept element, either directly from the study, or from data imputation of missing elements.

RESULTS

Table 1 shows specifics for the 12 studies. Table 1 can only summarise a small part of the studies, due to the large number of concept elements, categories and resulting segments.

EXAMPLE OF ADDITIVE MODEL FOR ELEMENTS: TOTAL PANEL

Table 2 shows a typical example of the part-worth contributions of the

Table 2: Example of best three elements for a health-oriented cooking oil — by total and concept response segments

Element	Total	Segment 1	Segment 2
Total panel			
After 30 years of testing — proven to significantly reduce cholesterol	7	1	12
Contains 90 per cent unsaturated fat	7	5	9
Lets you eat healthy and keep your cholesterol under control	6	3	9
Segment 1 (Food Oriented)			
The best oil for salads	3	8	1
The right oil for sautéing, salads and baking	4	7	2
Lets you prepare a healthy, delicious meal your whole family will enjoy	3	7	1
Segment 2 (Health Oriented)			
Has more of a blood pressure-reducing ingredient than canola and olive oils	4	−6	12
Per American Heart Association, reduces cholesterol 17 per cent when part of a healthy diet	5	−3	12
After 30 years of testing — proven to significantly reduce cholesterol	7	1	12

elements to interest. The product category is a cooking oil (part of a 13th study, not shown). These results are shown here for illustrative purposes only. What is important is the nature of the winning elements. Sometimes these elements differ across segments quite dramatically, other times they are identical. Also of note is the fact that the total panel often shows a relatively narrow range of impact values, whereas the concept response segmentation generates subgroups of respondents whose impact values are far more polarised.

CATEGORY IMPORTANCE AND THE RII — RELATIVE SUM OF SQUARES

To measure relative importance as suggested in the introduction, the following formula can be used.¹⁶ The formula is one of a class of formulas that deconstruct the total variation of the concept elements into the components, and assign that variation to different categories.

$$\text{Importance of a Category} = (\text{Category SS})/(\text{Total SS})$$

where SS = sum of squares = sum of squared coefficients. This formula using the squares of the utility values (impacts, coefficients) corrects for the fact that the impacts can be both positive and negative. It is sensitive to the number of elements in a category. The greater the number of elements the greater the sum of squares, all other factors held equal. Thus, this organising principle is appropriate when comparing two segments from a single study, where both segments generate impacts for the same elements.

Table 3A–3L show the sums of squares for the total panel and the concept-response segments, for each of the 12 studies. There are two emergent patterns that govern the importance of categories. These patterns appear when the relative importance index of the same category is compared across the different segments in the same study. One pattern is different importance values by the category. That is, some categories are important for one segment, whereas other categories are important for the other segment. An example of this is the mid-size car study (Table 3A). Segment 1 shows no major likes. Segment 2 likes safety, Segment 3 likes luxury.

Table 3A: Relative sums of squares (RII) across categories — Mid-size car

(Mid-size car)	Total	Seg1	Seg2	Seg3
Total sum squares	2,121	2,265	5,150	3,109
Safety	26%	4%	24%	9%
Interior	12%	5%	11%	10%
Treatment	12%	9%	12%	8%
Ride/Handling	10%	11%	10%	6%
Versatility/Range	8%	6%	7%	4%
Value/Luxury balance	7%	3%	7%	14%
Life stage/User	5%	5%	5%	3%
Quality	5%	6%	4%	6%
Fully equipped	5%	2%	2%	12%
Personal statement	4%	16%	5%	4%
Prestige	2%	6%	7%	15%
Environment	2%	9%	3%	1%
Exterior style	2%	12%	2%	5%
Product range	1%	6%	1%	1%

A second type of pattern emerges, wherein the segments appear to like the same categories, but show preferences for different elements within the same category. One segment may be very sensitive to elements within the category whereas another segment is far less sensitive to these same elements, even though both segments find the same categories to be most important. An example of this pattern is credit card (Table 3G). All segments are interested in fees, credit lines and

interest statements, but the relative importance of those three categories differs by segment.

Mid-size car (Table 3A)

- 1 Total panel shows the greatest interest in safety (26% of the total SS)
- 2 Segment 1 is interested primarily in elements that convey a 'personal statement' (viz., about the driver of the car).
- 3 Segment 2 is primarily interested in safety. Furthermore, the impacts for Segment 2 are far greater than the impacts for Segment 1.
- 4 Segment 3 is primarily interested in value, equipment and prestige.
- 5 As shown by the total sum of squares for the impacts, Segment 2 (safety) shows the greatest range of impacts, followed by Segment 3 (prestige), followed by Segment 1.

Luxury car (Table 3B)

- 1 Total panel shows greatest interest in safety and service.
- 2 Segment 1 shows greatest interest in safety and ongoing product development/improvement.

Table 3B: Relative sums of squares (RII) across categories — Luxury car

(Luxury car)	Total	Seg1	Seg2	Seg3	Seg4	Seg5	Seg6
Total sum squares	4,522	504	15,801	7,764	15,506	13,869	7,448
Safety	17%	14%	21%	11%	11%	19%	4%
Service	13%	4%	20%	11%	3%	7%	3%
Ride	12%	16%	16%	19%	9%	7%	8%
Performance	10%	9%	15%	10%	4%	5%	3%
Interior	8%	7%	2%	8%	11%	11%	20%
Value for money	7%	3%	3%	12%	7%	3%	20%
Family	6%	2%	1%	4%	5%	5%	12%
Environment	6%	7%	10%	1%	3%	11%	2%
Product development	6%	10%	2%	10%	10%	6%	6%
Exterior	4%	7%	1%	5%	15%	7%	8%
Up to date	4%	5%	5%	1%	4%	9%	2%
Comfort	3%	1%	0%	3%	4%	6%	9%
Consumer image	1%	4%	0%	2%	4%	1%	1%
Quality	1%	10%	2%	2%	2%	2%	1%
Successes	1%	1%	1%	1%	7%	2%	1%

Table 3C: Relative sums of squares (Rll) across categories — Car oil additive

(Car oil additive)	Total	Seg1	Seg2
Total sum squares	8,084	13,003	11,219
Engine wear/friction	44%	45%	43%
Longevity	12%	13%	10%
Clean engine	12%	10%	10%
User imagery	7%	8%	14%
Quality/value	5%	4%	3%
Visuals	5%	5%	3%
Influential support	5%	5%	5%
Smooth running	4%	3%	5%
Taglines	3%	2%	4%
Descriptor	2%	2%	1%
Heritage	1%	1%	2%

- 3 Segment 2 shows greatest interest in safety and service.
- 4 Segment 3 shows greatest interest in ride.
- 5 Segment 4 shows greatest interest in safety, and design of interior and exterior.
- 6 Segment 5 shows greatest interest in safety.
- 7 Segment 6 shows greatest interest in interior and value for money.
- 8 The sums of squares of the impacts dramatically differ across segments. Segment 2 (safety and service) and Segment 4 (safety and design) are by far the most conscious of the elements because their sums of squares are very high. Segments 3 (safety and service) and 6 (interior and value for money) are conscious of the elements, but far less.

Segment 1 is hardly conscious of the elements at all, because it has a very low total SS.

Car oil additive (Table 3C)

- 1 The total panel is interested primarily in statements about reducing engine wear and friction, as well as statements about longevity of the engine, and cleanliness of the engine.
- 2 Segment 1 is interested in the same things as the total panel.
- 3 Segment 2 is interested in the same things as the total panel, along with being interested in user imagery.
- 4 Both Segment 1 and Segment 2 show substantially total greater sum of squares compared to the full panel. The total panel shows less sensitivity to elements (based upon impact values) than do the two segments.

Laundry detergent product (Table 3D)

- 1 The total panel is interested in sensory-oriented statements about the fragrance, and in the visuals.
- 2 Segment 1 is interested in the visuals, and in clothes protection.
- 3 Segment 2 is interested in the fragrance.
- 4 Segment 3 is interested in the fragrance, the visuals and the non-fragrance experience.

Table 3D: Relative Sums of Squares (Rll) Across Categories: Laundry product

(Laundry product)	Total	Seg1	Seg2	Seg3	Seg4
Total sum of squares	1,115	2,822	8,622	4,995	2,887
Fragrance experience	28%	12%	32%	20%	8%
Visuals	23%	22%	18%	17%	14%
Non-fragrance experience	17%	12%	15%	19%	5%
Generation X	9%	5%	3%	7%	15%
Protection	8%	18%	5%	9%	26%
Personal care	7%	11%	8%	12%	9%
Control	6%	9%	9%	10%	13%
Purity/rinsing	2%	5%	6%	5%	8%
Baby/family	1%	6%	4%	1%	2%

Table 3E: Relative sums of squares (RII) across categories — Baby sanitary protection

(Baby sanitary protection)	Total	Seg1	Seg2
Total sum squares	1,495	1,910	4,839
Ingredients/construction	22%	15%	13%
Fit	16%	7%	34%
Material	17%	10%	12%
Form	16%	44%	13%
Benefits to mum	7%	6%	7%
Baby benefit	7%	11%	11%
Environmental	16%	7%	9%

- Segment 4 is interested primarily in protection.
- Again, the segments show greater sums of squares of elements than does the total panel.
- Segment 2 (fragrance) shows the greatest sensitivity to elements, followed by Segment 3 (experience, visuals), followed by both Segments 1 and 4.

Baby sanitary protection product (Table 3E)

- The total panel is interested in the physical construction of the product.
- Segment 1 is interested in the product form.
- Segment 2 is interested in the fit of the product to the baby's body.
- Segments 1 and 2 radically differ from each other in what elements drive interest.
- Segment 2 (fit to body) shows the greater sensitivity to elements.

OTC regimen for smoking cessation (Table 3F)

- The total panel is interested in efficacy and brand image.
- Segment 1 is interested in efficacy and user image.
- Segment 2 is interested in brand image and efficacy.

Table 3F: Relative sums of squares (RII) across categories — OTC regimen

(OTC regimen)	Total	Seg1	Seg2	Seg3
Total sum squares	6,048	4,636	20,295	16,093
Efficacy	19%	7%	22%	7%
Brand image	17%	17%	27%	2%
Dosage	13%	1%	12%	7%
User image	8%	19%	2%	28%
Lifestyle	7%	2%	4%	6%
Mode of action	7%	1%	9%	4%
Support system	6%	6%	4%	5%
Tagline	5%	5%	4%	8%
Program aids	4%	7%	2%	3%
Visual	3%	3%	3%	3%
Timing	3%	2%	4%	4%
Endorsement	2%	7%	1%	11%
Cost	2%	3%	1%	3%
Safety	2%	5%	2%	3%
Aesthetics	1%	6%	2%	1%
Package	1%	5%	1%	2%
Ease	1%	1%	0%	1%
Manufacturer	0%	2%	1%	2%

- Segment 3 is interested in user image.
- Segments 2 (brand image) and 3 (user image) are the most sensitive to elements. Segment 1 (brand image and user image together) is the least sensitive.

Credit card (Table 3G)

- The total panel is interested in fees, credit line and interest.
- Segment 1 is interested in fees and interest.
- Segment 2 is interested in credit.
- Segment 3 is interested in the credit line, but is not particularly involved.
- Segment 4 is interested in fees, credit line and interest.
- Segment 5 is interested in feeds and interest.
- The key differences among segments appear to be the interest in credit lines versus fees, and the sensitivity to elements. Segments 2 and 4 are most sensitive to elements, Segments 1 and 5 are moderately sensitive to elements, whereas Segment 3 is fairly indifferent to elements.

Table 3G: Relative sums of squares (RII) across categories — Credit card

(Credit card)	Total	Seg1	Seg2	Seg3	Seg4	Seg5
Total sum squares	3,437	8,573	11,446	4,014	10,696	6,236
Fees	17%	19%	11%	8%	14%	15%
Credit lines	15%	3%	16%	14%	10%	4%
Interest claims	13%	16%	9%	8%	10%	11%
Cash advance	9%	5%	9%	9%	7%	3%
Visuals	9%	13%	11%	6%	8%	10%
Service	4%	5%	4%	6%	6%	8%
Incentives — specific	4%	6%	7%	8%	4%	3%
Cash back	4%	6%	4%	7%	3%	6%
Incentives — general	3%	3%	6%	6%	5%	4%
Travel benefits	3%	3%	2%	4%	5%	6%
Rebates	3%	4%	3%	3%	3%	5%
General claims	2%	2%	2%	2%	4%	1%
Transfers	2%	2%	5%	3%	2%	5%
Availability	2%	2%	2%	2%	5%	3%
Gifts	2%	3%	2%	6%	3%	6%
Taglines	2%	2%	1%	2%	4%	3%
Combination services	2%	1%	2%	1%	3%	1%
Value	2%	1%	2%	2%	3%	3%
Security	1%	1%	0%	1%	1%	2%
User image	1%	2%	1%	1%	1%	2%

Italian condiment (Table 3H)

- 1 The total panel is interested in positioning, flavour, usage and the pictures of the product and usage conditions.
- 2 Segment 1 is interested in positioning and pricing.
- 3 Segment 2 (the more sensitive segment) is interested in flavour and usage.
- 4 For condiment there does not appear to be the same dramatic polarisation of interest by segment.

Table 3H: Relative sums of squares (RII) across categories — Italian condiment

(Italian condiment)	Total	Seg1	Seg2
Total sum squares	5,181	5,720	7,195
Positioning	17%	14%	20%
Flavour	15%	9%	19%
Usage	14%	9%	18%
Visual	13%	13%	10%
Pricing	10%	18%	6%
Health statement	7%	9%	5%
Sub-brand # 1	6%	5%	7%
Sub-brand # 2	5%	4%	7%
Product line	5%	6%	3%
Light flavour	4%	8%	2%
Brands	4%	5%	3%

Mexican condiment (Table 3I)

- 1 The total panel is interested in fresh and natural.
- 2 Segment 1 (the less sensitive to elements) is interested in fresh and natural.
- 3 Segment 2 (the more sensitive to elements) is interested in the Mexican imagery.

Table 3I: Relative sums of squares (RII) across categories — Mexican condiment

(Mexican condiment)	Total	Seg1	Seg2
Total sum squares	2,544	3,999	7,121
Fresh/natural	20%	25%	8%
Image	14%	12%	16%
Claims	9%	8%	7%
Texture	9%	6%	6%
Freshness benefits	8%	8%	4%
Flavour/taste	7%	5%	8%
Heritage	6%	4%	3%
Ingredient	6%	4%	11%
Texture benefits	4%	4%	3%
Usage	4%	14%	13%
Flavour strengths	4%	1%	7%
Product types	3%	3%	4%
Visuals	3%	4%	7%
Brand names	2%	3%	4%

Table 3J: Relative sums of squares (RII) across categories — Frozen pastry snack

(Frozen pastry snack)	Total	Seg1	Seg2	Seg3
Total sum square	5,094	6,700	10,024	9,510
Taste description	16%	17%	7%	11%
Product image	12%	12%	4%	7%
Ingredients	10%	11%	3%	5%
Nutritional claims	10%	11%	7%	5%
Flavour	8%	8%	9%	9%
Texture	8%	9%	4%	4%
Convenience	7%	4%	15%	4%
Product quality	6%	6%	4%	3%
Product heritage	5%	6%	13%	24%
Bread mentions	5%	5%	3%	5%
User type	4%	4%	7%	6%
Satisfying	3%	2%	7%	3%
Brand names	2%	4%	11%	12%
Visuals	2%	1%	4%	2%
Use occasions	1%	1%	2%	1%

Frozen pastry snack (Table 3J)

- 1 The total panel is interested in taste description and product image.
- 2 Segment 1 is interested in taste description.
- 3 Segment 2 is interested in convenience, heritage and brand names. This is the most sensitive segment to elements.
- 4 Segment 3 is interested in product heritage, and is almost as sensitive as Segment 2.

Nutritionally-oriented carbonated beverage (Table 3K)

- 1 The total panel is interested in visual.
- 2 Segment 1 and Segment 2 are interested in ingredients, but in different ways, and to different degrees. Segment 2 is more sensitive to elements than is Segment 1.

Smoked meat — Deli meat (Table 3L)

- 1 The total panel is interested in smoked flavour, health benefits and flavour/taste.
- 2 Segment 1 is interested in quality and ingredients.

Table 3K: Relative sums of squares (RII) across categories — Nutritional beverage

(Nutritional beverage)	Total	Seg1	Seg2
Total sum squares	1,172	2,340	3,850
Visual	18%	12%	18%
Ingredients	12%	22%	32%
Taste descriptors	11%	7%	6%
Choice	8%	9%	7%
Product benefits	8%	10%	9%
User image	7%	6%	5%
Health claims	7%	7%	6%
Heritage	5%	4%	2%
Texture/mouthfeel	4%	3%	2%
Flavour descriptor	4%	2%	3%
Carbonation	4%	2%	2%
Taste image	3%	6%	2%
Comparative taste	2%	1%	2%
Colour	2%	1%	1%
Physical benefits	1%	3%	1%
Product descriptor	1%	2%	1%
Emotional benefits	1%	3%	2%
Usage	0%	0%	0%

Table 3L: Relative sums of squares (RII) across categories — Deli meat

(Deli meat)	Total	Seg1	Seg2	Seg3
Total sum squares	3,279	3,862	10,293	8,166
Smoked flavour	13%	7%	16%	5%
Health benefits	11%	6%	5%	15%
Flavor/taste	10%	6%	10%	9%
Texture	7%	3%	6%	7%
Ingredients	7%	13%	7%	15%
Quality	7%	14%	7%	6%
Process: Smoking	7%	4%	6%	6%
Heritage/experience	6%	4%	5%	7%
Convenience	6%	4%	5%	3%
Product specific	5%	7%	5%	4%
Claims	4%	5%	5%	4%
Value	3%	3%	4%	2%
Versatility	3%	3%	3%	1%
Processing: General	2%	4%	2%	1%
Casing	2%	2%	3%	3%
Emotional benefits	2%	5%	3%	1%
Visuals	2%	4%	1%	4%
Comparison claims	1%	5%	3%	3%
Brands	1%	2%	1%	2%
Process: Curing	1%	1%	3%	2%

- 3 Segment 2 is interested in smoked flavour.
- 4 Segment 3 is interested in health benefits.
- 5 Segments 2 and 3 are more sensitive to elements than is Segment 1.

Table 4: Key categories with high sum of squares — By total panel and first two-three segments (where the segments agree the category itself is a primary driver; where the segments disagree the category may be a secondary, idiosyncratic driver)

	Total panel	Segment 1	Segment 2	Segment 3
Mid-size car	Safety	Personal statement Exterior style Ride/handling	Safety	Prestige Value/luxury Balance Fully equipped
Luxury car	Safety Service	Safety Product Development	Safety Service	Ride
Car oil additive	Engine wear Longevity Clean engine	Engine wear Longevity Clean engine	Engine wear User imagery Longevity Clean engine	
Laundry product	Fragrance Visuals	Visuals Protection	Fragrance	Fragrance Non-fragrance Experience Visuals
Baby sanitary	Construction	Form	Fit	
OTC smoking cessation	Efficacy Brand image	User image Brand image	Efficacy Brand image	User Image
Credit card	Fees Credit lines Interest Claims	Fees Interest claims	Credit lines	Fees Credit lines Interest claims
Italian condiment	Positioning Flavour Usage Visual	Pricing Positioning	Positioning Flavour Usage	
Mexican condiment	Fresh/natural	Fresh natural	Image Usage	
Frozen pastry snack	Taste descriptor Product image	Taste descriptor	Convenience Product heritage Brand names	Product heritage
Nutritional beverage	Visual	Ingredients	Ingredients	
Smoked deli meat	Smoked flavour Health benefit Flavour/taste	Ingredients Quality	Smoked flavour	Health benefits Ingredients

CATEGORIES: PRIMARY VERSUS SECONDARY, IDIOSYNCRATIC DRIVERS

Looking at the general patterns across the 12 studies, two interesting sets of patterns (see Table 4) can be seen. These reveal themselves in the Pattern A, which shows one or a few categories being most important (*viz.*, generating the greatest sum of squares) across total panel and all segments. There are some modest variations across segments. This means

that the segments differ in the relative importance of elements, but the category is equally important to the different segments. Products or services showing Pattern A may be those where consumers' opinions of what is important are deeply entrenched. The specific elements within the category may differ across consumers, but the category itself is important. An example of Pattern A is exhibited by credit cards, where the key interests are fees, interest charges and credit lines. It

may be very difficult to come up with new ideas because the thinking here is rigid. From a managerial perspective, knowledge of this pattern suggest that the strategy should be to find better executions of current ideas, in terms of better communications or lower costs to do business. It is unlikely that new breakthroughs will occur for this type of category, unless there is a significant technological or cost breakthrough.

Pattern B shows big segment to segment differences, suggesting polarisation. To one segment it may be an ingredient, to another segment it may be heritage. Products or services showing Pattern B may be more open to new ideas, because consumers themselves pay attention to radically different aspects of the products. Examples of Pattern B come from the different foods (Mexican condiment, Italian condiment, frozen pastry snack and deli meat). Products or services showing Pattern B may be those where differentiated appeal to one segment may prove very powerful. It may not be necessary to create a dramatic or technical breakthrough. Rather, it may be just as productive to identify the features and launch more effective communications to highlight those features that appeal to one of the segments.

Do these two patterns represent different types of motivation patterns? That is, does Pattern A suggest that the category is an obvious primary motivator, and cannot be changed by segmentation? Does Pattern B suggest that the category is a secondary motivator, effective for some individuals but not for others? This question needs more investigation.

DISCUSSION

Categories are not created equal

The data in Tables 3A–3L and the summary in Table 4 suggest that there

are some categories which continue to be critical in driving interest, and other categories which continue to be irrelevant. Emotional benefits, often touted as critical to acceptance, are generally not important. Nor, in most cases, are visuals as important as one might think (even though some pictures may be important in and of themselves). What tend to be important are elements that convey specific information of relevance to the consumer. This may be mode of action for a drug, safety features (but not necessary claims) for a car, ultimate benefits for a car oil additive, etc.

The same category may appear in different studies, and in one study the category will be important whereas in the other study the category will be deemed unimportant. There are two reasons for the study-to-study differences in the importance of the category:

- sheer number of elements: the number of elements in the category may vary across studies. With everything held equal, those categories having the greater number of elements stand a greater chance of having more importance simply because they have more elements to contribute to the total sum of squares
- specific execution varies across categories: the same category may have different types of elements, depending upon the product or service to which it refers. Thus nutritional/health benefits may be quite different for a meat product than for a nutritional beverage product.

Absolute versus differential importance of categories

The many possible elements in a category, left up to the discretion of the

researcher, make it impossible truly to measure absolute category importance for two reasons:

- arbitrary number of elements: a category can have an arbitrary number of elements, depending upon the predilection of the researcher, the nature of the category itself (brand or positioning or feature), and the number of available elements that could fit into the study. The researcher might wish to investigate three, five, ten or 20 brands. There is no reason why the research design should be limited to the same number of elements in each category. That would pose a great limitation on the overall usefulness of conjoint measurement. Assume, for instance, that there are only four brands. Does this mean that the four brands dictate using only four statements about convenience, when in reality there may be 20, 30 or more ways of talking about convenience
- elements are not all created equal: a category can have a high sum of squares even with a few elements because the particular elements chosen for that study, for that category happen to be highly effective. Yet, a different set of elements appropriate for that category may have a low sum of squares, because those particular elements expressing the same idea are ineffective. Thus, even equalising the number of elements in a category, or in this case estimating the average sum of squares of an element would be incorrect, because the importance of a category would then still depend upon the particular choice of elements used.

As can be seen from the different studies discussed here, it is possible to work with hundreds of elements in a conjoint

analysis study, and to create an index for the relative importance of categories.

The categories can be compared for importance, but the relative importance within a single subgroup is not critical, due to the arbitrary design of the study. The approach presented here is best used to quantify the relative importance of concept-element categories for two or more segments that have been exposed to the same elements. This is probably the best that one can do, given the fact that the choice of elements is arbitrary in any study, as is the choice of number of categories, and the number of elements within each category, respectively.

Two types of segments — interested versus non interested

A recurring pattern in these data is the existence of two types of segment, sensitive and insensitive, respectively. Sensitive segments comprise individuals who generate high sums of squares for their impacts. These high sums of squares appear at the top of each of the tables (3A-3L). Two segments, one sensitive and the other insensitive, may show similar patterns of what is important to them, based upon the proportion of variability attributable to each category. Yet, one segment will generate very high sums of squares, indicating that the impacts are numerically high (either positive or negative or both). The other segment(s) will show relatively low sums of squares, indicating that the impacts are numerically low, hovering around 0. In most cases the total sum of squares for each of the segments exceeds the total sum of squares for the entire panel. This result suggests that even in the case of the 'less sensitive' segment, however, there is more sensitivity to the elements than would have been supposed by looking at the entire panel.

Practical applications in understanding the consumer decision-making process

One of the goals of conjoint measurement is to understand the decision-making process in a quantitative fashion, and by so doing create more effective products or product/positioning concepts. To the extent that the relative sum of squares represents the relative importance, the marketer can identify which of the particular categories should be used to construct the concepts. More importantly, however, the data for the segments show that the decision-making criteria are different. Categories and elements appropriate for one segment may be less relevant or irrelevant for another. The general objective of this study has been the linking of salient product features to consumer preferences. The procedure presented contributes to the measurement of sensitivity of consumers' perceptions and preferences as affected by changes in product features.

Some segments in this set of studies appear to focus principally on one category of elements, and are relatively indifferent to the remaining categories. A good example of this is Segment 2 for smoked deli meat, which appears to be interested primarily in statements about 'smoked flavour'. This type of segment may require specific messages. In contrast, Segment 3 meat is interested in health benefits and ingredients. This type of segment may be harder to reach through conventional product-based messages, because they respond to a different, and perhaps unusual, message for the category.

Management implications

The discovery of two types of patterns of category importance presented in this paper is particularly helpful in situations where the identified categories and elements are deemed to be particularly

relevant to only one of the segments. It is this segment, and not the others, that may be the most easily convinced, and therefore that would constitute the prime prospects. The information can be employed by marketing managers in order to define the core benefits proposition of the product to the more receptive target. Core benefits can be integrated during the product launch phase into the advertising and promotional campaigns aiding differentiation from competing products. Specifically, the campaigns can articulate selling points that underscore the unique features of the product, its relative quality, or its ability to reduce the customer's perceived costs. Furthermore, since the research identifies the general categories of elements that are important, the data can be used later on to suggest re-launches or continuity programmes with the prime prospects. In sum, when appropriately applied, the model described here can result in an optimal integration of features into a customised design desired by the defined segment.

The second pattern of category importance, wherein categories and elements are relevant to more than an individual segment (eg credit card), provide another marketing opportunity, albeit of a different type. The similarity of importance of categories means that an opportunity exists to create a platform for product design. In this situation the focus is not on the optimisation of the single product but rather the emphasis is on the integration of some common features into a design platform of a product line. Some possible gains might include spreading fixed costs while jointly planning products enhancing overall sales, contribution and margin.

One key remaining issue needs to be addressed. This is the 'assignment problem'. Further research is necessary to create an approach that identifies new

individuals as belonging to a segment. This will help correlate segment membership with other aspects of the individual. With a method for assigning many people to segments, the marketer and researcher can begin to understand potential differences in decision processes between those individuals who are influenced primarily by one category of elements, and those who can be influenced by any number of different types of categories of elements. Relevant questions include the differences in the way these types of segments process information about products, the degree to which their purchase is brand loyal, and the degree to which their preferences are stable over time. More global questions, of a 'profiling nature', in which the data and patterns hint at deeper aspects of the consumer's decision making remain to be answered. For example, if a person exhibits one pattern for a product (*viz.*, a few categories only are important, the rest are irrelevant), then does the person exhibit the same pattern for other products as well? That is, do these patterns of importance hint at a general type of information processing, or are they limited to specific products, with no general patterns transcending the products? Such questions await further research, with conjoint measurement able to provide some of these answers in a convincing, quantitative manner.

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