The applications of conjoint analysis and their possible uses in Sensometrics

Howard R. Moskowitz
Matthias Silcher
Moskowitz Jacobs Inc.
1025 Westchester Ave.
White Plains, NY 10604 USA
Email: Mjihrm@sprynet.com

Abstract

This paper presents a history of conjoint analysis and the basics of the approach, focusing on the possible areas of intersection of conjoint analysis with Sensometrics research. The paper presents ten substantive applications, ranging from an analysis of element performance, on to the scalability of conjoint analysis in order to accommodate many hundreds of elements, and into concept-response segmentation. The paper then deals in depth with Internet-based interviews, the evolution of conjoint analysis from text + pictures to purely visual approaches, and the introduction of response time as another dependent variable along side direct ratings. The paper finishes with two new areas. One area is the assessment of pair-wise interactions and their magnitude, a topic that is easy to do in response surface analysis but difficult to do in studies where the variables are 'absent/present'. The second area comprises the integrated databases using linked conjoint analyses, with extensive classification questionnaires. This approach, stimulated by the genomics revolution, aims to create a multi-faceted snapshot of a large scale category, such as beverages, across products and over time.

Introduction – Where conjoint analysis came from, and why Sensometrics should find it useful

Conjoint measurement refers to a set of procedures which investigate responses to mixtures of independent stimuli in an attempt to understand the contributions of these stimuli to the mixture. An academic history of conjoint measurement would trace to the seminal paper by Luce and Tukey (1964) in the first issue of Journal of Mathematical Psychology and the work of Kruskal (1965). Luce and Tukey worked in a period of profound change in mathematical psychology, where emphasis on axiomatic measurement theory drove interest in understanding the rules of 'subjective measurement'. The original paper by Luce and Tukey is replete with mathematical derivations, more on the order of mathematical logic, than of the form familiar to most practitioners. Nonetheless, the original paper deserves mention for it led to a wellspring of approaches which have enriched consumer research, and are now enriching sensometrics. The varied developments and variants of 'conjoint measurement' are summarized by Green und Srinivasan (1978, page. 104).

A short history of conjoint measurement would not be properly presented without mention of the functional measurement theories of Norman Anderson whose research is less oriented towards the formalities of measurement, but more in keeping with the world view of sensometricians (Anderson, 1970). Anderson's point of view is that one can learn a lot from mixtures, simply by applying analysis of variance methods, or more generally regression methods. Anderson is worth reading, if only because his work on mixtures is approachable by the non-mathematician, and because many of his articles deal with the decomposition of complex stimuli and responses into their components. Indeed, it is as much due to Anderson as to Luce and Tukey that today's conjoint owes its very great popularity in applied research circles. It is the manifold application of conjoint measurement, first to psychological issues, then to marketing issues, and now to Sensometrics issues that must be recognized as the important story of conjoint analysis, rather than the elegant mathematics.

The first major applications of conjoint analysis really begin with the realization by Paul Green and Yoram (Jerry) Wind at Wharton that a decompositional method would be useful in the world of consumer research (Green & Rao, 1971; Green & Srinivasan, 1980 and 1990; Green & Wind, 1975). In the case of conjoint measurement, the product is taken as a composite of characteristics like package, taste or price. Concepts comprise combinations of benefits. Rather than having the respondent rate the individual importance of each component, Green and Wind quickly recognized that they could identify the part-worth utility or contributory value of the component without having the respondent labor through an intellectualized process. By identifying the utility values through decomposition they also realized it would be possible to create newer and better concepts leading to better developed products or advertising campaigns.

Needless to say, this early realization some thirty years ago has led to an enormous set of applications in the consumer research industry. A search done July 16, 2004 on Google® for conjoint measurement showed 5,230 hits. A search for the term conjoint analysis, the same method with a slightly different term, shows 24,500 hits. Many of these hits come from the academic literature, where conjoint analysis is very popular as a research technique because it can be expanded to incorporate decision rules as well. Others come from the offerings of market research companies, which provide design and analysis of these studies for commercial projects. Over the past decades conjoint measurement has been a popular method for measuring customers´ preferences structure. Wittink and Catin (1989) estimated that about 400 commercial applications were carried out per year during the early 1980s. In the 1990s this number probably exceeded 1000 (Sattler & Börner, 2000). The identification of the impact of the price of the product resulted in a multitude of conjoint measurement based studies (Dodds, Monroe & D. Grewal, 1991). Still other pages come from novel applications by individuals outside of the conventional consumer research world, such as those involved in public policy (Dufhues, Heidhues & Buchennrieder, 2004). It would be fair to say that conjoint analysis has been used in areas as diverse as design of product concepts of cereals to assessment of consumer reactions to public policy statements i.e., from food to public policy (e.g., Holmes, Zinkhan, Alger& Mercer, 1996).

The power of conjoint analysis may find application in Sensometrics, just as it has found application in various areas of consumer research. Traditionally, researchers in Sensometrics have focused on quantitative analysis of subjective reactions. There is every reason to believe that conjoint analysis can find a new and productive home in the Sensometrics world as well. By focusing on responses to concept stimuli, rather than actual concepts, the researcher may well open up entirely new areas of understanding subjective processes. The remainder of this paper will deal with both how conjoint analyses are done, and how the approaches can be applied in the spirit of Sensometrics research.

The basics of conjoint analysis

The original approach to conjoint analysis comprised a systematic set of trade-offs between pairs of items, which trade-offs would then be analyzed to show the part-worth utilities of the separate items. This early approach, called *'trade-off' analysis* (Johnson, 1974; Green & Krieger, 1996) assumed that the respondent would not have to have to act as a measuring instrument, *per se*, but rather merely needed to select between two alternatives. Trade-off analysis is a relatively time-consuming, rather cumbersome procedure in which the respondents must evaluate a number of pairs of test stimuli. In some respects the trade-off paradigm resembles the method of indirect measurement proposed by the psychometrician, Leon Louis Thurstone (1927), who believed in measurement by processing variability to develop a psychological scale. That is, rather than allowing the respondent to assign numbers to test stimuli to reflect magnitude (e.g., degree of liking) the respondent was instructed to choose the item from the pair that had more of the attribute being considered (i.e., which was liked more). An analysis of the variability of choice across or even within respondents would generate the scale through a defined set of transformations.

A simpler world-view of measurement, including conjoint analysis, emerges when the respondent is instructed to rate test stimuli on a scale. The respondent acts as a direct measuring instrument with the ratings assumed to represent the perceived magnitude of the stimulus on the particular attribute being rated. With this world-view in place, the respondent can as easily respond to systematically varied combinations of stimuli as to simple stimuli, either comprising one element, or comprising a number of elements but without the experimental design behind the combinations.

The proper design of combinations in conjoint analysis is a critical factor for the types of conclusions one can draw. Often researchers create categories or buckets of elements, with the property that the elements or individual components within the category are related to each other (e.g., brand names, flavor descriptions, etc.) Many researchers prefer to have the respondent rate concepts comprising one element from each category. This is known as the full profile approach to conjoint analysis. The analysis of data is very weak when the researcher uses this strategy, because the elements themselves within a category do not appear independently of each other. There is multi-collinearity, so that the analysis of the data can only show differences between pairs of elements in terms of their contribution to the rating. A more effective, less biased approach uses a main effects design in which a concept has either one or no elements from a category. The analysis of these data is then done using dummy variable methods, with ordinary least squares. The contributions of the elements then can be assessed in terms of their absolute values, not simply in terms of their relative values.

When the respondent evaluates these systematically created mixtures the elements of the concept constitute the independent variables, and the attribute rating becomes the dependent variable. The concept elements must satisfy two criteria. First they have to be independent of each other or else the criteria to create an additive model by regression would be violated (Hair et. al., 1995). Second, these elements have to be meaningful within a concept, and ideally realizable in an actual product. At the very practical level the concept must be readable. The number of elements in a concept should not exceed the amount of 4-5 elements per concept; otherwise the concept becomes ponderous, difficult to read, and judged only superficially. With long concepts the respondent is no longer able to see this concept as a whole and starts to use simplifying criteria to make judgments; e.g. to concentrate just on the first and last element. To the extent that such strategies do not mimic real market place activity such task-simplification behavior will negatively affect the external validity of the conjoint results (Vriens, 1995). The analysis of data by linear regression shows the part-worth contribution of each element. The rating scale might be 'interest' (e.g., how interested are you in this product?), or fit to an end use (e.g., how appropriate is this product for breakfast?)

The world of Sensometrics in the 1960's – 1990's

Sensometrics, a field that appears to have matured greatly in the past 20 years has itself a venerable history, albeit one far afield from experimental design and conjoint measurement. This history is worth summarizing because it gives us a starting point from which we can understand how practitioners in Sensometrics have responded to, and are likely to respond to conjoint analysis.

Sensometrics, the quantitative methods applied to sensory analysis, began with inferential statistics in that direction during the 1930's, and continued into the 1940's and 1950's. Strongly influenced on the one hand by trends in experimental psychology and on the other by agricultural statistics, Sensometrics began its life as simple tests of significance and treatment effects. The notion of experimental design was not so much to create a model by which to understand the quantitative contribution of treatments as to identify which specific treatments made a difference, and in what direction, i.e., increase the effect or decrease the effect. The notion of using the human judge as an instrument on par with other instruments simply was not in the realm of consideration. One can read about this early development in Sensometrics, not so much in a historical review paper, but rather in the hundreds of papers that deal with issues that we would call Sensometrics, and which in turn refer to this early historical work in their citation of the literature. (Lawless & Klein, 1991; Lawless, & Heymann, 1998; O'Mahony, 1986; Civille & Lyon, 1996). The reader will be struck by the plethora of inferential statistics.

As Sensometrics matured many of its practitioners came from other fields, and were conversant with methods such as mapping, i.e., multidimensional scaling. With the influx of these new practitioners came a willingness to assess the usefulness of methods beyond conventional inferential statistics. Modeling became popular, but mapping became even more popular owing to its apparent simplicity and directness. Mapping test stimuli using computer packages leads naturally to questions about the meaning of the the map's coordinates, and the next steps one might take after identifying where products fit on the map. Those questions remain with us today.

Our topic, conjoint analysis, had a harder time gaining acceptance in the Sensometrics community, perhaps because its initial applications were in decision making and concept development, two areas that Sensometrics did not deal with in great detail.. The mathematics underlying conjoint analysis (i.e., dummy variable modeling) was certainly acceptable to sensometricians, but it would take until the middle 1990's for the field to embrace concept research as a new opportunity (Cattin & Wittink, 1982; Wittink & Cattin, 1989).

There are at least three reasons for this late adoption of conjoint analysis in Sensometrics (as well as conjoint analysis in general in other areas of consumer research):

1. Delay due to satisfaction with current procedures: Why change into tomorrow when there is no reason to do so, no discomfort with today. Part of the delay can be traced to the corporate satisfaction with installed profiling processes, whose infrastructure consumes a great deal of time and resources. Profiling emphasizes process, accurate data from well trained respondents, and the reporting of subjective data in the same fashion as one might report the results of instrumental measurements. With attention and funding taken up by profiling neither time nor funds were available to consider other methods. This corporate satisfaction would delay conjoint analysis and concept research for at least twenty years, but would inevitably give way to an emerging interest in concept research and conjoint analysis by the late 1990's.

2. Delay due to turf wars: Another reason for the delay in embracing conjoint analysis research is the often-bloody turf wars which erupted between market research departments and sensory research departments. Market research was loath to give up control of concept testing (and design by conjoint analysis), feeling that the sensory researchers had better stay in their narrowly circumscribed world of physical product studies, leaving the concept research to the market research department. Whether this position has merit, whether the sensory researcher and sensometrician can really deal with concepts is a subject entirely unto itself. All that is important here is that turf battles significantly retarded even the consideration of concept research, and in turn of conjoint measurement.

3. Delay due to budgets: Sensometrics emerged primarily from the sensory evaluation departments of companies or from food science departments in universities. Both groups are chronically under-funded by management. The departments do not emerge into the corporate limelight. Conjoint measurement studies, at least the studies run from the 1970's to the late 1990's, tended to be higher scale, more expensive pieces of research, out of the reach of the sensory evaluation professional in a company. A number of market research companies offered conjoint measurement studies, but the costs of even the smallest of these studies tended to be greater than the typical R&D-based Sensometrics professional could afford. The high budget made these studies discretionary, rather than part of the researcher's daily routine, with the inevitable consequence that these professionals never got around to exploring the field. The 1980's and 1990's saw the emergence of computerized conjoint analysis promoted by for-profit companies (e.g., Bretton-Clark Inc., SAS Inc., SPSS, Inc., Sawtooth, Inc). These programs were not easy to use, but served to introduce conjoint analysis to many practitioners and academics.

<u>Sensometrics in the 1990's and the recognition of value in conjoint analysis</u>

Sensometrics professionals began to investigate conjoint measurement in the very late 1990's. There had been several earlier forays into conjoint measurement, both in terms of working with systematically varied texts and with graphics designs. During the very late 1990's the development of inexpensive software, first implemented on the PC and later on the Internet, evolved conjoint measurement from an esoteric and expensive procedure to one that could be easily afforded. As Sensometrics professionals became increasingly comfortable with PC-based statistical packages, where computation was done at effectively zero cost and minimal effort, researchers began to revisit the notion of experimentally designed concepts.

Sensometrics, like every other field of science, tries to develop its technologies and their applications. As old areas of sensory research such as panel management, profiling, discrimination testing and inferential statistics became saturated the more adventurous researchers turned their sights to other problems. Cognitive processes in sensory analysis, long hidden in the background and overshadowed by the puritanical profiling methods and emphasis on rigid reliability, emerged. The turf wars receded into the background, as conjoint methods with their emphasis on cognitive processes rather than expert training became known and tantalizing to the a number of adventurous sensometricians, looking for new worlds to explore, conquer, and cultivate..

Today (2005) Sensometrics is finally beginning to embrace conjoint analysis as a new domain of research opportunities, perceived to be important not only methodologically because of its quantitative features, but also important because it is a practical tool to answer cognitive problems in product research. Good business decisions are based on realistic information, easily provided by conjoint analysis. Some of the forays into conjoint analysis comprise small, diffident steps by individuals new to this way of thinking. Nonetheless, the desire to expand the field, at witnessed by a session on conjoint analysis at Sensometrics 2004 suggest that this statistical-based approach and the area of cognitive processes provides a fertile ground for the next research generation.

The substantive topics researched by conjoint analysis are limited only by one's imagination and scope of interest. Sensometrics professionals might find a gentle introduction to conjoint analysis through a study of the persuasive power of food or fragrance concepts. For example, one might test systematically varied concepts about fragrances, with these concepts comprising statements about the fragrance smell, as well as brand, and emotion. The output of this type of conjoint analysis reveals what are the important, driving elements in fragrance concepts (Moskowitz, 2003a). At the more ‘rough and tumble’ end, conjoint analysis has been used to understand the persuasive power of different communications in food advertising, by deconstructing or ‘ripping apart’ the existing competitive frame of communications into concept elements and recombining these elements by conjoint analysis (e.g., for fast food or QSR’s; Moskowitz, Itty, Manchaiah & Ma, 2002).

Conjoint analysis in action – ten applications

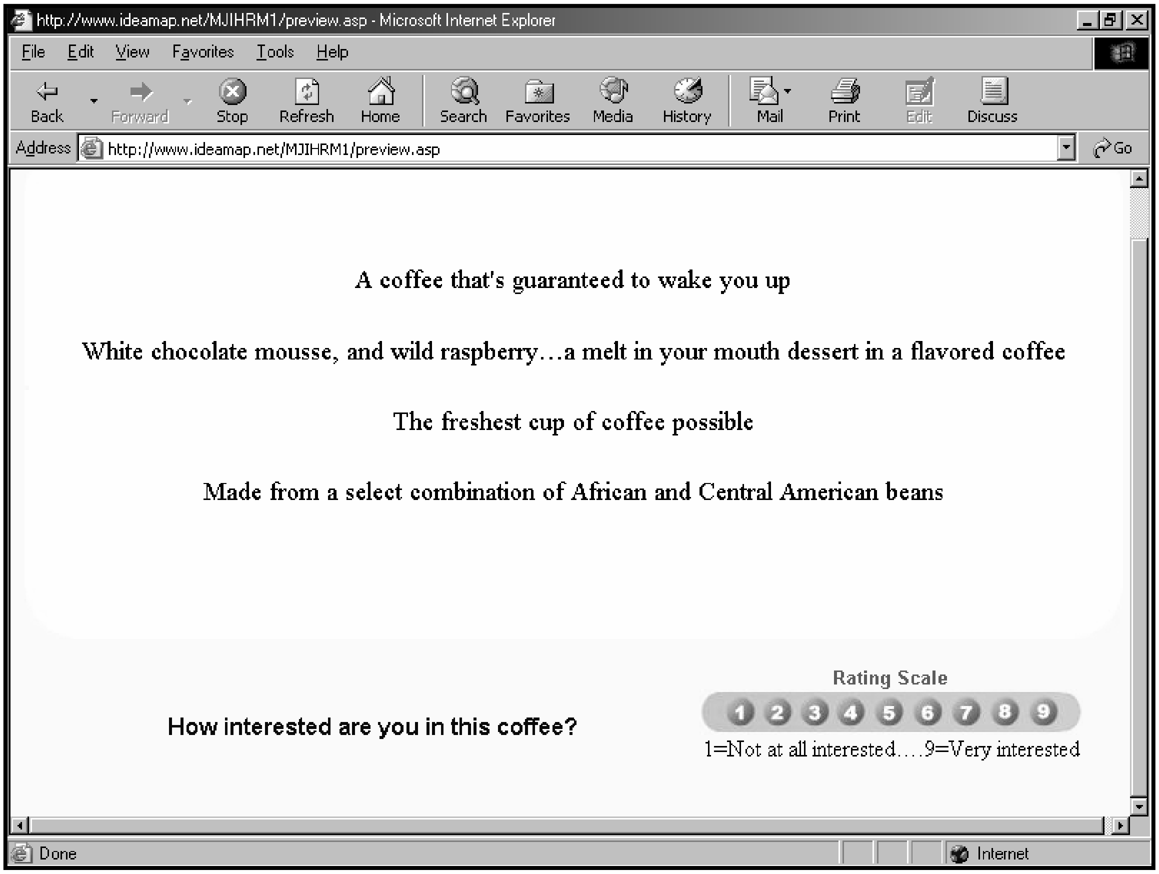
Whether the applications of conjoint be basic research into cognitive drivers of basic product acceptance or the applied work of competitive intelligence, we are today witnessing the growing acceptance of this new field. It is certainly worth the researcher’s attention, as will be suggested in the next sections on applications.

The applications of conjoint analysis vary widely. We will look at ten applications relevant to Sensometrics. These applications range from a simple analysis of components in a concept that drive acceptance, through issues such as graphics features as concept elements (instead of text features), and onto the notions of synergy in concepts, and ending up with conjoint analysis providing a large-scale data set of the consumer ‘mind’, inspired by the broad-scale tests used in genomics research to understand how genes may express themselves.

Application 1: Identifying which individual elements in concepts drive acceptance versus rejection

The original goal of conjoint analysis was to identify the performance of concept elements from the measurement of reactions to entire concepts. For example, consider the concept in Figure 1. This concept discusses the features of a coffee. The concept comprises elements that might be called product-related, as well as elements that are emotional, and even elements that are visual. Which of the elements in this test concept really drive acceptability? Do all the elements perform equally well, or are some elements more important than others?

Figure 1: Example of a concept for coffee



The traditional methods to answer this question require that the respondent either circle the key phrases that are perceived to be important, or describe in his own terms (open ended questions) the features that are important. The respondent has to 'operate' on the stimulus in some way to directly identify the key drivers. Another way might be to rate the individual elements on a scale of importance. These different methods will eventually identify the important elements, but will not generate an easy to by which the researcher can re-construct a better performing concept. Nor will these methods identify how the elements of the concept perform in combination, or even whether there are synergistic or suppressive effects going on.

In contrast, the researcher using conjoint analysis follows these seven direct steps to measure quantitative importance. The steps go beyond simply looking at a single concept, on to creating new concepts, testing them, and uncovering patterns of responses to the elements. It is from those patterns emerging from reactions to systematically varied concepts that the researcher learns what is important, whether there are organizing principles regarding consumer perceptions, and how to create better combinations:

Step 1: Identify the different and relevant variables or categories for coffee (e.g., flavor, country of origin, etc.)
Step 2: Create a set of alternative elements for each category (e.g., different flavors, different countries of origin).

Step 3: Create test combinations, or test concepts, comprising different elements, one from each category. Some of these test combinations might be missing a category. These test combinations are created by experimental design, so that the individual elements appear in the concepts, albeit as 'free agents', that are statistically independent of each other.
Step 4: Present these test combinations to a respondent who rates the combinations on a scale.
Step 5: Code the combinations as a set of 1's and 0's (1=if the element is present; 0 if the element is absent. Each test concept comprises a single row. Each column is an element. The last column is the rating. The rating may be either the actual numerical scale assigned by the respondent, or re-code (e.g., a binary value) to denote that the respondent accepts or rejects the concept.
Step 6: Use regression analysis to estimate the part-worth contribution of the different elements. The regression analysis may incorporate interactions as well, allowing the researcher to identify those pairs of elements that synergize with each other or suppress each other, beyond their individual linear contributions to the concept.
Step 7: Now that the researcher knows the contribution of each element, the researcher can either stop, or re-create the concept in an improved form, by removing poor performing elements from the concept and replacing these poorer performers with better performers.

Often researchers feel that the effort involved in conjoint analysis is either too difficult, or that it will not result in superior insights. All too often the reason, unstated, underlying the negative feel towards conjoint, is that conjoint analysis requires effort to think up test stimuli, to work with experimentally designed combinations, and then to do statistical analyses. This drive to experimentation is far different than the passive work required in analyzing one's response to a concept by focus groups, by identifying drivers, or by rating single elements. In some respects experimental design and conjoint analysis for concepts has the same 'emotional baggage' as experimental design and response surface methods have for product. Both require effort, creativity, and structured analysis, rather than well disciplined reporting limited to that which exists alone in the stimulus itself.

The foregoing exercise is, of course, involved for both researcher and respondent than the simplistic approach of having the respondent identify the important elements directly. However, the quantitative results allow for many applications, making this exercise worthwhile. Furthermore, respondents are simply asked to give their intuitive reaction, rather than having to dissect the concepts at a more intellectualized level. This simple 'stimulus-response' structure is easier for the researcher because the analysis is straightforward, although the evaluation of many concepts may be somewhat more tedious for respondent who has to evaluate many more stimuli.

This disciplined approach generates these three types of learning about the respondent:

1. Importance is now measured ‘behaviorally’, rather than ‘attitudinally’. Instead of requiring the respondent to identify which elements are important in the concept, importance is *deduced by the degree to which the presence of the element drives the concept rating*. The utility value (i.e., coefficient from the regression equation emerging from the analysis) shows the contribution of the element to the magnitude of rating (e.g., degree of interest) when the rating is the dependent variable itself, or to the probability that the concept will be rated as falling into the class of ‘definitely/probably interesting’ if the rating is transformed into this binary variable ‘not interested versus interested’ prior to regression
2. Importance is estimated by the performance of the same element across many backgrounds, thus providing a more robust measure.. A key benefit of experiment design is the ability to identify how different elements perform when combined with a variety of backgrounds. All of the combinations differ, so that elements with high coefficients or utility values tend to perform well across different backgrounds. The performance of these elements is achieved by virtue of a ‘torture test’, because only the good elements in general will perform well across the backgrounds.
3. Importance is operationally defined as contribution to a specified rating scale, allowing experimental investigation of the respondent’s mindset. If the rating scale is changed, shifting *attention* say from evaluating liking to evaluating ‘fit to a specific end use’ (e.g., appropriate in a certain venue; appropriate for a specific day-part), then the meaning of importance is immediately and unambiguously shifted as well. In this way the researcher need not to specify the definition of ‘importance’. That definition is automatically specified by the rating scale. Consequently, a concept element can achieve a variety of different importance values depending upon the different criteria against which the concept is rated.

A sense of the nature of these results can be seen from the utilities achieved by different elements in a coffee concept study. The concepts comprised different elements which were systematically varied according to the experimental design. Different, non-overlapping groups of respondents rated the various experimentally designed coffee concepts on a set of attributes. In each specific study the respondent rated concepts on a single specific response scale such as interest (column B), appropriate for a given venue (e.g., Starbucks, column C), appropriate for a situation (e.g., with family, column D), or appropriate for a specific day-part (e.g., for breakfast, lunch or early dinner, columns E-G, respectively). Table 1 shows the utilities for four elements. These utilities were developed by dummy variable regression analysis, with the independent variables (concept elements) taking on the value 0 (absence) or 1 (presence), and with the dependent variable (rating) taking on the value 0 (corresponding to ratings 1-6 on a nine-point scale) or taking on the value 100 (corresponding to ratings 7-9 on a nine-point scale). The rating scale is assumed to drive the respondent’s mind-set.

Table 1: Utility values for four coffee elements, when these elements were evaluated against six rating scales that focus the respondent’s mind-set in different directions.

A	B	C	D	E	F	G
Focus	Interest	Venue	Situati on	Day-Part	Day-Part	Day-Part
	Interest	Star-	With	Break-	Lunch	Early

		bucks	family	fast		dinner
Additive constant	46	65	46	50	56	48
A distinctive, well rounded cup of coffee…the ideal way to start a busy day	5	1	3	11	-6	-6
Dark fancy houseblend…an extremely rich cup of coffee	2	2	1	6	-2	-3
A masterful combination of carefully chosen coffee from each year's harvest	1	0	6	2	0	-1
Invigorate your senses with Cinnamon Apple Spice & French Caramel	-18	-7	-12	-26	-14	-2

Application 2: The complexity of nature, and need for research-tool *scalability*

Many advances in conjoint measurement come from the demands that emerge in actual use. Early applications of conjoint analysis used relatively few concept elements. These elements tended be the more rational features found in products, since these early studies focused on the design of products using conjoint analysis.

Practical problems have a way of increasing the scope of conjoint analysis projects beyond the limited number of concept elements often featured in demonstrations and academic projects. Whereas, early practitioners were satisfied to work with 20-30 elements, once a user accepts conjoint analysis as a method by which to understand the respondent's mind, the focus becomes the measurement of utilities for many more elements, e.g., beyond the previously 'generous' 20-30 to more realistic 100-300 elements. The novice professional when first introduced to the possibilities of conjoint measurement generally reacts with incredulity when told that the study may require 100-300 elements, averring that in no way would a study ever comprise that many elements. However, with increasingly aggressive goals for product and positioning development it becomes perfectly reasonable to demand this, and then ask how they would perform in concepts.

One traditional way for coping with many elements is to have each respondent select the concept elements that would be most appropriate to him, and to discard the rest. This procedure requires that the respondent explicate importance before participating in the conjoint analysis. This general strategy, called Adaptive Conjoint Analysis (ACA) (Johnson, 1987) works only with relevant concept elements and respondents willing to explicate their preferences ahead of time, or at least explicate directly those elements that are relevant. Today, Adaptive Conjoint Analysis has become the most popular method for hybrid conjoint analysis among researchers as well as managers (Johnson, 1987). According to Wittink, Vriens and Burhenne (1994) ACA is the most used method in Europe, and Green, Krieger and Agarwal (1991) reported a similar growth in for the US. Adaptive conjoint, used widely by researchers, works best when all of the elements are similar in terms of quality (e.g., simple statements about product functionality that can be judged alone, and accepted or discarded as being relevant or irrelevant).

There are at least three problems with such adaptive approaches which make adaptive conjoint analysis a less than desirable approach to deal with a large number of concept elements:

1. Up-front effort: The respondent must go through the different concept elements, one at a time and prior to the conjoint portion of the study in order to select the relevant elements. With 100-300 elements this exercise in and of itself can be time consuming, and will necessarily limit the time allocated to the conjoint portion of the study.
2. Rational decisions at the level of the individual concept element: The respondent must act at a rational level, because the judgment is to include/exclude. For the typical respondent many of the elements to be included might be the standard elements, that a product or service must have, whereas many of the elements to be rejected might be precisely those novel elements that would differentiate the product or service from competition. By having the respondent act in a rational manner to select the elements ahead of time the researcher decreases the chances of identifying really new elements.
3. No individual-level utility model can be easily created: The adaptive method works with different subsets of elements, so that it is impossible to create a full utility model for all elements, for each respondent. Each respondent generates his own profile of utilities, but how does one aggregate the data? There are approaches that use estimation procedures to fill in missing elements, but these procedures are at once cumbersome and are removed from the utility data. Procedures known collectively as hierarchical Bayes analysis are typically used in this estimation procedure, but the statistical procedures themselves are arcane, time consumers, and exceptionally indirect (Lenk, DeSarbo, Green & Young, 1996).

In the early 1990's and again in 2005 the author proposed an alternative method to deal with many elements (Moskowitz & Martin, 1993; Moskowitz, Porretta & Silcher, 2005). This method (IdeaMap®) overcame many of the issues that confront adaptive conjoint, as well as created a utility model at the individual respondent level, for each rating attribute. IdeaMap uses three assumptions and principles:

1. Constant interview length, independent of number of elements: The respondent has a fixed time in which to participate in the conjoint interview. No matter how many elements are involved the respondent spends only a relatively short time in the interview Thus, whether the study involves 30 elements or 300 elements, the respondent spends the same time completing the interview.. This time could be as short as 10 minutes or as long as 30 minutes. *The length of time spent by any respondent should be independent of the number of elements*. The independence of session time means that the adaptive conjoint method of selecting relevant concept elements could not apply here, because that time is proportional to the number of items.
2. Complete model at the level of the individual respondent, independent of the number of elements: The analysis generates a model for all elements for each respondent. That is, the model is 'complete' at the individual respondent level. A

key benefit of this completeness is the ability to 'slice/dice' the data many different ways. Since each respondent generates a complete utility function across all of the elements, for each rating attribute, the data can be analyzed without worry that the base sizes for some elements are different from the base sizes of other elements.

3. Simple, robust, intuitively meaningful estimate of utilities for missing elements: The utility values of the missing elements are estimated at the individual respondent level by a method that was fairly robust, yet easy to implement. The method uses semantic profiling. Semantic scales have been used for almost fifty years to understand meaning (Osgood, Suci & Tannenbaum, 1957). The rationale is that by having a matched group of respondents profile the concept element on a set of attributes one obtains a "snapshot" of the concept element. This semantic profile, operationally defining the meaning of the concept element, is used in the estimation of missing utilities. All estimation of missing utilities is done by using utilities from the same respondent, for 'similar' elements as defined by the semantic profiling. There is no need to use variables other than utilities for concept elements in the data imputation. Thus other, and far more indirect, estimation methods using Bayesian procedures are not necessary.

Application 3: Concept response segmentation

Segmentation refers to the division of respondents by one or another set of criteria such that respondents in one segment are more similar on a set of criterion attributes. In general segmentation can be accomplished in two different ways.

1. *A priori segmentation*. The segments are developed by certain theory-derived assumption about the preference of the respondent (Hahn, 1997). A great deal of segmentation is done using exogenous variables such as geo-demographic characteristics, where the assumption is that people from different geo-demographic 'breaks' may exhibit different utilities
2. *A posteriori or latent-based segmentation* emerges from the individual utilities in the conjoint analysis (Green & Krieger, 1991) or psychographic characteristics such as responses to a series of attitudinal questions. The results generate an interesting and often profitable way to divide a group of respondents (Wells, 1975). The utility values from conjoint analysis can and have been used as bases for segmentation. One method was adapted from sensory preference segmentation first introduced in food research (Moskowitz, Jacobs & Lazar, 1985), and based on the observation that an inverted U relation relates sensory intensity and liking for the total panel, but not necessary for individual respondents (Pangborn, 1970). Another method uses the pattern of utilities themselves, developing a distance measure between pairs of respondents based upon a distance metric such as (1-R; R = Pearson correlation coefficient between two sets of utilities). Moskowitz, Porretta & Silcher (2005) discuss the different segmentation methods.

Applying this segmentation algorithm to concept data provides the Sensometrics researcher with a way to identify different groups of respondents with varying mind-sets. An early application, also with coffee, dealt with respondents from ten different countries who participated in study on coffee. The study comprised 237 text elements, and 38 picture elements. The text elements spanned the range from sensory attributes to emotions to product features. The results of that study generated four clear segments that transcended conventional geo-demographics. The segments were the *Indifferents*, the *Waker-Uppers*; the *Relaxers*, and the *Flavor-Seekers*. The segments were present in different proportions in each country. The most important data outcome of that study was the set of utilities, which differed dramatically across segments, but did not differ dramatically across countries.

Application 4: Making conjoint easier through Internet-based study execution

Whenever a research tool becomes popular because it provides significant benefits in insight, there emerges the demand to make the tool more easy to use, more accessible, and more powerful. Historically, conjoint analysis was perceived to be expensive, relatively hard to execute set of research procedures, generally relegated to a statistician to design, and to a research company for data acquisition. For the most part the conjoint studies were reserved for the most important, high profile projects. More recently, however, the availability of the personal computer and then the availability of the Internet have changed the status of conjoint analysis from an esoteric, high powered, expensive and arcane procedure to a straightforward, system.

We focus here on the latest version of conjoint, implemented on the Internet. Internet-based research has grown extensively world-wide due to the low cost, ease of data acquisition, and general simplicity of the entire process. Over the past decade, beginning in the middle 1990's an increasing percent of market research studies have been fielded on the Internet. Questions such as the reliability and validity of the data, sampling issues with populations based on Internet availability, and complexity of studies that can be fielded have all receded in importance. At the end of the 1990's, for example, ESOMAR (World Society of Market Researchers) sponsored conferences about Internet-based research, to deal with interest in the growing area. These well-attended conferences resulted first in the so-called Net Effects conferences dealing with internet-based research, which soon morphed into Technovate Conferences dealing with technology innovations in market research, and finally morphing into the Innovate Conference dealing with the topic of market-research innovation in general. The change in focus from Internet-based research to innovation was not accidental – the change arose because over a period of five or six years Internet research evolved from 'new and interesting' to 'must have, standard operating procedure'.

The internet provides a perfect venue for conducting conjoint studies. One of a number of methods is known as IdeaMap.Net™ (Moskowitz, Gofman, Itty, Katz, Manchaiah & Ma, 2001). This method exemplifies a group of Internet-based procedures known as ASP's (application service providers). The entire ASP system is implemented on the Internet. The program is run from a server. A user who wants to run a conjoint analysis study on the Internet first logs in to his account, and through a set of menus designs the study, fills out the content (i.e., the elements, and the classification questionnaire, as well as the rating questionnaire), launches the study which provides a URL, and then invites respondents to participate.

At the respondent side the process is equally simple. Respondents receive the link, which comprises an invitation, often accompanied by a reward such as a sweepstakes, i.e., a chance to win a prize. The email invitation is sent to the appropriate group of respondents, which may be target individuals who have exhibited a certain behavior (e.g., known purchasers of a product or patrons of a restaurant). Equally often and for more general studies, however, the email invitation is sent to a large number of individuals who have previously agreed to participate in on-line surveys. These are so-called 'opt-in' respondents. The respondents click on the link and then participate in the study. About half of the respondents drop out during the course of the study. This 50% represents the typical drop rate, and occurs for most studies. The drop rate is anticipated and corrected for by doubling the number of invitations.

The data from the complete interview at the respondent level is stored and immediately analyzed by regression analysis in order to generate the individual's model. Often the respondents receive feedback immediately about their responses, such as a synthesized concept representing their 'optimum' versus a synthesized concept representing the 'optimal' for the total panel that has previously participated. This feedback acts as a second reinforcement for the respondent, the first reinforcement being the sweepstakes prize.

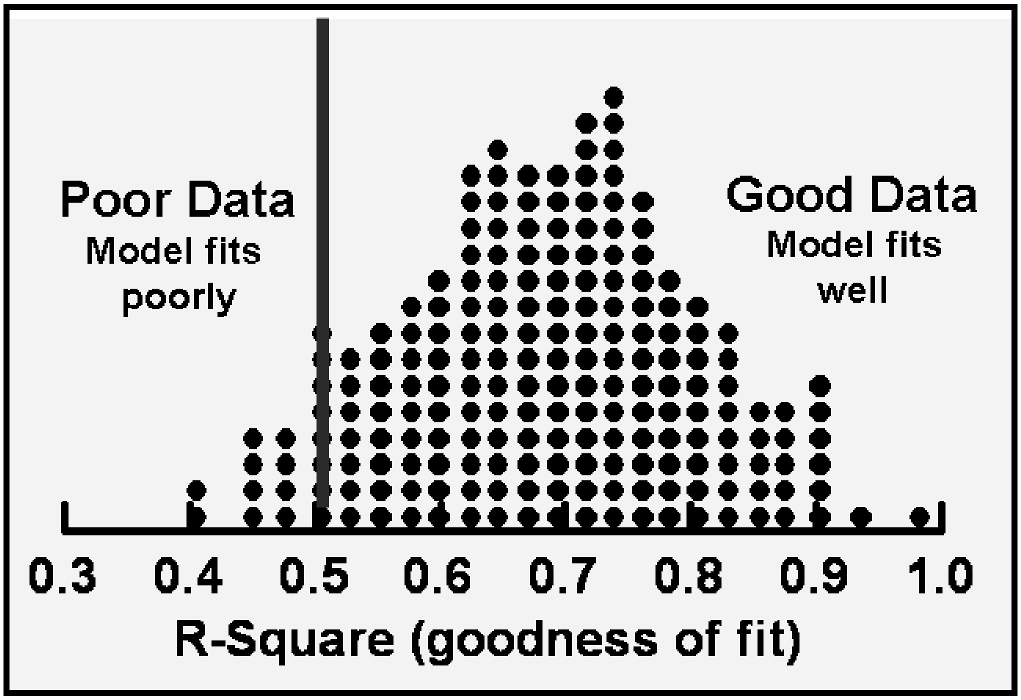
The complete computerization of the method forced by the Internet produces at least seven clear benefits to the researcher:

1. <u>Reduced cost in terms of research labor</u>: The process is very affordable. All the work has been done. The studies are generally template driven, at least for most of the studies. Being template driven means that the researcher merely needs to follow the directions, and type the appropriate text or load up the appropriate picture. There are no costly intermediate researchers.
2. <u>Efficient set-up process, encouraging iterative research</u>: The process is very quick. The researcher can set up the study in one or two hours, assuming of course that the respondent has thought through the problem. This speed of research stands in sharp contrast to the usual course of events where different groups of people have to participate because the project is expensive and everyone needs to 'sign off'.
3. <u>Better experimental designs due to permutation strategies.</u> Each respondent can evaluate the same set of concept elements, albeit, in a different set of combinations. This systematized permutation of the experimental designs allows the researcher to avoid having a particular concept with specific sets of elements 'drive' the ratings because they are unexpectedly powerful together. The systematic permutation reduces any bias due to combinations of elements by allowing each respondent to have his own experimental design, isomorphically related to the basic design structure. The systematized permutation will also become relevant for the study of pair-wise interactions.
4. <u>Convenient for the respondent</u>. The respondents enter when they wish, and participate for as long as they wish. In a variety of conjoint studies we have seen distributions of interview times, with 8-12 minutes being the typical length of an interview. The respondents may even interrupt the interview, and return later, although this

interruption is only important when dealing with professionals such as doctors who may not be able to complete the interview within one session.

5. Easier acquisition of data in terms of filling quotas. By sending out thousands of invitations to the relevant respondents, the research can acquire the data in one evening. Typical response rates range from a low of 3% to a high of 20%. Response rate and response dropout are a function of the intrinsic interest of the study and the reward. As noted above a good estimate is that 50% of the respondents who begin a study by logging-in will drop out before completing the study. With conjoint analysis of the type featured here ('full profile'), the researcher needs about 50-100 respondents to achieve meaningful, robust, and projectable data. With a 3% completion rate, it takes 1700-3300 respondents to be invited. An email to 3300 respondent can go out in a matter of minutes.
6. Clean data from the start: All of the data acquisition is controlled through a computer database making data entry automatic, and data analysis quite easy. There are no messy interviews with missing data, unless the researcher has left provision to accept missing answers. To complete the study the respondent must fill out all of the answers.
7. Individual level analysis of data, and consistency make the 'grainy data' very robust. Individual level modeling and individual-level measures of consistency to identify poor performers. The modeling is done at an individual respondent level, and then the data combined into subgroups. As noted above, the individual models can be used as input to a segmentation program (e.g. k-means). The consistency of each individual can be checked by a goodness of fit program, which shows the degree to which the individual level model tracks the respondent's data. All of these can be done automatically by having the analysis selected ahead of time through a menu.
8. Ability to track individual respondent performance to identify those whose data may be good versus those whose data may be poor. Generally about 80% of the respondents generate data of demonstrably high quality. Quality can be assessed by computing the multiple R^2 statistic for the linear equation relating the presence/absence of concept elements to the scalar rating. Figure 2 shows the distribution of the R^2 statistic across a study of 200 respondents for a study on weaning foods (Moskowitz, 2004). This type of distribution occurs again and again, across studies, suggesting that the respondents are paying attention to the test combinations, and giving answers which are consistent.

Figure 2: Distribution of the R^2 statistic from an Internet study on consumer responses to concepts dealing with weaning foods. The distribution of R^2 values is similar to that found in other studies.

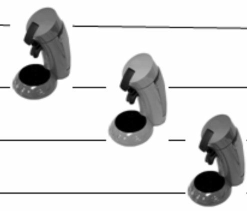
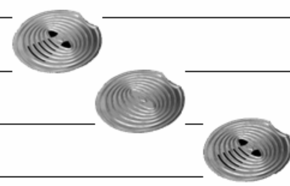
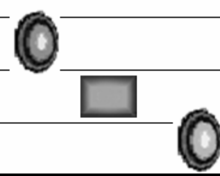


Application 5: Graphics design and visual-based conjoint analysis

We usually think of concepts as comprising phrases and pictures, but why not work with concepts which comprise combinations of visuals? Recent advances in computer technology allow the researcher to layer visual stimuli using an experimental design. To the respondent the combination of these layered visuals appear as a simple gestalt, but underneath these gestalts one can clearly identify a set of different visual elements that are being systematically combined with each other.

This capacity to treat visual stimuli in a systematic way presents new opportunities for conjoint analysis and in turn for Sensometrics. Some recent data, not with food per se, but rather with coffee makers, give a sense of the power of conjoint analysis. Rather than varying the text messages, the researcher varied features of the coffee maker, to create different equipment designs, comprising various colors and style features... The results give a sense of how the respondent processes visual information. The study comprised five variables, three options each. The combinations were systematically created. Each respondent tested a different set of 40 combinations, generating an individual model. The data for the set of respondents were then segmented based upon the pattern utilities. Table 2 shows the utility values for nine of the elements, for the total panel and for the three segments. There are clear different segments, but unlike segmentation based on response to text elements the patterns are not clear nor compelling, despite the belief of many marketers and advertising agencies that most of the response to stimuli comes from the unconscious and cannot be tapped by textual information. For Sensometrics the study of graphics-based stimuli moves attention to more complex issues, such as the visual composition of product pictures and packaging designs. There is much to explore here.

Table 2: Utility values for the nine of the 15 visual concept elements, based upon reactions to combinations of elements presented graphically as an overlay. The utility values were calculated after the 1-9 rating were converted to a binary scale (1-6 converted to 0; 7-9 converted to 100).

		TOT	S1	S2	S3
Constant		18	13	18	22
	Body				
A1	Blue 	8	15	3	3
A3	Forest Green	3	10	-7	0
A2	Burgundy	-4	0	8	-18
	Coil				
B1	Brownish Silver 	2	-2	8	3
B2	Silver	0	-3	3	1
B3	Blue	-1	-3	5	-2
	Button/Light				
C1	Salmon 	2	1	1	3
C3	Light Blue	-1	-2	-6	2
C2	Avocado	-2	-2	-4	1

__Application 6: Response time as a second dependent variable__

Response time is the traditional 'reaction time' that has been used as a dependent measure to indicate underlying cognitive processes. Reaction time was a mainstay measurement in the early days of experimental psychology, and has been used in various applications as a dependent measure (Boring, 1929). Conjoint measurement provides an added benefit when one works with conjoint analysis; the rating scale itself creates the psychological framework against which the respondent evaluates the concept, and thus the rating scale provides the clues to the nature of the cognitive process underlying the response time. The actual stimuli show what is being reacted to. The response time may indicate the complexity of the underlying process.

The combination of conjoint analysis, utility measures, response time measures, and specific stimuli provide a promising opportunity for Sensometrics research. In previous studies, not with food concepts but rather with children's toys, the results from conjoint studies with children versus adults showed differences in the patterns of response time. Adult response time was proportion to the length of the; children's response time was not (Moskowitz, Hjelleset & Rabino, 2000). Other work on response times with coffee showed modestly different patterns of response times versus length of concept on a country-to-country basis (Moskowitz, Porretta & Silcher, 2005).

A sense of the response times and utilities involved in food products can be seen in Table 3. The respondents rated the concepts on interest. The response times show how long it takes to process the information. The study was on grapefruit. Parts of the data were reported previously (Moskowitz, 2003b). We focus here on a comparison of the utility values and the response time, to show that they differ, and can lead to different research avenues.

In the specific grapefruit study the respondent evaluated many combinations of concept elements dealing with grapefruit. Details are presented elsewhere, as noted above. The study itself was an IdeaMap® design so that each respondent evaluated only a portion of the possible combinations, with utilities for missing elements estimated by the an imputation procedure. The response time was estimated in tenths of a second. The model was generated for each respondent and then aggregated.

We see that while the data in Table 3 for 15 elements is a small part of the full data set it is sufficient to explicate the approach. The additive constant for utility is the conditional probability that the concept would be accepted if there were no elements. This is clearly an estimated value and is 62. What is more interesting, however, is the RT or response time utility. The average concept without elements requires 73 tenths of seconds, or 7.3 seconds to generate a response. This is 'dead time'. The elements add to response time, but to different degrees. For example, inserting the phrase 'a healthy alternative to soda' increases the response time. The element is interesting to respondents (utility = +5) and the element is not particular long. A visual element can show the same pattern (viz., the picture of a grapefruit slice) meaning that the response time is not a function of text alone. Another element, 'surprisingly sweet grapefruit juice' has a utility only slightly lower (+4 instead of +5), but is responded to more quickly (RT = 6 or 6 tenths of a second). The limited set of data results shown in Table 3 suggest a rich vein of research opportunity to be mined by combining conjoint analysis and response time. It remains for the enterprising researcher to do the work on deconstructing both interest levels and response times to the same set of elements, and then extracting the insights that may lurk therein.

Table 3: Interest level (utility) versus response time (RT) for 15 elements from an IdeaMap study on concepts for grapefruit juice.

	Utility	RT
Additive Constant	62	73
Elements with the highest utilities for the total panel		
A healthy alternative to soda	5	14
Visual ….Sliced grapefruit	5	14
The best of both worlds – indulgent, exciting taste in a healthier refresher	4	20

If you crave healthy refreshment	4	12
Made from tangy-sweet Indian River Ruby fruit	4	11
Surprisingly sweet grapefruit juice	4	6
Visual…Hiker with sports bottle	4	13
Be healthy but have fun doing it	4	9
Healthy indulgence	4	9
Elements that take the longest time to be 'processed' based on response time values		
If you think fruit juices are boring, but carbonated drinks aren't healthy enough	1	25
All the goodness of grapefruit with the taste you will love	3	22
The healthier fruit refresher with an exciting, snappy taste	3	21
A better, not bitter grapefruit taste	3	20
The best of both worlds – indulgent, exciting taste in a healthier refresher	4	20
The sweetness makes it fun to drink, the tanginess makes it unusually refreshing	3	20

<u>Application 7: Identifying pair-wise interactions and their magnitudes</u>

Pair-wise interactions among continuous variables are a straightforward statistical issue whose estimation has been dealt with in countless articles (Box, Hunter & Hunter, 1978). Sensometrics researchers use regression models and analysis of variance approaches to identify the existence of, and then and partial out the magnitudes of these interactions. Certainly when it comes to stimuli in the chemical senses (taste, or smell) interactions often dictate the quality and intensity of the percept. Most response surface modeling take into account interactions, at least in simplistic form, by using a function with easy to estimate interaction terms. For example, one of the most popular equations for product optimization in two variables, the quadratic model, can be expressed as:

$$\text{Response} = k_0 + k_1(A) + k_2(A^2) + k_3(B) + k_4(B^2) + k_5(AxB)$$

The term AxB represents one way to express these pair-wise interactions, although the researcher might legitimately use terms such as the ratio A/B, especially when the interaction is driven by ratios of ingredients. Nonetheless, for continuous variables the issue of pair-wise interactions is fairly tractable at a statistical level.

Conjoint analysis introduces a whole new level of complexity into the issue of pair-wise interactions. Keep in mind that the basic stimulus unit of conjoint analysis is an element, which in itself in not necessarily locatable on a continuum. Sensory descriptions, emotional benefits, and even pictures are essentially yes/no, present or absent, even if in many cases the element is defined as a level of an attribute (e.g., moderately salty). In conjoint analysis we estimate the separate utility values of the different elements by standard statistical methods, such as dummy variable regression analysis. Experimental designs can be developed to handle reasonable numbers of such elements (e.g., up to 50 or so), with data imputation to handle the utilities of missing elements (see above). Missing, however, is a statistically sound way to efficiently discover and then estimate the utilities of the pair-wise interactions in a set of elements. The problem is not trivial.

Let us explore a simple example to show the magnitude of this problem, and then look at the empirical solution to the problem using a new algorithm. Consider the case of a conjoint study comprising 20 elements, i.e., a design comprising four independent variables (viz., categories), and five elements or options per category. The basic experimental design comprising 20 elements can be developed with 40 or more combinations, which enables dummy variable regression to estimate the 20 utilities. In this case the more combinations one tests with a single respondent the better the estimate will be. In this case the respondents evaluated 48 combinations, with the combinations systematically permuted. Each respondent thus evaluated a different set of combinations, even though each respondent eventually evaluated all of the 20 elements embedded in his unique set of 48 combinations.

We are not finished, however, if we want to deal with interactions. Without any prior information on which to base next steps, we are faced with a massive problem. This small set of 20 elements comprises many more interactions than we can possibly handle with a single respondent. There are four categories of elements, and thus 4x3/2 or six *pairs of categories*, from which interactions can be drawn. Each pair of categories, in turn, has five elements from one category, five elements from the second category, and therefore 5x5 or 25 possible combinations. We are now left with 6 possible pairs of categories, and 25 possible interactions for each pair, or a total of 150 pairs. We do not even know which particular pairs of elements will generate a significant interaction. The problem gets worse with experimental designs comprising more elements. For instance, a design comprising six categories, each with six elements generates 15 unique pairs of categories, 36 pairs of elements per category, or 540 possible interactions. Which pairs of interactions can be shown to be statistically significant? What the magnitude of the interaction between any pair of elements?

One pragmatic consequence of this enormous issue ignores the problem entirely. Most simple methods for conjoint analysis ignore interactions, claiming that the interactions are ‘contained within by virtue to mixing of elements yet not estimable. In some brave cases the researcher specifies ahead of time which particular interactions are to be explored further, and modifies the conjoint experimental design in order to accommodate these pair-wise interactions. Occasionally researchers use small sets of elements, and a choice modeling paradigm to estimate pair-wise interactions. The analysis identifies which pairs of elements interact, but does not show the magnitude of the interaction in an easy to understand manner. Choice modeling has a very difficult time dealing with the aforementioned, relatively simple design comprising 20 elements, and 150 possible pair-wise interactions. Choice modeling becomes almost impossible with today’s tools when we deal with the ‘bigger design’ comprising six categories and six elements per category.

Recently, Moskowitz & Gofman (2004) were granted a provisional patent (US) on a new method for detecting and quantifying interactions in conjoint analysis. The patent pending process follows a series of ten simple steps that begin with a simple, main effects design, but through the aforementioned permutation allow the interactions to be identified and their magnitudes then estimated.

1. <u>Design structure</u>: Create a main effects experimental design (so-called *basis design*) to be used as the design structure for each respondent. For discussion below assume there are C concepts in the basis design.
2. <u>Design permutation</u>: Permute this basis design to maintain the design structure, but shuffle the elements within a category. There may be as many as 300 or more permuted designs created by this permutation strategy. Each permutation is isomorphic to the basis design, so each permutation will comprise C concepts.
3. <u>Respondent assignment</u>: Assign a given respondent to a specific permutation, and if possible try to create as many permutations as there are respondents. There may be more respondents than permutations, in which case two respondents or perhaps more will be assigned to the same permutation.
4. <u>Randomize concepts</u>: Randomize the order of appearance of concepts within a permutation, so that even if two respondents are assigned the same permutation, their orders of concepts differ.
5. <u>Acquire data</u>: Run the conjoint interview with the respondents, obtain ratings for each test concept, and store the data in a rectangular file.
6. <u>Create the raw data matrix</u>: After all the respondents have run through the study for R respondents, the data comprises RxC rows. Each row comprises the respondent ID, experimental design, and rating.
7. <u>Create the interaction terms by multiplying the appropriate columns</u>: Create all possible interactions between pairs of elements from different categories, coding the pair-wise interaction as ‘1’ if it appears for a specific row (i.e., both elements are ‘1’ and therefore their product is ‘1’) or ‘0’ if the interaction does not appear for a specific row (i.e., one element is present, and the other element is absent). For the case of 4 categories, 5 elements per category, there are 6 pairs of categories, 25 combinations of two elements, one from each category, and thus 150 (i.e., 6x25) combinations. Each newly developed interaction has its own separate column. Each interaction takes on the value of either a ‘1’ or a ‘0’ for any particular row, depending upon the presence of both elements, or the absence or one or both elements from that particular concept, for that particular respondent.
8. <u>Regression modeling</u>: Run a stepwise ordinary least-squares regression, forcing the linear terms and allowing significant pair-wise interactions to enter afterward if the interaction is significant. Use either the original ratings (e.g., 1-9 scale), or the binary transformed ratings, depending upon the nature of the response (i.e., focus on degree of liking versus membership in the class of *acceptors*, for a particular combination). For discovery of interactions it is important that the data be as ‘grainy’ as possible, with as much information as possible. The regression analysis uses standard, off-the-shelf software (e.g., Systat, 1997).
9. <u>Identify the significant interaction in the raw data from significant terms in the regression model</u>: The equation comprises linear terms and highly significant

interactions. The degree of significant is left to the researcher, with the caveat that by setting the significance criteria too low there will be an extraordinary number of interaction terms entering the equation, whereas by setting the significance criteria too high there will be very few interaction terms.

10. <u>Estimate the magnitude of the interaction effect</u>: For any pair of elements, use two models to estimate the impact of the interaction. The first estimate uses the additive constant and coefficients from the simple linear model, without interactions. This estimate, the sum of three variables, can be compared to the corresponding second estimate, which uses the model with interactions, and comprises the additive constant, the two linear terms, and the interaction term. The magnitude of the interaction gives a sense of what really changes when interactions are accounted for.

The five key benefits to this analytical approach to interactions which transcend conventional methods are:

1. <u>No prior knowledge necessary</u>: The statistically significant interactions need not be built into the system at the start of the study. The interactions emerge from the permutations.
2. <u>Individual level analysis</u>: The modeling is efficient; each respondent evaluates only a limited set of combinations.
3. <u>Scalability to many categories and many elements</u>. The approach is 'scalable' to many categories and elements. The limiting factor is the number of independent variables allowed by the regression package. Current standard studies deal with as many as 36 elements and 540 potential interactions.
4. <u>Estimation of effect of interaction above and beyond the individual components</u>. The modeling shows the numerical effect of the interaction, whether positive or negative, and allows estimation of the effect of modeling the interaction on the concept rating.
5. <u>Potential for estimating higher order interactions</u>. The same logic has been applied in large data sets to assess the existence of three-way interactions. The problems with these higher order interactions are the relatively few specific three-way combinations unless there are a 1,000+ respondents, and the meaning of the interaction. At the level of computation, however, there is no problem dealing with three-way interactions.

A sense of the interaction results appears in Table 4, which represents a typical analysis for the four category, five element problem. The raw data from 281 respondents, and 48 concepts/respondent was analyzed two ways; first without any interactions (i.e., just main effects), and then following the approach above analyzed with main effects forced in, and then interactions allowed in if they were significant. The decision regarding statistical significance plays an important role in determining the number of interaction terms. More stringent criteria for significance mean fewer terms, and a possibly weaker model, but yet one that is more conservative. For this study, as well as for other conjoint studies of a similar nature, the F ratio was set at 4.0, meaning that beyond the linear terms an interaction term had to add dramatically greater predictability to the model. Only four terms enter. The interactions lead to changes of approximately 1/3 of a scale point on a 9-point scale, sufficient to be statistically significant and meaningful, albeit not very large. Other criteria such as the p value for the interaction may be substituted for the F ratio.

Table 4: Significant pair-wise interactions from a conjoint study comprising four categories, and five elements per category. Data analysis based on 281 respondents, each of whom evaluated 48 concepts. The independent variable was interest in the concept, rated on a 9-point scale.

	Simple Linear Model	Model With Statistically Significant Interactions
Additive constant	-0.35	-0.34
A1	0.91	0.91
A2	0.62	0.62
A3	0.81	0.81
A4	1.00	0.93
A5	1.17	1.16
B1	3.10	3.10
B2	2.91	2.90
B3	1.67	1.73
B4	2.99	2.99
B5	2.64	2.57
C1	1.15	1.10
C2	1.05	1.11
C3	1.02	1.01
C4	1.11	1.11
C5	1.16	1.16
D1	0.94	0.93
D2	1.01	1.07
D3	0.99	0.99
D4	0.88	0.87
D5	0.86	0.86
Interactions emerging as significant after the linear terms were forced into the model		
A3C1	0.00 (by definition)	0.30
A3C2	0.00 (by definition)	-0.31
A4B5	0.00 (by definition)	0.38
B3D2	0.00 (by definition)	-0.36

<u>Application 8: What combinations of elements perform well together (scenarios)?</u>

Experimental design of concept elements coupled with systematic permutation provides an additional benefit -- namely allowing the researcher to identify what combination of elements performs well. The aforementioned strategy of creating one large database comprising all the concepts permits the researcher to take slices through the database, where one element is held constant (e.g., brand name or sensory characteristic), and for that particular 'slice' identify the contribution of the remaining elements in the other categories. This approach has been labeled scenario analysis, and represents a further step in the analysis of interactions. The approach is relatively new, having been developed in late 2004, and therefore only presented in conferences (e.g., Ewald & Moskowitz, 2005). The application is worth a note here as well.

The strategy for scenario analysis is straightforward, following these steps:

1. Starting matrix: Create the very large matrix of ‘raw data’, with the columns corresponding to the concept elements. For example, with four categories and nine elements there are 36 such columns and the 37^{th} column corresponding to the respondent’s rating for that particular combination. For the aforementioned ‘4 x 9’ basis each respondent evaluates a unique set of 60 combinations.
2. Create the full dataset by appending the designs: In the particular study using scenario analysis, a total of 644 respondents participated, generating 38,640 combinations, with each respondent evaluating a different set of combinations.
3. Identify the ‘pivot’ or key category: One of the categories (Category D) was brand/venue, with nine elements. The data were sorted by the nine brands/venues.
4. Run a regression for each element in the pivot category: A separate linear regression was run for each brand/venue, looking at the utilities of the remaining 27 elements in the other three categories. This stratification allows the researcher to estimate how every other concept element performs when the concepts being study have one single brand or venue.
5. Example: Table 5 shows nine columns, one for each brand or venue. All the utilities refer to how the 27 elements in the remaining three categories perform when the brand or venue is held constant as Quaker Oats, Newman’s Own …. WalMart, respectively.
6. Performance of elements: It becomes clear from Table 5 that the utility of an element can vary depending upon the brand or venue with which it is paired. However, the performance of an element should be computed by adding together the additive constant and the utility value. The additive constant provides a measure of basic interest in the brand. The utility value of the element shows the incremental or decremental contribution of that element to that specific brand.

Table 5: Utilities of 27 elements from three categories, for concepts having in common one specific brand or venue (scenario analysis).

		Quaker Oats	Newman's Own	Kellogg's	Kraft Foods	Betty Crocker	Campbell's	Trader Joe's	Whole Foods	Wal-Mart
	Additive constant	47	34	44	48	41	46	31	37	33
A1	As part of a lowfat diet, this food may reduce the risk of some types of cancers	4	8	-2	2	-1	0	8	13	10
A2	This food includes calcium and other nutrients that give you bright teeth, shinier hair, and smoother skin	2	7	5	4	13	4	15	7	12

A3	Food that contains 20% of your daily requirement for fiber...important for reducing your risk of chronic diseases like heart disease	12	7	5	12	3	10	11	8	7
A4	Good food. Easy to eat on the GO!	-1	4	-4	2	9	2	9	1	5
A5	Meals that require NO preparation. Just heat and eat!	-4	9	6	10	5	4	3	16	11
A6	One pot. One step to a meal. Start it in the morning, and have it in the evening just as you walk in the door	7	13	9	8	16	7	16	20	4
A7	Fresh juicy slices, slow roasted for added flavor, hot off the rack	3	11	8	11	8	5	11	3	6
A8	Prepared just to your liking...just the way your mom or someone special made it...so close to homemade you can almost smell the meal	19	17	4	3	8	8	12	6	13
A9	Luscious, creamy texture. So rich, so moist... dotted with juicy jewels of fruit,	1	11	5	1	5	-4	5	1	7
B1	Just one serving provides important cancer protective benefits	-1	11	6	0	3	0	6	15	4
B2	Contains essential omega-3 fatty acids, which may reduce your risk of heart disease	10	5	0	2	6	5	4	5	9
B3	Provides essential vitamins and minerals your body needs including potassium, magnesium, and zinc	3	4	7	1	5	0	12	2	-1
B4	Doesn't make a mess while you eat it	-7	-1	4	-2	0	-3	3	0	1
B5	It's Convenient	-8	3	-2	-1	3	-1	3	5	-2
B6	Tastes freshly made	1	0	1	9	3	2	2	3	-2
B7	Premium Quality	-6	4	9	-3	-3	0	4	1	-4
B8	Wholesome goodness	6	1	-4	-4	8	6	-3	5	-6
B9	Tastes like it was prepared by someone who cared about you	1	3	-2	-4	15	6	3	0	0
C1	Calms you...	1	-1	0	-11	-12	-1	-8	5	5
C2	Better for you than you thought...	-2	3	-5	1	-3	1	3	-1	9
C3	Feeling good about feeding your family...	5	9	1	-1	5	11	7	0	6
C4	It's good for you and your body, soul and mind...	4	-2	3	5	1	7	3	-3	7
C5	Looks great, smells great, tastes delicious...	0	11	1	2	3	2	2	3	-2
C6	Quick and easy...doesn't have to take a long time to get a good thing ...	0	5	3	-4	4	4	7	6	3
C7	A joy for your senses....seeing, smelling, tasting	-1	4	10	-2	6	4	1	2	-3
C8	Imagine the taste....	7	-1	-5	1	5	4	-5	-2	2
C9	So irresistible, just thinking about it makes your mouth water ...	0	9	2	-1	5	-2	-6	2	2

Application 9: Databasing the consumer mind and the vision of a *mind genomics*

There is no systematic knowledge or database available which reveals how consumers respond to different brand names, features of products, emotional aspects of products, or aspects of the buying situation. Most of the knowledge resides in unrelated sources, such as corporate offices, trade and academic journals, and the experience of development and marketing professionals. A lot of information resides in disparate documents available to the public, and accessed either by some intelligent search engine such as Google®, or by some 'pay as you go' system such as Lexis/Nexis®. Some of this information about the consumer mind-set resides in the numerous different segmentation studies, run by corporations almost as period exercise by which to measure what night considers be thinking. For the most part these studies are disparate, of different character, different questions, set up for different analytic strategies, and certain commissioned by corporate professionals espousing professional coats and goals of many colors. In a word that the studies are not integrated, designed for momentary use rather than designs as components one a large, integrated database comprising many facets.

Creating a cross-sectional *and* longitudinal database to understand the 'algebra of the consumer mind' can become a major contribution to academic and business oriented product development, marketing, and consumer sciences. It also has the benefit of being unique, difficult to replicate, and expandable to a variety of different topics. If such a database can be developed easily, at low cost, with data which 'excites' the user in terms of scientific and commercial applicability, then it may be an aspect of conjoint analysis that will provide a rich analytical landscape for Sensometrics.

This type of database, using conjoint analysis as the engine, has been recently created for a number of categories, using the self-authored method of conjoint analysis. The specifications of the system can be summarized by the following 11 points, which apply to the 'It!' databases, a name given to the integrated system (Beckley & Moskowitz, 2002; Moskowitz, Saguy & German, 2005; Moskowitz, Porretta & Silcher, 2005).

1. Structured conjoint study of similar form across the different products:. Each conjoint study in an It! database is structured in the same way. The similar construction allows comparison of utility values for elements both within a product and across products. It is straightforward to compare within the product but there must be some general organizing principle to link one study to another. The structure is set up by having the same types of categories across all of the studies, and the same types of elements within the categories. Of course the elements are particularized to the individual product. Table 6 shows an example of this organizing principle for cola, from the 'Drink It!tm database. The remaining beverage studies comprise elements arranged in a similar fashion, with the elements particularized to the specific beverage.
2. Identical classification questionnaires: Each structured conjoint study in the database is followed by the same classification questionnaire, which further ties together the

studies. It becomes straightforward to compare the profiles of respondents across studies on geo-demographics, as well as on attitudes to the products and lifestyles.

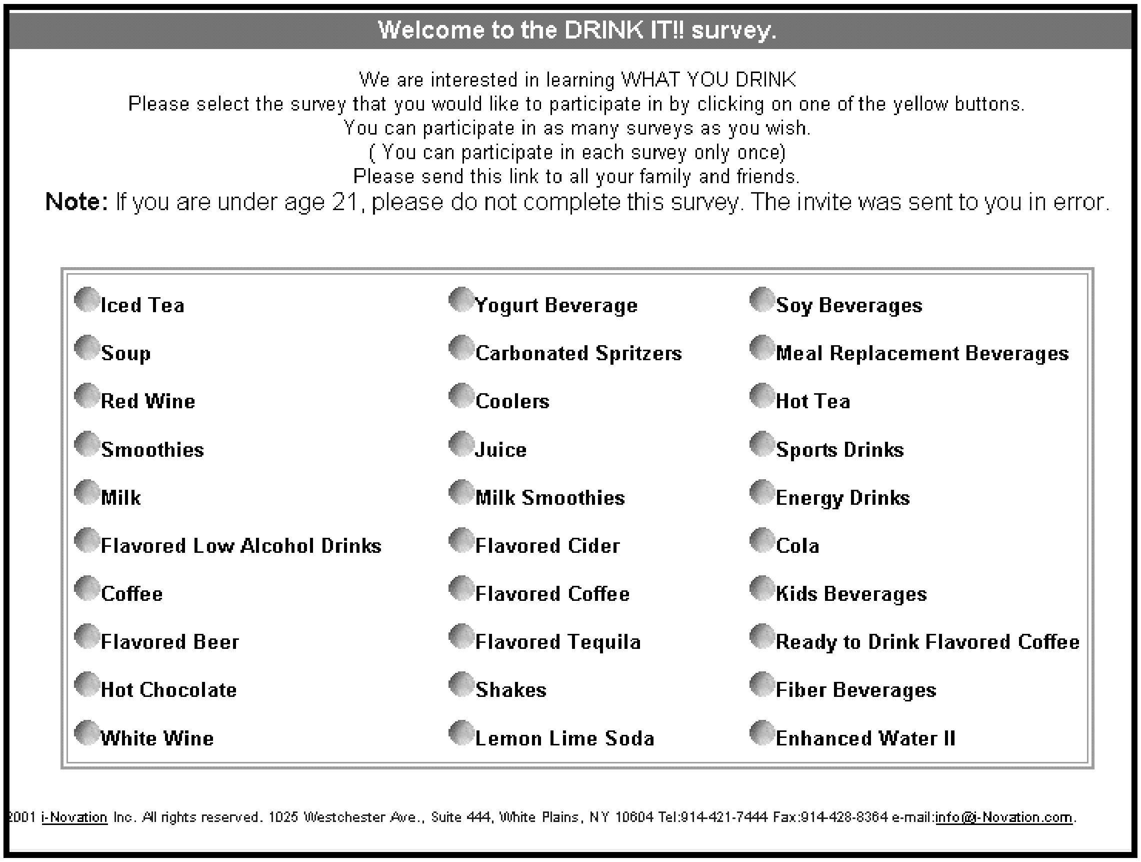
3. Set-up by self authoring conjoint analysis: The different studies are created by the user, using the principles of self-authoring conjoint. The self-authoring system makes it reasonably straightforward to 'copy' one study, and then 'paste' it in the same directory, and finally particularize the study for the new product. The major changes come in the text of the elements, not so much in the classification.
4. Implement the study on the Internet. With 20-40 parallel studies in the database it would become prohibitively expensive to have the respondents come to a central location to participate. With Internet-executed research, the costs plummet, because the respondents select the study to participate in the comfort of their own home. The entire interview is about 15-20 minutes.
5. Respondents choose the study that interests them. The respondent receives an invitation letter to participate. The letter is sent by an email company that specializes in recruiting respondents. The respondent incentive is a chance to win a cash prize (sweepstakes). The respondent who chooses to participate is led to a 'wall' showing the available studies (Figure 3). The position of the studies varies on this wall in a dynamic fashion, so that the most popular studies are on the bottom right, whereas the least popular studies are on the top left. This strategy to balance the location of the 'buttons' for the studies attempts to increase the response rate of the less popular studies. The wall is set up so that when the study is complete (i.e., it reaches its quota, or the researcher wants other studies to fill up), the study can be suspended. Suspended studies disappear from the wall. Generally 150-250 respondents complete each study, comprising about half of the 300-500 respondents who originally logged on. This completion rate appears to hold for most Internet-based studies of this type.
6. Orientation. The respondent begins the study with an orientation page, describing the purpose of the study. The respondent is not aware that the remaining beverages in the Drink It! database are created in a parallel fashion.
7. Modeling the ratings at the individual respondent level.. Each respondent evaluates a full set of concept elements arranged according to a permuted design. The ratings from 1-6 are transformed to 0; the ratings of 7-9 are transformed to 100. The ratings are modeled using ordinary least-squares regression.
8. Large scale data set for each beverage that can be analyzed according to various criteria. Each beverage generates its own data set, showing the utility values for the different concept elements, by total panel, by different pre-defined subgroups, and by emergent concept-response segments. The segmentation puts respondents into groups based upon similar patterns of utilities across their 36 elements.
9. Results summarized across products in one year, and across years for the same product. A key ingoing strategy for the It! databases was to find trends in the population, i.e., ideas that were emerging, and which might appear in more than one beverage. Thus the studies are run across years, with Drink It! going into its third year. In this way one can see what ideas, flavor directions, etc. are becoming popular. Insights generated in one beverage can be checked in another beverage to see whether the trend is localized to one product, or appears to be moving across many products.
10. The structure of the It! databases makes it feasible to create such databases relatively easily, and in many different fields. Databases have been created for food (Crave It!,

Teen Crave!, Eurocrave!), beverages (Drink It!), healthful foods (Healthy You!), and food on the good (Grab It! and Go). A similar approach has led to databases for insurance (Protect It!), not for profit (Give It!), and the shopping experience (Buy It!). The databases provide both key information for the business community and a wealth of information for academic papers and statistical analyses. With the ability to generate data almost effortlessly on the Internet, and the capacity to track data over time and across products, we should be able to see many new insights about the food and beverage world emerge from Sensometricians who work with this rich database. The insights will range from an analysis of broad 'mega' principles (viz., the view from '30,000 feet'), down to the creation of new products by mixing popular features for beverages in two different product categories into a syncretistic new combination.

Table 6: Structure of the concepts within the Drink It! Study, as exemplified by cola. Each beverage in the Drink It!(tm) comprises the same types of elements, particularized to the beverage. Where possible the elements are maintained identical across the different beverages to facilitate comparison, and to allow patterns to emerge. Table courtesy of It! Ventures Inc.

	Primary Attributes	Secondary Attributes	Emotional Attributes	Brands/ Benefits
E1	A classic cola ... just the way you like it	Drinking Cola is cool and inviting	Quick and fun … ready to drink	From Dr Pepper
E2	Carbonated, sparkling Cola...just the right amount of taste and bubbles	Caffeine-free	With twice the jolt from caffeine … gives you just the added energy you need	From Wal-Mart
E3	A perfect beverage…with breakfast, lunch, a break, or dinner	Cools you down	Simply the best	From RC Cola
E4	Cola blended with real coffee	Premium quality	Relaxes you after a busy day	From Pepsi
E5	Cola ... all the taste but only one calorie	Fortified with important vitamins and minerals for your body	Take a break from your busy day	From Coca-Cola
E6	Cola blended with chocolate	100% natural	Looks great, smells great, tastes delicious	Multi serve containers … so you always have enough!
E7	A thick slushie of cola and ice	With natural botanicals	Perfect complement to your meal	From Jones Soda
E8	Cola ... the perfect mixer for everything you drink	Made with organic ingredients	Pure satisfaction	Resealable single serve container … to take with you on the go
E9	An ice cream float - cola, ice cream … chilled and tasty	So refreshing … you have to drink some more	To keep you going throughout the day	With the safety, care and quality that makes you trust it all the more

Figure 3: The 'wall' for the Drink It! database. Respondents opting to participate can choose one of the studies by clicking its button. Figure courtesy of It! Ventures, Inc.



Welcome to the DRINK IT!! survey.

We are interested in learning WHAT YOU DRINK
Please select the survey that you would like to participate in by clicking on one of the yellow buttons.
You can participate in as many surveys as you wish.
(You can participate in each survey only once)
Please send this link to all your family and friends.
Note: If you are under age 21, please do not complete this survey. The invite was sent to you in error.

Iced Tea	Yogurt Beverage	Soy Beverages
Soup	Carbonated Spritzers	Meal Replacement Beverages
Red Wine	Coolers	Hot Tea
Smoothies	Juice	Sports Drinks
Milk	Milk Smoothies	Energy Drinks
Flavored Low Alcohol Drinks	Flavored Cider	Cola
Coffee	Flavored Coffee	Kids Beverages
Flavored Beer	Flavored Tequila	Ready to Drink Flavored Coffee
Hot Chocolate	Shakes	Fiber Beverages
White Wine	Lemon Lime Soda	Enhanced Water II

Application 10: Synthesis of new product ideas by syncretistic combinations

Developing new products constitutes a key objective for today's businesses. Many sensometricians work in companies, and are in one or another fashion involved in new product development. The conventional approaches for new product development range from ideation to competitive analysis, followed by focus groups, concept screens, conjoint analysis, prototype development, and either simulated or actual test markets.

As noted in the introduction to this paper, conjoint analysis traditionally was used for so-called 'high profile' projects in new product development, where the respondent responded to concepts about the features of a product. There is absolutely no reason why conjoint studies of the type presented here should be limited to one product alone, with the element categories limited to that specific product. Conjoint analysis might make further contributions by mixing and matching the features from many products, even disconnected ones that have only a modest number of aspects in common with each other.

A recent pair of papers discussed this type of innovation. Those steps were followed for the development of at least one food idea (a combination of chocolate, doughnut and cookie (Moskowitz, Reisner & Krieger, 2005; Moskowitz, Reisner, Krieger & Oksendal, 2005), and at least one consumer electronics idea (a combination of Tablet PC, portable DVD player, and electronic game Moskowitz, Itty, McDonough & Katz, 2005). Although the results of this syncretistic innovation have not yet been made public by the companies who sponsored the research, there is every reason to assume that over time conjoint analysis will be used to combine features from different types of products and services into totally new-to-the-world combinations. As such, conjoint analysis will have evolved from a branch of axiomatic measurement theory into one of the workhorses of true consumer-driven co-creation and innovation. A happy outcome will be that hitherto the less easy-to-articulate but nonetheless strong consumer needs will more easily drive the combination of ideas into new products.

An overview

We may feel certain that some forty years ago, when Luce and Tukey first published their article on conjoint measurement, they probably could not have envisioned the practical and theoretical ramifications from that seminal paper. One way to characterize the 1960's is to liken it to a crucible in which many ideas were poured and allowed to mix. The 1960's in many ways were about advancing knowledge, and expanding one's intellectual frontiers. Mathematical psychologists in particular were interested in creating a more solid foundation for their axioms underlying subjective measurement. We owe a great deal to these pioneers, and to that extraordinarily rich *zeitgeist* which promoted such notions as conjoint measurement, albeit in rather esoteric form, presented in a formidable 36 page paper in an arcane, newly founded journal (Journal of Mathematical Psychology, volume 1, number 1).

It was to the particular genius of researchers and marketers, however, that we owe the explosive growth and the wonderful maturation of conjoint analysis. In the hands of academic researchers alone the field would have matured, but the applications would not have been particularly broad. Perhaps the mathematical treatment would have become somewhat easier, and a bit less arcane. However, the use of conjoint analysis for concept research, so important in the business world, might never have happened. Without that explosive growth by practitioners facing everyday business problems we probably would not be seeing the flourishing field of conjoint measurement, ranging from the capability to deal with hundreds of concept elements, the inexpensive implementation on the Internet, the expansion into pure visual stimuli, and the culmination (so far) into integrated databases (i.e., the 'genomics approach') as exemplified by the It! databases, and the tool by which to combine disparate ideas from unconnected fields into new products. Perhaps we are witnessing only the start of an even bigger revolution in understanding, spurred on by conjoint analysis, not so much in its formal foundations as in its myriad applications by those who profit from its practical applications.

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