Conjoint Analysis, Related Modeling, and Applications

Chapter prepared for

Advances in Marketing Research: Progress and Prospects

[A Tribute to Paul Green's Contributions to Marketing Research Methodology]

John R. Hauser

Massachusetts Institute of Technology

Vithala R. Rao

Cornell University

September 23, 2002

Origins of Conjoint Analysis

Conjoint analysis has as its roots the need to solve important academic and industry problems. Elsewhere in this volume, Carroll, Arabie, and Chaturvedi (2002) detail Paul Green's interest and contributions to the theory and practice of multidimensional scaling (MDS) and clustering to address marketing problems. See also Green and Carmone (1970) and Green and Rao (1972). The strengths of MDS include the ability to represent consumer multidimensional perceptions and consumer preferences relative to an existing set of products. MDS decomposes more holistic judgments to uncover these perceptions and preferences.

Paul, with extensive experience in product development from his days at Dupont, sought to augment the power to MDS. He sought a means to decompose consumer preferences into the partial contribution (partworth) of product features. In this manner, researchers could not only explain the preferences of existing products, but could simulate preferences for entirely new products that were defined by feature combinations. Such a method could also be used to decompose perceptions if a perceptual variable, say "ease of use" was used as the dependent measure rather than "preference." This would solve the problem of reverse mapping in MDS – the challenge of translating a point from perceptual space into a corresponding point (or set of points) in product-feature space.

This mapping challenge was related to axiomatic work in psychometrics. Authors such as Luce and Tukey (1964) and Krantz, Luce, Suppes, and Tversky (1971) were exploring the behavioral axioms that would enable a decomposition of an overall judgment. In a seminal paper (Green and Rao 1971), Paul drew upon this conjoint measurement theory, adapted it to the solution of marketing and product-development problems, considered carefully the practical measurement issues, and opened a flood-gate of research opportunities and applications.[1]

Conjoint Measurement or Conjoint Analysis

Conjoint measurement has psychometric origins as a theory to decompose an ordinal scale of holistic judgment into interval scales for each component attributes. The theory details how the transformation depends on the satisfaction of various axioms such as additivity and independence. However, in real problems we expect that such axioms are approximate at best.

[1] The reviewers of the article were quite apprehensive of the value of this approach. But, the Editor at the time, Professor Ralph Day had the vision to see the enormous potential for this research stream.

The real genius is making appropriate tradeoffs so that real consumers in real market research settings are answering questions from which useful information can be inferred.

In the thirty years since the original conjoint analysis article, researchers in marketing and other disciplines, led by the insight and creativity of Paul Green, have explored these tradeoffs. While valid and interesting intellectual debates remain today and while the field continues to advance with new insights, theory, and methodology, we are left with the legacy of an elegant theory being transformed into an evolving research stream of great practical import. While the earlier, axiomatic work is often called conjoint measurement, we choose to call the expanded focus conjoint analysis.

Paul Green's Contributions

Paul Green himself has contributed almost 100 articles and books on conjoint analysis. He was there in the beginning and he is there now. He has embraced (or led) new developments including the move to metric measures (Carmone, Green, and Jain 1978), evaluations of non-additivity (Green and Devita 1975), hybrid methods to combine data sources and reduce respondent burden (Green 1984), and new estimation methods such as hierarchical Bayes methods (Lenk, et. al. 1996). He has further led the way with seminal applications such as the application of conjoint analysis to really new products such as Marriott's Courtyard (Wind, et al. 1989) and the EZPass system (Green, Krieger, and Vavra 1999). It is safe to say that conjoint analysis would not be where it is today without Paul's leadership.

In this paper we pay homage to Paul by reviewing some of the enormous breadth of research in conjoint analysis. We try to highlight many of the theoretical and practical issues and we try to illustrate many of the contributions of the past thirty years. In a field so vast, we can provide but an overview. We encourage our readers to explore this field further. Our focus is on the measurement and representation of consumer preferences. A companion paper in this volume reviews buyer choice simulators, optimizers, and the dynamic models that use conjoint-analysis data (Green, Krieger, and Wind 2002).

Conjoint Analysis is a Journey not a Destination

The essence of conjoint analysis is to identify and measure a mapping from more detailed descriptors of a product or service onto a overall measure of the customer's evaluation of that product. We begin with an example from Paul's classic paper (with Jerry Wind) that was published in the *Harvard Business Review* (1975). Paul and Jerry were designing a carpet cleaner and chose to describe the carpet cleaners by five features:

- package design – one of three levels illustrated in Figure 1
- brand name – one of three brand names – K2R, Glory, and Bissell
- seal – either the carpet cleaner had a Good Housekeeping seal of approval or it did not
- guarantee – either the carpet cleaner had a money-back guarantee or it did not
- price – specified at the three discrete levels of $1.19, $1.39, and $$1.59

Respondents were given a fractional factorial design of profiles, each of which was described by the levels of the features it contained, and were asked to rank order cards representing the profiles in order to indicate their preferences for the profiles. Because a full 3x3x2x2x3 design would have yielded 108 profiles, they chose a balanced orthogonal design kept the respondent's task within reason – each respondent had to rank but 18 profiles.

When the data collection was complete, Paul and Jerry assumed that the overall preference was an additive sum of the "partworths" of the features, represented each feature by a series of dummy variables, and used monotonic regression to estimate the contribution of each feature to overall preference. In this manner partworths were obtained for each respondent enabling the researchers flexibility to (1) cluster the partworths to identify segments and (2) simulate preferences for new products by adding those products to the respondents' choice sets and re-computing the implied preferences. (Here they assumed that each respondent would purchase their most preferred product.)

In the twenty-seven years since this article was published (thirty-one years since the pioneering Green and Rao 1971 article), much has changed, but the basic structure of the conjoint challenge remains. We organize this short review around the elements pioneered by Paul and provide examples of how each element has evolved. Because of the sheer breadth of today's applications, we have space but to highlight the most common examples. The basic elements of our review are:

- how a product or service is decomposed (additive function of five features in 1975)
- stimuli representation (cards in 1975)
- methods to reduce respondent burden (orthogonal factorial design in 1975)
- data collection format (rank order of cards in 1975)

- estimation (monotonic regression in 1975)

In another paper in this volume, Green, Krieger, and Wind (2002) address how conjoint estimates are used to segment the market, identify high-potential product designs, plan product lines, and forecast purchase potential.

Decomposing the Product or Service

There are at least two considerations in decomposing the product or the service: (1) the elements into which the product is decomposed and (2) the function by which the elemental decomposition is mapped onto overall preference.

In the carpet-cleaner example, the elemental decomposition was into physical features. This has been the most common application of conjoint analysis in the last thirty years and is the most relevant if the product-development team is facing the decision about which features to include in a product design. However, conjoint analysis has also been used with more qualitative features such as "personalness," "convenience," and "quality" of health care, (e.g., Hauser and Urban 1977). Such applications occur early in the product-development process when the team is trying to understand the basic perceptual positioning of the product or service.

The key consideration in the decomposition is that the elements be as complete as feasible, understandable to the respondents, useful to the product-development team, and as separable as feasible. Researchers have used detailed qualitative interviews, focus groups, contextual engineering, and lead-user analyses to identify the appropriate elements. In some cases, more elaborate methods are used in which detailed phrases (obtained from customer interviews) are clustered based on similarity or factor-analyzed based on evaluations to identify groups of phrases which are then represented by a summary feature (e.g., Green, Carmone and Fox (1969); Green and McMennamin (1973); Griffin and Hauser 1993; Hauser and Koppelman 1979; Rao and Katz 1971).

If the features are chosen carefully, then they will satisfy a property known as "preferential independence." Basically, two features, f_1 and f_2, are preferentially independent of the remaining features if tradeoffs among f_1 and f_2 do not depend upon the remaining features. Preferential independence is extremely important to the researcher because if each set of features is preferentially independent of its complement set, then the (riskless) conjoint function can be represented by an additive (or multiplicative) decomposition (Keeney and Raiffa 1976, Theorem

3.6). Whenever preferential independence is not satisfied, the conjoint function is more difficult to estimate and interactions among features are necessary as illustrated for food menus by Green and Devita (1975) and Carmone and Green (1981). There are many decompositional forms and related independence conditions.

In some cases, the preference is defined over risky features – that is, the features are described by a probability density function rather than simply as know features. In this case, some researchers have represented the features as lotteries and have applied von Neumann-Morgenstern utility measurement (Eliashberg 1980; Eliashberg and Hauser 1985; Hauser and Urban 1979). See Farquhar (1977) for a review of related independence conditions and functional forms.

Representation of Stimuli

In the carpet-cleaner example, Paul and Jerry represented the product profiles by verbal and pictorial descriptions on cards that were then sorted by respondents. In the past thirty years, stimuli representations have been limited only the by imagination of the researchers. For example, in the design of the EZ Pass system, Vavra, Green, and Krieger (1999) sent videotapes and other descriptive materials to respondents so that they fully understood the innovation and its features. Wind, et al. (1989) used combinations of physical models, photographs, and verbal descriptions. Recently, with the development of the Internet, researchers have begun to exploit the rich multi-media capabilities of the web to provide virtual prototypes to web-based respondents (Dahan and Srinivasan 2000). Indeed, this area of conjoint analysis is growing rapidly with many firms providing panels of literally millions of respondents who can respond within days (Buckmann 2000, Dahan and Hauser 2002; Gonier 1999, Nadilo 1999).

Have Mercy on the Respondents

From the beginning, researchers have recognized that conjoint-analysis estimates are only as good as the data from which they are obtained. In the carpet-cleaner example, Paul and Jerry were concerned with respondent wear-out if respondents were asked to rank 108 product profiles. To avoid such wear-out they chose an orthogonal design to reduce the number of profiles (to 18) that any respondent would see. Of course, this design was not without tradeoffs – an orthogonal design implicitly assumes preferential independence and does not allow any interactions to be estimated. Such tradeoffs continue today – there are many methods to reduce respondent burden, each requires careful consideration of the empirical application so that the method is tailored to the information required for the managerial application and is appropriate for the feature structure and respondent task.

We review briefly a few of the methods that have been proposed. As early as 1978, Carmone, Green, and Jain (p. 300) found that most applications demanded a dozen or more features, but that it was difficult for customers to rank more than a dozen profiles. Many researchers have documented that the respondents' task can be burdensome and have suggested that accuracy degrades as the number of questions increases (Bateson, Reibstein, and Boulding, 1987; Green, Carroll, and Goldberg 1981, p. 34; Green, Goldberg, and Montemayor 1981, p. 337; Huber, et. al. 1993; Lenk, et. al. 1996, p. 183; Malhotra 1982, 1986, p. 33; Moore and Semenik 1988; Srinivasan and Park 1997, p. 286). When appropriate, efficient experimental designs are used so that the respondent need consider only a small fraction of all possible product profiles (Addelman 1962; Kuhfeld, Tobias, and Garratt 1994). Tradeoff analysis presents respondents with two attributes at a time and has them evaluate the reduced sets (Jain, et. al. 1979; Johnson 1974; Segal 1982). Two stages can be introduced in which respondents eliminate unacceptable products, unacceptable attributes, or use prior sorting tasks to simplify the evaluation task (Acito and Jain 1980; Green, Krieger, and Bansal 1988; Klein 1988; Malhotra 1986; Srinivasan 1988). Hierarchical integration provides a means to measure preferences among higher-level benefits and then again for features that drive those benefits (Oppewal, Louviere, and Timmermans 1994; Wind, et. al. 1989; Srinivasan and Park 1997).

Many researchers combine these methods with intensity questions (interval and ratio scales) or with self-explicated tasks (Griffin and Hauser 1993; Hauser and Shugan 1980; Neslin 1981; Srinivasan and Wyner 1988; Wilkie and Pessemier 1973). Other researchers have simplified the task. In choice-based conjoint analysis (CBC) respondents simply choose one profile each from many sets of profiles (Carroll and Green 1995; Elrod, Louviere, and Davy 1992; Haaijer, Kamakura, and Wedel 2000; Haaijer, et. al. 1998; Oppewal, Louviere, and Timmermans 1994; Orme 1999). Hybrid conjoint analysis combines self-explicated tasks for each respondent with a master design across respondents of profile-based questions (Akaah and Korgaonkar 1983; Green 1984; Green, Goldberg, and Montemayor 1981). Finally, Hierarchical Bayes (HB) methods improve the predictability of the partworths that have been collected by other means (Lenk, et. al. 1996; Johnson 1999; Sawtooth 1999) and thus, in theory, enable the researcher to obtain estimates with fewer questions.

Each of these methods, when used carefully and responsibly, reduces the respondents' burden and is feasible in large commercial applications. As this remains an area of active research, we expect further developments and, specifically, we expect researchers to experiment with many hybrid combinations of these methods.

Formats of Data Collection

Paul and Jerry asked their respondents to rank order the profiles. Conjoint analysis was born in the belief that the data collection method should ask as little of the respondents as feasible and infer the rest. Most of the early applications relied on ordinal preference data. Even the linear-programming methods transformed overall rank orders into rank orders among pairs (Srinivasan and Shocker 1973a, 1973b). However, toward the end of the 1970s, both academic and industrial researchers began to notice that respondents could, indeed, provide interval, or even ratio, data on preferences among product or service profiles. For example, Carmone, Green, and Jain (1978) state: "(in industrial applications) rating scales … have substituted for strict ranking procedures. … metric analysis … is very robust." In parallel, in their well-know Assessor model, Silk and Urban (1978) and Urban and Katz (1983) were using constant-sum-paired-comparison preference measurements for extremely accurate forecasts for new products. During this period, researchers experimented with many different formats for collecting data on preferences.

Research into question formats continues today with new forms, such as configurators, being used with success. However, this area remains one of strongly-held beliefs and debates. For example, in their defense of the choice-based (CBC) format, Louviere, Hensher and Swait (2000) state: "We suggest that researchers consider transforming ratings data in this way rather than blindly assuming that ratings produced by human subjects satisfy demanding measurement properties." Green, Krieger, Wind (2001) take a more two-sided view and, while acknowledging the potential benefits of the format suggest that "choice-based conjoint studies can be a mixed blessing. The respondent's tasks are extensive." Finally, Orme (1999) suggests that "(CBC) often press the limits of how much information can be successfully evaluated before respondents either quit, glaze over, or start to employ sub-optimal shortcut methods for making choices."

We do not take a stand on which format is best, primarily because each format has its strengths and weaknesses and because the researcher should choose the format carefully as appropriate to the managerial problem and the stimuli being presented. We instead review five major formats: full-profile, partial profile, stated preferences (CBC), self-explicated preferences, and configurators.

Full Profile Evaluations

Full-profile stimuli are similar to those in Figure 1. Each product is described by the levels of the features that it contains. The respondent can be asked to rank order all stimuli or to provide a metric rating of each stimulus. In some hybrid methods, the experimental designs are blocked across respondents. Full-profile analysis remains the most common form of conjoint analysis and has the advantage that the respondent evaluates each profile holistically and in the context of all other stimuli. Its weakness is that the respondent's burden grows dramatically with the number of profiles that must be ranked or rated.

Partial Profile Evaluations

Whenever preferential independence is satisfied, perhaps approximately, tradeoffs among a reduced set of features do not depend upon the levels of the other features. In this case, respondents can evaluate partial profiles in which some of the features are explicit and the other features are assumed constant. Although the number of stimuli can vary from two to many, two stimuli are most common. Although the respondent can be asked only to choose among the partial profiles, it is common to obtain an interval evaluation of the profiles. Figure 2a illustrates a pairwise partial-profile evaluation in which the respondent is asked to provide a metric rating to indicate his or her strength of preference. In fixed designs, the partial stimuli are chosen from a partial design. Recently, there has been significant research on the most efficient manner in which to choose the partial profiles (e.g., Kuhfeld, Tobias, and Garratt 1994).

Because partial profiles are well suited to presentation on computer monitors, researchers have developed adaptive methods in which the n^{th} set of partial profiles presented to respondents is based on the answers to the preceding *n-1* sets of partial profiles. The best-know example of such adaptive selection of partial profiles is Johnson's (1987) adaptive conjoint analysis (ACA). In ACA, respondents are first asked a set of self-explicated questions (see below) to establish initial estimates of importances. Then, ordinary-least-squares (OLS) regression, based on the initial importances and the preceding *n-1* metric paired-comparison questions, provides intermediate estimates of the partworths of each feature and level. The n^{th} pair of profiles are chosen so that they are as equal as feasible in terms of estimated preference – a procedure known as utility balance. ACA has proved robust in practice and is, perhaps, the second most common form of conjoint analysis. Recently, researchers have re-estimated the partworths obtained from ACA with Hierarchical Bayes (HB) methods. (That is, OLS estimates the intermediate partworths that are used to select questions, but, once the data collection is complete, the partworths are re-estimated with HB.) HB appears to be quite effective when fewer questions are asked of each respondent than are typical in the standard ACA interview.

The advantage of ACA is that the questions are chosen for high information content. However, because it is OLS-based, ACA has the potential for endogeneity bias, that is, the n^{th} question, and hence the n^{th} set of independent variables, depend upon the answers, and hence the errors, in the first *n-1* questions. Furthermore, the utility-balance criterion suggests that this bias is always upward and is greater for features that have higher (true) partworths (Hauser, Simester, and Toubia 2002). However, to date, there has been no research to establish whether or not this theoretical bias is managerially relevant.

Recently, new methods for adaptive question selection have been proposed that are not OLS based and, instead, choose questions to minimize the uncertainty in parameter estimation. In these "polyhedral" methods each question constraints the feasible set of partworths. Multiple constraints imply that the set of partworths is a multi-dimensional polyhedron in partworth-space. The polyhedron is approximated with an ellipsoid and the longest axis of the ellipsoid provides the means to select the next question. Specifically, if the question vector is selected parallel to the longest axis, then the constraints imposed by the next answer perpendicular to that axis and are most likely to result in the smallest new polyhedron. In addition, this question vector is most likely to lead to constraints that intersect the feasible polyhedron. In this manner, the questions reduce the set of feasible partworths as rapidly as possible. In initial applications and simulations, these question-select methods appear superior to OLS-based utility-balance estimates (Dahan, et. al. 2002; Toubia, Simester, and Hauser 2002). These methods are available as stand-alone options (e.g., FastPace) and are now offered as an option within ACA. In addition, other major suppliers are developing polyhedral-based methods.

<u>Stated Preferences</u>

In 1974 McFadden provided a random utility interpretation of the logit model renewing interest in disaggregate choice models in transportation demand analysis and in econometrics. In random utility models (RUM), the respondent's utility is represented as a (usually linear-in-the-parameters) combination of product or service features, plus an error term. Then, based on the distributional assumptions that are made about the error term, a researcher can calculate the probability that a product, defined by its features, is purchased. For example, if the error terms are independent Gumbel extreme value random variables, then we obtain the logit model. If the error terms are multivariate normal, we obtain the probit model. Initially, such RUM were estimated based on observing (1) the product features of existing products and (2) the choices made by individual consumers. Because such partworths are "revealed" by the marketplace such models became known as "revealed preference models."

While RUM models have many advantages, they suffer from sample selection bias when the set of existing products represents an efficient frontier of the product space. Very often, the data upon which RUM are based is highly collinear. If a new product "stretches" a feature not currently in the data, predictions are difficult. Thus, RUM models have been extended to stated preferences in which the researcher creates product profiles to span the set of feature combinations. The respondent's task is redefined as a choice among product profiles (cf. Louviere, Hensher and Swait 2000). In this form, RUM models have all the characteristics of conjoint analysis, except that the data collection format is varied. See Figure 2b. Specifically, rather than ranking or rating the full product profiles, respondents are asked to choose one profile from each choice set. Each respondent sees multiple choice sets and, usually, the experimental design is completed across many respondents. A null product is often included in the choice sets so that forecasts can be calibrated. The partworths are estimated either with standard RUM analysis (logit or probit) or, increasingly, with Hierarchical Bayes estimation.

Unlike OLS estimation, the experimental design that maximizes efficiency depends upon the parameters of the model, e.g., the partworths. Thus, recent papers have explored "aggregate customization" in which data are collected with an initial experimental design, parameters are estimated, and the experimental design is re-optimized. See, for example, Huber and Zwerina (1996), Arora and Huber (2001), and Sandor and Wedel (2001). More recently, polyhedral methods have been extended to the choice-based format and provide a means to customize experimental designs within respondents. Early research suggests that, for some levels of heterogeneity and for some levels of uncertainty the polyhedral methods produce experimental designs that lead to better estimates than those obtained by aggregate customization (Toubia, Simester, and Hauser 2002).

Self-explicated Methods

In the carpet-cleaner example, Paul and Jerry decomposed each respondent's preferences into partworths which represented the values of the various levels of the carpet-cleaner features. However, it is possible to compose preferences by asking respondents questions about the features themselves. Such compositional methods require two types of questions. First, the respondent must provide the relative value of each level within a feature and, second, provide the relative value of the features. Figure 2c provides examples of the latter.

In theory, it should be difficult for respondents to provide such judgments, but empirical experience suggests that they are quite accurate. For example, one conjoint method, Casemap, relies entirely on self-explicated judgments and has proven to predict well (Bucklin and Srinivasan 1991; Srinivasan 1988; Srinivasan and Wyner 1988). For an interesting review of self-explicated models, see Wilkie and Pessemier (1973) and for a comparison of alternative formats, see Griffin and Hauser (1993).

Self-explicated methods have also proven powerful when used in conjunction with decompositional methods. For example, Paul has used self-explicated methods effectively in hybrid conjoint analysis – a method in which each respondent's self-explicated partworths modify overall partworths that are estimated with an experimental design that is blocked across respondents. ACA, reviewed earlier, is another hybrid in which self-explicated and metric partial profile data are combined effectively to enhance accuracy.

Configurators

Configurators represent a relatively recent form of conjoint-analysis data. With configurators, the respondent is given the choice of all levels of all features and uses a web interface to select his or her preferred set of features. For example, at Dell.com potential computer purchasers "configure" their machine by choosing memory, processor speed, peripherals, and other features. Figure 2d is an example of a configurator for laptop computer bags. The form of data collection is relatively new. Applications include Franke and von Hippel

(2002), Liechty, Ramaswamy and Cohen (2001), Urban and Hauser (2002) and von Hippel (2001).

Estimation Methods

Because Paul and Jerry asked their respondents to rank order the eighteen carpet-cleaner profiles, the natural choice for estimation was monotonic regression. Since 1975, researchers have expanded greatly the repertoire of estimation tools. We review here five classes of estimation methods.

<u>Regression-based Methods</u>

The basic conjoint problem is to estimate the partworths that best explain the overall preference judgments made by respondents. If the preference judgment is an approximately interval scale, then the partworths can be represented by dummy variables and ordinary least-squares (OLS) regression is a natural and relatively straight-forward means with which to estimate the partworths.[2] If the data are only monotonic, then the least-squares criterion is replaced with a "stress" criterion. Further, if there are known constraints, such as the constraint that a lower price is preferred to a higher price, then such constraints can be added to either the metric or monotonic regressions. One particularly interesting form of regression is the Linmap algorithm (Srinivasan and Shocker 1973a, 1973b). In Linmap the profile ranks are converted to pairwise ranks and the resulting inequality constraints are noted. A linear loss function is defined such that any violations of the constraints are weighted by the magnitude of the violation and a linear program is used to minimize the sum of these violations. Not only has Linmap proven accurate in a number of applications, but it provides a natural structure to handle constraints.

The advantages of the regression-based methods are their simplicity and the wide availability of software with which to perform estimations. If all the appropriate normality assumptions are satisfied, then regression may be the most efficient. However, regression requires at least as many observations as parameters. This presents a real challenge with large conjoint designs (many features and levels). In some cases respondent fatigue suggests much smaller designs. Even when the number of observations exceeds the number of parameters, the number of degrees of freedom may not be sufficient for good estimation. Fortunately,

[2] Naturally, there is dependence among the dummy variables for a feature. One value can be set arbitrarily.

researchers have mitigated this problem by combining data from self-explicated preferences with data from either full- or partial-profile methods (Green 1984, Johnson 1987). Such hybrid methods have been used very successfully in large conjoint applications (e.g., Wind, et. al. 1989).

Random-Utility Models

When the data are choice-based (CBC), researchers have turned to random-utility models. The basic idea is that the assumption of utility maximization combined with distributional assumptions on the unobserved errors implies a known function that maps the partworth levels onto the probabilities that each profile is chosen from a given choice set. Many specifications of RUM lend themselves nicely to maximum-likelihood estimation (MLE). The most common models are the logit model (Gumbel errors), the probit model (multivariate normal errors), and the nested-logit model (generalized extreme value errors). See Ben-Akiva and Lerman (1985), Louviere, Hensher and Swait (2000), or McFadden (2000).

The advantages of RUM models are that they are derived from transparent assumptions about utility maximization, that they lend themselves naturally to efficient MLE estimation, that estimation software is widely available, and that they are a natural means to estimate partworths from choice-based data. Not only have they proven accurate, but Louviere, Hensher and Swait (2000) review sixteen empirical studies in marketing, transportation, and environmental valuation in which stated-choice models (CBC) provide estimates similar to those obtained by revealed preference choice models.[3] The disadvantage of the RUM models is that, prior to HB estimation, the number of choice observations required for partworth estimation was too large to obtain practical estimates for each respondent. Most experimental designs are blocked across respondents. However, like regression-based hybrids, this, too, can be mitigated with the judicious use of self-explicated importances (Ter Hofstede, Kim, Wedel 2002).

Hierarchical Bayes Estimation

One of the greatest practical challenges in conjoint analysis is to get sufficient data for partworth estimates with relatively few questions. This leads to tension in the experimental design. The researcher would like partworth estimates for each respondent so that (1) he or she

[3] By similar we mean similar relative values of the partworths. Stated-preference partworths may need to be rescaled for choice predictions if they are to provide the same predictions as revealed-preference models (Louviere, Hensher, and Swait 2000). It depends on the application.

could capture the heterogeneity of preferences, (2) design a product line, and (3) segment the market if necessary. On the other hand, if the respondent is asked too many questions, the respondent might become fatigued and either quit the interview, especially in web-based formats, or provide data that are extremely noisy.

Hierarchical Bayes (HB) estimation addresses this tension in at least three ways. First, HB recognizes that the researcher's goals can be achieved if he or she knows the distribution of partworths. Second, while consumers are heterogeneous, there is information in the population distribution that can be used to constrain the estimates of the partworths for each respondent. And, third, prior information and beliefs can be used effectively. In addition, the philosophy is changed slightly. The researcher does not attempt to estimate point-values of the partworths, but endeavors to fully characterize the uncertainty about those estimates (mean and posterior distribution).

The basic idea behind HB is quite simple. For each respondent, the uncertainty about that respondent's partworths is characterized by a known distribution. However, the parameters of that distribution are themselves distributed across the population (hence the hierarchy). We then establish prior beliefs and update those beliefs based on the data and Bayes theorem. The challenge is that the equations do not lend themselves to simple analytical solutions. Fortunately, with the aid of Gibbs sampling and the Metropolis Hastings Algorithm, it is feasible to obtain updates for the specified parameters (Allenby and Rossi 1999; Arora, Allenby and Ginter 1998; Johnson 1999; Lenk, et. al. 1996; Liechty, Ramaswamy and Cohen 2001; Sawtooth Software 1999). HB estimates have proven quite accurate in simulation and in empirical applications (Andrews, Ansari, and Currim 2002, Lenk, et. al. 1996, Dahan, et. al. 2002). Hierarchical Bayes estimates appear particularly useful for situations in which the partworths are relatively homogeneous and/or there is significant response errors (Toubia, Simester, and Hauser, 2002).

The details of HB estimation are beyond the scope of this paper. However, we note that HB estimation has been applied to all forms of conjoint analysis data collection. For example, although ACA uses a form of OLS for intermediate estimates and FastPace uses analytic-center methods for intermediate estimates, both have used HB successfully to re-estimate partworths after all data have been collected.

Direct Computation Based on Self-Explicated Importances

In methods such as Casemap, the partworths are computed directly. In addition, as discussed above, such direct computations can be combined with other forms of estimation.

Estimation Based on New Optimization Methods

In the last few years, researchers have recognized the power of new optimization methods. These optimization methods run extremely fast on today's computers and provide the means to do extensive computations between questions (for intermediate estimates) or after all the data are collected (for revised estimates). There are many such approaches. We review three.

Analytic-center estimation. When there are fewer questions than there are partworths to be estimated, the questions can be viewed as constraints on the parameter space. The resulting feasible region is a multidimensional polyhedron. One estimate is the center of the polyhedron. Such estimates are justified based on either uniform priors or the proven (local) robustness of equally-weighted models (Dawes and Corrigan 1974; Einhorn 1971, Huber 1975; Moore and Semenik 1988; Srinivasan and Park 1997). Although computing the true center of a polyhedron is computationally intractable, the analytic center provides an extremely close approximation and can be computed rapidly (Freund (1993), Nesterov and Nemirovskii (1994), Sonnevend (1985a, 1985b), and Vaidja (1989).[4] For the specific algorithm, and methods to handle response errors, see Toubia, Simester, and Hauser (2002). Simulations suggest that AC estimation is quite accurate and provides relative advantages when the partworths are heterogeneous and/or response errors are not too large. It is particularly useful for estimates when there are fewer questions than there are parameters.

Support-vector machines. One challenge in conjoint has been the specification of the preference function. If each pair of features is not preferentially independent of its complement set, then the preference function is not separable. However, estimating all interactions often requires more data than are feasible to collect. Evgeniou, Boussios, and Zacharia (2002) propose a solution using support-vector machines (SVM). SVM are common in machine learning and artificial intelligence. The basic idea is to create new variables to represent both interactions and non-linearities, but to write the function as linear in its parameters. This leads to a large number of parameters to be estimated. However, SVM machines control for this complexity by

[4] The analytic center is the point that minimizes the geometric mean of the distances to the faces of the polyhedron.

imposing a constraint on the sum of squares of the linear parameters. A quadratic program then identifies the key parameters. Early applications suggest strong promise for the method.

Genetic algorithms. Conjoint analysis identifies high-potential product concepts by first estimating the partworths of the features of those products. Recently, researchers have experimented with genetic algorithms to identify those product concepts directly (Affinnova.com). As in conjoint analysis, each product is represented by its features and these features are reinterpreted as "genes." A respondent is shown a representative set of concepts, each of which is a set of genes. The respondent rates the product on a three-point scale (green, yellow, red). This rating determines the likelihood that the product concept will "reproduce" into the next generation. Then, following a genetic algorithm, new progeny concepts are generated based on the genes of their parents. These progeny concepts are shown to further respondents and the process continues until the population stabilizes on a small set of product concepts.

Conjoint Analysis is Alive, Well, and Growing

Little could anyone have known that, when Paul pioneered conjoint analysis, the field would grow to be what it is today. Theory and practice have exploded to address a myriad of issues. But the journey is not over; indeed it has just begun. We are confident that the field will continue to be as vibrant for many years to come. With this vibrancy comes challenges. We review a few of those challenges here, arranged by pragmatic issues, conceptual issues, and methodological issues.

Pragmatic Issues

Conjoint analysis has solved many managerial problems and will continue to do so. Such applications encourage a focus on both expanding the frontier of capabilities and on tradeoffs along that frontier. Some of these pragmatic issues include the following:

1. Analysis of tradeoffs between complexity of analysis, cost and difficulty of data collection, and managerial application. Currently, no method dominates in all situations with each method providing both strengths and weaknesses. To date there is no comprehensive theory to guide decisions among methods.
2. Matching analysis methods to new forms of data collection including web-based methods, rich multimedia representations, configurators (e.g., Dell.com) and computational applets that run during data collection. With more computing power

available during data collection, new heuristics, new methods, and new representations are now feasible.

3. Meta-analyses of the varied applications under a variety of managerial problems, e.g., tourism, entertainment, health maintenance, gambling, development of complex products and systems, legal disputes, and corporate acquisitions. There are literally hundreds, perhaps thousands, of applications completed each year. Meta-analyses of these applications could raise interesting research hypotheses.
4. Comparative empirical studies of the reliability and validity including internal validity, convergent validity, and external validity. It is common to test internal validity (e.g., holdout profiles), but much less common to test external validity. More importantly, there is amble opportunity to test the <u>comparative</u> strengths of the various methods.
5. Methods to handle larger numbers of features, especially, for use in the new product development processes. Complex products such as automobiles and office equipment (e.g., copiers) often require consumer information on hundreds of features. More importantly, the fuzzy front end of product development is focused on screening large numbers of potential features to identify opportunities. New methods such as HB, polyhedral methods, and hybrid methods have greatly expanded the data collection capabilities of conjoint analysis. But industry demands continue for even larger numbers of features and levels.

Conceptual Issues

It is common in any scientific field that new applications and new challenges spawn new theory. This is certainly true in the field of conjoint analysis. We cite here but a few of the conceptual issues.

6. One of the most hotly debated issues in the field is the relative merits of the various data-collection methods. We see substantial opportunities for an underlying theory coupled with empirical tests to explore which situations favor one or more of the various forms of data collection including full-profile ratings, (metric) paired comparison data, self-explicated data, and (quantal) stated preference.

7. Price plays a special role in consumer preferences. It is not a feature of a product *per se*, but rather that which the consumer pays in return for features. It can be a signal, interact with the prices of other products, and be a strategic weapon. See, for example, Rao and Sattler (2000) and Foutz, Rao and Yang (2002). Among the many price related issues are:
    a. Effects of reference points on partworth measurement and evaluation
    b. Relative accuracy of price partworths (across methods and data collection) and their relationship to pricing decisions
8. Conjoint analysis provides an exacting measurement of consumer preferences, but to design a product or set marketing variables a firm must often do so in light of the actions and potential actions of its competitors. We are now beginning to see equilibrium (or non-equilibrium) models, which include the reactions of firms, competitors, and customers, coupled to conjoint analyses. One example is Kadiyali, Sudhir and Rao (2001).
9. Conjoint analysis is based on measurements that inform respondents about product features. However, in real markets such information diffuses and does not happen instantaneously. Thus, we expect further development of methods that combine the diffusion of information among customers with models of how customers will choose based on that information.
10. Conjoint analysis is based on consumer measurement. But consumer measurement means real consumers answering questions about potential behavior in situations that may differ from the situation of the measurement. This opens the opportunities for research on learning, wear-out, self-perception biases, and other phenomena such as task presentation and task order.

Methodological Issues

As application and theory advance, so will methodology. Today we can handle larger designs, with more complex tasks, and more relevant stimuli. These advancements will continue. Among the methodological issues are:

11. With the advent of web-based interviewing, each consumer can be asked multiple types of questions. We can also image studies in which the type of question is varied across respondents. Hybrid methods such as Green's Hybrid Conjoint Analysis and

Johnson's Adaptive Conjoint Analysis have been successful . We anticipate further exploration of hybrid methods that combine data from multiple data sources.

12. A related issue is the use of information from other respondents to inform each respondent's partworth estimates. This includes methods such as:
    a. Hybrid Conjoint approaches
    b. Hierarchical Bayes methods
    c. Use aggregate market shares and product archeology. For example, see the models proposed by Berry, Levinsohn and Pakes 1995, 1998).
13. Improved methods for adaptive data collection based on data from either prior respondents (aggregate customization), prior questions, or both.
14. Many new methods have been proposed in the last few years. There are ample research opportunities to evaluate these many methods including:
    a. Support-vector machines for higher-level interactions,
    b. Genetic algorithms for question design,
    c. Discrete optimization for adaptive full profile tasks,
    d. Polyhedral question design for CBC and for metric paired comparisons,
    e. Analytic center estimation,
    f. Neural networks for improved estimation,
    g. Genetic programming methods for analysis (Koza 1992),
    h. Bayesian methods to "listen in" on trusted Internet agents.
15. And, finally, managers are always seeking insight with which to make cost vs. benefit tradeoffs. This includes the analysis of the value of sample information to effect tradeoffs among the cost of a study and the value of the study. This is particularly relevant in the early stages of product development.

Summary and Conclusions

Thirty years ago, in the time before time, or at least before the PC, he took pen in hand and scribbled a few equations. Conjoint analysis was born. Looking back we can simply say that we've come a long way, but that the journey continues. Mostly importantly, Paul will continue to lead the way.

References

Acito, Franklin and Arun K. Jain (1980), “Evaluation of Conjoint Analysis Results: A Comparison of Methods,” *Journal of Marketing Research*, 17, (February), 106-112.

Addelman, S. (1962), “Orthogonal Main-Effect Plans for Asymmetrical Factorial Experiments,” *Technometrics*, 4, 1, (February), 21-46.

Addelman, S. (1962), “Symmetrical and Asymmetrical Fractional Factorial Plans,” *Technometrics*, 4, 1, (February), 47-58.

Akaah, Ishmael P. and Pradeep K. Korgaonkar (1983), “An Empirical Comparison of the Predictive Validity of Self-explicated, Huber-hybrid, Traditional Conjoint, and Hybrid Conjoint Models,” *Journal of Marketing Research*, 20, (May), 187-197.

Allenby, Greg M. and Peter E. Rossi (1999), “Marketing Models of Consumer Heterogeneity,” *Journal of Econometrics*, 89, (March/April), 57-78.

Andrews, Rick L., Asim Ansari, and Imran S. Currim (2002), “Hierarchical Bayes versus Finite Mixture Conjoint Analysis Models: A Comparison of Fit, Prediction, and Partworth Recovery,” *Journal of Marketing Research*, 39, (February), 87-98.

Arora, Neeraj, Greg M. Allenby and James L. Ginter (1998), “A Hierarchical Bayes Model of Primary and Secondary Demand,” *Marketing Science*, 17, 1, 29-44.

Arora, Neeraj and Joel Huber (2001), “Improving Parameter Estimates and Model Prediction by Aggregate Customization in Choice Experiments,” *Journal of Consumer Research*, 28, (September), 273-283.

Bateson, John E. G., David Reibstein, and William Boulding (1987), “Conjoint Analysis Reliability and Validity: A Framework for Future Research,” *Review of Marketing*, Michael Houston, Ed., 451-481.

Ben-Akiva, Moshe and Steven R. Lerman (1985), *Discrete Choice Analysis*, (Cambridge, MA; MIT Press).

Berry, Steven , James Levinsohn and Ariel Pakes (1995), “Automobile Prices in market Equilibrium,” Econometrica, 63 (4), 841-890.

Berry, Steven , James Levinsohn and Ariel Pakes (1998), “Differentiated Products Demand Systems from a Combination of Micro and macro Data: The New Car Market,” Working Paper, (New Haven, CT: Yale University).

Bucklin, Randolph E. and V. Srinivasan (1991), “Determining Interbrand Substitutability Through Survey Measurement of Consumer Preference Structures,” *Journal of Marketing Research*, 28, (February), 58-71.

Buckman, Rebecca (2000), “Knowledge Networks’ Internet Polls Will Expand to Track Web Surfers,” *Wall Street Journal*, (September 7).

Carmone, Frank J. and Paul E. Green (1981), “Model Misspecification in Multiattribute Parameter Estimation,” *Journal of Marketing Research*, 18, (February), 87-93.

Carmone, Frank J., Paul E. Green, and Arun K. Jain (1978), “Robustness of Conjoint Analysis: Some Monte Carlo Results,” *Journal of Marketing Research*, 15, (May), 300-303.

Carroll, Doug, Phipps Arabie, and Anil Chaturvedi (2002), “Multidimensional Scaling and Clustering and their Applications,” *Advances in Marketing Research: Progress and Prospects*, (Philadelphia, PA: Wharton School Press).

Cattin, Philippe and Girish Punj (1984), “Factors Influencing the Selection of Preference Model Form for Continuous Utility Functions in Conjoint Analysis,” *Marketing Science*, 3, 1, (Winter), 73-82.

Cattin, Philippe and Dick R. Wittink (1982), “Commercial Use of Conjoint Analysis: A Survey,” *Journal of Marketing*, 46, (Summer), 44-53.

Corstjens, Marcel L. and David A. Gautschi (1987), “Formal Choice Models in Marketing”, Marketing Science, 2 (Winter), 19-56.

Dahan, Ely and John R. Hauser (2002), “The Virtual Customer,” forthcoming, *Journal of Product Innovation Management*, 19, (September).

Dahan, Ely and V. Srinivasan (2000), “The Predictive Power of Internet-Based Product Concept Testing Using Visual Depiction and Animation,” *Journal of Product Innovation Management*, 17, 99-109.

Dawes, Robin M. and Bernard Corrigan (1974), “Linear Models in Decision Making,” *Psychological Bulletin*, 81, (March), 95-106.

Einhorn, Hillel J. (1971), “Use of Nonlinear, Noncompensatory, Models as a Function of Task and Amount of Information,” *Organizational Behavior and Human Performance*, 6, 1-27.

Eliashberg, Jehoshua (1980), "Consumer Preference Judgments: An Exposition with Empirical Applications," *Management Science*, 26, 1, (January), 60-77.

Eliashberg, Jehoshua and John R. Hauser (1985), “A Measurement Error Approach for Modeling Consumer Risk Preference,” *Management Science*, 31, 1, (January), 1-25.

Elrod, Terry, Jordan Louviere, and Krishnakumar S. Davey (1992), “An Empirical Comparison of Ratings-Based and Choice-based Conjoint Models,” *Journal of Marketing Research* 29, 3, (August), 368-377.

Evgenoiu, Theodoros, Constantinos Boussios, and Giorgos Zacharia (2002), “Generalized Robust Conjoint Estimation,” Working Paper, (Fontainebleau, FR.: INSEAD).

Farquhar, Peter H. (1977), “A survey of Multiattribute Utility Theory and Applications,” *Studies in Management Sciences*, 59-89.

Foutz, Y. Natasha Zhang, Vithala R. Rao and Sha Yang (202), “Incorporating Consumer Reference Effects into Choice-based Conjoint Analysis: An Application to Online and Offline Channel Choices” Working paper, (Ithaca, NY: Johnson Graduate School of management, Cornell University).

Franke, Nikolaus and Eric von Hippel (2002), “Satisfying Heterogeneous User Needs via Innovation Toolkits: The Case of Apache Security Software,” Working Paper #4341-02, (Cambridge, MA: MIT Sloan School of Management).

Freund, Robert (1993), “Projective Transformations for Interior-Point Algorithms, and a Superlinearly Convergent Algorithm for the W-Center Problem,” *Mathematical Programming*, 58, 385-414.

Gonier, Dennis E. (1999), “The Emperor Gets New Clothes,” Paper presented at the Advertising Research Foundation’s On-line Research Day and available at www.dmsdallas.com. (January).

Green, Paul E. (1974), “On the Design of Choice Experiments Involving Multifactor Alternatives,” *Journal of Consumer Research*, 1, (September).

Green, Paul E., (1984), “Hybrid Models for Conjoint Analysis: An Expository Review,” *Journal of Marketing Research*, 21, (May), 155-169.

Green, Paul E., Frank J. Carmone, and Leo B. Fox (1969), "Television Programme Similarities: An Application of Subjective Clustering," *Journal of the Market Research Society*, 11, 1, 70-90.

Green, Paul E., J. Douglas Carroll and Frank J. Carmone (1977-78), "Superordinate Factorial Designs in the Analysis of Consumer Judgments," *Journal of Economics and Business*, 30, 1977-78.

Green Paul E., J. Douglas Carroll and S. M. Goldberg (1981), "A General Approach to Product Design Optimization via Conjoint Analysis," *Journal of Marketing*, 45, (Summer), 17-37.

Green, Paul E., W. S. DeSarbo and P. K. Kedia (1980), "On the Insensitivity of Brand Choice Simulations to Attribute Importance Weights," *Decision Sciences*, (July), 11, 439-450.

Green Paul E. and M. Devita (1974), "A Complementary Model of Consumer Utility for Item Collections," *Journal of Consumer Research*, 1, (December). 56-67

Green, Paul E. and M. T. Devita (1975), "An Interaction Model of Consumer Utility," *Journal of Consumer Research*, 2, (September), 146-153.

Green, Paul E., Stephen M. Goldberg, and Mila Montemayor (1981), "A Hybrid Utility Estimation Model for Conjoint Analysis," *Journal of Marketing*, 45, 1, (Winter), 33-41.

Green, Paul E., Stephen M. Goldberg, and James B. Wiley (1982), "A Cross Validation Test of Hybrid Conjoint Models," in *Advances in Consumer Research*, 10, Richard P. Bagozzi and Alice M. Tybout, eds., (Ann Arbor, MI: Association for Consumer Research), 147-150.

Green, Paul E. and Kristiaan Helsen (1989), "Cross-Validation Assessment of Alternatives to Individual-Level Conjoint Analysis: A Case Study," *Journal of Marketing Research*, 24, 3, (August), 346-350.

Green, Paul E., Kristiaan Helsen, and Bruce Shandler (1988), "Conjoint Internal Validity Under Alternative Profile Presentations," *Journal of Consumer Research*, 15, (December), 392-397.

Green Paul E. and A. M. Krieger (1991), "Product Design Strategies for Target-Market Positioning," *Journal of Product Innovation Management*, 8 (Fall), 189-202.

Green Paul E. and A. M. Krieger (1992), "An Application of a Product Positioning Model to Pharmaceutical Products," *Marketing Science*, 11, 2, (Spring), 117-132.

Green, Paul E. and Abba Krieger (1996) "Individual Hybrid Models for Conjoint Analysis," *Management Science*, 42, 6, (June), 850-867.

Green, Paul E. and Abba Krieger (1985),"Choice Rules and Sensitivity Analysis in Conjoint Simulations," *Journal of the Academy of Marketing Science*, (Spring) 1988.

Green, Paul E. and Abba Krieger (1985), “Models and Heuristics for Product Line Selection,” *Marketing Science*, 4, 1, (Winter), 1-19.

Green, Paul E. and Abba Krieger (1989), “Recent Contributions to Optimal Product Positioning and Buyer Segmentation,” *European Journal of Operational Research*, 41, 2,127-141.

Green, Paul E., Abba Krieger, and Manoj K. Agarwal (1991), “Adaptive Conjoint Analysis: Some Caveats and Suggestions,” *Journal of Marketing Research*, 23, 2, (May), 215-222.

Green, Paul E., Abba Krieger, and Pradeep Bansal (1988), “Completely Unacceptable Levels in Conjoint Analysis: A Cautionary Note,” *Journal of Marketing Research*, 25, 3, (August), 293-300.

Green Paul E., A. M. Krieger and T. Vavra (1999), “Evaluating EZ-Pass: Using Conjoint Analysis to Assess Consumer Response to a New Tollway Technology,” Marketing Research, Vol. (Summer), 5-16,

Green, Paul E., Abba M. Krieger, and Yoram Wind (2001), “Thirty Years of Conjoint Analysis: Reflections and Prospects,” *Interfaces,* 31, 3, Part 2, (May-June), S56-S73.

Green, Paul E., Abba M. Krieger, and Yoram Wind (2002), “Buyer Choice Simulators, Optimizers, and Dynamic Models,” *Advances in Marketing Research: Progress and Prospects,* (Philadelphia, PA: Wharton School Press).

Green, Paul E. and John L. McMennamin (1973), "Market Position Analysis," in Stewart Henderson Britt and Norma F. Guess (eds.), *Marketing Manager's Handbook*, (Dartnell Press: Chicago IL), 543-554.

Green, Paul E. and Vithala R. Rao (1971), “Conjoint Measurement for Quantifying Judgmental Data,” *Journal of Marketing Research*, 8, (August), 355-363.

Green, Paul E. and Vithala R. Rao. *Applied Multidimensional Scaling*. Dryden Press, 1972.

Green, Paul E., Vithala R. Rao and Wayne DeSarbo (1978), “A Procedure for Incorporating Group-Level Similarity Judgments in Conjoint Analysis,” *Journal of Consumer Research*, , (December), 5, 187-193.

Green, Paul E. and V. Srinivasan (1990), “Conjoint Analysis in Marketing: New Developments With Implications for Research and Practice,” *Journal of Marketing*, 54, 4, (October), 3-19.

Green, Paul E. and V. Srinivasan (1978), “Conjoint Analysis in Consumer Research: Issues and Outlook,” *Journal of Consumer Research*, 5, 2, (September), 103-123.

Green, Paul E. and Jerry Wind (1975), “New Way to Measure Consumers’ Judgments,” *Harvard Business Review*, (July-August),107-117.

Green, Paul E., Yoram Wind and Arun K. Jain (1972), “Preference Measurement of Item Collections,” *Journal of Marketing Research*, 9 (November),371-377.

Green, Paul E. and Jerry Wind, *Multiattribute Decisions in Marketing*. Dryden Press, 1973.

Griffin, Abbie J. and John R. Hauser (1993), "The Voice of the Customer," *Marketing Science*, 12, (Winter), 1-27.

Haaijer, Rinus, Michel Wedel, Marco Vriens, and Tom Wansbeek (1998), “Utility Covariances and Context Effects in Conjoint MNP Models,” *Marketing Science*, 17, 3, 236-252.

Haaijer, Rinus, Wagner Kamakura, and Michel Wedel (2000), “Response Latencies in the Analysis of Conjoint Choice Experiments,” *Journal of Marketing Research* 37, (August), 376-382.

Hauser, John R. and Steven M. Shugan (1980), "Intensity Measures of Consumer Preference," *Operation Research*, Vol. 28, No. 2, (March-April), 278-320.

Hauser, John R., Duncan I. Simester, and Olivier Toubia (2002), “Configurators, Utility Balance, and Managerial Use,” working paper, Cambridge, MA: Center for Innovation in Product Development, MIT, (June).

Hauser, John R., and Frank S. Koppelman (1979), "Alternative Perceptual Mapping Techniques: Relative Accuracy and Usefulness, *Journal of Marketing Research*, Vol. 16, No. 4, (November), 495-506.

Hauser, John R. and Glen L. Urban (1977), “A Normative Methodology for Modeling Consumer Response to Innovation,” *Operations Research, 25, 5, (July-August), 579-619.*

Hauser, John R. and Glen L. Urban (1979), "Assessment of Attribute Importances and Consumer Utility Functions: von Neumann-Morgenstern Theory Applied to Consumer Behavior," *Journal of Consumer Research*, Vol. 5, (March), 251-262.

Huber, Joel (1975), “Predicting Preferences on Experimental bundles of Attributes: A Comparison of Models,” *Journal of Marketing Research*, 12, (August), 290-297.

Huber, Joel (1987), “Conjoint Analysis: How We Got Here and Where We Are,” *Proceedings of the Sawtooth Software Conference on Perceptual Mapping, Conjoint Analysis, and Computer Interviewing*. 237-252.

Huber, Joel, Dick R. Wittink, John A. Fiedler, and Richard Miller (1993), "The Effectiveness of Alternative Preference Elicitation Procedures in Predicting Choice," *Journal of Marketing Research*, pp. 105-114.

Huber, Joel and Klaus Zwerina (1996), "The Importance of Utility Balance in Efficient Choice Designs," *Journal of Marketing Research,* 33, (August), 307-317.

Jain, Arun K., Franklin Acito, Naresh K. Malhotra, and Vijay Mahajan (1979), "A Comparison of the Internal Validity of Alternative Parameter Estimation Methods in Decompositional Multiattribute Preference Models," *Journal of Marketing Research*, 16, (August), 313-322.

Johnson, Richard (1974), "Tradeoff Analysis of Consumer Values," *Journal of Marketing Research*, (May), 121-127.

Johnson, Richard (1987), "Accuracy of Utility Estimation in ACA," Working Paper, Sawtooth Software, Sequim, WA, (April).

Johnson, Richard (1991), "Comment on `Adaptive Conjoint Analysis: Some Caveats and Suggestions," *Journal of Marketing Research*, 28, (May), 223-225.

Johnson, Richard (1999), "The Joys and Sorrows of Implementing HB Methods for Conjoint Analysis," Working Paper, Sawtooth Software, Sequim, WA, (November).

Kadiyali, V., K. Sudhir, V. R. Rao (2000), "Structural Analysis of Competitive Behavior," *International Journal of Research in Marketing*, 18, 161-185.

Keeney, Ralph and Howard Raiffa (1976), *Decisions with Multiple Consequences: Preferences and Value Tradeoffs*, (New York, NY: John Wiley & Sons).

Klein, Noreen M., "Assessing Unacceptable Attribute Levels in Conjoint Analysis," *Advances in Consumer Research* vol. XIV, pp. 154-158.

Krantz, David H., R. Duncan Luce, Patrick Suppes, and Amos Tversky (1971), *Foundations of Measurement*, (New York, NY: Academic Press).

Koza, John R., *Genetic Programming*. Cambridge, Mass.: The MIT Press, 1992.

Kuhfeld, Warren E. , Randall D. Tobias, and Mark Garratt (1994), "Efficient Experimental Design with Marketing Research Applications," *Journal of Marketing Research*, 31, 4, (November), 545-557.

Lenk, Peter J., Wayne S. DeSarbo, Paul E. Green, and Martin R. Young (1996), "Hierarchical Bayes Conjoint Analysis: Recovery of Partworth Heterogeneity from Reduced Experimental Designs," *Marketing Science*, 15, 2, 173-191.

Liechty, John, Venkatram Ramaswamy, Steven Cohen (2001), "Choice-Menus for Mass Customization: An Experimental Approach for Analyzing Customer Demand With an Application to a Web-based Information Service," *Journal of Marketing Research*, 38, 2, (May).

Louviere, Jordan J., David A. Hensher, and Joffre D. Swait (2000), *Stated Choice Methods: Analysis and Application*, (New York, NY: Cambridge University Press).

Luce, R. Duncan and John W. Tukey (1964), "Simultaneous Conjoint Measurement: A New Type of Fundamental Measurement," *Journal of Mathematical Psychology*, 1, 1-27.

Malhotra, Naresh (1982), "Structural Reliability and Stability of Nonmetric Conjoint Analysis," *Journal of Marketing Research*, 19, (May), 1999-207.

Malhotra, Naresh (1986), "An Approach to the Measurement of Consumer Preferences Using Limited Information," *Journal of Marketing Research*, 23, (February), 33-40.

McFadden, Daniel (1974), "Conditional Logit Analysis of Qualitative Choice Behavior," *Frontiers in Econometrics*, P. Zarembka, ed., (New York: Academic Press), 105-142.

McFadden, Daniel (2000), "Disaggregate Behavioral Travel Demand's RUM Side: A Thirty-Year Retrospective," Working Paper, University of California, Berkeley, (July).

Montgomery, David B. and Dick R. Wittink (1980), "The Predictive Validity of Conjoint Analysis for Alternative Aggregation Schemes," in *Market Measurement and Analysis: Proceedings of the 1979 ORSA/TIMS Conference on Marketing*, David B. Montgomery and Dick R. Wittink, eds, Cambridge, MA: Marketing Science Institute, 298-309.

Moore, William L. (1980), "Levels of Aggregation in Conjoint Analysis: An Empirical Comparison," *Journal of Marketing Research*, 17, 4, (November), 516-523.

Nadilo, Rudy (1999), "On-line Research: The Methodology for the Next Millennium," *Advertising Research Foundation Journal*, (Spring). Available at www.greenfield.com.

Neslin, Scott A. (1981), "Linking Product Features to Perceptions: Self-Stated versus Statistically Revealed Importance Weights," *Journal of Marketing Research*, 18, (February), 80-86.

Nesterov, Y. and A. Nemirovskii (1994), “Interior-Point Polynomial Algorithms in Convex Programming,” SIAM, Philadelphia.

Oppewal, Harmen, Jordan J. Louviere, and Harry J. P. Timmermans (1994), “Modeling Hierarchical Conjoint Processes with Integrated Choice Experiments,” *Journal of Marketing Research*, 31, (February), 92-105.

Orme, Bryan (1999), “ACA, CBC, of Both?: Effective Strategies for Conjoint Research,” Working Paper, Sawtooth Software, Sequim, WA.

Rao, Vithala R. (1977) “ Conjoint Measurement in marketing Analysis,” in J. Sheth (ed.) Multivariate Methods for Market and Survey Research. Chicago: American marketing Association, 257-286.

Rao, Vithala R. and Ralph Katz (1971), "Alternative Multidimensional Scaling Methods for Large Stimulus Sets," *Journal of Marketing Research*, 8, (November), 488-494.

Rao, Vithala R. and Henrik Sattler (2000), "Measurement of Informational and Allocative Effects of Price" (with H. Sattler) in Gustafsson, A., A. Herrmann, and F. Huber (eds.), *Conjoint Measurement: Methods and Applications,* Berlin: Springer-Verlag,pp.47-66..

Reibstein, David, John E. G. Bateson, and William Boulding (1988), “Conjoint Analysis Reliability: Empirical Findings,” *Marketing Science*, 7, 3, (Summer), 271-286.

Sandor, Zsolt and Michel Wedel (2001), “Designing Conjoint Choice Experiments Using Managers’ Prior Beliefs,” *Journal of Marketing Research*, 38, 4, (November), 430-444.

Sawtooth Software, Inc. (1996), “ACA System: Adaptive Conjoint Analysis,” *ACA Manual*, (Sequim, WA: Sawtooth Software, Inc.)

Sawtooth Software, Inc. (1999), “The ACA/HB Module for Hierarchical Bayes Estimation,” *ACA/HB Manual*, (Sequim, WA: Sawtooth Software, Inc.)

Segal, Madhav N. (1982), “Reliability of Conjoint Analysis: Contrasting Data Collection Procedures,” *Journal of Marketing Research*, 19, 139-143.

Silk, Alvin J., and Glen L. Urban (1978), “Pre-Test-Market Evaluation of New Packaged Goods: A Model and Measurement Methodology,” Journal of Marketing Research, 15 (May), 171-191.

Sonnevend, G. (1985a), “An ‘Analytic’ Center for Polyhedrons and New Classes of Global Algorithms for Linear (Smooth, Convex) Programming,” *Proceedings of the 12th IFIP Conference on System Modeling and Optimization*, Budapest.

Sonnevend, G. (1985b), "A New Method for Solving a Set of Linear (Convex) Inequalities and its Applications for Identification and Optimization," Preprint, Department of Numerical Analysis, Institute of Mathematics, Eőtvős University, Budapest, 1985.

Srinivasan, V. (1988), "A Conjunctive-Compensatory Approach to The Self-Explication of Multiattributed Preferences," *Decision Sciences,* 19, (Spring), 295-305.

Srinivasan, V. and Chan Su Park (1997), "Surprising Robustness of the Self-Explicated Approach to Customer Preference Structure Measurement," *Journal of Marketing Research*, 34, (May), 286-291.

Srinivasan, V. and Allen D. Shocker (1973a), "Estimating the Weights for Multiple Attributes in a Composite Criterion Using Pairwise Judgments," *Psychometrika*, 38, 4, (December), 473-493.

Srinivasan, V. and Allen D. Shocker (1973b), "Linear Programming Techniques for Multidimensional Analysis of Preferences," *Psychometrika,* 38, 3, (September), 337-369.

Srinivasan, V. and Gordon A. Wyner (1988), "Casemap: Computer-Assisted Self-Explication of Multiattributed Preferences," in W. Henry, M. Menasco, and K. Takada, Eds, *Handbook on New Product Development and Testing*, (Lexington, MA: D. C. Heath), 91-112.

Ter Hofstede, Frenkel, Youngchan Kim, and Michel Wedel (2002), "Bayesian Prediction in Hybrid Conjoint Analysis," *Journal of Marketing Research*, 36, (May), 253-261.

Toubia, Olivier, Duncan Simester, John R. Hauser (2002), "Fast Polyhedral Adaptive Conjoint Estimation," working paper, Cambridge, MA: Center for Innovation in Product Development, MIT, (January).

Toubia, Olivier, Duncan Simester, John R. Hauser (2002), "Adaptive Choice-Based Conjoint Analysis with Polyhedral Methods," working paper, Cambridge, MA: Center for Innovation in Product Development, MIT, (October).

Urban, Glen L. and John R. Hauser (2002), "`Listening In' to Find Consumer Needs and Solutions," working paper, Cambridge, MA: Center for Innovation in Product Development, MIT, (January).

Urban, Glen L. and Gerald M. Katz, "Pre-Test Market Models: Validation and Managerial Implications," *Journal of Marketing Research*, Vol. 20 (August 1983), 221-34.

Vaidja, P. (1989), "A Locally Well-Behaved Potential Function and a Simple Newton-Type Method for Finding the Center of a Polytope," in: N. Megiddo, ed., *Progress in*

Mathematical Programming: Interior Points and Related Methods, Springer: New York, 79-90.

Vavra, Terry G., Paul E. Green, and Abba Krieger (1999), "Evaluating EZ-Pass," *Marketing Research*, 11, 3, (Summer), 5-16.

von Hippel, Eric (2001b), "Perspective: User Toolkits for Innovation," *Journal of Product Innovation Management*, 18, 247-257.

Wilkie, William L. and Edgar A. Pessemier (1973), "Issues in Marketing's Use of Multi-attribute Attitude Models," *Journal of Marketing Research*, 10, (November), 428-441.

Wind, Jerry, Paul E. Green, Douglas Shifflet, and Marsha Scarbrough (1989), "Courtyard by Marriott: Designing a Hotel Facility with Consumer-Based Marketing Models," *Interfaces*, pp. 25-47.

Wittink, Dick R. and Philippe Cattin (1981), "Alternative Estimation Methods for Conjoint Analysis: A Monte Carlo Study," *Journal of Marketing Research*, 18, (February), 101-106.

Wittink, Dick R. and Philippe Cattin (1989), "Commercial Use of Conjoint Analysis: An Update," *Journal of Marketing*, 53, 3, (July), 91-96.

Wittink, Dick R. and David B. Montgomery (1979), "Predictive Validity of Trade-off Analysis for Alternative Segmentation Schemes," *1979 AMA Educators' Conference Proceedings*, Neil Beckwith ed., Chicago, IL: American Marketing Association.

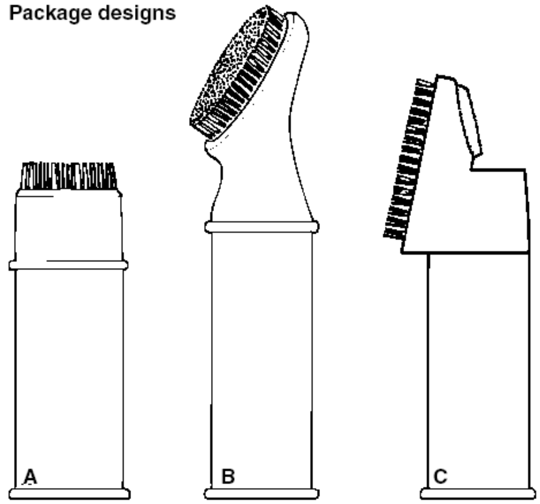
Wright, Peter and Mary Ann Kriewall (1980), "State-of-Mind Effects on Accuracy with which Utility Functions Predict Marketplace Utility," *Journal of Marketing Research*, 17, (August), 277-293.

Figure 1: Experimental Design for Carpet Cleaner

(from Green and Wind 1975)

EXHIBIT I

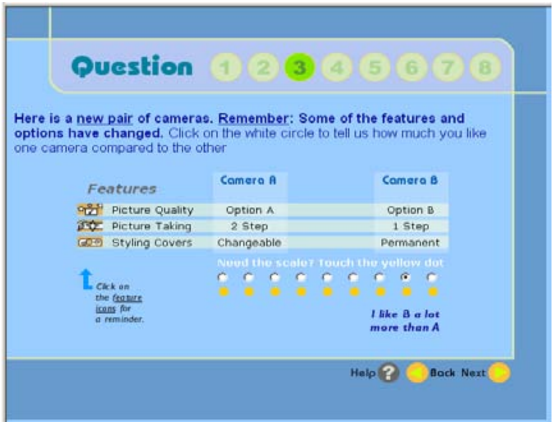
Experimental design for evaluation of a carpet cleaner



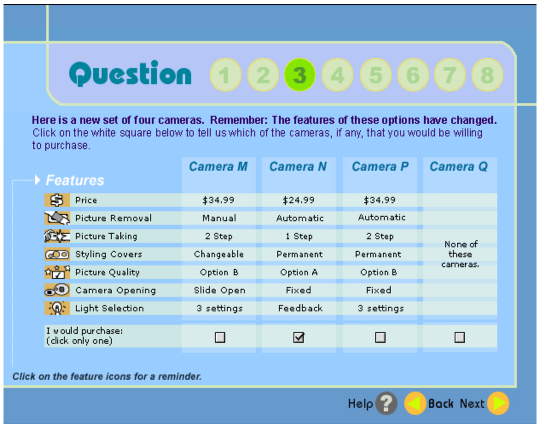
Package design	Brand name	Price	Good House-keeping seal?	Money-back guarantee?	Respondent's evaluation (rank number)
1 A	K2R	$1.19	No	No	13
2 A	Glory	1.39	No	Yes	11
3 A	Bissel	1.59	Yes	No	17
4 B	K2R	1.39	Yes	Yes	2
5 B	Glory	1.59	No	No	14
6 B	Bissel	1.19	No	No	3
7 C	K2R	1.59	No	Yes	12
8 C	Glory	1.19	Yes	No	7
9 C	Bissel	1.39	No	No	9
10 A	K2R	1.59	Yes	No	18
11 A	Glory	1.19	No	Yes	8
12 A	Bissel	1.39	No	No	15
13 B	K2R	1.19	No	No	4
14 B	Glory	1.39	Yes	No	6
15 B	Bissel	1.59	No	Yes	5
16 C	K2R	1.39	No	No	10
17 C	Glory	1.59	No	No	16
18 C	Bissel	1.19	Yes	Yes	1*

Figure 2: Examples of Data-Collection Formats

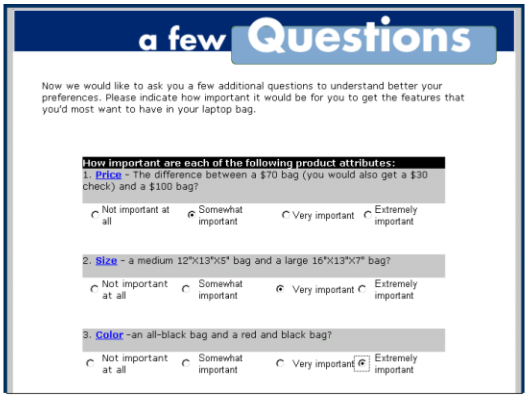
(from Dahan, Hauser, Simester, and Toubia 2002)



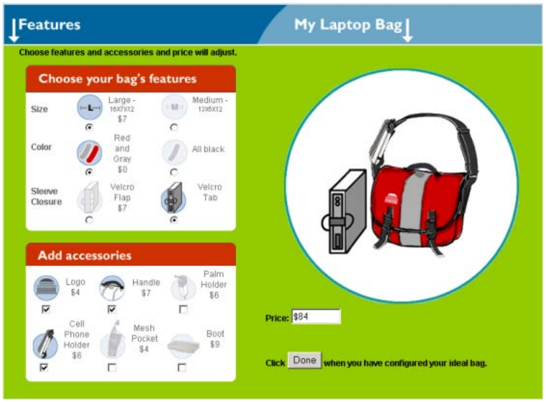
(a) Partial Profile (Metric Pairs)



(b) Self-explicated Questions



(c) Stated Preference (CBC)



(d) Configurators