Thirty Years of Conjoint Analysis: Reflections and Prospects

Article *in* Interfaces · June 2001

DOI: 10.1287/inte.31.4.56.9676

3 authors, including:

Abba M Krieger
University of Pennsylvania

Yoram Wind
University of Pennsylvania

Thirty Years of Conjoint Analysis: Reflections and Prospects

PAUL E. GREEN
greene@wharton.upenn.edu
Suite 1400, Steinberg Hall-Dietrich Hall
The Wharton School
University of Pennsylvania
Philadelphia, Pennsylvania 19104-6371

ABBA M. KRIEGER
krieger@wharton.upenn.edu
Suite 3000, Steinberg Hall-Dietrich Hall
The Wharton School

YORAM (JERRY) WIND
windj@wharton.upenn.edu
Suite 1400, Steinberg Hall-Dietrich Hall
The Wharton School

Conjoint analysis is marketers' favorite methodology for finding out how buyers make trade-offs among competing products and suppliers. Conjoint analysts develop and present descriptions of alternative products or services that are prepared from fractional factorial, experimental designs. They use various models to infer buyers' part-worths for attribute levels, and enter the part-worths into buyer-choice simulators to predict how buyers will choose among products and services. Easy-to-use software has been important for applying these models. Thousands of applications of conjoint analysis have been carried out over the past three decades.

Readers of *Interfaces* are no strangers to multiattribute utility models [Keeney and Raiffa 1976; Starr and Zeleny 1977; Bell, Raiffa, and Tversky 1988]. Thomas Saaty [1980] introduced a different approach to multiattribute utility measurement: the analytic hierarchy process [AHP]. Both approaches emphasized small numbers of decision makers facing high-level decisions. Operations researchers and management scientists have applied both methods extensively to important problems in management and government decision making.

OR/MS researchers may be less familiar with another method—conjoint analysis—that has been applied for over 30 years, primarily by researchers in marketing and business. Conjoint analysis evolved from the seminal research of Luce and Tukey [1964]. Their theoretical contributions were put to use by a number of psychometri-

0092-2102/01/3103/S056/$05.00
1526-551X electronic ISSN
This paper was refereed.

MARKETING—CHOICE MODELS
MARKETING—NEW PRODUCTS

cians, including Carroll [1969], Kruskal [1965], and Young [1969]. These researchers developed a variety of nonmetric models for computing part-worths (attribute-level values) from respondents' preference orderings across multiattributed stimuli, such as descriptions of products or services.

Conjoint analysis is, by far, the most used marketing research method for analyzing consumer trade-offs. Surveys conducted by Wittink and Cattin [1989] and Wittink, Vriens, and Burhenne [1994] attest to its worldwide popularity.

It is not difficult to see why researchers developed and applied conjoint analysis so rapidly. Conjoint analysis deals with a central management question: Why do consumers choose one brand or one supplier over another? Also, marketing research practitioners want to be part of something new, and computer software for implementing the methodology became readily available.

The Basic Ideas of Conjoint Analysis

Conjoint analysis is one of many techniques for handling situations in which a decision maker has to deal with options that simultaneously vary across two or more attributes. The problem the decision maker faces is how to trade off the possibility that option X is better than option Y on attribute A while Y is better than X on attribute B, and various extensions of these conflicts.

Conjoint analysis concerns the day-to-day decisions of consumers—what brand of toothpaste, automobile, or photocopying machine to buy [or lease]? Marketing researchers may collect trade-off information for hundreds or even thousands of respondents. Data collection and processing techniques must be fairly simple and routinized to handle problems of this scope.

Conjoint analysis is a technique for measuring trade-offs for analyzing survey responses concerning preferences and intentions to buy, and it is a method for simulating how consumers might react to changes in current products or to new products introduced into an existing competitive array. Researchers have used conjoint analysis for consumer and industrial products and services and for not-for-profit offerings.

To understand the basic concepts of conjoint analysis, assume that a marketer

Why do consumers choose one brand or one supplier over another?

of credit cards wishes to examine the possibility of modifying its current line of services. One of the first steps in designing a conjoint study is to develop a set of attributes and corresponding attribute levels to characterize the competitive domain. Focus groups, in-depth consumer interviews, and internal corporate expertise are some of the sources researchers use to structure the sets of attributes and levels that guide the rest of the study.

In an actual study of credit-card suppliers, researchers used a set of 12 attributes with two to six levels, for a total of 35 levels (Table 1). However, the total number of possible combinations of levels is 186,624. Conjoint analysts make extensive use of orthogonal arrays [Addelman 1962] and other types of fractional factorial designs to reduce the number of stimulus

Attribute	Levels
Annual price ($)	0; 10; 20; 50; 80; 100
Cash rebate (end-of-year, on total purchases)	None; $\frac{1}{2}$%; 1%
800 number for message forwarding	None; 9-5 weekdays; 24 hours per day
Retail purchase insurance	None; 90 days' coverage
Common carrier insurance (death, injury)	None; $50,000; $200,000
Rental car insurance (fire, theft, collision, vandalism)	None; $30,000
Baggage insurance	None; $2,500 depreciated cost; $2,500 replacement cost
Airport club admission (based on small entrance fee)	No admission; $5 per visit; $2 per visit
Card acceptance	Air, hotel, rental cars (AHC); AHC and most restaurants (AHCR); AHCR and most general retailers (AHCRG); AHCR and department stores only (AHCRD)
24-hour medical/legal referral network	No; Yes
Airport limousine to city destination	Not offered; Available at 20% discount
800 number for emergency car service	Not offered; Available at 20% discount

Table 1: These attributes (and levels within attributes) describe the set of potential services that would be offered to credit-card subscribers.

descriptions that a respondent sees to a small fraction of the total number of combinations. In this problem, an array of 64 profiles (less than 0.04 percent of the total) is sufficient to estimate all attribute-level main effects on an uncorrelated basis. The study designers used a hybrid conjoint design [Green and Krieger 1996], and each respondent was asked to consider only eight (balanced) profile descriptions drawn from the 64 profiles.

For such studies, researchers may prepare prop cards (Figure 1). After the respondent sorts the prop cards in terms of preference, each card is rated on a 0 to 100 likelihood-of-acquisition scale. In small conjoint studies (for example, six or seven attributes, each at two or three levels), respondents are given all of the full profiles—16 to 32 prop cards. In these cases, respondents typically sort the prop cards into four to eight ordered categories before they give likelihood-of-purchase ratings for each separate profile within each category.

Types of Conjoint Data Collection

Four major types of data collection procedures are currently used for conjoint analysis:

(1) In full profile techniques, each respondent sees a complete set of the full-profile prop cards. After sorting the cards into ordered categories, the respondent rates each card on a 0 to 100 likelihood-of-purchase scale.

(2) In compositional techniques, such as the CASEMAP procedure [Srinivasan 1988], each respondent rates the desirability of each set of attribute levels on a 0 to 100 scale and then rates the attributes on an importance scale. (This approach is typically called self-explicated preference-data collection.)

(3) In hybrid techniques, each respondent performs a self-explicated evaluation task and evaluates a subset of the full-profile cards [Green, Goldberg, and Montemayor

1

Annual price
$20
Cash rebate
None
800 number for message forwarding
None
Retail purchase insurance
None
Common carrier insurance
$50,000
Rental car insurance
$30,000
Baggage insurance
$2,500 depreciated cost
Airport club admission
$2 per visit
Card acceptance
Air, hotel, rental cars
Medical-Legal
No
Airport limousine
Not offered
800 number for emergency car
Available at 20% discount

2

Annual price
$50
Cash rebate
½ %
800 number for message forwarding
24 hours per day
Retail purchase insurance
None
Common carrier insurance
None
Rental car insurance
$30,000
Baggage insurance
None
Airport club admission
$5 per visit
Card acceptance
Air, hotel, rental cars and most restaurants
Medical-Legal
Yes
Airport limousine
Available at 20% discount
800 number for emergency car
Not offered

Figure 1: These prop cards illustrate specific services that a credit card could offer. For each card the respondent indicates how likely she would be to subscribe to the credit card on a 0–100 point scale.

1981]. The resulting utility function is a composite of data obtained from both tasks.

(4) In adaptive conjoint analysis, a hybrid technique developed by Sawtooth Software [Johnson 1987], each respondent first performs a self-explication task and then evaluates a set of partial-profile descriptions, two at a time. Partial profiles usually consist of two or three attributes per stimulus card. Researchers vary the partial profile descriptions depending upon responses to earlier paired comparisons. The respondent evaluates each pair of partial profiles on a graded, paired comparisons scale. Both tasks are administered by computer [Johnson 1987].

Conjoint Models

Most conjoint analysts fit what is known as the *part-worth model* to respondents' evaluative judgments, whether they obtain these judgments using full-profile, self-explicated, or hybrid approaches. However, they occasionally use vector and ideal-point models. We assume that there are P attributes and J stimuli used in the study design. For a given respondent, we let y_{jp} denote the desirability of the pth attribute for the jth stimulus; we first assume that y_{jp} is inherently continuous. The

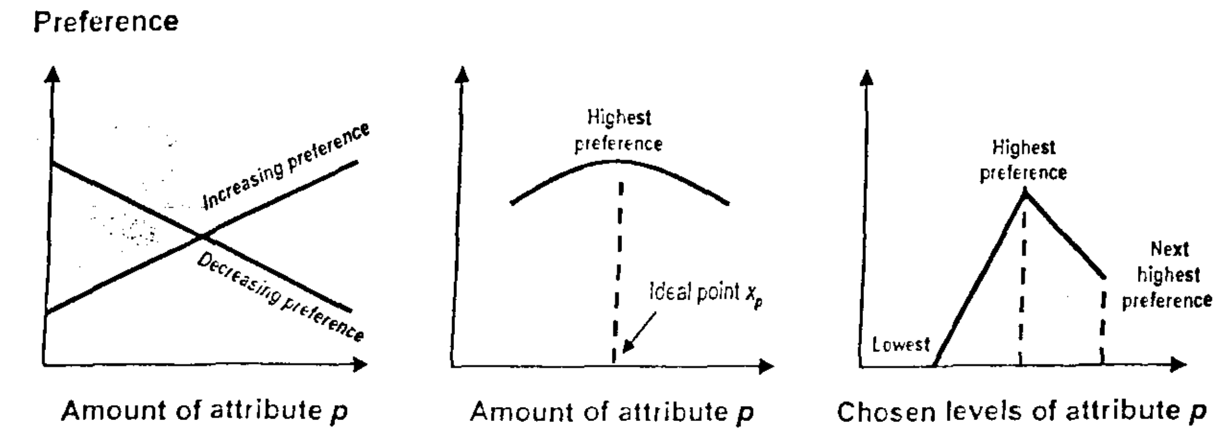

Figure 2: These diagrams illustrate what is meant by linear preferences, idea-point preferences, and discrete (part-worth) preferences. The third graph shows three part-worths. Source: Green and Srinivasan [1978].

vector model assumes that the respondent's preference s_j for the jth stimulus is given by

$$s_j = \sum_{p=1}^{P} w_p y_{jp}$$

where w_p denotes the respondent's importance weight for each of the P attributes (Figure 2).

In the *ideal-point model*, the analyst posits that preference s_j is inversely related to the weighted squared distance d_j^2 of the location y_{jp} of the jth stimulus from the individual's ideal point x_p, where d_j^2 is defined as

$$d_j^2 = \sum_{p=1}^{P} w_p (y_{jp} - x_p)^2.$$

In the *part-worth model*, the analyst assumes that

$$s_j = \sum_{p=1}^{P} f_p(y_{jp})$$

where y_{jp} is the category level and f_p is a function denoting the part-worth corresponding to level y_{jp}. In practice, the analyst estimates $f_p(y_{jp})$ for a selected set of discrete levels of y_{jp}.

In Figure 3, we show illustrative (averaged) part-worths for the attribute levels described in Table 1. Part-worths are often

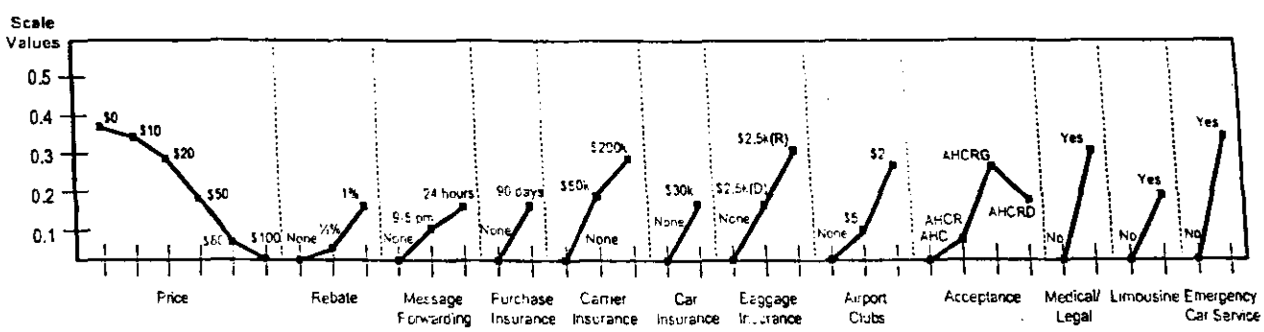

Figure 3: This chart illustrates how part-worth scale values depend on price, message forwarding, . . . emergency car service. For example, the most preferred price is \$0 and the least preferred price is \$100.

scaled so that the lowest part-worth is zero, within each attribute. Strictly speaking, analysts evaluate part-worth functions at discrete levels for each attribute. However, in many applications, analysts interpolate between levels of continuous attributes, such as price, when they enter the part-worths in buyer-choice simulators. The scaling (vertical axis) is common across all attributes; this allows the analyst to add up part-worths across each attribute level to obtain the overall (product or service) utility of any profile composable from the basic attribute levels.

Stimulus Presentation

In collecting conjoint data, analysts currently emphasize the full-profile and hybrid procedures, including Sawtooth's adaptive conjoint analysis. While they still employ paragraph descriptions of attribute levels in some industry studies, they usually use profile cards with terse attribute-level descriptions (Figure 1). Analysts increasingly use pictorial material; these kinds of props make the respondent's task more interesting and convey information easily with little ambiguity. Moreover, conjoint methods are increasingly being applied to the design of physical products (for example, foods and beverages, fragrances, and personal-care products). In these cases, researchers use actual, experimentally designed prototypes.

Precursors to Conjoint Analysis

How did conjoint analysis come about? For marketing researchers working in data analysis and modeling, the 1970s provided a rich bounty of tools and techniques. Unlike the 1960s (a decade of borrowing tools from operations researchers), the late '60s and early '70s saw the strong influence of developments in the behavioral sciences (primarily psychometrics and mathematical psychology) on marketing-research methods. In particular, three techniques, cluster analysis, multidimensional scaling [MDS], often called perceptual and preference mapping, and conjoint analysis, were introduced to marketing at that time.

Cluster analytic methods almost immediately found application in market segmentation [Green, Frank, and Robinson 1967]. Unlike a priori market segmentation, where researchers assume they know segment identifiers at the outset, cluster analysis provided researchers and practitioners with tools for implementing post hoc, or cluster-based segmentation. Researchers could then base segmentation on the needs or benefits sought, brand preferences, problem-solving alternatives, psychographics, and a host of other variables. The idea of cluster-based segmentation was to let the data speak for themselves in terms of finding groups of consumers who share similar needs, attitudes, trade-offs, or benefits.

Multidimensional scaling methods also received considerable attention in the 1970s. Marketing researchers learned the value of constructing attractive "maps" for pictorially representing large two-way (or multiway) numerical tables as point or point-and-vector geometric representations in two (or possibly three) dimensions. They could also profitably combine MDS with hierarchical clustering methods to augment two-dimensional configurations with cluster-based representations based on solutions in higher dimensionalities (Carroll and Green [1997] summarize the history of the MDS field).

As early appliers of MDS found (often to their dismay), the brand-positioning maps generated using MDS techniques appeared to be largely of diagnostic rather than predictive value. Researchers who wanted to use MDS to develop new or restaged products faced a two-part problem: translating brand scores on perceived dimensions to manipulable dimensions and relating manipulable attribute levels to their counterparts in perceptual or preference space. These problems illustrate the general problem of *reverse engineering*, in which back-translation from perceived attributes to physical and chemical product characteristics is typically not one to one [Kaul and Rao 1994]. It is little wonder that conjoint analysis, with its emphasis on researcher-specified attribute levels, provided a basis for relating preference or choice responses to explicit arguments, including physical attributes as well as verbal descriptions of product and service attribute levels.

The Era of Conjoint Analysis

Conjoint analysis has been blessed with several sets of parents. The seminal precursory paper to conjoint analysis, Luce and Tukey's paper on conjoint measurement, appeared in the *Journal of Mathematical Psychology* in 1964. The authors focused on axiomatic approaches to fundamental measurement. The idea was to obtain ordered metric-scale data from rank-order response data and a set of factorially designed stimuli. Not surprisingly, the initial conjoint algorithm, called Monanova, designed by Kruskal [1965] and programmed by Kruskal and Carmone, used ranked response data.

In the late '60s, Green and his colleagues (Vithala Rao, Frank Carmone, and Arun Jain) started running numerous experiments with the Monanova program. A working paper by Green and Rao appeared in 1969, followed by the first marketing journal article on conjoint analysis [Green and Rao 1971]. Following this, Johnson [1974] and Westwood, Lunn, and Beazley [1974] published articles on Johnson's two-attributes-at-a-time tradeoff model.

Users of Kruskal's Monanova and Shocker and Srinivasan's [1977] Linmap programs (both nonmetric models) soon learned, however, that ratings-based dependent variables analyzed with dummy-variable regression techniques provided a

Choice-based conjoint studies can be a mixed blessing.

robust alternative to ordinally based data procedures [Carmone, Green, and Jain 1978; Cattin and Wittink 1976]. Orthogonal main-effects plans, based on Addelman's [1962] fractional factorial designs, significantly reduced respondents' cognitive burdens in responding to full-profile descriptions.

Hence, in the mid-'70s conditions were ripe for the quick diffusion of metric methods of conjoint analysis (using dummy-variable regression). In the mid-'80s, Johnson [1987] introduced his adaptive conjoint analysis program that used graded paired comparisons as one set of inputs to the model. About the same time, Herman [1988] introduced a PC-based package that used full-profile stimuli based on orthogonal designs. Both packages contained conjoint simulators. Both software packages were also easy to use and moderately priced for commercial research firms. The advent of PC-based conjoint packages opened a large and eager market for applying the methodology.

By the late '70s, conjoint analysis had truly come of age. Wittink and his coauthors [Wittink and Cattin 1989; Wittink, Vriens, and Burhenne 1994] provided extensive surveys attesting to the rapidity with which conjoint analysis was being adopted by researchers. Myers, Massy, and Greyser [1980] used conjoint analysis as a canonical case of how new ideas diffuse throughout the research community. Green and Srinivasan [1978] published a review of conjoint's progress, which they followed with a further review 12 years later [Green and Srinivasan 1990]. The impetus behind conjoint's diffusion reflected the joint influence of academic and practitioners' contributions to the methodology, the availability of easy-to-use software, and the early credibility of results from business applications.

Conjoint analysis, unlike MDS and clustering, dealt with central problems—measuring buyer trade-offs for developing new or reformulated products and estimating price-demand functions. In contrast, cluster analysis and MDS tools are often used as ancillary techniques for data analysis and presentation. Both, however, have been gainfully employed in conjoint studies involving buyer segmentation [Green and Krieger 1991] and in presenting perceptual maps of conjoint results [Green, Krieger, and Carroll 1987].

Distant relatives to conjoint analysis include the decompositional approaches of Hoffman, Slovic, and Rorer [1968] and the functional measurement approach of Anderson [1970]. However, the seminal paper by Luce and Tukey [1964] and the experimental-design papers by Addelman [1962] and Plackett and Burman [1946], among others, provided key theoretical underpinnings and motivation for developing conjoint analysis. In particular, orthogonal main-effects designs and their more sophisticated extensions still constitute a major activity in the continuing development of efficient experimental designs. Considerable new research [Anderson and Wiley 1992; Huber and Zwerina 1996; Kuhfeld, Tobias, and Garratt 1994; Lazari and Anderson 1994] on this topic occurred during the '90s.

The most publicized early paper on conjoint analysis appeared in *Harvard Business Review* [Green and Wind 1975]. Ironically Green and Wind [1973] had earlier published a research monograph on conjoint analysis and multiattribute decision making that met with much less reader interest.

Conjoint Development in the '80s

Technical developments in conjoint analysis have proceeded swiftly over the past two decades, accompanied by thousands of applications (Table 2). During the '80s, two developments stand out with regard to model development and application:

—Choice-based conjoint models, and
—Hybrid conjoint models, including Johnson's adaptive conjoint analysis model.

In traditional conjoint analysis, respondents typically rate various product or supplier profiles presented one at a time.

Choice-based conjoint [McFadden 1974; Gensch and Recker 1979; Batsell and Lodish 1981; Mahajan, Green, and Goldberg 1982; Louviere and Woodworth 1983]	
Three-way multivariate conjoint analysis [DeSarbo et al. 1982]	
Number of attribute levels effects on derived conjoint importance [Wittink, Krishnamurthi, and Nutter 1982]	
Constrained parameter estimation in conjoint analysis [Srinivasan, Jain, and Malhotra 1983]	
Hybrid models for conjoint analysis [Green, Goldberg, and Montemayor 1981; Green 1984]	
Introduction in 1985 of Bretton-Clark's full-profile conjoint techniques [Herman 1988]	
Introduction in 1985 of Sawtooth Software's adaptive conjoint analysis [Johnson 1987]	
Factor analytic approaches to individualized conjoint analysis [Hagerty 1985]	
Conjoint analysis and MDS in tandem [Green, Krieger, and Carroll 1987]	
Reliability and validity testing [Bateson, Reibstein, and Boulding 1987]	
Simultaneous conjoint parameter estimation and segmentation [Kamakura 1988]	
Bretton-Clark's second generation, full-profile suite of programs [Herman 1988]	
Conjunctive-compensatory self-explicated models [Srinivasan 1988]	
Componential segmentation with optimization features [Green, Krieger, and Zelnio 1989]	
Compensatory model problems in negatively correlated environments [Johnson, Meyer, and Ghose 1989]	
New experimental designs for conjoint [Steckel, DeSarbo, and Mahajan 1991]	
A reservation price model for optimal pricing [Kohli and Mahajan 1991]	
A review of experimental choice analysis [Batsell and Louviere 1991]	
Latent class conjoint analysis [DeSarbo et al. 1992]	
Constrained part-worth estimation [van der Lans and Helsen 1992]	
Modeling hierarchical conjoint processes [Oppewal, Louviere, and Timmermans 1994]	
Concomitant variable latent class modeling [Kamakura, Wedel, and Agrawal 1994]	
Hierarchical Bayes models for conjoint analysis [Allenby, Arora, and Ginter 1995; Allenby and Ginter 1995; Lenk et al. 1996]	
A comparison of metric conjoint models [Vriens, Wedel, and Wilms 1996]	
Utility balanced experimental designs [Huber and Zwerina 1996]	
Competitive interaction simulators [Choi, DeSarbo, and Harker 1990; Green and Krieger 1997]	
Mixture models for segmentation [Wedel and Kamakura 1998]	
Commercial windows-based, choice-based conjoint [Sawtooth Software 1999]	
Krieger and Green's hybrid choice-based conjoint model [Vavra, Green, and Krieger 1999]	
Latent class conjoint analysis [Ramaswamy and Cohen 2000]	
Hierarchical Bayes applied to Internet recommendation systems [Ansari, Essegaier, and Kohli 2000]	
Response latencies and conjoint analysis [Haaijer, Kamakura, and Wedel 2000]	

Table 2: This is a partial list of contributions to conjoint analysis over the 1974–2000 period.

on a likelihood-of-purchase scale. In choice-based conjoint, respondents typically see profile descriptions of two or more explicit competitors, which vary on one or more attributes. In this case, the task is either to pick one's most preferred profile from the set or alternatively to allocate 100 points across the set of profiles, reflecting one's relative strength of preferences.

In choice-based conjoint analysis, analysts typically employ multinomial logit models, although occasionally they use probit-based models. They usually employ traditional conjoint analysis when a new product is entering a new or stable market in which competitors are either nonexistent or treated as passive in terms of responding competitively to the new entry. In choice-based conjoint analysis, however, the analyst assumes active competitors who can modify their profiles (including price and nonprice attributes) as well. Sawtooth Software's Adaptive Conjoint Analysis is a traditional (hybrid) conjoint model. Its choice-based conjoint model deals with the case of explicit, active competitors. In choice-based conjoint analysis, analysts originally estimated parameters at the total-sample level. Newer methods (hierarchical Bayes) now permit measurement of individual differences as well.

The seminal precursory paper to choice-based conjoint [using the multinomial logit model] was written by an econometrician [McFadden 1974]. McFadden's work was soon recognized and adopted by a number of marketing researchers, including Punj and Staelin [1978]. Gensch and Recker [1979] also used this model in developing an alternative to regression for analyzing cross-sectional choice data. Batsell and Lodish [1981] illustrated the multinomial logit's use in modeling individual choices over replicated choice sets. Their model yields a share-of-choice prediction for alternatives in competitive choice sets. They indicate that the model can be profitably applied to market segments, as well. Mahajan, Green, and Goldberg [1982] applied Theil's logit model to a choice-based conjoint problem.

Despite its maturity, conjoint analysis is far from stagnant.

Louviere and Woodworth [1983] extended the preceding research. They discuss experimental designs that lend themselves to choice-based conjoint problems. They also provide an extensive and rich set of empirical examples based on various sets of fractional factorial designs. They focus on aggregate (pooled-over individuals) consumer-choice studies. Their paper spawned subsequent research for dealing with the more complex experimental designs needed for choice-based conjoint analysis.

Choice-based conjoint studies can be a mixed blessing. The respondent's tasks are extensive, since respondents may have to evaluate 10 (or more) scenarios. Each scenario could contain eight or more brands, each with several attributes and with several levels within attributes. Nonetheless, choice-based conjoint analysis has markedly increased in popularity because it can deal with the complexity of choosing among two or more competitive profiles, each of which can vary idiosyncratically across attributes and levels.

In the early '80s, hybrid models [Green 1984; Green, Goldberg, and Montemayor 1981] appeared in direct response to the increasing popularity of conjoint analysis. Along with conjoint's increased application came the desire to expand the number of attributes and the levels that could be accommodated. Hybrid models employ self-explicated data collected on both the desirability and the importance of attributes and levels. Respondents then consider small subsets of the full profiles to evaluate.

The early hybrid models initially used

stagewise regression to fit simplified compositional models to the self-explicated data, later augmented by decompositional models (fitted at the segment level). The value of these models lies in the greater accuracy they achieve, compared to nonhybrid models, in within-attribute estimation. The full-profile responses mainly serve to refine self-explicated attribute importances.

More recently, Green and Krieger [1996] extended hybrid models to allow parameter estimation at the individual level. They describe four separate models of increasing generality. Again, the objective is to use the self-explicated data primarily for within-attribute part-worth estimation while using the full-profile analysis to produce improved estimates of attribute importances.

The most-used commercial conjoint model is Johnson's adaptive-conjoint-analysis program. ACA is a hybrid model that incorporates self-explicated desirabilities and importances, followed by the presentation of pairs of partial profiles (typically consisting of levels on two or perhaps three attributes) drawn from the full set of attributes. A respondent is asked to choose between the members of each pair and to include his or her preference intensity as well via graded paired comparison; ACA developers [Sawtooth Software 1999] have continued to introduce useful refinements to the original version [Johnson 1987].

Conjoint Developments in the '90s

Probably the most far-reaching developments in the '90s use hierarchical Bayesian modeling of individual differences in choice-based models. Before this, choice-based models were either estimated from data pooled across all individuals or by latent class methods (partial dissaggregation) as applied by DeSarbo et al., [1992] and Ramaswamy and Cohen [2000].

The work of Allenby, Arora, and Ginter [1995], Allenby and Ginter [1995], and Lenk, DeSarbo, Green, and Young [1996] has enabled choice-based-conjoint users to obtain individual-level, part-worth estimates based on hierarchical Bayesian methods. (Sawtooth Software has recently added this type of module to its choice-based conjoint software.) To the extent that an individual's parameters are both self-consistent and different from the aggregated data, the individual's data will receive more weight in the estimation of his or her part-worths. Individuals whose part-worths are estimated poorly (that is, with large error from his or her own data) will receive more weight from the aggregate data.

Recently, Vavra, Green, and Krieger [1999] proposed another approach to the choice-based-conjoint problem. They developed a hybrid choice-based model that combines self-explicated data with full-profile responses. This model requires no weighted averaging of an individual's data with that from the entire group. On the downside, however, it requires self-explicated (in addition to full-profile) data.

Illustrative Applications

Of the extensive list (Table 3) of conjoint applications, two are of particular interest: the customer-driven design of Marriott's Courtyard Hotels [Wind et al. 1989], and the design and evaluation of the New Jersey and New York EZ-Pass electronic toll collection system [Vavra, Green, and

AT&T's first cellular telephone—Chicago-based study of 1,000 drivers' reactions to cell phone features of the new "honey-comb" relay system
Ford Fairlane—conjoint analysis used in redesign of Ford to reflect general automotive downsizing objectives
IBM RISC 6000 workstation—conjoint used to measure potential buyer reactions to variations in performance and reliability features of a new workstation
Squibb's captopril antihypertensive—six-country study of physicians' evaluations of Capoten's efficacy and safety features
Tagamet (SKF) and Zantac (Glaxo) ulcer drugs—competitive pricing and analysis of demand elasticities
Health maintenance plans—study conducted by the American Association of Retired Persons; results submitted to Congress
US Navy benefit packages for reenlistment—conjoint used to develop menu of new reenlistment plans based on individual differences in types of duties, health needs, and sign-over bonuses
Antidumping litigation—AT&T vs. Pacific-rim manufacturers legal dispute regarding small business telephone equipment; case adjudicated in AT&T's favor
Continental vs. American Airlines litigation—conjoint study of travel agents' trade-offs among airline flight selections
FedEx new services study—trade-off study of customer reactions to new methods for tracking delayed and lost letters and packages
Intermittent windshield wipers litigation—study to determine consumer evaluations of the derived "willingness to pay" for the intermittent wiper feature
MasterCard and Diner's Club—new travel and entertainment features evaluated for each case
Monsanto's herbicide packaging study—consumer reactions to advanced packaging devices for liquids, solids, and aerosols
Polaroid's instant camera design—study of consumer reactions to new features and camera design aesthetics
Marriott time-share units—development of optimal interior and exterior décors, services, and price
Ritz Carlton—conjoint used to develop hotel décor and services
Japanese cable TV—conjoint survey of Japanese consumers' trade-offs among services and prices of satellite TV
Shell and Texaco's brand equity—conjoint study of price, brand, and alternative company positions for the Shell and Texaco Corporations
UPS services study—conjoint used to examine customers' evaluations of four major suppliers of overnight letter and package delivery

Table 3: These illustrative conjoint applications were conducted by the authors and their colleagues.

Krieger 1999].

To the best of our knowledge, Courtyard by Marriott is the largest project in terms of attributes and levels ever undertaken using conjoint analysis. In the early '80s, Marriott management wished to design an "optimal" hotel chain catering primarily to business travelers who had no need for many of the features provided by up-scale hotels, such as Marriott and Hyatt.

In addition to price, the study design included seven hotel facets—external decor, room decor, food service, lounge facilities general services, leisure activities (for example, a fitness club), and security features. Analysts developed some 50 attributes with a total of 160 attribute levels. The models included hybrid conjoint and an early type of choice-based conjoint. The analysts also used computer simulators. The study made extensive use of visual props (pictures and three-dimensional models) as well as experimental rooms in which the furnishings and decor were systematically varied according to experimental designs.

By all counts, the Courtyard study was a success. Marriott implemented almost all of the design recommendations and later extended the approach to other new products (for example, Marriott Suites) and used the findings in the design of Courtyard advertisements and brochures. By 1990, Marriott had over 300 Courtyards, employing over 15,000 people. Today, there are 450 Courtyards worldwide, with annual sales in the billions of dollars. Marriott has since used conjoint analysis in such related endeavors as designing time-share vacation units and in room and amenities pricing.

In the EZ-Pass toll collection project, New Jersey and New York developed a really new product aimed at speeding up and simplifying vehicle passage on their toll highways, bridges, and tunnels. Commuters use an electronic tag (transponder) attached to the vehicle's inside windshield. As the vehicle approaches a toll lane, an antenna in the lane reads the customer's vehicle and account information embedded in the tag. The information is electronically forwarded to an in-line computer. The computer, in turn, deducts the toll from the customer's account.

The project began in 1992. There were two main questions:

—How should EZ-Pass be configured?
—What level of resources should be allocated to its implementation?

The two states conducted a large conjoint study (over 3,000 respondents) by a telephone-mail-telephone procedure in which qualified respondents received a packet of questionnaire materials and a video cassette. The video contained an 11-minute infomercial that described the problems associated with the current toll-road system and the benefits provided by EZ-Pass.

Analysts used seven conjoint attributes dealing with such issues as number of lanes available, tag acquisition, cost, toll prices, invoicing, and other uses of the tag. The study designers analyzed the individual respondents' data at both the overall sample level and by region and facility. The overall (at equilibrium) forecast made in 1992 of "take rate" was 49-percent usage. The actual take rate (seven years later) was 44 percent; future usage is expected to be higher than 49 percent. (Even David Letterman liked the system!)

Both projects, Courtyard by Marriott and EZ-Pass, illustrate the ability of conjoint analyses to lead to actionable findings that provide customer-driven design features and consumer-usage or sales forecasts.

Future Prospects

After 30 years of development and application, conjoint analysis seems to have survived the test of time. While new breakthroughs may well be less frequent, the method continues to grow in depth and breadth of usage. We expect to see the following further developments:

—New simulator-optimizers that can maximize either financial return or market share [Vavra, Green, and Krieger 1999];

—New classes of problems, including menu selection and bundling models for telecommunications and banking services [Ben-Akiva and Gershenfeld 1998];

—More realistic imagery for describing attribute levels, for example, using virtual reality displays;

—Continued extensions of conjoint applications to such fields as tourism, entertainment, health maintenance, gambling, and legal disputes;

—New application venues, such as conjoint's recent implementation on the Internet, including activebuyersguide.com, personalogic.com, and conjointonline.com, sites that typically use hybrid conjoint models to elicit buyer preferences for Web-based merchandise [Ansari, Essegaier, and Kohl 2000];

—Additional studies of conjoint reliability and validity [Haaijer, Kamakura, and Wedel 2000; Vriens, Wedel, and Wilms 1996];

—Extension of consumer-based applications to other stakeholder groups, such as employees, suppliers, stockholders, and municipalities;

—New "dynamic" conjoint simulators that consider competitive action-reaction sequences [Choi, DeSarbo, and Harker 1990; Green and Krieger 1997]; and

—Prototype simulators (for example, test cars) that permit analysts to measure respondents' preferences for type of ride, acceleration, cornering, and so forth in realistic surroundings.

In short, despite its maturity, conjoint analysis is still far from stagnant. Because the methods deal with the pervasive problem of buyer preferences and choices, conjoint's future promises continued development and application.

The Role of Software Development in the Diffusion of Conjoint Analysis

Throughout the development of conjoint analysis and the precursory techniques of cluster analysis and MDS, the availability of inexpensive and easy-to-use software has been crucial to their dissemination. Early on, Bell Laboratories and the Marketing Science Institute played important roles in making mainframe software available to both academic and industry users. With the growth of the personal computer, Johnson's Sawtooth Software and Herman's Bretton-Clark companies provided affordable PC software to business users and academic versions for teaching purposes. Sawtooth Software has maintained contact with business and academia through its newsletters, annual meetings, and continued development of software [Sawtooth Software 1999] to implement new research ideas, such as choice-based models. The American Marketing Association's annual Advanced Research Techniques Forum provides a meeting place for the fruitful exchange of ideas between academics and practitioners.

A Science vs. Engineering Postscript

From its inception, conjoint analysis has drawn on ideas from mathematical psychologists, psychometricians, statisticians, econometricians, and operations researchers. These ideas concern experimental design, parameter estimation, descriptive model building, normative model building, and the comparative evaluation of various models' reliability and validity. The method's practical consequences attest to its value and staying power [Gustaffsson, Hermann, and Huber 2000].

Through the interplay of theoretical contributions and practical applications, conjoint methodology continues to grow, as academics and practitioners learn useful things from each other.

Acknowledgments

We thank Eric Bradlow and Wes Hutchinson of the Wharton School, an anonymous reviewer, and the editors for helpful comments on the paper's initial draft.

References

Addelman, Sidney 1962, "Orthogonal main-effect plans for asymmetrical factorial experiments," *Technometrics*, Vol. 4, No. 1, pp. 21–46.

Allenby, Greg M.; Arora, Neeraj; and Ginter, James L. 1995, "Incorporating prior knowledge into the analysis of conjoint studies," *Journal of Marketing Research*, Vol. 32, No. 2 (May), pp. 152–162.

Allenby, Greg M. and Ginter, James L. 1995, "Using extremes to design products and segment markets," *Journal of Marketing Research*, Vol. 32, No. 4 (May), pp. 152–162.

Anderson, D. A. and Wiley, James B. 1992, "Efficient choice set designs for estimating cross-effects models," *Marketing Letters*, Vol. 3, No. 4 (October), pp. 357–70.

Anderson, Norman H. 1970, "Functional measurement and psychophysical judgment," *Psychological Review*, Vol. 77, No. 3, pp. 153–70.

Ansari, Asim; Essegaier, Skander; and Kohli, Rajeev 2000, "Internet recommendation systems," *Journal of Marketing Research*, Vol. 37, No. 3 (August), pp. 363–375.

Bateson, John E. G.; Reibstein, David J; and Boulding, William 1987, "Conjoint analysis reliability and validity: A framework for future research," *Review of Marketing*, ed. M. J. Houston, American Marketing Association, Chicago, Ilinois, pp. 451–481.

Batsell, Richard R. and Lodish, Leonard M. 1981, "A model and measurement methodology for predicting individual consumer choice," *Journal of Marketing Research*, Vol. 18, No. 1 (February), pp. 1–12.

Batsell, Richard R. and Louviere, Jordan J. 1991, "Experimental analysis of choice," *Marketing Letters*, Vol. 2, No. 3 (August), pp. 199–214.

Bell, D. F.; Raiffa, Howard; and Tversky, Amos, eds. 1988, *Decision Making: Descriptive, Normative, and Prescriptive Interactions*, Cambridge University Press, New York.

Ben-Akiva, Moshe and Gershenfeld, Shari 1998, "Multi-featured products and services: Analyzing pricing and bundling strategies," *Journal of Forecasting*, Vol. 17, No. 3, pp. 175–196.

Carmone, Frank J.; Green, Paul E.; and Jain, Arun K. 1978, "The robustness of conjoint analysis: Some Monte Carlo results," *Journal of Marketing Research*, Vol. 15, No. 2, pp. 300–303.

Carroll, J. Douglas 1969, "Categorical conjoint measurement," paper presented at the Annual Meeting of the Association of Mathematical Psychology, Ann Arbor, Michigan.

Carroll, J. Douglas and Green, Paul E. 1997, "Psychometric methods in marketing research: Part 2, multidimensional scaling," *Journal of Marketing Research*, Vol. 34, No. 2 (May), pp. 193–204.

Cattin, Philippe and Wittink, Dick R. 1976, "A Monte Carlo study of metric and nonmetric estimation techniques," Paper 341, Graduate School of Business, Stanford University.

Choi, S. C.; DeSarbo, Wayne S.; and Harker, Patrick T. 1990, "Product positioning under price competition," *Management Science*, Vol. 30, No. 3, pp. 175–199.

DeSarbo, Wayne S.; Carroll, J. Douglas; Lehmann, Donald R.; and O'Shaugnhessy, John 1982, "Three-way multivariate conjoint analysis," *Marketing Science*, Vol. 1, No. 4 (Fall), pp. 323–350.

DeSarbo, Wayne S.; Wedel, Michel; Vriens, Marco; and Ramaswamy, Venkatram 1992, "Latent class metric conjoint analysis," *Marketing Letters*, Vol. 3, No. 4 (July), pp. 273–288.

Gensch, Dennis H. and Recker, Wilfred W. 1979, "The multinominal multiattribute logit choice model," *Journal of Marketing Research*, Vol. 16, No. 1 (February), pp. 124–132.

Green, Paul E. 1984, "Hybrid models for conjoint analysis: An expository review," *Journal of Marketing Research*, Vol. 21, No. 3 (May), pp. 155–159.

Green, Paul E.; Frank, Ronald E.; and Robinson, Patrick J. 1967, "Cluster analysis in test market selection," *Management Science*, Vol. 13, No. 8, pp. B387–400.

Green, Paul E.; Goldberg, Stephen M.; and Montemayor, Mila 1981, "A hybrid utility estimation model for conjoint analysis," *Journal of Marketing*, Vol. 45, No. 1 (Winter), pp. 33–41.

Green, Paul E. and Krieger, Abba M. 1991, "Segmenting markets with conjoint analysis," *Journal of Marketing*, Vol. 55, No. 4 (October), pp. 20–31.

Green, Paul E. and Krieger, Abba M. 1996, "Individualized hybrid models for conjoint analysis," *Management Science*, Vol. 42, No. 6 (June), pp. 850–867.

Green, Paul E. and Krieger, Abba M. 1997, "Using conjoint analysis to view competitive interaction through the customer's eyes," in *Wharton on Dynamic Competitive Strategy*, eds., George S. Day, D. J. Reibstein, and R. E. Gunther, John Wiley and Sons, New York, pp. 343–367.

Green, Paul E.; Krieger, Abba M.; and Carroll, J. Douglas 1987, "Conjoint analysis and multidimensional scaling: A complementary approach," *Journal of Advertising Research*, Vol. 27, No. 5 (October/November), pp. 21–27.

Green, Paul E.; Krieger, Abba M.; and Zelnio, Robert N. 1989, "A componential segmentation model with optimal design features," *Decision Sciences*, Vol. 20, No. 2 (Spring), pp. 221–238.

Green, Paul E. and Rao, Vithala R. 1971, "Conjoint measurement for quantifying judgmental data," *Journal of Marketing Research*, Vol. 8, No. 3 (August), pp. 355–363.

Green, Paul E. and Srinivasan, V. 1978, "Conjoint analysis in consumer research: issues and outlook, " *Journal of Consumer Research*, Vol. 5, No. 2 (September), pp. 103–123.

Green, Paul E. and Srinivasan, V. 1990, "Conjoint analysis in marketing: New developments with implications for research and practice," *Journal of Marketing*, Vol. 54, No. 1 (October), pp. 3–19.

Green, Paul E. and Wind, Yoram 1973, *Multiattribute Decisions in Marketing: A Measurement Approach*, Dryden Press, Hinsdale, Illinos.

Green, Paul E. and Wind, Yoram 1975, "New way to measure consumers' judgments," *Harvard Business Review*, Vol. 53, No. 4 (July–August), pp. 107–117.

Gustaffsson, Anders; Hermann, Andress; and Huber, Frank, eds. 2000, *Conjoint Measurement: Methods and Applications*, Springer-Verlag, Berlin, Germany.

Haaijer, Rinus; Kamakura, Wagner; and Wedel, Michel 2000, "Response latencies in the analysis of conjoint choice experiments," *Journal of Marketing Research*, Vol. 37, No. 3 (August), pp. 376–382.

Hagerty, Michael R. 1985, "Improving the predictive power of conjoint analysis: The use of factor analysis and cluster analysis," *Journal of Marketing Research*, Vol. 22, No. 2 (May), 168–184.

Herman, Steve 1988, "Software for full-profile conjoint analysis," in *Proceedings of the Sawtooth Conference on Perceptual Mapping, Conjoint Analysis, and Computer Interviewing*, ed. M. Metegrano, Sawtooth Software, Ketchum, Idaho, pp. 117–130.

Hoffman, Paul J.; Slovic, Paul; and Rorer, L. G. 1968, "An analysis of variance model for the assessment of configural cue utilization in clinical judgment," *Psychological Bulletin*, Vol. 69, No. 5, pp. 338–349.

Huber, Joel and Zwerina, Klaus 1996, "The importance of utility balance in efficient choice designs," *Journal of Marketing Research*, Vol. 33, No. 3 (August), pp. 307–317.

Johnson, Eric; Meyer, Robert J.; and Ghose, Sanjay 1989, "When choice models fail: Compensatory models in negatively correlated environments," *Journal of Marketing Research*, Vol. 26, No. 3 (August), pp. 255–270.

Johnson, Richard M. 1974, "Trade-off analysis of consumer values," *Journal of Marketing Research*, Vol. 11, No. 2 (May), pp. 121–127.

Johnson, Richard M. 1987, "Adaptive conjoint analysis," in *Proceedings of the Sawtooth Software Conference on Perceptual Mapping, Conjoint Analysis, and Computer Interviewing*, ed. M. Metegrano, Sawtooth Software, Ketchum Idaho, pp. 253–265.

Kamakura, Wagner 1988, "A least squares procedure for benefit segmentation with conjoint experiments," *Journal of Marketing Research*,

Vol. 25, No. 2 (May), pp. 157-167.
Kamakura, Wagner; Wedel, Michel; and Agrawal, Jagdish 1994, "Concomitant variable latent class models for conjoint analysis," *International Journal of Research in Marketing*, Vol. 11, No. 5, pp. 451-464.
Kaul, Anil and Rao, Vithala R. 1994, "Research for product position and design decisions: An integrative review," *International Journal of Research on Marketing*, Vol. 12, No. 4, pp. 293-320.
Keeney, Ralph L. and Raiffa, Howard 1976, *Decisions with Multiple Objectives: Preferences and Value Tradoffs*, John Wiley and Sons, New York.
Kohli, Rajeev and Mahajan, Vijay 1991, "A reservation price model for optimal pricing of multiattribute products in conjoint analysis," *Journal of Marketing Research*, Vol. 28, No. 3 (August), pp. 347-354.
Kruskal, Joseph B. 1965, "Analysis of factorial experiments by estimating monotone transformations of the data," *Journal of the Royal Statistical Society*, Series B, Vol. 27, No. 2, pp. 251-263.
Kuhfeld, Warren F.; Tobias, Randall D.; and Garratt, Mark 1994, "Efficient experimental designs with marketing research applications," *Journal of Marketing Research*, Vol. 31, No. 4 (November), pp. 545-557.
Lazari, Andreas G. and Anderson, Donald A. 1994, "Designs of discrete choice set experiments for estimating both attribute and availability cross effects," *Journal of Marketing Research*, Vol. 31, No. 3 (August), pp. 375-383.
Lenk, Peter J.; DeSarbo, Wayne S.; Green, Paul E.; and Young, Martin R. 1996, "Hierarchical Bayes conjoint analysis: Recovery of partworth heterogeneity from reduced experimental designs," *Marketing Science*, Vol. 15, No. 2, pp. 173-191.
Louviere, Jordan and Woodworth, George 1983, "Design and analysis of simulated consumer choice or allocation experiments, *Journal of Marketing Research*, Vol. 20, No. 4 (November), pp. 350-367.
Luce, R. Duncan and Tukey, John W. 1964, "Simultaneous conjoint measurement: A new type of fundamental measurement," *Journal of Mathematical Psychology*, Vol. 1, pp. 1-27.
Mahajan, Vijay; Green, Paul E.; and Goldberg, Stephen M. 1982, "A conjoint model for measuring self- and cross-price demand relationships," *Journal of Marketing Research*, Vol. 19, No. 3 (August), pp. 334-342.
McFadden, Daniel 1974, "Conditional logit analysis of qualitative choice behavior," in *Frontiers on Econometrics*, ed. P. Zarembka, Academic Press, New York, pp. 105-421.
Myers, John G.; Massy, William F.; and Greyser, Stephen A. 1980, *Marketing Research and Knowledge Development*, Prentice-Hall, Englewood Cliffs, New Jersey.
Oppewal, Harmen; Louviere, Jordan; and Timmermans, Harry 1994, "Modeling hierarchical conjoint processes with integrated choice experiments," *Journal of Marketing Research*, Vol. 31, No. 1 (February), pp. 92-105.
Plackett, R. L. and Burman, J. P. 1946, "The design of optimum multifactorial experiments," *Biometrika*, Vol. 33, No. 4, pp. 305-325.
Punj, Girish N. and Staelin, Richard 1978, "The choice process for graduate business schools," *Journal of Marketing Research*, Vol. 15, No. 4 (November), pp. 588-598.
Ramaswamy, Venkatram and Cohen, Steven H. 2000, "Latent class models for conjoint analysis," in *Conjoint Measurement: Methods and Applications*, eds. A. Gustafsson, A. Hermann, and F. Huber, Springer-Verlag, Berlin, Germany.
Saaty, Thomas L. 1980, *The Analytical Hierarchy Process*, McGraw-Hill, New York.
Sawtooth Software 1999, *CBC for Windows*, Sequim, Washington.
Shocker, Allan D. and Srinivasan, V. 1977, "LINMAP (Version II): A FORTRAN IV computer program for analyzing ordinal preference (dominance) judgments via linear programming techniques and for conjoint measurement," *Journal of Marketing Research*, Vol. 14, No. 1, pp. 101-103.
Srinivasan, V. 1988, "A conjunctive-compensatory approach to the self-explication of multiattributed preferences," *Decision Sciences*, Vol. 19, No. 2 (Spring), pp. 295-305.
Srinivasan, V.; Jain, Arun K.; and Malhotra, Naresh K. 1983, "Improving the predictive power of conjoint analysis by constrained parameter estimation," *Journal of Marketing Research*, Vol. 20, No. 4 (November), pp. 433-438.
Starr, Martin K. and Zeleny, M. 1977, *Multiple Criteria Decisions Making*, North-Holland,

Amsterdam, Holland.
Steckel, Joel H.; DeSarbo, Wayne S.; and Mahajan, Vijay 1991, "On the creation of feasible conjoint analysis experimental designs," *Decision Sciences*, Vol. 22, No. 2, pp. 435–442.
van der Lans, Ivo A. and Helsen, Willem H. 1992, "Constrained part-worth estimation in conjoint analysis using the self-explicated utility model," *International Journal of Research in Marketing*, Vol. 9, No. 3, pp. 325–344.
Vavra, Terry G.; Green, Paul E.; and Krieger, Abba M. 1999, "Evaluating EZ-Pass," *Marketing Research*, Vol. 11, No. 3 (Summer), pp. 5–16.
Vriens, Marco; Wedel, Michel; and Wilms, Tom 1996, "Metric conjoint segmentation methods: A Monte Carlo comparison, *Journal of Marketing Research*, Vol. 33, No. 1 (February), pp. 73–85.
Wedel, Michel and Kamakura, Wagner A. 1998, *Market Segmentation: Conceptual and Methodological Foundations*, Kluwer, Boston, Massachusetts.
Westwood, Dick; Lunn, Tony; and Beazley, David 1974, "The trade-off model and its extensions," *Journal of the Market Research Society*, Vol. 16, No. 3, pp. 227–241.
Wind, Jerry; Green, Paul E.; Shifflet, Douglas; and Scarbrough, Marsha 1989, "Courtyard by Marriott: Designing a hotel facility with consumer-based marketing models," *Interfaces*, Vol. 19, No. 1 (January-February), pp. 25–47.
Wittink, Dick and Cattin, Philippe 1989, "Commercial use of conjoint analysis: An update," *Journal of Marketing*, Vol. 53, No. 3 (July), pp. 91–96
Wittink, Dick R.; Krishnamurthi, Lakshman; and Nutter, Julia B. 1982, "Comparing derived importance weights across attributes," *Journal of Consumer Research*, Vol. 8, No. 4, (March), pp. 471–474.
Wittink, Dick; Vriens, Marco; and Burhenne, Wim 1994, "Commercial use of conjoint in Europe: Results and critical reflections," *International Journal of Research in Marketing*, Vol. 11, No. 1, pp. 41–52.
Young, Forrest W. 1969, "Polynomial conjoint analysis of similarities: Definitions for a special algorithm," Research paper No. 76, Psychometric Laboratory, University of North Carolina.