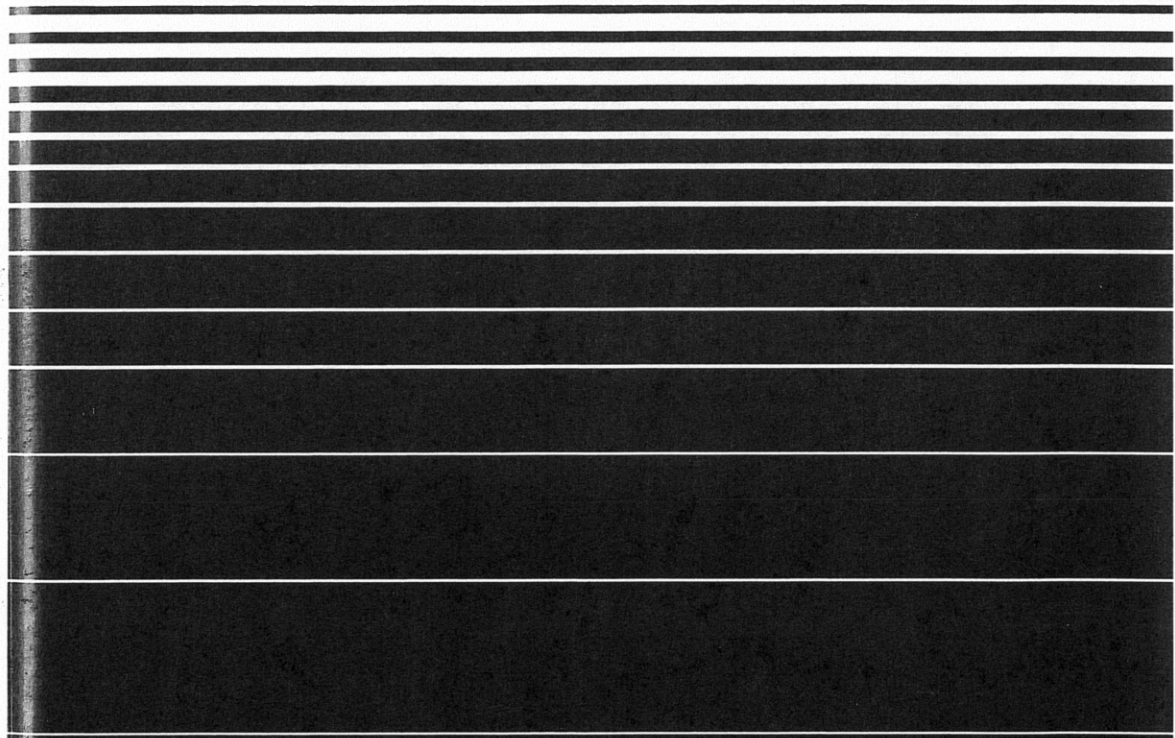


MARKETING RESEARCH AND MODELING: PROGRESS AND PROSPECTS

A Tribute to Paul E. Green

Edited by
YORAM (JERRY) WIND
PAUL E. GREEN



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INTRODUCTION

Paul Green and a Brief History of Marketing Research

Unraveling the tradeoffs between personal memoir and intellectual history in telling Paul Green's story is perhaps a problem worthy of the sophisticated research tools that he pioneered. He has been so directly involved in the development of the field of marketing research over more than four decades that it is difficult to separate the life of Paul Green from the story of the field. A retrospective on marketing research and the man who shaped it must go hand in hand. A conference to celebrate Green's intellectual contributions and the development of the field, such as the one to celebrate his 40th anniversary at Wharton in May of 2002 – an event that launched this book – inevitably turns into a personal celebration of Paul Green himself. He is a pioneer in marketing research, a prolific scholar, and a mentor to the next generation of scholars, not to mention an accomplished pianist.

In weighing the “partworths” of these two aspects of the book – personal biography and intellectual history – we give a bit more emphasis to his contributions to the progress of marketing research than to his personal story. But to set the stage in this introduction, we take a “full profile” approach, exploring the man, his work, and the evolution of the discipline simultaneously. This “multidimensional” portrait is admittedly idiosyncratic and incomplete, although there are number of excellent histories of the field, many written by Green himself, as noted in the following chapters and the appendix of this book. Through this sketch, we hope to trace the interwoven paths of Green's career and the evolution of marketing research.

The field of marketing research has grown considerably in rigor and stature during Green's more than four decades of involvement. The emeritus professor at the Wharton School has played a central role in the development

and evolution of powerful tools such as conjoint analysis, multivariate data analysis, multidimensional scaling, and the application of Bayesian statistics.

Called "the father of conjoint analysis," Green is one of the most published and widely cited researchers in the field of marketing, with more than 200 books and articles. He has also made many direct contributions to marketing practice that have proven the business value of the theoretical concepts and tools he developed and refined. He has used conjoint analysis to help Marriott create the original concept for its Courtyard hotels for business travelers, AT&T's first cellular phone system, the E-Z Pass automated toll collection system, and the design and pricing for IBM's Risc 6000 and AS400 computer systems. Green also has used cluster analysis to help develop AT&T's "Reach out and touch someone" campaign and applied multidimensional scaling to issues such as Life cereal's "Mikey" ad campaign and Coca-Cola's "It's the real thing" slogan. His projects have ranged from technology to drugs to ladies panties (to assess the importance of DuPont brands). Green's students have applied his work even more broadly in their own corporations and in developing commercial software for conjoint analysis.

But at the heart of this work is the life story of a talented and persistent researcher. Paul Green arrives early and keeps a steady stream of new research flowing out of his Wharton office, most often with long-time collaborator Abba Krieger, professor of statistics at Wharton, who has described himself as "Paul Green's sidekick." Green draws upon his own varied background in statistics, operations research, and other disciplines to develop innovative solutions to marketing research challenges.

In this book, leaders in marketing research explore key concepts and current challenges in the field. But we begin with the story of the man whose life is inextricably bound to the progress of marketing research during its formative years in the last half of the 20th century. We first meet Paul Green.

"That's Paul Green"

To meet the soft-spoken and thoughtful Paul Green in the hallway at the Wharton School, you probably would not be immediately aware of his quiet power, prominence, and profound influence on the field of marketing research.

In remarks shared at the anniversary conference (included in Chapter 12 with the personal reflections of other colleagues), David Schmittlein, professor of marketing and deputy dean at Wharton, describes the experience of bumping into Green in the hallway and listening to him discuss his current research:

This scene is one of contrast, Paul calmly, logically, smoothly articulating a point of algebra, or data manipulation, or probability models – me in near panic, holding on by my fingernails to

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the ideas that are flying by with the speed – and yes, the elegance
– of the Concorde. Scary – but exhilarating.

Years earlier, Schmittlein, then a newly minted Ph.D. graduate from Columbia, first met Green and was “struck by the force of Paul’s intellect and graced by the warmth of his humanity.” Around that same time, Schmittlein also was exposed to another side of the multi-faceted Green at a doctoral consortium in Madison, Wisconsin. Standing with friends, Schmittlein remarked upon the wonderful piano player in the corner.

“You don’t know who that is?” remarked a colleague. “That’s Paul Green.”

A Random Walk into Academia

Paul Green came into marketing by what he describes as a “random walk.” This walk led from chemistry to mathematics to operations research to statistics and across a dozen years in business practice before finally joining the marketing faculty at the University of Pennsylvania’s Wharton School.

Returning from World War II in the fall of 1946, Green entered the University of Pennsylvania’s School of Arts and Sciences on the GI Bill. He seemed destined to be a chemist, which had been his passion since fifth grade, punctuated by a near-death experience in his parents’ attic involving a Tesla high-voltage coil when he accidentally brushed against a water pipe.

To Green’s dismay, Penn’s chemistry courses were reserved for GI’s in pre-med, so by this chance his career veered away from chemistry to the less perilous study of mathematics and economics. In college, he was already pursuing his lifelong musical interest. He helped to pay his way through college by performing a few nights a week at local bars and bistros, among the few venues of his illustrious career that he could accurately describe as being “of dubious reputation.”

Green did not go directly into academia. When he graduated in 1950, he went to work for Sun Oil Company in Philadelphia as a statistical research analyst. At the same time, he earned his master’s degree at Penn in statistics, working with Simon Kuznets, who was later to win the Nobel Prize in economics. Three years later, Green switched from petroleum to steel, joining Lukens Steel Company in its marketing research department. While there, he began working in the fledgling field of operations research, studying with West Churchman and Russ Ackoff, and using the insights to tackle scheduling, inventory control, and simulation problems for the steel manufacturer. With an ever-curious mind, he entered Penn’s doctoral program in statistics, a pursuit that he continued after he moved from Lukens to DuPont. In 1961, eight years after completing his master’s degree, he received his Ph.D. in statistics from Penn.

A Test of Bayesian Analysis

His doctoral dissertation advisor Morris Hamburg recalls that he was intrigued when Green came to him with a proposal to apply a relatively new approach in statistics, Bayesian analysis, to real-world marketing challenges at DuPont. Hamburg describes one application of the work:

DuPont, at that time, produced an industrial end-use fiber for which top management was considering a price decrease. The decision problem was quite complex. Three other firms produced this fiber at identical prices to DuPont, and product quality and service among all four producers were comparable. There were four interrelated market segments. Furthermore, there was a competitive fiber produced by six other firms in the four market segments. Paul designed and carried out a complex Bayesian decision analysis of four pricing alternatives. Most of the data consisted of informed judgments by sales management personnel. One of the price decreases emerged from the analysis as the recommended best course of action.

The work on Green's dissertation, "Some Intra-firm Applications of Bayesian Decision Theory to Problems in Business Planning," reflected key interests that would shape Green's future work. As Hamburg notes:

After completion of his thesis, Paul had a phenomenally prolific run of publications in a variety of fields using Bayesian decision theory and analysis. His work was extremely widely cited, and he developed a well-deserved reputation as an outstanding researcher.

However, with his fertile and creative mind, Paul went on to make seminal contributions to the other areas of modeling and applications ... such as multivariate data analysis, multi-dimensional scaling and clustering, and conjoint and related analyses. Nevertheless, I believe that it is fair to say that Paul carried over, throughout the succeeding decades, concepts and techniques that he dealt with in his doctoral dissertation, such as the multiplicity of goals in decision making under uncertainty, alternative concepts of optimization, and the intellectual wrestling match that takes place in the application of normative theories to real-world problems, Von Neumann-Morgenstern utility functions, tradeoffs and sensitivity analysis.

In his doctoral research, Green also demonstrated his lifelong interest in applied theory, which he continued even after he left DuPont to start a new career in academia.

Meeting Wroe Alderson and the Origins of Marketing Research

During his last years in Penn's doctoral program, Green sat in on lectures by Wroe Alderson of the Marketing Department, who was *the* leading figure in marketing theory from the early 1950s until his death in 1965. Alderson started the annual Marketing Theory seminars that defined the frontiers of the field and authored the influential book *Marketing Behavior and Executive Action* in 1957. Alderson set an example of combining theory and practice through his own consulting work – with university presidents, corporate chief executives, and government leaders – that Green was to follow.

In 1962, Alderson invited Green to join Wharton's Marketing Department, an invitation that Green willingly accepted, leaving DuPont for the university. Together, Green and Alderson authored *Planning and Problem Solving in Marketing*, published in 1964, showing how some relatively new tools such as Bayesian analysis could be used to address marketing problems. Two years later, Green and Don Tull – who worked through the mails and never met one another until after their book was published – co-authored the textbook *Research for Marketing Decisions*, which has shaped education in marketing research.

In their book, they defined marketing research as: “The systematic and objective search for, and analysis of, information relevant to the identification and solution of any problem in the field of marketing.”¹ Explaining the importance of marketing research, they note that colonial silversmith Paul Revere personally knew the customers who bought his tankards, platters, and teapots, while the modern president of Revere Copper and Brass, Inc., is isolated from the thousands of customers of his products. Advertising and personal selling represent communication to the market, while marketing research is a formally organized “feedback loop” from the market to the company.²

As Green found in his research at DuPont, the complexity and uncertainty of large modern businesses required more sophisticated tools. Drawing on his experience in statistics and other disciplines, Green helped to create and refine these tools for marketing and put them into practice. He pursued this research with a passion and prolific output that in large part defined the field.

Defining Marketing Research

The chapters of this book explore some of these streams of scholarship in marketing research that were initiated or strengthened through Green's work.

Current leaders in these research areas examine the history of research and future directions in four key streams of knowledge:

Bayesian Decision Theory (BDT)

As noted, Green's thesis represented an early application of the Bayesian approach to marketing research. Bayes theorem is named for eighteenth-century clergyman, Thomas Bayes. The theorem is the cornerstone of what has become known as the Bayesian approach, or Bayesian Decision Theory (BDT). In contrast to traditional statistics, based on determining the limit of a relative frequency over the long run, the Bayesian approach to making decisions under partial ignorance makes use of the confidence that the decision maker has in the truth of specific propositions. It allows marketing executives, who rarely have enough solid information to determine the relative frequency of outside events, to consider both objective probabilities and subjective probabilities based on judgment. It also allows researchers to update their probabilities, based on new information, and to determine whether it is worthwhile to seek that information through marketing research. As Eric Bradlow, Peter Lenk, Greg Allenby, and Peter Rossi consider in Chapter 1, even with the emergence of richer data sets, marketing remains a "decision-oriented discipline," and, as such, Bayesian approaches continue to make important contributions to these decisions.

Multivariate Data Analysis

Paul Green was one of the first to introduce latent variable models in marketing research, using latent class analysis and logit models. As Wayne DeSarbo, Wagner Kamakura, and Michel Wedel note in Chapter 2, "a multivariate statistical model specifies the joint distributions of a set of random variables and it becomes a latent variable model when some of these variables – the latent variables – are unobservable." These models can be used to help marketing managers and researchers in "depicting market structure, market segmentation, product design and positioning, competitive influences and patterns, and relationships between consumer perceptions and choice." They discuss the development of a large variety of models and approaches – including unrestricted latent class, latent class regression, latent class multidimensional scaling, generalized factor analysis, and factor regression models – in the three decades since Paul Green introduced multivariate data analysis to marketing. They also examine applications to problems such as new product development in personal computers and customer satisfaction in financial services.

Multidimensional Scaling and Clustering

While multidimensional scaling was developed in the late 1930s by Gale Young and Alton Householder, followed quickly by Marion Richardson, it was not until the development of computing technology in the 1950s and 1960s that the field took off, including applications to marketing. Multidimensional scaling (MDS), which transforms Euclidian distances into a set of point coordinates, offers a powerful tool for addressing problems of consumer perceptions and evaluation through perceptual and preference mapping. Applications in marketing research rapidly expanded after 1962, when Roger Shepard published the first operational procedure for the multidimensional scaling of rank order (nonmetric) input data. Paul Green and Frank Carmone, writing the first marketing-oriented book on the subject in 1970, extended its applications to problems such as market segmentation, product life cycle analysis, and product/service evaluation. As Douglas Carroll, Phipps Arabie, Anil Chaturvedi, and Lawrence Hubert write in Chapter 3, Green has continued to play a role in the evolution of research in this area. They note in the chapter that MDS modeling has become increasingly complex and sophisticated, incorporating "all the best features associated with new models and methods applied to marketing."

In Chapter 4, Wolfgang Gaul explores the implications of enabling technologies such as the Internet for extending and applying these marketing research approaches.

Conjoint Analysis and Related Modeling

Green's interest in applying conjoint analysis to marketing research grew out of frustration with the limits of multidimensional scaling as a way to define consumer perceptions and preferences. MDS users might plot a pair of cars based on two or three dimensions, such as expense and performance, to create a brand-positioning map that allows one to separate the lower-cost, lower-performance Ford Focus from the high-cost, high-performance Porsche. But the product might really need 10 or 20 dimensions or more to provide a rich picture of customer perceptions and desires. (Courtyard by Marriott, for example, looked at 50 different attributes before developing its new hotel format for business travelers.)

"The earlier methodology was not powerful enough," Green said in an interview with the Marketing Science Institute (MSI).³ "It becomes a many-to-one function. Do we change the paint job, engine, or transmission? Which one do we choose? There was a feeling that we could only go so far. Multidimensional scaling is good in showing product positioning in current markets that are out there, but it is not good from a dynamic point of view in helping you design a new item or change the character of an old item."

As he wrestled with the limits of multidimensional scaling in the 1960s, Green found the beginnings of an answer. "Fortunately, I was reading a lot of the literature that was outside the field of marketing," he said. He came across a 1964 study in the *Journal of Mathematical Psychology* by mathematical psychologist R. Duncan Luce and statistician John Tukey that pointed him in a new direction. The research dealt with making tradeoffs among different attributes to develop scales and rankings. Green realized these principles could be applied to marketing research and, along with Vithala Rao, introduced conjoint analysis to the marketing research community in 1971. Since then, conjoint has become one of the most documented methods in marketing research and one of the most popular multi-attribute choice models in marketing, with thousands of applications.

Conjoint analysis is both a tradeoff measurement technique for analyzing preferences and intentions-to-buy responses and a method for simulating how consumers might react to changes in current product/services or the introduction of new products as well as not-for-profit offerings.

Conjoint offers an extremely efficient process for weighing diverse attributes of a product or service offering. For example, in one study a financial services company designing a new credit card offering needed to make decisions about setting annual fees, cash rebates, an 800 number, different types of insurance, and other features. To consider 12 attributes, each of which had two to five options, the total number of possible combinations is an overwhelming 186,624. Conjoint combines options into profiles using orthogonal arrays, reducing these thousands of combinations to just 64 different profiles.

"It was a very exciting time," Green said of the birth of conjoint analysis. "We knew we were on to some new stuff. The students at that time, even some of our master's students, were doing very top-notch work in this area. It was like a little club, and that was very exciting."

In Chapter 5, Green and colleague Abba Krieger reflect on three decades of conjoint analysis. In Chapter 6, John Hauser and Vithala Rao explore some recent developments in conjoint analysis and related modeling. In Chapter 7, Green, Krieger, and Wind examine buyer choice models, optimizers and dynamic models. In Chapter 8, Jordan Louviere, Deborah Street, and Leonie Burgess offer a broad perspective on conjoint-based choice experiments. Finally, in Chapter 9, Howard Moskowitz offers insights on applications, particularly through conjoint analysis software.

As noted in the discussion of the four research streams above, Paul Green's impact on colleagues, students and the field cannot be completely assessed in academic tributes and retrospectives. Part Six offers some of these more personal and biographical perspectives from Paul and the many colleagues who have been influenced by his work and benefited from his personal presence.

Finally, the concluding chapter examines strategies for bridging research and practice, one of the key concerns of Paul's work, and an ongoing challenge for the field.

The Parlin Award

In May 1977, just 15 years after embarking on his career in marketing research, Green followed in Alderson's footsteps to receive the Charles Coolidge Parlin Award for outstanding contributions to marketing research. In making the award, the Parlin Board of Governors called Green "one of the major architects of modern marketing science and practice. The marketing discipline's familiarity with the utilization of Bayesian statistics, multidimensional scaling, conjoint measurement, and more recently, the analysis of qualitative data are all due to the pioneering work of Paul Green." At that time, he had already written more than 12 books and 100 articles, and had spoken to audiences at more than 50 universities around the world. As a reviewer and editor, he helped to "structure the current marketing literature." As an educator, he helped to "mold a new generation of marketing researchers."

Any professor might hope to win such praise as a capstone to a successful career. But Green was just warming up. For a quarter century after the award, he has continued to broaden and deepen his contributions to the field. His students and collaborators – more than 50 different co-authors – read like a *Who's Who* of marketing research. (Green, with typical attention to statistics, actually analyzed and ranked his top seven collaborators, noting that while these individuals account for just 13 percent of the names, they worked with him on half of all his joint publications, roughly reflecting his own "80/20" rule of scholarship.)

Not only has Green won virtually every major award in the field of marketing, he even has an award named in his honor. Established by the AMA's *Journal of Marketing Research*, the Paul Green Award is given to the *JMR* paper that "shows or demonstrates the most potential to contribute significantly to the practice of marketing research and research in marketing."

Some of his admirers are still not satisfied. As Morris Hamburg comments, referring to the Nobel Prize: "If there was such an award in the field of marketing research, I think you would agree that a prime candidate to be the first recipient of that prize would be Paul Green."

Future Generations

Green continues to actively participate in scholarship and applications in business. He also helps to shape the next generation of marketing professors. Among the personal reflections of Chapter 12, Raymond Burke, a former Wharton faculty member and professor at Indiana University, recalls:

When I joined the Wharton faculty, I had the good fortune to be assigned to an office next door to Paul Green. Fresh out of school from the University of Florida's Ph.D. program, my mind was focused on theoretical issues in consumer psychology. Given Paul's reputation in marketing research and modeling, I did not think we would have much to talk about. In fact, our conversations were some of the most stimulating and enriching experiences that I had during my years at Wharton. Paul valued interdisciplinary research, and his innovations in the field of marketing reflected a deep understanding of consumer behavior, psychometrics, and statistics. He was continually exploring ways in which the science of consumer psychology could be used to improve management decisions, including product design, pricing, advertising, promotion, and assortment planning. Paul also recognized the importance of working with practitioners on real world problems, and developing software to make his analytic techniques broadly accessible. His work set an example for the Wharton faculty and profoundly affected my view of the discipline and future research.

Green, himself, looks back on his career with typical humility. "Big ideas in market research methodology are rare, and any researcher is fortunate to be associated with one, let alone several, over the course of a career," he wrote in a retrospective on his career for the *Journal of Marketing*, reprinted in Chapter 10. "I have tried to develop the methodological skills needed to tackle various substantive problems, be they research questions on segmentation, pricing, competition, product positioning, or whatever."

Asked in an interview by MSI to offer advice for people starting out in the field, Green recommended that students to pick an area in which they can make contributions to theory to establish themselves. As they progress in their careers, they will very likely move to more applied challenges. While not stated explicitly, additional insights can be drawn from Green's own experience:

- *Find a strong mentor:* Green's relationship with Wroe Alderson was what attracted him to the university and shaped his early work.
- *Read widely:* Green's background in mathematics and statistics, and interests in other areas, gave him fresh perspectives on his marketing work. The most interesting new ideas and approaches may come from outside the field.
- *Tackle applied challenges:* While there is much fruitful work to be done in theory, Green's focus has been on "marketing

engineering.” His 12 years in industry before entering academia helped to sharpen this focus, and his continued interaction with the challenges of practice helped him develop solutions that have immediate application.

Paul Green has a passion for research, a spark that remains undimmed by four decades of achievements. Colleague Abba Krieger notes that even after hundreds of papers and more than a dozen books, Green is still “delighted to have a paper accepted or a program running that makes an idea accessible.”

While he is officially an emeritus professor, there are still many questions to be answered in the field of marketing research, as noted in this book and particularly in the closing chapter by the editors. And, while he may have a little more time for piano playing, skiing or his grandchildren, Green will continue to play a role in answering these questions.

Over the course of his career, Paul Green has traded off corporate and consulting careers to enter academia. He has passed by the allures and titles of academic administration to focus on research and teaching. But for someone with a passion for discovery and devotion to offering new insights and tools to practitioners, it is a career that undoubtedly has been optimized.

One theme you will hear echoed throughout this book is the deep respect and personal appreciation so many leaders of marketing research hold for Paul. I share that sentiment. I hope through this volume, in a small way, we can do justice to the far-reaching contributions Paul has already made to the field and to his professional and personal impact on so many of us.

Yoram (Jerry) Wind
The Wharton School, University of Pennsylvania

NOTES

¹ Paul E. Green and Donald S. Tull, *Research for Marketing Decisions, Third Edition*, Englewood Cliffs, NJ: Prentice-Hall, Inc., 1975, p. 4.

² Green and Tull, p. 5.

³ “Paul Green: Mastering Tradeoffs,” *MSI Featured Academic*, <http://www.msi.org/msi/facad-pg.cfm>.

Chapter 5

Thirty Years of Conjoint Analysis: Reflections and Prospects¹

Paul E. Green

Abba M. Krieger

Yoram (Jerry) Wind

The Wharton School, University of Pennsylvania

Conjoint analysis is marketers' favorite methodology for finding out how buyers make tradeoffs 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' partworths for attribute levels, and enter the partworths 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 psychometricians, including Carroll (1969), Kruskal (1965), and Young (1969). These researchers developed a variety of nonmetric models for

computing partworths (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 tradeoffs. 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 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 tradeoff 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 tradeoffs 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 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.

Table 5-1. These attributes (and levels within attributes) describe the set of potential services that would be offered to credit card subscribers.

Annual price (\$)	0	10	20	50	80	100
Cash rebate (end-of-year, on total purchases)	None	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				

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 5-1). 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 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. Since the study designers used a hybrid conjoint design (Green and Krieger 1996), 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 5-1). 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.

1	2
Annual price \$20	Annual price \$50
Cash rebate None	Cash rebate ½ %
800 number for message forwarding None	800 number for message forwarding 24 hours per day
Retail purchase insurance None	Retail purchase insurance None
Common carrier insurance \$50,000	Common carrier insurance None
Rental car insurance \$30,000	Rental car insurance \$30,000
Baggage insurance \$2,500 depreciated cost	Baggage insurance None
Airport club admission \$2 per visit	Airport club admission \$5 per visit
Card acceptance Air, hotel, rental cars	Card acceptance Air, hotel, rental cars and most restaurants
Medical-Legal No	Medical-Legal Yes
Airport limousine Not offered	Airport limousine Available at 20% discount
800 number for emergency car Available at 20% discount	800 number for emergency car Not offered

Figure 5-1. 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.

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 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 *partworth 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 p th attribute for the j th stimulus; we first assume that y_{jp} is inherently continuous. The *vector* model assumes that the respondent's preference s_j for the j th 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 5-2).

Preference

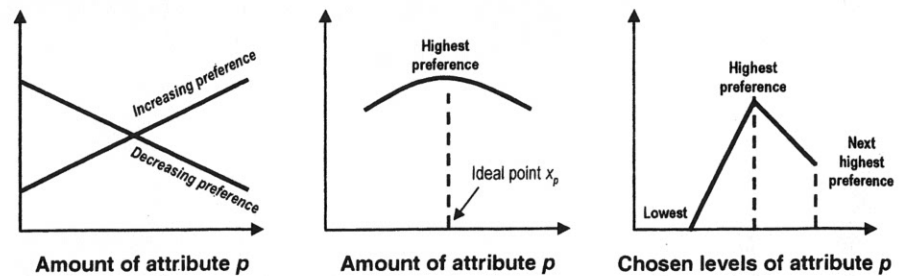


Figure 5-2. These diagrams illustrate what is meant by linear preferences, ideal point preferences, and discrete (partworth) preferences. The third graph shows three partworths. (From Green, P.E., and Srinivasan, V. (1978), *Journal of Consumer Research*, 5, 103-123.)

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 j th 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 *partworth 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 partworth 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 5-3, we show illustrative (averaged) partworths for the attribute levels described in Table 5-1. Partworths are often scaled so that the lowest partworth is zero, within each attribute. Strictly speaking, analysts evaluate partworth 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 partworths in buyer-choice simulators. The scaling (vertical axis) is common across all attributes; this allows the analyst to add up partworths across each attribute level to obtain the overall (product or service) utility of any profile composable from the basic attribute levels.

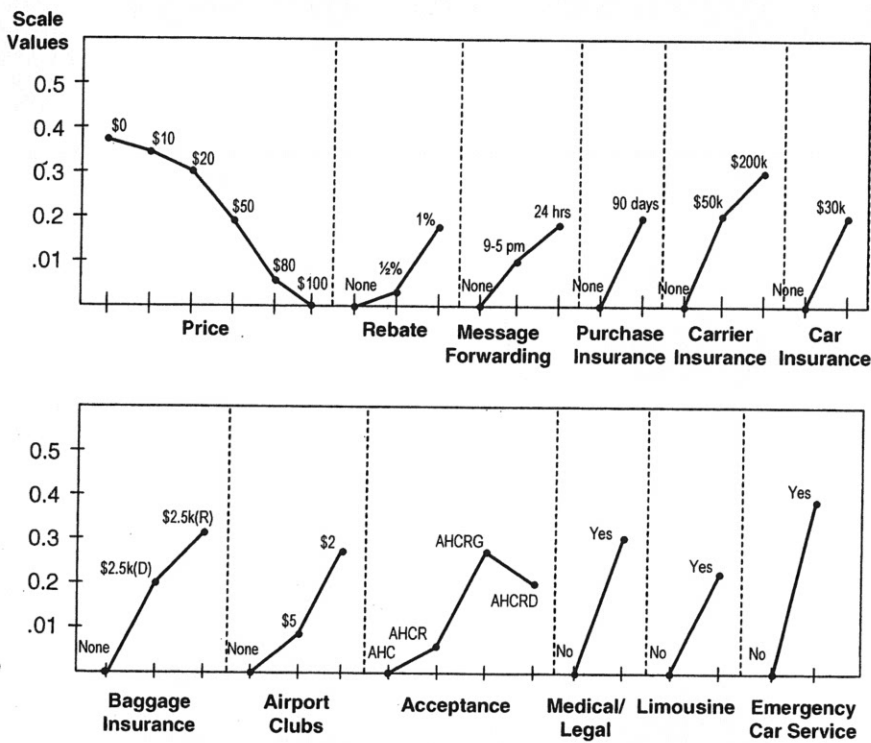


Figure 5-3. This chart illustrates how partworth scale values depend on price, message forwarding, ... emergency car service. For example, the most preferred price is \$0 and the least preferred price is \$100.

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 5-1). 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, tradeoffs, 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 multi-way) 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 1960s, 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 robust alternative to ordinally based data procedures (Cattin and Wittink 1976; Carmone, Green, and Jain 1978). 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-1970s conditions were ripe for the quick diffusion of metric methods of conjoint analysis, using dummy-variable regression. In the mid-1980s, 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 1970s, conjoint analysis had truly come of age. Wittink and his co-authors (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 tradeoffs 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 Adelman (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; Kuhfeld, Tobias, and Garratt 1994; Lazari and Anderson 1994; Huber and Zwerina 1996) on this topic occurred during the 1990s.

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 1980s

Technical developments in conjoint analysis have proceeded swiftly over the past two decades, accompanied by thousands of methodological contributions (Table 5-2). During the 1980s, 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.

Table 5-2. A Partial List of Contributions to Conjoint Analysis 1974-2000

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, Carroll, Lehmann, O'Shaughnessy 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 <i>Adaptive Conjoint Analysis</i> (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, Wedel, Vriens, and Ramaswamy 1992)
Constrained partworth estimation (van der Lans and Heiser 1992)
Modeling hierarchical conjoint processes (Oppewal, Louviere, and Timmermans 1994)
Concomitant variable latent class modeling (Kamakura, Wedel, and Agrawal 1994)
Hierarchical Bayes (HB) models for conjoint analysis (Allenby, Arora, and Ginter 1995; Allenby and Ginter 1995; Lenk, DeSarbo, Green, and Young 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)
HB applied to Internet recommendation systems (Ansari, Essegaiar and Kohli 2000)
Response latencies and conjoint analysis (Haaijer, Kamakura, and Wedel 2000)

In traditional conjoint analysis, respondents typically rate various product or supplier profiles, presented one at a time, on a likelihood-of-purchase scale. In choice-based conjoint analysis, 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.

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. This 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 1980s, hybrid models (Green, Goldberg, and Montemayor 1981; Green 1984) 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 non-hybrid 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 partworth 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 (ACA) 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 1990s

Probably the most far-reaching developments in the 1990s 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 disaggregation) as applied by DeSarbo, Wedel, Vriens, and Ramaswamy (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, partworth 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 aggre-

Table 5-3. Illustrative Applications of Conjoint Analysis

<i>Antidumping litigation</i> – AT&T vs. Pacific-rim manufacturers legal dispute regarding small business telephone equipment; case adjudicated in AT&T's favor
<i>AT&T's first cellular telephone</i> – Chicago-based study of 1,000 drivers' reactions to cell phone features of the new "honey-comb" relay system
<i>Continental vs. American Airlines litigation</i> – study of travel agents' tradeoffs among airline flight selections
<i>Courtyard by Marriott</i> – used to design new hotel chain catering to business travelers (largest known conjoint project in terms of attributes and levels)
<i>E-Z Pass</i> – used to design new electronic toll collection service in northeast U.S.
<i>FedEx new services study</i> – tradeoff study of customer reactions to new methods for tracking delayed and lost letters and packages
<i>Ford Fairlane</i> – used in redesign of Ford to reflect automotive downsizing objectives
<i>Health maintenance plans</i> – study conducted by the American Association of Retired Persons; results submitted to Congress
<i>IBM RISC 6000 workstation</i> – measured potential buyer reactions to variations in performance and reliability features of a new workstation
<i>Intermittent windshield wipers litigation</i> – study to determine consumer evaluations of the derived "willingness to pay" for the intermittent wiper feature
<i>Japanese cable TV</i> – survey of Japanese consumers' tradeoffs among services and prices of satellite TV
<i>Marriott time-share units</i> – development of optimal interior and exterior decors, services, and price
<i>MasterCard and Diner's Club</i> – new travel and entertainment features evaluated
<i>Monsanto's herbicide packaging study</i> – consumer reactions to advanced packaging devices for liquids, solids, and aerosols
<i>Polaroid's instant camera design</i> – study of consumer reactions to new features and camera design aesthetics
<i>Squibb's captopril antihypertensive</i> – six-country study of physicians' evaluations of Capoten's efficacy and safety features
<i>Tagamet (SKF) and Zantac (Glaxo) ulcer drugs</i> – competitive pricing and analysis of demand elasticities
<i>TrafficPulse</i> – a study of consumer reactions to a new system for providing updates on traffic conditions
<i>Ritz Carlton</i> – used to develop hotel decor and services
<i>UPS services study</i> – examined customers' evaluations of four major suppliers of overnight letter and package delivery
<i>US Navy reenlistment benefit packages</i> – used to develop menu of plans based on individual differences in types of duties, health needs, sign-over bonuses

aggregated data, the individual's data will receive more weight in the estimation of his or her partworths. Individuals whose partworths are estimated poorly (that is, with large error in 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 and simulator 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 5-3) of conjoint applications, three are of particular interest: the customer-driven design of Marriott's Courtyard Hotels (Wind, Green, Shifflet, and Scarbrough 1989), the design and evaluation of the New Jersey and New York E-Z Pass electronic toll collection system (Vavra, Green, and Krieger 1999), and the TrafficPulse system for receiving updates on traffic conditions (Krieger, Green, Lodish, D'Arcangelo, Rothey and Thirty 2002).

Courtyard by Marriott

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 1980s, 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 more than 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.

E-Z Pass

In the E-Z Pass toll collection project, New Jersey and New York developed a genuinely 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 E-Z 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 E-Z 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!)

The TrafficPulse System

The study of TrafficPulse also addressed the challenge of assessing reactions to a "really new" product, a new service that enables subscribers to obtain continuous 24/7 updates on traffic conditions, travel times, and alternate routes, should congestion occur. In the process, the researchers embellished traditional conjoint analysis to educate the prospective consumer and then obtain relevant information about consumer evaluations of the service prior to their actual introduction and use.

The study, with responses from 401 prospective consumers in the Pittsburgh market, helped the sponsoring company (Mobility Technologies, Inc.) to assess the attributes that would have the most value for different

segments and the optimal bundle pricing strategies for different combinations of delivery mode add-ons, cost per call, and payment mode.

The project provided concrete feedback to Mobility Technologies and also advanced research and practice by developing strategies for handling restrictions on which attribute levels can appear together across which attributes, for paying more attention to the "no interest case" and emphasizing the use of market "norms" in converting respondents' buying intention scores into purchase likelihoods.

These projects illustrate the ability of conjoint analysis 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 Gershfeld 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 such sites as *activebuyersguide.com*, *personallogic.com*, and *conjointonline.com*, that typically use hybrid conjoint models to elicit buyer preferences for Web-based merchandise (Ansari, Essegai, and Kohli 2000);
- Additional studies of conjoint reliability and validity (Vriens, Wedel, and Wilms 1996; Haaijer, Kamakura, and Wedel 2000);

- 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 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 op-

erations 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.

NOTES

¹ Adapted from *Interfaces*, 31 (3), Part 2 of 2, May/June 2001, S56-S73.

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Chapter 7

Buyer Choice Simulators, Optimizers, and Dynamic Models

Pául E. Green

Abba M. Krieger

Yoram (Jerry) Wind

The Wharton School, University of Pennsylvania

Collecting and analyzing respondents' conjoint data is an essential part of the analytical process. As noted by John Hauser and Vithala Rao in their excellent discussion of conjoint analysis over the past 30 years (see Chapter 6), marketing researchers have expended intense efforts on data collection and partworth estimation. Partworths have been estimated by full profile, Adaptive Conjoint Analysis, hybrid conjoint, and categorical conjoint, with or without empirical or hierarchical Bayes enhancement. Partworth measurement and estimation processes are central to the accuracy and usefulness of all conjoint studies. Accordingly, much has been written about the pros and cons of various conjoint data collection and parameter estimation methods.

At the end of the day, however, it is *what is done with the partworths* that interests marketing managers. Hence, an important part of the applications process involves the design and use of "if-then" models: simulators and optimizers that provide bottom-line forecasts and comparisons of alternative strategic options.

Ironically, descriptions of simulators/optimizers have received much less attention in the literature than they deserve. This chapter attempts to redress this imbalance. Our main objective is to describe a variety of descriptive and prescriptive models whose goal is to forecast (or optimize) the sponsor firm's share or financial return position, given a set of actions that are played out in the simulator/optimizer modules. We try to show that such descriptive (or prescriptive) models are essential to both the tactical and strategic roles that conjoint models play in finding good (or even optimal) courses of action. The

chapter also includes a real world application of conjoint modeling, as used in the design of the Northeast U.S.A.'s E-Z Pass travel system.

Most conjoint software distributors (e.g., Sawtooth Software and SPSS CATEGORIES) provide a market simulator in the software packages. These simulators, while highly useful, are not meant to fully cover the various features that a simulator/optimizer could have. Hence, we describe more elaborate simulation modules that consulting firms (in particular) have developed to extend the range of commercial conjoint applications.

We start from a set of basic operations and progress to more elaborate models that are typically proprietary to a specific consulting firm. We describe three classes of models:

- *Simulators*, designed to implement if-then tactics on the part of a single supplier (with competitors)
- *Optimizers*, that solve for the highest market share or return product configuration, conditioned on known (or assumed) competitors' strategies, and
- *Dynamic optimizers*, that examine longer-term returns that reflect several "rounds" of competitive interplay (and the associated concept of Nash equilibrium).

COMMERCIAL CONJOINT SIMULATORS

Both Sawtooth Software and SPSS conjoint procedures have serviceable and easy-to-use simulators. Sawtooth's simulator is considerably more elaborate than that of SPSS and has the virtue of being appropriate for each of its three tradeoff models – Adaptive Conjoint Analysis (ACA), Conjoint Value Analysis (CVA), and Choice-Based Conjoint (CBC) – as well as its ancillary software, such as hierarchical Bayes, Latent Class, and ICE. The SPSS simulator is a basic choice simulator that is modeled after Bretton-Clark's package (which is no longer being promoted). The SPSS simulator utilizes holdout profiles (for reliability and validity checks) and computes a preference score for each respondent. It offers three choice rules: max utility, the Bradley-Terry-Luce probability of choice model, and logit, which uses the natural log of the utilities before normalizing market shares. The SPSS simulator also computes attribute importances from the partworths. In addition, Pearson's R and Kendall's tau are computed as summary measures of goodness-of-fit. Both Sawtooth and SPSS produce basic simulator outputs. However, Sawtooth's simulator is considerably more flexible in its ability to handle simulations for all of its conjoint models (ACA, CVA, and CBC) on a standardized basis.

Table 7-1. Typical Characteristics of Buyer Choice Simulators

-
- Product simulation flexibility
 - Single product (vs. status quo)
 - Likelihood-of-purchase (averaged response)
 - Proportion of respondents whose predicted likelihood of purchase exceeds a user-supplied criterion level
 - Multiple products (sponsors and competitors): share received by each
 - Sponsor's product bundle (vs. competitors' products): share received by bundle and its separate components
 - Choice rules for the multiple-product and bundle cases
 - Max-utility rule
 - Share of utility (STL) rule
 - Logit rule
 - Other substantive features of choice simulators
 - Interpolation of partworths
 - Base-case entry with adjusted current-product comparisons
 - Parametric confidence intervals around output measures
 - Nonparametric (bootstrapped) intervals
 - Frequency tabulations and histograms of responses
 - Replicated cases in a single run
 - Inclusion of price and cost parameters
 - Brand-switching matrices
 - Derived attribute-level importances (based on choice data)
 - Consumer characteristics
 - Respondent background data for market-segment summaries
 - Respondent importance weights
 - Respondent perceptual distributions of brand attributes
 - Individual/respondent output file (for additional analyses)
 - Sensitivity features
 - Runs through all levels of a single attribute
 - Flexibility for fixing attribute levels at user-present values (in all runs)
 - Cosmetic features
 - Menu-driven
 - Graphics output
 - Pie charts and histograms of market share; partworth graphs
 - Average partworths for total sample and segments
-

Some consulting firms have developed their own simulator, which accompanies each of their completed conjoint studies. While detailed information on these tailor-made simulators is difficult to obtain, Table 7-1 contains a reasonable set of features that a commercial conjoint simulator could (or should) have. Some consulting firms also offer a sensitivity simulator, in addition to their primary simulator. Table 7-2 shows the typical characteristics of a sensitivity analysis simulator.

Table 7-2. Illustrative Outputs of Sensitivity Analysis Simulator

-
- Preliminary detail-proportion of sample selecting each attribute level as displaying the highest partworths, by attribute
 - Sensitivity analyses (assuming a bundle of two or more new products) to compute bundle share (and individual item-shares), given:
 - Deletion of each item in bundle, in turn
 - Change levels of each attribute of each product, holding all others at initial levels
 - Fixing or lowering all status quo utilities by a fixed (user-supplied) percentage
 - Selection of a specified segment (based on background-variable categories or cluster-based segments)
 - Random selection of K bundles (up to 1,000) where random bundles can be constrained to include user-specified profiles and/or restricted attribute-level variation
 - Additions to basic sensitivity analyses
 - Inclusion of attribute-level returns to the user's product line
 - Inclusion of price vs. utility relationship for adjusting respondent utilities to price increases/decreases
 - Inclusion of effect on firm's existing products (cannibalization) due to new product(s) introduction
-

In sum, most of the early conjoint simulators, commercial or consultant-based, have similar choice rule capabilities and some have sensitivity analysis features as well. Until recently, this was pretty much the state of practice.

CONJOINT OPTIMIZERS

More recently, there has been a trend toward increasing the sophistication of simulators to handle attribute-level costs, thus leading to the potential development of conjoint optimizers. To the best of our knowledge, consultants' optimizers, at least tentatively, are proprietary models, rather than being offered for outright sale (although Sawtooth Software will soon be marketing a conjoint optimizer). Optimizers require the firm's management to be able to estimate variable costs at the product attribute level. Moreover, the researcher may also want to add associated price increments to the enhancement levels of a basic attribute offering. For example, hotel rooms may carry different prices according to room size and the extent of the room's

amenities. These components naturally complicate the model and make additional demands on already difficult-to-estimate parameters.

We begin by describing three simulation/optimization models: CONJOINT DISPLAY, SIMOPT, and SIMACT. The first, CONJOINT DISPLAY, is a simulator that utilizes partworths typically estimated from ratings data, as obtained from Sawtooth's ADAPTIVE CONJOINT ANALYSIS (ACA) procedure. SIMOPT and SIMACT are typically (but not necessarily) used for choice-based conjoint data. CONJOINT DISPLAY, SIMOPT, and SIMACT are all proprietary (i.e., not-for-sale) software. We then describe SIMDYN (SIMulation via DYNamic modeling), which extends the capabilities of conjoint optimizing models to consider dynamic competitive moves.

CONJOINT DISPLAY

CONJOINT DISPLAY is a versatile simulator that typically utilizes partworths obtained from conjoint ratings data, e.g., Sawtooth's ACA data collection procedure. The input to CONJOINT DISPLAY consists of each individual's:

- Set of partworths (including intercept term)
- Set of desired attribute importances
- Most preferred level within each attribute
- Set of background-variable category assignments
- Respondent weights (optional)

These inputs can, incidentally, be obtained from almost any conjoint data collection procedure, including Sawtooth software or SPSS's CATEGORIES software.

CONJOINT DISPLAY then produces the following results:

- Displays (with pie charts) the market shares and most preferred levels within each attribute across respondents.
- Displays each attribute's partworths in terms of a dollar metric, where each enhanced attribute level is expressed in dollar terms, relative to the price attribute's base (or least-preferred) level.
- Displays derived attribute importances, at either the total-sample level or by any user-selected background (e.g., demographic) attribute. In addition, the user can compose a selected segment

and find the associated attribute importances for only members of this composed segment.

- Composes one or more product profiles and finds the share of choices received by each profile, either for the total sample or for a segment composed by the user.
- Includes two kinds of simulations. In the single product case, the user selects one product profile (from those composed) and finds the group-average probability that it will be chosen. One can also find the number of consumers whose probability of selecting the profile exceeds a user-specified cutoff (say, 80%) value.
- In the multiple product case, the simulator can compose two or more profiles and obtain estimated market shares of each. CONJOINT DISPLAY's choice rule employs a flexible model that can emulate share of utility, max utility (winner takes all), or gradations in between.
- Employs a bootstrapping (resampling) procedure to show the degree of possible variation around the expected market shares of each profile.
- With the compose-a-segment module, CONJOINT DISPLAY prepares an a priori segment description and shows how it behaves throughout various descriptive and analytical operations in the software package.
- With the perceptual mapping module, CONJOINT DISPLAY selects any background attribute (e.g., age) and obtains a similarities map that relates attribute importance to the various age categories. Alternatively, one can also show attribute importances and demographics in terms of a hierarchical tree (based on two up to six dimensions in the multidimensional space obtained from the mapping).
- In sum, CONJOINT DISPLAY has been designed to incorporate descriptive summaries, choice simulations, and perceptual mapping/clustering in a coherent package that combines user flexibility with attractive graphics.

The SIMOPT Model

SIMOPT (SIMulation and OPTimization) is an optimal product-positioning model that can be used for either the single-product or the product-line case. Its principal inputs are a matrix of K buyers' partworths and a set of competitive product profiles. As in CONJOINT DISPLAY, the partworths may come from any conjoint procedure, including the programs of

Sawtooth and SPSS. In particular, partworths obtained from hybrid conjoint models are appropriate.

In addition to input matrices of buyer partworths and competitive-supplier profiles, the model has options for including:

- Buyer importance weights (reflecting buyers' frequency and/or amount of purchase)
- Demographic or other background attributes
- Demographic weights for use in market-segment selection and market-share forecasting
- Current market-share estimates of all supplier (brand) profiles under consideration (used in model calibration), and
- Costs/returns data, measured at the individual-attribute level.

SIMOPT uses a general choice rule, based on share of utility. This rule is called the alpha rule, and is capable of mimicking the more traditional Bradley-Terry-Luce (BTL), logit, or max-utility choice rules. The alpha rule assumes that the probability, π_{ks} , of buyer k selecting brand s is given by:

$$\pi_{ks} = \frac{U_{ks}^{\alpha}}{\sum_{s=1}^S U_{ks}^{\alpha}}$$

where U_{ks} is the utility of buyer k for brand s ; α (which is typically set to at least 1.0) is chosen by the user; and S is the number of suppliers. If $\alpha = 1$, the model mimics the BTL share-of-utility rule; as α approaches infinity the model mimics the max-utility rule.

The primary data input to the SIMOPT model consists of a matrix of K individuals' partworths. In the simple case where no interaction effects are included, the general entry is

$$p_{i,j}^{(k)} = \text{partworth for level } i \text{ of attribute } j \text{ for individual } k; i = 1, \dots, L_j;$$

$$j = 1, \dots, M;$$

$$a^{(k)} = \text{intercept term for individual } k,$$

where L_j denotes the number of levels for attribute j , and M is the number of attributes. Each vector of partworths enables the user to compute a utility for any product/supplier profile for any individual k . A profile is defined by its levels (i_1, \dots, i_M). The utility of this profile to individual k is given by

$$U_k(i_1, \dots, i_M) = \sum_{j=1}^M p_{i_j, j}^{(k)} + a^{(k)}.$$

We assume that in any given run of SIMOPT, each supplier is represented by a profile vector i_s ; $s = 1, 2, \dots, S$. Hence, we can compute

$$U_{k,s} = U_k(i_s)$$

as the utility of individual k for supplier s . The "market share" of individual k for supplier s is

$$\pi_{k,s} = \frac{U_k^\alpha(i_s)}{\sum_{s=1}^S U_k^\alpha(i_s)}$$

for a specified value of α .

Once we have computed the $\pi_{k,s}$, we can combine them into a total market share by using $\sum_{k=1}^K W^{(k)} \pi_{k,s}$ where $W^{(k)}$, the weight for individual k , is non-negative with $\sum_{k=1}^K W^{(k)} = 1$. The individual weights can be further modified by considering various market segments. We generally assume that an input matrix of demographic (or general background) classification variables is available. We let

$D_n^{(k)}$ = the demographic category of individual k for variable n ; $n = 1, 2, \dots, N$, where N denotes the total number of demographic variables.

We also have weights E_n , one weight for each of the N demographics: $E_n > 0$;
 $\sum_{n=1}^N E_n = 1$.

In SIMOPT we can specify the number of demographics H we want to use, which demographics, t_1, t_2, \dots, t_H , and the level for each demographic, l_h . More than one level within demographic can be included (but for expository purposes only one level for each demographic is shown here). We then have

$$V^{(k)} = W^{(k)} \sum_{h=1}^H I_h^{(k)} E_{t_h}$$

where

$$I_h^{(k)} = \begin{cases} 1 & \text{if } D_{t_h}^{(k)} = I_h, \\ 0 & \text{otherwise.} \end{cases}$$

and

$$V^{(k)} = \frac{V^{(k)}}{\sum_{k=1}^K V^{(k)}}.$$

The overall market share for supplier product s is given by

$$M_s^* = \sum_{k=1}^K V^{(k)} \pi_{k,s}.$$

(Note that M_s^* implicitly depends on the profiles of each of the S suppliers.)

Starting conditions for applying the model entail a set of initial supplier profiles and initial market shares, I_s . These initial supplier profiles are associated with market shares M_s^* and, hence, multipliers given by $f_s \equiv I_s/M_s^*$.

The adjusted market shares are the given by:

$$\hat{M}_s = \frac{f_s M_s^*}{\sum_{s=1}^S f_s M_s^*}.$$

Costs/Returns

Finally, the model can incorporate costs and returns and can optimize over this measure (as well as over market share). First, we let $R_{i,j}$ = return for level

i of attribute j . (Note: the default value is $R_{i,j} = 1/M$ for all j and i .) We can then compute total return as:

$$T(i_1, i_2, \dots, i_M) = \sum_{j=1}^M R_{i_j, j}.$$

Hence, for each supplier we have a total return: $T_s = T(i_s)$. This gives us, respectively, an adjusted and an unadjusted return for each supplier of:

$$O_s^* = M_s^* T_s, \quad \hat{O}_s = \hat{M}_s T_s.$$

SIMOPT's Features

The SIMOPT model's outputs consist of market shares or dollar contributions to overhead and profits for each supplier. In the latter case, direct (or variable) costs/returns have to be estimated at the individual-attribute level for each supplier – a daunting task in most real-world settings. In any given run of the model, the user obtains market share (return) for each supplier on both an unadjusted and adjusted (for initial share) basis. Outputs can be obtained for both the total market and for any segment defined by the user from the available demographic variables.

The user is then able to perform four types of analysis:

1. A sensitivity analysis. This shows how shares (returns) change for all suppliers as one varies the levels within each attribute, in turn.
2. An optimal attribute-level analysis. If this option is chosen, the model computes the best attribute profile for a given supplier, conditioned on specified attribute levels for all competing suppliers.
3. A cannibalization analysis. The user can also specify one or more ancillary products. If so, the model finds the optimal profile that maximizes share (return) for the set of chosen products (that can include the firm's existing products). This profile can be compared to the best product for a given supplier that does not take into account interactions with the firm's existing products.
4. A Pareto frontier analysis. In most real-world problems the marketing strategist is not only interested in finding the "best" product in terms of (say) return, but also wishes to get some feel

for the tradeoff between return and market share. SIMOPT provides a capability to trace out the (Pareto) frontier of all profiles that are undominated with respect to return and share. The user can then find out what the potential value may be in giving up some amount of return for an increase in market share.

Practical Implications

As we have tried to show, SIMOPT has been designed as a practical model that can be operationalized by market-based, conjoint data. We believe its value lies in its versatility for considering:

- market share and/or profit-return optimization;
- total market and/or individual-segment forecasts;
- sensitivity analysis as well as optimal profile seeking;
- cannibalization issues related to product complementarities and line-extension strategies;
- calibration of results to existing market conditions;
- constrained optimization, through fixing selected attribute levels for any or all suppliers;
- a decision parameter (alpha) that can be used to mimic any of the principal conjoint choice rules (max utility, logit, BTL);
- sequential competitive moves, such as line extensions or competitor actions/reactions; and
- detailed information on who chooses which product under any specified set of conditions.

Like any model, SIMOPT no doubt will be modified and extended as further information about its performance and user reception is obtained. Perhaps its most significant contribution lies in illustrating how current conjoint-based simulators can be extended beyond their traditional application to estimating market shares for a few user-selected profiles.

Additional Features of SIMOPT

There are two additional aspects of the SIMOPT model that are of interest:

1. ALPH, the model used to find the *optimal* value of alpha, and
2. The divide-and-conquer heuristic, used to find optimal products and product lines in SIMOPT.

The ALPH Model

For any value of α , we obtain a set of predicted market shares, $\hat{\Pi}_1(\alpha), \dots, \hat{\Pi}_S(\alpha)$. We also assume that we have *external* market shares Π_1, \dots, Π_S . The problem is to find α such that the vector $\hat{\Pi} = \hat{\Pi}_1(\alpha), \dots, \hat{\Pi}_S(\alpha)$ is as close as possible to $\Pi = (\Pi_1, \dots, \Pi_S)$.

There are many possible distance metrics between the probability measures that can be considered. The ones most commonly employed are:

1. chi-squared:

$$d_c(\hat{\Pi}, \Pi) = \sum_{s=1}^S (\hat{\Pi}_s - \Pi_s)^2 / \Pi_s$$

2. entropy:

$$d_E(\hat{\Pi}, \Pi) = \sum_{s=1}^S \Pi_s \ln \Pi_s / \hat{\Pi}_s$$

3. Kolmogorov-Smirnov:

$$d_K(\hat{\Pi}, \Pi) = \max_S |\Pi_s - \hat{\Pi}_s|$$

4. absolute:

$$d_A(\hat{\Pi}, \Pi) = \sum_{s=1}^S |\Pi_s - \hat{\Pi}_s|$$

The problem is to find the α that minimizes the distance function.

Clearly, if there is an α such that $\hat{\Pi}(\alpha) = \Pi$, then all four distance measures would lead to the same α , since all distances are non-negative and equal to zero when $\Pi = \hat{\Pi}$. When no such α exists, then the choice of an α that minimizes distance depends on the metric that is used. In practice, α does not vary widely across d_c , d_E , d_K and d_A . The differences arise because in comparing α_1 to α_2 , $\hat{\Pi}_1(\alpha_1)$ could be closer to Π_1 than $\hat{\Pi}_1(\alpha_2)$, but $\hat{\Pi}_2(\alpha_1)$ could be farther from Π_2 than $\hat{\Pi}_2(\alpha_2)$. Which is viewed as superior would then depend on the metric.

Since there is no strong theoretical basis for choosing among d_C , d_E , d_K and d_A , on practical grounds we choose the distance metric that has useful mathematical properties. It can be shown that d_C , d_K and d_A are *not* unimodal in α . Although the value of α that minimizes each of the three distance metrics can be found by a numerical search procedure, this is time-consuming and not very elegant. In contrast, it can be shown that d_E is convex in α so there is only *one* optimum.

The Divide-and-Conquer Heuristic

To find the best product profile, conditional or specified competitive product configurations, SIMOPT employs a divide-and-conquer heuristic. We now discuss the nature of this heuristic.

In implementing the heuristic, we want to find the levels (i_1^*, \dots, i_M^*) that maximize share or return for the supplier of interest, possibly in an environment in which the supplier has more than one product in the product class. The objective we want to maximize can be written in the form $\Phi(i_1, \dots, i_M)$, where i_m denotes the attribute level for attribute m ; $m = 1, \dots, M$.

The levels (i_1^*, \dots, i_M^*) that maximize Φ can be found by complete enumeration. The number of possible solutions is $B = \prod_{m=1}^M L_m$. In practice, B could be large, although with high-speed computing if $b \leq 1,000,000$, this is certainly a viable approach. Alternatively, we can divide the attributes into subsets. To see how this approach works, assume that we divide the M attributes into two subsets, so that attributes 1 to M_1 define subset 1 and attributes $(M_1 + 1)$ to M define subset 2.

We begin the process by finding levels (i_1, \dots, i_M) that are reasonable first approximations to (i_1^*, \dots, i_M^*) . One approach is to average the partworths within each level of each attribute and choose the level, within attribute, that has the highest average. Label these levels as $[i_1^{(0)}, \dots, i_M^{(0)}]$. We find $[i_1^{(p)}, \dots, i_M^{(p)}]$ from $[i_1^{(p-1)}, \dots, i_M^{(p-1)}]$ in two steps:

1. Find $[i_1^{(p)}, \dots, i_{M_1}^{(p)}]$ by choosing the levels for attributes 1, ..., M_1 that maximize $\Phi[i_1, \dots, i_{M_1}, i_{M_1+1}^{(p-1)}, \dots, i_M^{(p-1)}]$.
2. Find $[i_1^{(p)}, \dots, i_M^{(p)}]$ by choosing the levels for attributes $M_1 + 1, \dots, M_1$ that maximize $\Phi[i_1^{(p)}, \dots, i_{M_1}^{(p)}, i_{M_1+1}, \dots, i_M]$.

If $\Phi(i^{(p)}) = \Phi(i^{(p-1)})$, then stop. Since Φ cannot decrease at each iteration, this approach leads to a local optimum.

Of course, the procedure can be extended to an arbitrary number of subsets. It should be pointed out that the effect of increasing the number of subsets is to reduce the amount of computation at the risk of not finding the global optimum.

There is no foolproof way of knowing whether this "divide-and-conquer" approach has produced the global optimum except by checking it with complete enumeration. In applications where we have applied this technique, the optimum *was* found. If we were to simulate data that are independently and identically distributed, then, intuitively, divide-and-conquer would work very well. Environments in which there are many interactions among attributes are ones in which the divide-and-conquer heuristic could potentially lead to a suboptimal solution.

SIMOPT is designed so that the user can specify the subset compositions. In general, subsets should be formed so as to minimize the correlation of partworths *across* subsets of attributes. Intuitively, attributes that are more closely related to each other should be assigned to the same subset and attributes that are more nearly independent should be assigned to different subsets. This suggests that we might like to cluster attributes based on distances between attributes.

We need a distance measure between attributes that reflects the extent to which individual's partworths for levels of one attribute are related to the partworths for levels of the other attribute. We propose two reasonable, albeit ad hoc, measures. Consider two attributes with I and J levels, respectively. We can create an $I \times J$ contingency table with entry n_{ij} indicating the number of individuals whose preferred levels are i for the first attribute and j for the second attribute. The distance between the two attributes can be defined as a $(1 - p\text{-value})$ of the chi-squared test; we use P -values for calibration when the number of levels differ across attributes and a $(1 - p\text{-value})$ so that similar attributes have small distances.

Another possibility is to create an $I \times J$ matrix where the (i, j) entry is the squared correlation between the partworths of level i of the first attribute and level j of the second attribute. Then, $1 - \bar{R}^2$ defines another measure where \bar{R}^2 is the average of the IJ entries in this matrix. (In either case the SIMOPT model contains an option where the user can choose the make-up of the subsets in the divide-and-conquer heuristic; as noted above, the subsets can be designed in several different ways.)

The SIMACT Model

The SIMACT model represents an extension of SIMOPT that has the following features:

- The researcher can estimate (via hierarchical Bayes) two-way interactions for the non-price attributes.
- The user can also factorially generate various sets of scenario descriptions, against which one can compute optimal returns for any selected scenario.
- SIMACT includes confidence levels around selected output measures (e.g., market shares, returns) of interest.

In so doing, SIMACT also maintains all of the features found in SIMOPT.

The SIMDYN Model

As described above, the SIMOPT and SIMACT models are basically static optimizing models where competitor's product profiles and consumers' tastes (i.e., partworths) are assumed to remain fixed over the firm's planning horizon. SIMDYN (SIMulation via DYNamic modeling) extends the SIMOPT model to explicitly consider a sequence of competitive moves and countermoves. (See Choi, DeSarbo, and Harker 1990; Hauser and Simmie 1988; and Hauser and Shugan 1983.)

In addition, SIMDYN allows the user to input differential attribute-level costs, by competitor, and to fix certain attribute levels (e.g., brand name). SIMDYN maintains a running record of each competitor's optimal profile (when it makes a move) and associated market shares and returns (i.e., contributions to overhead and profits) for all competitors at any stage in the sequence.

Thus, SIMDYN is concerned with game theoretic modeling in which a group of competitors are allowed to sequentially choose product/price formulations, based on strategies adopted by earlier competitive moves. The main practical use of SIMDYN so far has been in the examination of those attributes and levels, for a given competitor (i.e., "your" supplier), that are reasonably robust to rational competitive retaliations.

How can conjoint analysis of two or more competitors be brought together into a model of competitive interactions? The key idea is the concept of Nash equilibrium. To understand Nash equilibrium, imagine two or more competing suppliers, each independently trying to formulate its competitive strategy to maximize its own profits, given a specific set of competitive products, market strategies, and consumers' preferences. Since the market

shares of competing products would usually be affected by a given firm's strategy, we would expect their attribute levels to change in response to the initiating firm's actions. The Nash equilibrium represents a market situation (perhaps unattainable) where no individual firm can make further gains for itself by *unilaterally* departing from the Nash equilibrium.

There are two iterative problems available for finding a Nash equilibrium: simultaneous and sequential. In the latter case, players (competitors) select strategies, in turn, in a predetermined order. We believe that the sequential approach is a more realistic portrayal of real action/reaction sequences; this is the approach considered here.

To answer these questions we construct a small, fictitious example involved three competing firms: Alpha, Beta, and Gamma. However, our account is based on real conjoint data obtained from an actual study of cellular phone buyers. For illustrative purposes, we assume the role of Alpha's management.

Table 7-3. List of Attributes and Levels in Cellular Phone Application

Attribute	Level	Features (Absent = 1 or Present = 2)
<i>Initial Price</i>	\$125	1
	\$175	2
	\$250	3
<i>Brand</i>	Alpha	1
	Beta	2
	Gamma	3
<i>Warranty</i>	3 years	1
	1 year	2
<i>Weight</i>	7.5 ounces	1
	8.5 ounces	2
	9.5 ounces	3

A Study Using the SIMDYN Model

Alpha's management commissioned a hybrid conjoint study among potential cellular phone buyers in the southwestern United States. Prospective buyers were defined as those who expressed interest in purchasing (primarily for personal use) a cellular phone during the next six months. Interviewing was conducted via a telephone-mail-telephone procedure. Initial screening of qualified respondents was done by telephone and followed by a mailing of questionnaires and conjoint materials. This, in turn, was followed by the main telephone call in which the conjoint exercise was conducted and responses were recorded. A total of 600 questionnaires were completed.

Color photographs and detailed descriptions of each telephone feature were included with the questionnaire booklet. The list of 15 attributes and their levels is shown in Table 7-3. Respondents' self-explicated desirability ratings on each attribute's level were obtained, along with a constant-sum importance point assignment across the 15 attributes.

Following the self-explicated tasks, each respondent received eight profile cards drawn from a master orthogonal design of 32; each set of eight cards represented a balanced block from the set of 32. After examining all eight cards, the respondent sorted them into three graded piles: least desirable, neutral, most desirable. Profiles were then ranked within subgroup. Starting from the top-ranked profile, the respondent rated each of the ranked profiles on a 0-100 likelihood-of-purchase scale. The respondents then answered some demographic questions. Conjoint (averaged) partworths are shown in Figure 7-1.

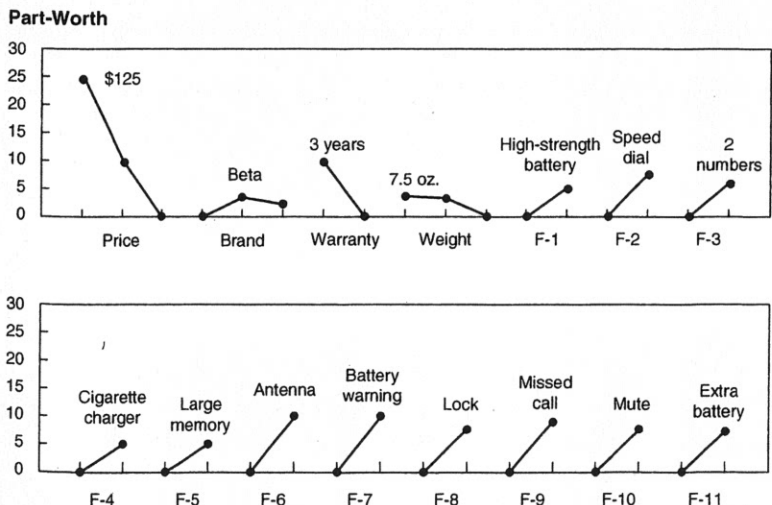


Figure 7-1. Partworths for Convex Combination Model

Experimental Assumptions

There are many factors that could influence competitive responses. In this experiment, we focused on two key variables: the cost structure of competitors and their participation in the market. For each of these variables, we examine two different assumptions:

1. Cost structure
 - a. All competitors are assumed to have the *same* variable costs (viz., those costs associated with Alpha).
 - b. Competitors are allowed to have different variable costs; see Table 7-4.
2. Active vs. passive participation
 - a. All competitors are assumed to be active, that is, participate in the action/reaction sequence.
 - b. One (out of three) competitors is assumed to be passive and does *not* change its product-price profile in response to others' moves.

Attribute-level variable costs were estimated (crudely) by the sponsoring firm. Net prices per unit are shown first, followed by variable costs per unit for each attribute level. Under the initially-assumed *equal* cost condition, Alpha's cost data apply to all three competitors. Table 7-4 shows the cost structures.

Table 7-4. Estimated Attribute-Level Cost Structures

Attribute	Levels		
	Alpha	Beta	Gamma
Net price	75; 105; 150	75; 105; 150	65; 95; 140
Brand	0; 0; 0	0; 0; 0	0; 0; 0
Warranty	-10; 0	-15; 0	-5; 0
Weight	-20; -10; 0	-30; -15; 0	-15; -5; 0
Battery	0; -2	0; -2	0; -2
Speed dialing	0; -2	0; -2	0; -2
Program numbers	0; -4	0; -2	0; -2
Battery charger	0; -5	0; -2	0; -4
Larger memory	0; -5	0; -5	0; -5
Antenna	0; -8	0; -7	0; -5
Low-battery beep	0; -5	0; -7	0; -5
Lock	0; -5	0; -7	0; -10
Missed call	0; -9	0; -8	0; -10
Mute function	0; -5	0; -2	0; -10
Extra battery	0; -10	0; -5	0; -15

The SIMDYN model was first applied to the equal costs and active participation case. There are six different sequences by which competitive moves can be initiated and reacted to, that is, six permutations. We started with the sequence: Alpha, Beta, Gamma, and continued through the five remaining sequences. A Nash equilibrium was achieved when three moves in a row resulted in the same shares and returns.

A Nash equilibrium was found in all six sequences, although the number of moves required to reach equilibrium varied from as few as 6 to as many as 11. By sequence, the number of moves required for equilibrium were:

Sequence	Number of Moves
Alpha, Beta, Gamma	7
Alpha, Gamma, Beta	6
Beta, Gamma, Alpha	6
Beta, Alpha, Gamma	8
Gamma, Alpha, Beta	11
Gamma, Beta, Alpha	9

As noted, when Alpha initiates the sequence, equilibrium occurs with as few as six moves. When Gamma initiates the sequence, as many as 11 moves are needed before equilibrium is reached.

Table 7-5 shows the history of the equilibrium process for one sequence: Alpha, Beta, Gamma. (In all cases, we permit all attributes to vary, except brand name.) We first examine the initial conditions and note that shares for Alpha, Beta, and Gamma are, respectively, 20.4%, 33.7%, and 45.9%, with associated unit returns of \$6.73, \$17.53, and \$13.31. These results correspond to the initial profile conditions of:

Alpha	11231
Beta	22112
Gamma	13231

where 11231 denotes \$125, Alpha, one-year warranty, 9.5 oz., and no high-strength battery, as shown in Table 7-5.

We next optimize Alpha's profile, conditioned on fixed profiles for Beta and Gamma. As Table 7-5 shows, the best levels for Alpha for the first five attributes are 31132, which, respectively, are \$150, Alpha, three-year warranty, 9.5 oz., and high-strength battery. As it turns out, in all cases, the optimal levels for the ten 2-state attributes, 6 through 15, are the *presence* of the feature (coded 2). We also note that when the Alpha profile is optimized, the share for Alpha increases to 61.1%, with an associated return of \$48.90.

We next shift from Alpha's perspective to Beta's. Given Alpha's newly optimized product, how should Beta optimize its own product? The process is updated as the sequence continues. Finally, we note that at move 5, the Nash

Table 7-5. Equilibrium History Based on the Alpha, Beta, Gamma Sequence (Equal Costs)

Move Initiator	Brand	Profile: First Five Attributes	Market Shares	Returns	Sum
<i>Initial Conditions</i>	Alpha	11231	20.4%	\$	
	Beta	22112	33.7	6.73	
	Gamma	13231	45.9	17.53	37.56
<i>Alpha</i>	Alpha	31132	61.1	48.90	
	Beta	(best)	15.1	7.84	
	Gamma		23.8	6.90	63.64
<i>Beta</i>	Alpha		34.2	27.39	
	Beta	32132	44.1	35.30	
	Gamma		21.6	6.27	68.69
<i>Gamma</i>	Alpha		26.2	20.95	
	Beta		29.5	23.63	
	Gamma	33122	44.3	31.01	75.59
<i>Alpha</i>	Alpha	31112	38.6	23.13	
	Beta		25.0	19.99	
	Gamma		36.3	25.52	58.64
<i>Beta</i>	Alpha		33.0	19.81	
	Beta	32112	37.8	22.67	Equilibrium
	Gamma		29.2	23.35	
<i>Gamma</i>	Alpha		33.0	19.81	
	Beta		37.8	22.67	Equilibrium
	Gamma	33132	29.2	23.35	
<i>Alpha</i>	Alpha	31112	33.0	19.81	
	Beta		37.8	22.67	Equilibrium
	Gamma		29.2	23.35	

Note: The *initial* (starting) conditions include battery strength as the fifth attribute (which is a 2-level feature). As the analysis turned out, for each of the eleven 2-level features, level 2 of each feature was *always* preferred to level 1; that is, having the feature was always preferred to not having it.

equilibrium is initiated; and at moves 6 and 7, the solution has stabilized with returns of \$19.81, \$22.67, and \$23.35, respectively, for Alpha, Beta, and Gamma.

It is worth noting that at equilibrium, all three brands are charging the highest price (\$150). All three brands also offer a three-year warranty, but Alpha's and Beta's weight is 7.5 oz. while Gamma's optimal weight is 9.5 oz.

Note that the optimal profile after competitive interactions are considered is different from the initial optimal profile. As shown in Table 7-5, Alpha's short-term optimal profile (31132) changes to 31112 at equilibrium, where the

weight changes from 9.5 oz. to 7.5 oz. We also note that Beta's initially optimized profile (32132) moves to 32112 at equilibrium, and Gamma's initially optimized profile (33122) moves to 33132 at equilibrium. Hence, optimal weight appears to be sensitive to the sequence of moves.

We conclude that for these conditions each competitor should offer all 11 features, a three-year warranty, and a \$150 price. However, optimal phone weight still varies by brand. It is worth noting that at initial conditions, the returns vary relatively widely, with a low of \$6.73 (Alpha) to a high of \$17.53 (Beta). However, at equilibrium, the returns are much less varied; Gamma is now-highest at \$23.35.

The Unequal Costs Case

A similar analysis was conducted for the unequal costs case (Table 7-6). Starting conditions were the same as before; the only characteristic that

Table 7-6. Equilibrium History Based on the Alpha, Beta, Gamma Sequence (Unequal Costs)

Move Initiator	Brand	Profile: First Five Attributes	Market Shares	Returns	Sum
<i>Initial Conditions</i>	Alpha	11231	20.4%	\$ 6.73	
	Beta	22112	33.7	15.17	
	Gamma	13231	45.9	8.26	30.16
<i>Alpha</i>	Alpha	31132	61.1	48.90	
	Beta	(best)	15.1	6.78	
	Gamma		23.8	4.28	59.96
<i>Beta</i>	Alpha		34.7	27.39	
	Beta	32122	44.1	35.95	
	Gamma		21.6	3.89	67.13
<i>Gamma</i>	Alpha		26.2	20.95	
	Beta		29.5	25.39	
	Gamma	33122	44.3	26.13	72.47
<i>Alpha</i>	Alpha	31112	38.6	23.13	
	Beta		25.0	21.49	
	Gamma		36.5	21.52	Equilibrium
<i>Beta</i>	Alpha		38.6	23.13	
	Beta	32132	25.0	21.49	Equilibrium
	Gamma		36.5	21.52	
<i>Gamma</i>	Alpha		38.6	23.13	
	Beta		25.0	21.49	Equilibrium
	Gamma	33122	31.5	21.52	

varied was the assumption of different attribute-level costs across brands. Again, a Nash equilibrium was reached over all six sequences of moves. Table 7-6 shows the results from the sequence Alpha, Beta, Gamma.

As noted in Table 7-6, equilibrium was reached after six moves. In comparing Table 7-6 to Table 7-5, we note that under initial conditions, the returns for Beta and Gamma differ from the equal costs case because of the different cost structure assumptions. Although not shown in the table, we found, as before, that it was optimal to have all 10 features. The equilibrium profile for Alpha (31112) is the same as it was in the equal costs case of Table 7-5. The equilibrium profile for Beta (32132) differs, however; the optimal weight is now 9.5 oz. (rather than 7.5 oz.). The equilibrium profile for Gamma (33122) also differs in that the optimal weight is now 8.5 oz. (rather than 9.5 oz.). We also note that the initially optimum profile for Alpha changes from a weight of 9.5 oz. to a weight of 7.5 oz. at equilibrium.

Finally, we again see less disparity in returns across the three brands when the Nash equilibrium returns are compared to those associated with the initial conditions. It is also interesting to note that at equilibrium, Alpha's return is the highest of the three, even though it was lowest at the initial conditions stage.

The Passive Products Case

Suppose one competitor does not actively respond to the moves of its rivals? Companies sometimes choose to ignore moves of competitors or, if recognized, fail to respond to them. The analysis was repeated with the assumption that two companies were active and one was passive. Illustratively, we look at only the unequal cost condition. Again, Nash equilibria were obtained.

Table 7-7 shows the results for active products Alpha and Beta, and passive product, Gamma, under the unequal cost condition. An equilibrium is reached after only four moves. In this case, the players converge to an equilibrium more quickly if one player is passive. The profile of products may also differ. We use the same starting conditions as those shown in Table 7-6. At equilibrium, Alpha's profile (first five attributes) is the same as that shown in Table 7-6. Such is not the case for Beta. In Table 7-7, Beta's optimal weight is 8.5 oz. while in Table 7-6 its optimal weight is 9.5 oz. Apparently, the passivity of Gamma has an effect on the optimal profile for Beta (but not on Alpha).

Table 7-7. Equilibrium History Based on the Alpha, Beta Sequence
(Gamma Passive, Unequal Costs)

Move Initiator	Brand	Profile: First Five Attributes	Market Shares	Returns	Sum
Initial Conditions	Alpha	11231	20.4%	\$ 6.73	
	Beta	22112	33.7	15.17	
	Gamma	13231	45.9	8.26	30.16
Alpha	Alpha	31132	61.1	48.90	
	Beta	(best)	15.1	6.78	
	Gamma		23.8	4.28	59.96
Beta	Alpha		34.2	27.39	
	Beta	32132	44.1	37.95	
	Gamma		21.6	3.89	69.23
Alpha	Alpha	31112	41.5	29.04	
	Beta		38.2	32.84	
	Gamma		20.3	3.66	Equilibrium
Beta	Alpha		41.5	29.04	
	Beta	32122	38.2	32.84	Equilibrium
	Gamma		20.3	3.66	

Conclusions

As illustrated by the case just discussed, recognizing the potential moves of competitors can have an impact on optimal product design. In the cellular telephone case, when competitor moves are considered, the optimal products are often different from those in the initial optimization. In addition, the SIMDYN model permits managers to optimize their product under a variety of assumptions, allowing them to anticipate a variety of competitive situations (such as different cost structures) or competitive moves (such as a passive competitor). For this case, interactions among competitors did, in fact, converge to Nash equilibria. The speed of convergence, however, depended on the order in which companies made their moves.

In the complex and dynamic world where consumer preferences do change, where individual competitors may not try to optimize their strategies, and where new firms can enter and old firms can exit, it should be realized that the Nash equilibrium is essentially a theoretical concept, not a practical reality. Still, as many theoretical concepts have demonstrated, the Nash equilibrium concept can provide a useful way to study real competitive behavior by providing a rational norm and framework for examining a firm's strengths and weaknesses, under the concept's assumptions. (Indeed, the laws

of physics are idealizations as well; their predictions of empirical phenomena are always subject to statistical fluctuations.)

In addition, the cost of making attribute-level changes, internal constraints on which attribute levels can be changed, and the difficulty of accurately measuring attribute-level variable costs present serious research challenges. Also, more study is needed of the so-called first-move advantage and the possible muted effect of "me-too" followers that try to emulate innovative product designs.

Even with these limitations (many of which apply to any model), this dynamic approach to conjoint analysis can offer a powerful tool for developing strategy. At the minimum, it can point out those components of one's current brand profile that are most resistant to competitors' retaliations. Just as earlier work in conjoint analysis has proved very valuable to marketers, this extended model offers an important tool for the study of competitive interplay.

PRODUCT BUNDLING: A NEW AREA FOR APPLYING CONJOINT ANALYSIS

An additional new area in which a conjoint-like approach can be used is *bundling*. Specifically, in addition to the main attributes that form the product, one adds features that can be present or absent. For example, in long-distance calling plans, besides the main contract, there are added features such as call-waiting, unlimited minutes in a certain geographical area, calling-friend plants, etc. Besides being able to purchase individual features at a specified price, a customer is often given the option of purchasing a subset of features at a price that is lower than the aggregate costs of each of the separate features.

There are three phases for determining optimal bundles and their associated costs. The first phase is the questionnaire instrument. In this phase, an individual's "willingness to pay" for each feature needs to be elicited. One approach is to simply ask the respondent directly, "How much extra would you pay for feature x?" There are two problems with this approach. First, there is a tendency for individuals to understate the amount they are willing to pay. Second, if an individual has a budget constraint, then this will not be captured by direct questioning of the amount each individual is willing to pay for each feature separately.

An alternative approach is to present bundles of features in a conjoint framework. Each of the features is viewed as an attribute with two levels: present or absent. Hence, a profile that specifies the levels for each feature is equivalently representing a bundle of these features consisting of those

features that are present. Prices can also be embedded, thereby determining, through an appropriate estimation method, an individual's willingness to pay.

The second phase of the analysis is to estimate the parameters. One parametric form assumes that one's willingness to pay for the features can be characterized by a multivariate normal distribution with some unknown covariance matrix. A budget constraint can then be included as an additional parameter, based on a censoring model. Since it would be difficult to estimate the parameters separately at the individual level, a hierarchical Bayes approach can be employed.

Finally, in the third stage, the optimal bundles and associated prices can be determined from the underlying multivariate normal behavior for willingness-to-pay variables. In a seminal paper, Schmalensee (1984) considered the case of two features. An area for further research is to extend the problem to more than two features in the pure bundling and mixed bundling (features can also be purchased separately in addition to in bundles) cases.

NEW OPPORTUNITIES FOR THE APPLICATION OF CONJOINT ANALYSIS

Conjoint analysis is far from becoming moribund. As shown in Chapter 5 (Table 5-3, p. 130), high-profile applications of conjoint have included both consumer and industrial goods and a host of services: credit cards, cellular phones, employee benefit packages, time share units, and overnight letter/package delivery, to name a few.

To illustrate the nature of conjoint applications, we discuss one study in more detail: The E-Z Pass Electronic Toll Collection System, originally developed for New York and New Jersey and later extended to Delaware, Maryland, Pennsylvania, and Massachusetts.

The E-Z PASS Electronic Toll System

The E-Z Pass case is noteworthy in that it involved high technology applied to a common and pervasive problem: traffic congestion. The project also had a fair amount of drama – the study team's overseeing committee did not always see eye-to-eye with one another or, for that matter, with the study team, as well.

The Product

The E-Z Pass electronic toll collection (ETC) works like this: Commuters use an electronic "tag" (transponder) about the size of an audio tape cassette which is attached to a vehicle's inside windshield. As an equipped vehicle approaches a toll lane, an antenna alongside the lane reads the customer's vehicle and account information embedded in the tag. Using high frequency radio waves, the technology sends the information to an in-lane computer that checks the driver's data against a database of valid tags and active accounts, deducts the appropriate toll from the customer's account, and approves passage or raises a tollgate to allow the vehicle to pass through the toll plaza.

Each commuter's tag emits a signal assigned specifically to him or her. This enables the commuter's use of all ETC-equipped facilities to be tracked and logged. ETC users set up a prepaid account, which is debited for each use of an ETC-equipped roadway, bridge, or tunnel. (The tags are particularly advantageous to fleet operators who otherwise would have to advance cash to drivers for tolls or engage in time-consuming cash reimbursement.) Each tag contains an identification number, data identifying the issuing agency, tag type, a description of the vehicle, and other agency-specific data. The tag ID, agency ID, and tag type are encoded by the vendor and cannot be altered. The tag is based on read-write technology capable of storing highway entry and exit points for toll calculations in closed systems (i.e., where the toll is based on distance traveled). Vehicle gross weight (for toll calculations based on weight, or for checking on maximum highway weight) also can be obtained.

Issues to be Investigated

Ultimately, seven major design attributes, with varying numbers of levels, were selected as most likely to benefit from the research with potential users. They were:

1. How many facilities would the user need to open an E-Z Pass account and, therefore, how many periodic invoices would the user receive (two levels)?
2. How and where would a user apply and pay for a new E-Z Pass account (six levels)?
3. How many lanes would be available for E-Z Pass at a typical toll plaza and how would they be controlled (five levels)?
4. Would the E-Z Pass tag be transferable to different vehicles (two levels)?

5. What would be the acquisition cost (if any) for E-Z Pass and would there be a periodic service charge (four levels)?
6. What would the toll price be with E-Z Pass (four levels)?
7. What other uses, if any, such as parking at local airports or purchasing gasoline, would commuters find valuable for using E-Z Pass (three levels)?

Given the complexity of the design, a hybrid conjoint analysis model was chosen that incorporated a fractional factorial design. (A full factorial would have resulted in 5,760 possible combinations of products [$2 \times 6 \times 5 \times 2 \times 4 \times 4 \times 3$] – obviously an impractical number on which to gather preferences.) With this design, only 49 product descriptions were required.

Commuter Recruitment and Questionnaire Administration

Commuters (contacted through RDD telephone interviews) were informed of the survey and asked if they would participate. While a modest gratuity was offered (the opportunity to win one of 10 U.S. Savings Bonds each valued at \$100), the main inducement was providing them with an opportunity to voice their preferences for improvements in the area's automobile commuting situation. More than 6,500 potential participants were recruited within a three-week period.

The centerpiece of the survey was a videotape demonstration, accompanied by a set of survey materials to be examined and thoughtfully responded to. Instead of simply placing the materials in an envelope, the research team decided to "dimensionalize" the kit. A self-mailing box was designed with customized graphics and the E-Z Pass logo. The special illustration and the box helped ensure that the material would be examined and the survey completed. Kits were mailed to all 6,500 commuters recruited for the survey.

In addition to the videotape, the kit contained a glossary of terms (to serve as a reference for participants as they answered the questions), a questionnaire measuring self-explicated importance weights for the major options, and an envelope containing the eight scenario cards, where one card was a common reference card, appearing in each profile set. The sequence of the self-administered interview was clearly indicated in three steps on the inside flap of the box. Participants were asked to complete the importance rating questions first, then proceed to rate each of the eight scenario cards in terms of their likelihood of using the service.

To ensure that data were collected from a maximum number of participants, responses were collected by telephone, rather than relying on a mail return. Participants were given the choice of either waiting to be

contacted by a telephone interviewer, or calling a toll-free number at a convenient time for them to complete the interview. Of the 6,500 commuters recruited, 3,369 respondents successfully completed interviews within three weeks. The 52% response rate was considered quite satisfactory, given the complexity of the survey.

Conjoint Results

Results were analyzed at three levels: the total sample level (a view of the New York-New Jersey commuter), the agency level (an agency's typical commuter), and the facility level (the user of a bridge or tunnel). Some differences emerged at the facility level (probably as a result of commuters' adaptation to the different operational and pricing practices instituted over the years at particular facilities). At the agency level, however, only a few significant differences emerged. This finding allowed the committee to endorse an area-wide configuration as long as it was practical.

Among the seven design options, the option: "How many lanes would be available and how would they be controlled?" was judged by commuters as the most important. (See Table 7-8). This result was not anticipated by the committee members for the Interagency Group (IAG); the committee had thought that commuters would be more concerned with the "acquisition costs for the tag" option. The emergence of the "available lanes" option was interesting for another strategic reason: Some of the implementation levels of this option would have negated many of the promised advantages of E-Z Pass, had the system been implemented in these ways. Clearly, the high priority that commuters assigned to this attribute showed they understood the full benefits of the new system and did not want them compromised. The committee responded by placing a high priority on the implementation levels that were most desired. Table 7-8 shows the derived relative importance of each of the seven attributes. Price did enter as a concern, but in a more practical sense. The price of the toll with E-Z Pass was the second most important attribute. But acquisition cost for E-Z Pass and a periodic service charge were relegated to the middle of the priority listing. This ordering clearly showed commuters' willingness to undertake reasonable costs to enjoy the potential benefits of the E-Z Pass system.

Table 7-8. Judged Importance of E-Z Pass Design Attributes

Attribute (Feature)	Importance Rating
How many lanes would be available and how would they be controlled?	21%
Price of the toll with E-Z Pass	18%
How and where a user would apply and pay for a new E-Z Pass account	17%
The acquisition cost for E-Z Pass and any periodic service charges	15%
Number of E-Z Pass accounts necessary/number of periodic invoices received	13%
Would the E-Z Pass tag be transferable to different vehicles	12%
Other potential uses for the E-Z Pass tag	4%
	100%

The Forecast

As the process of working with the conjoint design placed committee members in a more "customer-centered" perspective, they began to speculate about the preferences that consumers might have for the levels within attributes. They also became more aware of the need to estimate the demand for the E-Z Pass system. Substantial capital investments needed to be made, not only for the purchase of electronic tags for distribution to users, but also for equipping toll gates for the hundreds of toll plazas operated by these agencies.

As results were presented and discussed, the most pressing issue for committee members was, "How many commuters will adopt E-Z Pass within the first year?" The research team had planned on answering this question in two ways: through use of a simulation model, and from answers to verbal purchase questions asked of each survey participant. The SIMPRO simulation model, developed by Green and Krieger, was first employed to produce overall service adoption estimates. SIMPRO requires the researcher to specify a configuration for the product tested. With this configuration, the model then predicts an adoption rate, using a function of the sum of each respondent's partworths for the attributes.

When the SIMPRO model was employed in the E-Z Pass project, very attractive adoption rates, on the order of a 45% penetration, were predicted. The committee was hesitant to trust these high rates, which essentially indicated that one out of every two area commuters would apply for an E-Z

Pass account. Still, the research team had confidence in the model. Fortunately, verbal purchase data were also available, so the research team turned to this source for corroboration.

Two versions of the verbal purchase data were used: the top two boxes (ratings of 10 or 9 on the "definitely would subscribe" scale) and top box only. While the verbal purchase rates were somewhat lower, either version still seemed too high to the committee. The high acceptance scores were heartening, but both the committee and the research team wanted to be certain they were valid and not the result of "demand bias" (the willingness of respondents to comply with their perceptions of a test's intention or an experimenter's hoped-for outcome). Ultimately the scores were factored down, using close to a "worst-case scenario" which was fed into the simulator as an indication of the lowest likely level of interest.

What's the E-Z Pass Penetration in 2002?

In 1999, the penetration rate of E-Z Pass approached 45 percent. In 2002, at the time of this writing, penetration rates have either been sustained or somewhat increased. Interestingly, this penetration rate was achieved with few expenditures on either advertising or promotion.

Some Unintended Consequences

Although the technological aspects of E-Z Pass continue to be lauded by most commuters, New Jersey's former governor Whitman has recently been excoriated by the state's Democrats, regarding her handling of the *financial* aspects of E-Z Pass.

In 2002, the new (Democratic) governor, James McGreevy, announced that E-Z Pass now faces a huge deficit. Unlike the governor of Massachusetts, former governor Whitman did not want the state to pay its share. She depended on the \$25 fines of toll cheats to finance much of the system.

In 2001, the plan called for \$101.8 million in fines; only \$10.3 million was actually collected. With one million users – 15 percent more than expected – customer service costs also soared. The result: New Jersey E-Z Pass now loses money on each new user. Hence, E-Z Pass has turned out to be a technical success but a financial embarrassment.

An additional prediction: E-Z Pass discounts will soon disappear. To add to McGreevy's troubles, in the future, \$50 million will be needed to replace the system's battery depletions in 2004. Such are the vagaries of modeling large-scale governmental developments.

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Chapter 13

Continuing the Aldersonian Research Tradition

Yoram (Jerry) Wind
Paul E. Green
The Wharton School, University of Pennsylvania

Wroe Alderson was *the* leading figure in marketing theory from the early fifties up to his death in 1965, at the age of 68. He defined marketing thought and helped to launch and shape the careers of other leaders of theory and practice in the field, including Paul Green. Very few marketing educators are aware of Wroe's writings and his accomplishments as a deep thinker in marketing theory, as well as a pragmatic consultant who easily worked in both theory and marketing practice.

Today, however, there appears to be a welcome renaissance in Aldersonian ideas, spearheaded by a number of current marketing scholars, including Stephen Brown, Morris Holbrook, and Ben Wooliscroft. We welcome this newfound interest in his work and this recognition of debt that current marketing theory and practice owe to the Aldersonian tradition.

WROE ALDERSON: HIS LIFE AND WORK

Wroe Alderson's academic training was spread over three universities: George Washington, MIT, and the University of Pennsylvania. His publications include *Marketing Behavior and Executive Action*, *Theory in Marketing* (with Reavis Cox) and *Planning and Problem Solving in Marketing* (with Paul Green). He served as past president of the American Marketing Association and was highly active in The Institute of Management Sciences.

From the inception of his business career with the U.S. Department of Commerce, Wroe Alderson was deeply involved in the advancement of

marketing science both in the business and academic communities. An eminent educator and consultant with truly interdisciplinary scope, he frequently contributed to the thought and literature of other fields. His wise counsel was sought by university presidents, corporate chief executives, and government leaders alike.

Among Wroe Alderson's many pursuits and accomplishments were: heading the internationally prominent marketing consulting firm of Alderson Associates; the establishment of the annual Marketing Theory Seminars; serving as a Trustee of the Marketing Science Institute; founding the Management Science Center at the University of Pennsylvania; and engineering the migration of the famed Operations Research group at Case Institute to Wharton in 1963. Alderson also received the prestigious Parlin Award in 1954.

AN INTRODUCTION TO SOME KEY ALDERSONIAN IDEAS

Alderson's landmark book, *Marketing Behavior and Executive Action*, published by Richard D. Irwin, provides a detailed review of his thoughts on the interface between marketing theory and executive decision making. We offer a brief overview of some of the ideas that we believe were central to this thinking and contributions to the field, including:

- *Heterogeneity of both supply and demand*: This notion was a precursor to the subsequent ideas of market segmentation and niche marketing. Increased product variety provides consumers with offerings nearer their ideal points. Firms can strive for differential advantage through product variety.
- *Organized behavior systems*: Firms are perceived as ecological systems that grow and adapt to change; each seeks its own niche (Alderson's functionalism).
- *Sorting functions*: The important role of providing marketing economies through intermediate sortings of goods; the associated principle of postponement was a precursor to the current use of just-in-time inventory control.
- *Inductive theorizing*: An approach that emphasized inductive theorizing from market place events, as a complementary viewpoint to neo-classical theories of firm behavior.

In order for the reader to get some measure of the man and his thoughts, excerpts from three sections of his 1957 book *Marketing Behavior and Executive Action* are reproduced here:

Part 1: Marketing and the Behavioral Sciences

The conception of an organized behavior system is the starting point for the present approach to marketing theory. Given only the elements of power and communication which characterize every group, the system may discharge certain primitive functions and exhibit survival value. All marketing activity is an aspect of the interaction among organized behavior systems related to each other in what may be described as an ecological network. Operating systems are a subclass of behavior systems, distinguished by inputs and outputs and the structuring of processes to achieve efficiency.

The functionalist approach is concerned with the functioning of systems, and the study of structure is essential to the analysis and interpretations of functions. Every phase of marketing can be understood as human behavior within the framework of some operating system. Survival and growth are implicit goals of every behavior system, including most particularly those that operate in the market place.

Part 2: The Theory of Market Behavior

The functionalist approach to competition emphasizes rivalry within and among behavior systems in the search for differential advantage. Negotiation is a major topic in the present view, accounting for what may be called the vertical relationships of behavior systems as compared to the horizontal relationships constituting competition. The treatment of consumer motivation takes the household as the fundamental unit and considers aspects of its structure and functions which determine the course of consumer buying. The discussion of exchange describes four aspects of sorting which produce economies in matching supply and demand. Price is discussed in terms of the uses and limitations of marginal analysis. The possibilities of creative marketing in stimulating demand are considered with respect to such processes as product innovation and advertising. The market transaction is analyzed to show how it has been modified to increase marketing efficiency.

Two general comments may be useful to the student in relating marketing theory to economic theory. Economics starts with certain assumptions as to market organization, while marketing starts further back with attempts to organize the market and to establish the processes

of orderly marketing which economics takes for granted. Marketing as well as economics is concerned about efficiency.

Part 3: Executive Action in Marketing

The culmination of marketing theory is in demonstrating its value as a perspective for marketing practice. The management of a marketing operation is first considered in terms of positive control over resources to meet predetermined goals. The principles of management take account of the fact that every operating system is necessarily a structure of power and communication. Next, the element of uncertainty is introduced, together with various approaches to problem solving in reducing uncertainty. Problem solving as an operation employs insight, systematic calculation, and selective exploration. The discussion of market planning shows how planning can become a technical and scientific procedure which can be delegated to staff specialists. Finally, the marketing viewpoint is shown to offer a constructive approach to management policy as a whole and to the reconciliation of management goals and public policy.

ANNUAL MARKETING THEORY SEMINARS AND ALDERSON LECTURES

One of Wroe Alderson's major achievements was the inauguration of the annual Marketing Theory Seminars, held in alternate years at the University of Vermont and the University of Colorado. These seminars were designed to foster fruitful exchanges among marketing educators, business executives, and consultants. The seminars offered a spirited and fruitful exchange among the "grand old scholars" of that period, who had much to say about the theory and practice of marketing. Wroe, a major contributor to the discussions, had interest and expertise not only in marketing but in operations research and economics as well.

Wroe Alderson Distinguished Lecture

1985-86	Charles Goodman
1986-87	V. "Seenu" Srinivasan
1987-88	Sidney J. Levy
1988-89	John R. Hauser
1989-90	Donald R. Lehmann
1990-91	John D.C. Little
1991-92	Robert C. Blattberg
1992-93	Louis W. Stern
1993-94	James R. Bettman
1994-95	Donald G. Morrison
1995-96	John U. Farley
1996-97	Harold H. Kassarian
1997-98	Richard Staelin
1998-99	Alvin J. Silk
1999-00	Glen F. Urban
2000-01	Frank M. Bass
2001-02	Paul E. Green

In the spirit of these discussions, the Wharton School's Marketing Department established the annual Wroe Alderson Distinguished Lecturer Series in 1985. The event honors the out-standing career of Wroe Alderson – teacher, consultant, and author – and provides a platform for sharing the insights of leading thinkers in the field (see box).

THE ALDERSON TRADITION

Wroe Alderson's research philosophy embodied three basic mandates about doing research in marketing:

- Select problems that, where possible, further marketing theory.
- Select problems whose solutions advance the state of marketing practice.
- Where possible, select problems that have high impact and transfer value across applications.

While these comments are easy to state, they are often difficult to implement. Researchers frequently encounter client resistance to change and reluctance to publicize methodology and results. It is hoped that future efforts in exposing general research ideas to wider audiences (without compromising clients' needs for discretion) will be both possible and favorably looked upon.

Wroe Alderson was a multifaceted person, not only in addressing theoretical and practical challenges in marketing, but also in his broader creativity and interests, as illustrated in the following poem. He established a rich tradition of combining research and application, as well as a high standard for those who followed. In his well-known quote, Sir Isaac Newton said that "if I have seen further . . . it is by standing upon the shoulders of giants." Wroe Alderson was one of the giants of the early development of marketing theory upon whose shoulders rests much of the later progress in the field.

A Poem by Wroe Alderson

Haverford Meeting, October 9, 1960

We have just had a week of golden October days beside the Chesapeake, with Heaven waiting in every sunset.

The hoarse cry of the wild goose is like a brute reaction to beauty too bright to be borne. A world in flames, over land and water, re-enacts the ancient and tragic mystery of Death-in-Life and Life-in-Death.

The dogwood leaves are dying in a burst of battle red. Oak and maple strew the lane with the vivid hues of passion and the soft shades of memory. And soaring there on a high stark limb is the scarlet banner of ivy.

On the water, where life first found its home, life is still harvesting life: a fisherman out in the chilly dawn; the sails of the oystermen at noon; a belated woman crabber poling her skiff through the ripples along the shore. Underneath the surface the living still feeds on the living – or faces death in the stab of the heron or the swoop of the osprey.

A philosopher speaking for the pantheism of the East has said that life is perpetual perishing. What we see now shall never be seen again. What we love most, even now is slipping away. We weep for beauty vanishing but beauty is its heir. The flower fading on its stalk will cast its seed for flowers to scent tomorrow.

A poet once prayed to be released from too much love of living. Let us rather pray to love life freely and to spend it freely. Time is our sovereign currency but let us not grasp it with a miser's hand.

And let no puny man fancy himself an Atlas, bearing the world on his shoulders. The world will not fall apart without us because God holds it together. Individually we are held and jointly we endure within the magnificent fabric of his grand design. The notes are transient – the symphony eternal. Our faith in a loving and eternal God is faith in the abundance of life.

Chapter 14

Reflections and Conclusions: The Link Between Advances in Marketing Research and Practice

Yoram (Jerry) Wind

Paul E. Green

The Wharton School, University of Pennsylvania

Methodological developments in marketing research would go for naught if the methodology and research techniques were not applied by practitioners (i.e., industry consultants, marketing research firms, and intra-company professionals) and adopted by management. As noted throughout this book, one of the hallmarks of work by pioneers such as Wroe Alderson has been an intense interest in both research and practice. While individuals have spanned these boundaries, there is still work to do in building bridges between research and practice. This will ensure that new ideas are disseminated quickly into the hands of those who can benefit most from them and also will help maintain the relevance of research advances in the field.

The *diffusion* process, by which new technical developments are tested and implemented in the real world, is critical for answering the questions:

- Does the new marketing model or technique actually work at the business enterprise level?
- If it does work, is it a significant improvement over existing techniques used for similar purposes?
- Does the new technique lend itself to "standardization," so that its success does not depend on its original developer?
- Can objective criteria be developed to permit accurate measurement of the new technique's value vis-à-vis current procedures?
- Is the new technique readily teachable to industry researchers?

In this chapter, we examine this diffusion process and the challenge of bridging the gap between academic research and management practice. We

explore the roles of organizations and journals in bridging or reinforcing the divisions between the two sides and we consider opportunities for bringing both sides closer together to improve the R&D and practice of marketing research and the adoption of its findings.

THE DIFFUSION PROCESS

Practitioners led the way in the early development of marketing research. "Modern" marketing research appears to be a phenomenon of post-World War II. However, as Wright-Isak and Prensky (1993) have pointed out, such early practitioners as Archibald Crossley, Elmo Roper, A. C. Nielsen, and Clark Hooper were already active in the 1930s. Academic marketing research tended to lag industry-based sample survey developments by several years.

If we take 1950 as a reasonable starting point for "more modern" marketing research, all was still far from sanguine in academia, as noted by marketing professor J. Howard Westing (1977):

So far as the present is concerned we marketing professors seem to be losing our mooring to economics.... It is very doubtful that today, after more than a decade of behavioral studies and theorizing, we know significantly more about consumer behavior than we did at the start.... Turning to refined statistical analysis and model building, ...it would appear that the "mountain has labored and brought forth a mouse."... Marketing professors can continue on their present course by trying to create an academic discipline of marketing. If they do, they will become pariahs in the community, because there is no basic body of thought, and marketing professors will be quite properly viewed as poachers and panderers.

While this is rather "over-the-top" prose, Westing had a point. A few years later, Myers, Massy, and Greyser (1980), hereafter called MMG, produced a study that demonstrated the growing gap between research and practice. MMG decided to examine the accuracy of Westing's remarks by asking respondents to indicate their current intensity of use of a set of 13 tools/techniques that might be part of a marketing practitioner's "tool kit." Table 14-1 lists the 13 tools/techniques and includes brief descriptions of each.

As shown in the table, the items ranged over such concepts as various kinds of segmentation, through data-collection methods, such as focus groups

and experimentation, to complicated decision models and multivariate statistical techniques. Each technique exemplifies a type of marketing "knowledge" that might play some part in a professional researcher's or manager's tool kit.

Table 14-1. Tools and Techniques of the Marketing Practitioner

Source: Myers, Massy, and Greyser (1980)

Technique	Description Used
Time-series analysis	a. Time-series analysis – the statistical analysis of trends over time
Bayesian analysis	b. Bayesian decision theory – decision trees, personalized decision analysis
Focus groups	c. Focus groups
Demographic segmentation	d. Market segmentation 1. Demographic (including socioeconomic) characteristics of present and/or potential consumers
User segmentation	2. Usage of product/brands by present and/or potential consumers
Psychographics	e. Psychographics – life-style analysis, attitude/interest/opinion studies
Multidimensional scaling	f. Multidimensional scaling – perceptual mapping
Cluster analysis	g. Cluster analysis
Factor analysis	h. Factor analysis
Conjoint analysis	i. Conjoint analysis and discrete choice
Formal experiments	j. Formal experiments using test and control areas and/or groups to test new products or elements of the marketing mix
Response models	k. Marketing models – computer simulations to help answer "what if" questions in formulating marketing strategy 1. Models to relate marketing expenditure inputs to markets share and/or sales response
Computer simulation	2. Computer simulations of alternative marketing mixes

Data collection involved a mail questionnaire sent to a sample of the American Marketing Association (AMA) membership. The AMA's membership roster was used as the sampling frame, and members were classified into three groups: marketing managers, research managers, and commercial research suppliers. A random sampling procedure was followed

in selecting respondents from each group. A total of 4,292 questionnaires were sent out and 1,271 usable replies were received.¹

Table 14-2 shows the results for (a) "used frequently" and (b) "used at least once," for the three respondent groups – entries are percentages:

- Operating Managers (Oper Mgrs)
- Research Managers (Res Mgrs)
- Research Suppliers (Res Spplrs)

Table 14-2. Use and Trial: 13 Techniques Used and/or Tried

Source: Myers, Massy, and Greyser (1980)

Technique	Used Frequently ("Use")			Used Sometime ("Trial")		
	Oper Mgrs	Res Mgrs	Res Spplrs	Oper Mgrs	Res Mgrs	Res Spplrs
Demographic segmentation	54.9	64.1	72.0	91.2	95.7	98.3
Usage segmentation	52.0	59.9	68.6	91.6	91.3	94.6
Time-series analysis	43.4	45.2	27.8	81.6	87.2	69.9
Focus groups	35.4	51.1	62.3	76.6	85.9	95.6
Formal experiments	24.6	36.6	45.9	71.9	73.2	87.7
Psychographics	12.7	22.3	37.9	71.1	78.1	88.1
Response models	10.6	10.6	7.0	50.0	52.5	35.6
Computer simulation	10.1	8.7	6.5	45.5	47.6	35.6
Cluster analysis	5.2	7.7	16.5	53.6	62.2	76.3
Conjoint analysis	4.8	3.8	11.7	32.6	43.8	55.5
Multidimensional scaling	4.3	7.0	15.7	38.2	53.9	65.7
Bayesian analysis	4.2	10.5	2.2	59.8	50.4	45.3
Factor analysis	3.8	12.4	23.6	56.5	70.4	85.2
Means	20.5	25.5	30.6	63.1	68.6	71.8
Standard deviations	19.4	22.8	24.5	19.3	18.1	22.6

As MMG note, research managers' and/or research suppliers' responses to the "frequently used" question tend to be higher than those of line managers. The authors conclude:

1. Overall, segmentation, time-series analysis, and focus groups (the older, more established techniques) are the most widely used. More recent and complex techniques, such as cluster analysis, MDS, conjoint analysis, Bayesian decision theory, and computer simulation, are less commonly used.
2. Trial usage of techniques tends to be highest among consumer-goods manufacturers and lowest among retail firms.

MMG report that a similar study, launched by Georgia State University, shows similar results. Not surprisingly, both study teams noted that simpler

techniques were adopted more quickly and used more frequently than the more complex methods.

In terms of frequency of use, research suppliers tended to lead in the use of segmentation, focus groups, experimentation, psychographics, cluster analysis, conjoint analysis, MDS, and factor analysis. These techniques all require specialization, either in terms of statistics or behavioral science (e.g., focus groups). In short, the (outside) research supplier plays an important role in information diffusion. The adoption sequence extends from technique developer (e.g., academic) to research consultant/supplier, to corporate research manager, to operating manager.

Tools Change, But the Gap Remains

While the techniques from 1980 (summarized in Table 14-1) are still used today, many new ones have been developed in recent decades. As reflected in the discussions in the previous chapters of the book, enormous developments have been made in the field. The tutorials and presentations made to the AMA's Advanced Research Techniques (A/R/T) Forum offer an illustration of some of these developments. A sample of the A/R/T Forum tutorials, shown in Table 14-3, indicates the range of the new approaches that were considered important for practitioners. The primary focus of the Forum is on a range of specific methods and their applications. Among the topics, for example: consumer evaluation of really new services, a presentation by Paul Green on the TrafficPulse study, the effect of removing "fence-sitting" options on consumer attitude and preference measurements, using a dual-response framework in choice modeling, capturing heterogeneity by allowing respondents to eliminate unacceptable attribute levels, fusing data of different sources, advances in data mining and stochastic gradient boostings.

Table 14-3. Examples of Topics Covered in A/R/T Forum Tutorials (1998-2002)

Applied probability models
Choice experiments
Bayesian models
Choice modeling
Data mining
Latent cluster and segmentation models
Cart decision trees
Web mining
Hierarchical Bayes
Segmentations with mixture models
Multivariate adaptive regression splines
Choice modeling with Gibbs sampling
Measuring and modeling brand loyalty

Although much has changed in the range and sophistication of these models, one thing probably has not changed. The findings of MMG and other studies still appear to hold today. The gap remains between research and practice.

As one indication of how this divide is perpetuated, the AMA itself holds separate conferences for academic and industry participants. Through this structure, the two sides are kept apart, yet, as the discussion of diffusion suggests, many advances in methodology come at the intersection of research and practice. In the future, we need to find ways to encourage more collaboration.

BRIDGING THE GAP

Figure 14-1 illustrates a typical diffusion process for new marketing research ideas. Most new methods and techniques are initiated by academics who are primarily interested in their publication in academic journals. Marketing research suppliers and industry consultants (whose groups may contain academics as well) respond to the new developments and, through their vested interests, move the technology along, typically in the form of consulting engagements. As indicated by the dotted lines, feedback then flows back to the researchers, helping to refine the research and suggest new directions and management challenges to address.

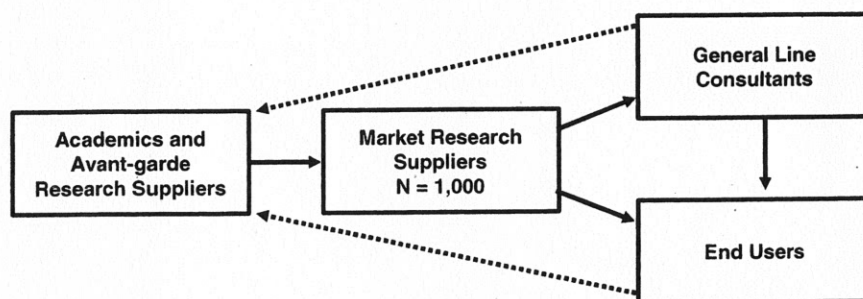


Figure 14-1. Typical Diffusion Process for New Models and Methods in Marketing Research

Hence, it behooves industry consultants and research suppliers to keep abreast of new developments and be flexible enough to incorporate those innovations into their own consulting practices. In so doing, their efforts can provide pragmatic “tests” of how the techniques work in practice, what their

pitfalls may be, and how deficiencies can be rectified. Applications-oriented journals, such as *Marketing Research* also provide an avenue for practitioner feedback and help "close the loop" between innovation and adoption.

There are a variety of strategies that researchers and practitioners are taking, or could take, to bridge this gap. This process, however, is often accompanied by changes in the original methodology of either a corrective or extended nature. Obviously, some new academic ideas do not hold up in practice, necessitating correction or, possibly, abandonment. There is a need for continuous interaction and feedback loops between idea and application.

Keeping Up with Research

William Neal (1998), founder and chief officer of Sophisticated Data Research, a major consulting firm in marketing research, has written extensively on the subject of information diffusion. Neal points out how important the marketing research methodologist has become in "spreading the word" regarding new models and techniques. He views the research methodologist as one with training in statistics, psychometrics, micro-economics, and marketing. He stresses the role of communicator and the ability to explain complex concepts to managers in relatively simple terms.

Neal also emphasizes the role that the availability of inexpensive and easy-to-use software (much of which was originally supplied free from Bell Laboratories) plays in the early adoption of new techniques. Neal then focuses on three avenues practitioners can use to keep up with the growing field of marketing research: Subscribe to and *read* the academic journals; follow what is happening among leading-edge academics; and keep adding to one's skills by attending advanced seminars in new methodology, such as the AMA's A/R/T Forum and the Management Sciences (INFORMS) conferences.

The American Marketing Association provides a wide variety of training programs to help practitioners keep up with new developments in research methodology. Perhaps the most visible is the A/R/T Forum, mentioned above, held once a year, which offers attendees new techniques, presented by top academics and industry consultants. In addition to plenary sessions, the Forum offers seminars and discussion sessions as well as poster presentations. Ample time is provided for audience participation, both formally and casually. The A/R/T Forum is now going into its fourteenth highly successful year. Another outstanding annual meeting is the Sawtooth Software Conference, which also emphasizes new methodology and research applications.

In 1980, the AMA launched its first Marketing Research Conference. It is now in its 23rd year. The AMA also runs annual Applied Research Methods Conferences that emphasize tutorial learning. Some 4,000 industry

researchers have attended at least one of these tutorials since the program began.

In addition to the AMA, a number of other organizations also promote marketing research in specific areas. For example, the Advertising Research Foundation (ARF) has helped disseminate advertising research, and other organizations have contributed to sales management, direct marketing and other specialized marketing domains.

In sum, the AMA, other professional organizations, and private companies such as Sawtooth Software, provide ongoing opportunities for corporate analysts to sharpen their skills and keep up with recent developments in marketing research.

Trends that Stimulate the Development and Diffusion of Marketing Research

Five recent trends have occurred that further the continued development of marketing research and modeling.

1. Marketing research firms, through mergers and acquisitions, are becoming larger and larger. Traditionally, the top 50 marketing research firms have dominated the field; if anything, the concentration is increasing. Moreover, research suppliers are rapidly becoming global in their operations.
2. General management consulting firms are adding marketing research capabilities, either by acquiring marketing research affiliates or forming strategic alliances with them. Mercer Consulting, for example, has a large and diversified group of marketing research professionals. McKinsey has close ties with a number of full-service marketing research firms.
3. Many of the research techniques with demonstrated performance, such as conjoint analysis and experimental choice analysis, are being accepted and appreciated by higher levels in end-user companies – including executives in corporate board rooms and strategic planning groups.
4. We have seen the increased use of CRM, the proliferation of direct marketing, and the increased importance of data base marketing, which includes appropriate analytics.
5. The current economic downturn increases the pressure for cost cutting, increased efficiency and effectiveness of marketing and marketing research, the focus on the ROI of marketing and the increased interest in optimal resource allocation among marketing tools, brands, segments, countries and businesses.

Taken in concert, these trends bode well for users of sophisticated research tools that can handle strategy-based problems. In addition, newer tools for data mining and targeted customer marketing have received increased attention in this age of computers and the Internet.

Recognizing Articles that Contribute to Marketing Practice

The practical focus of academic research can be reinforced through recognition. For example, the Paul E. Green Award is presented for the article in the *Journal of Marketing Research* of the preceding year that demonstrates the most potential to contribute significantly to the practice of marketing research or the practice of marketing. Table 14-4 list recipients of the award and illustrates the applied focus of their topics. As a further emphasis on practice, the award is presented at the AMA's A/R/T Forum.

Table 14-4. Winners of the *Journal of Marketing Research's* Paul E. Green Award

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- 2002:** William R. Dillon, Amna Kirmani, Thomas J. Madden, and Soumen Mukherjee, "Understanding What's in a Brand Rating: A Model for Assessing Brand and Attribute Effects and Their Relationship to Brand Equity," November 2001.
- 2001:** Carrie M. Heilman, Douglas Bowman, and Gordon P. Wright, "The Evolution of Brand Preferences and Choice Behaviors of Consumers New to a Market," May 2000.
- 2000:** Marnik Dekimpe and Dominique Hanssens, "Sustained Spending and Persistent Response: A New look at Long-Term Marketing Profitability," November 1999.
- 1999:** Gregory S. Carpenter, Venkatesh Shankar, and Lakshman Krishnamurthi, "Late Mover Advantage: How Innovative Late Entrants Outsell Pioneers," February 1998.
- 1998:** Carl F. Mela, Sunil Gupta, and Donald R. Lehmann, "The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice," May 1997.
- 1997:** Peter S. Fader and Bruce G. S. Hardie, "Modeling Consumer Choice Among SKUs," November 1996.
- 1996:** Leonard M. Lodish, Magid Abraham, Stuart Kalmenson, Jeanne Livelsberger, Beth Lubetkin, Bruce Richardson, and Mary Ellen Stevens, "How T.V. Advertising Works: A Meta-Analysis of 389 Real World Split Cable T.V. Advertising Experiments," May 1996.
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THE ROLE OF PROFESSIONAL JOURNALS IN DIFFUSION

As William Neal noted, professional journals have a central role to play in putting new ideas into practice. The heart of any applied research-oriented discipline contains two essential components:

- The availability of media for disseminating information (typically, technical journals, conference proceedings, industry tutorials, etc.), and
- Feedback on the extent to which corporate researchers and consulting groups have found the information to be useful in solving real business problems.

As emphasized earlier, this feedback loop is essential to evaluating how worthwhile new methods and techniques are and the directions in which they can be improved.

The field of marketing research and related disciplines currently are the focus of a wide assortment of journals, including:

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| • <i>Journal of Marketing Research</i> | • <i>Journal of Advertising Research</i> |
| • <i>Journal of Marketing</i> | • <i>Decision Sciences</i> |
| • <i>Journal of Consumer Research</i> | • <i>Management Science</i> |
| • <i>Marketing Science</i> | • <i>Marketing Letters</i> |
| • <i>Marketing Research</i> (for practitioners) | • <i>International Journal of Research in Marketing</i> |

As we look back across the 40 years of research in marketing, the *Journal of Marketing Research (JMR)* continues to be the flag bearer for research excellence, as discussed in Chapter 11. Historically, the American Marketing Association was composed of educators *and* practitioners. Its mandate, as described by William R. Davidson, President of AMA in 1964, was to seek articles of the following types:

- Presentations of new techniques for solving marketing problems, “new” in the sense of not having been previously used to solve *marketing* problems,
- Demonstrations of different ways in which known techniques may be used to solve marketing research problems,
- Clarifications of marketing theories or of methodology initially thought too difficult to understand,
- Contributions to marketing knowledge based on the use of experimental methods or other analytic techniques, and
- Reviews of developments and concepts in related fields that may be applicable to marketing research (Davidson 1964).

While the much older *Journal of Marketing (JM)* had earlier published a wide array of articles (including some involving marketing research), under the editorship of Stewart Britt, *JM*'s contents took a marked turn toward more general articles on marketing management, marketing education, and social significance. Hence the time seemed to be right for a *new* marketing journal – one that emphasized research techniques and methods useful for research professionals employed in consulting or corporate enterprises, as well as academics.

Under Bob Ferber's editorship, in 1964 an editorial board of nine members was recruited – three academics, five professional marketing researchers, and one corporate director of marketing research. *JMR*'s mission appeared to be very clear at that time: to publish developments in new models, techniques, and methods to advance *both* the state of the art and the state of practice in marketing research.

Subsequently, *JMR* was followed, a decade later in 1974, by the *Journal of Consumer Research (JCR)*, whose audience was made up of scholars primarily interested in the consumer (rather than the marketing manager). *JCR* focused on such questions as:

- How can consumers make better informed purchase decisions?
- How can research be used to improve consumer information regarding competing brands?
- How can governmental bodies be better informed regarding product quality and pricing decisions?
- How can truth in advertising and promotion be better regulated to protect consumer interests?

Ron Frank was the first editor of *JCR*, which was sponsored by ten professional organizations, clearly recognizing the interdisciplinary perspective of consumer research and behavior. Under his stewardship, the journal (and the Association of Consumer Research) was off to an excellent start. In addition, *JCR*'s audience and article contributors were sufficiently dissimilar to *JMR*'s audience and contributors that their domains of interest (business managers versus consumers) were demarcated.

In contrast, *Marketing Science* came on the scene almost two decades after *JMR*. The first *Marketing Science* board consisted of Don Morrison, editor, and three area editors: Seenu Srinivasan, Subrata Sen, and Jerry Wind. Its review board consisted of 32 members, 29 of whom were academics.

An Academic Focus

If there is one constant to today's admixture of marketing journals, it is the strong tendency for review boards and *ad hoc* reviewers to be drawn from the academic sector:

- In *JMR*, November 2002, 94 review board members were listed; all were academics.
- Between July 1, 2001 and June 30, 2002, *JMR* utilized over 150 *ad hoc* reviewers; only one was listed as a non-academic.
- In the first issue of *Marketing Science* (Winter 1982), there were three area editors and 32 reviewers listed; only three of the 32 were not from academia.
- In the Winter 2002 issue of *Marketing Science*, there were 14 area editors and 55 reviewers; only three of the reviewers were non-academics.

Good reasons for this situation can easily be found. Non-academics are rarely rewarded for their efforts as either senior author or coauthor. Indeed, instances have occurred where company employees have been dissuaded or even rebuked for requesting time off to write journal articles. This, of course, is in marked contrast to the cachet attached to preparing articles that both academics and research consultants enjoy.

Still, articles *do* get published by combinations of academic consultants and industry practitioners, even if it is the consultant who carries the brunt of the writing. As noted earlier, consultants also provide a useful bridge between academics and end-user firms through their help in explaining the more technical points of new methods and techniques.

Potential Journal "Wars": Boon or Bane?

Is there room for still more journals that publish marketing research articles? As shown earlier, there are at least eight journals that publish marketing articles on a regular basis. In addition, specialty journals (that at least have "marketing" in their titles) abound. The Haworth Press alone lists 19 journals with "marketing" somewhere in the title. Not to be outdone, the International Press lists 21.

Looking at closer competition among the primary journals, it would seem that *JCR* contributors have carved out a niche that is relatively immune to "encroachment." *JCR* appeals to a variety of tastes ranging from carefully-designed experiments (with ANOVA) to further-out forays into consumer post-modernism and other such venturesome market niches.

In contrast, *Marketing Science* would appear to be a stronger competitor to *JMR* than either *JCR* or *JM*. Papers on marketing science methods appear to be significantly increasing. Also, while *JMR* still rules when it comes to methodological techniques (e.g., hierarchical Bayes), it is not clear as to how the two journals, *Marketing Science* and *JMR*, will fare in the future.

The New Guy

As if the *JMR* vs. *Marketing Science* competition isn't enough, there's a new "kid on the block" about to enter the fray. The incipient journal is *Quantitative Marketing and Economics*. Its editors are Rajiv Lal and Peter Rossi. As the editors state: "*QME* will focus on the intersection of Marketing, Economics, and Statistics, with an emphasis on the analysis of important problems of relevance to marketing." Its aims and scope are as follows:

Quantitative Marketing and Economics publishes research in the intersection of Marketing, Economics, and Statistics. Our focus is on important applied problems of relevance to marketing using a quantitative approach. We define marketing broadly as the interface between firms, competitors, and consumers. This includes but is not limited to consumer preferences, consumer demand and decision-making, strategic interaction of firms, pricing, promotion, targeting, product design/positioning, and channel issues. We embrace a wide variety of research methods including applied economic theory, econometrics, and statistical methods. Empirical research using primary, secondary, or experimental data is also encouraged.

QME will be published quarterly by Kluwer Academic Press. Over 30 highly respected scholars have been selected for its review board. Publication of *QME* starts in early 2003 and it will be available in both hard copy and online. All journal correspondence, including submissions, will be electronic.

If *QME* makes good on its agenda, there is every reason to believe that it will invade the territory heretofore occupied by *JMR* and *Marketing Science*. It will be interesting to see how three top-rated journals, devoted to quantitative marketing, will fare in years to come.

For those who see this "triadic" competition as upsetting, only time will tell how the journal marketplace will settle down. For the more hardy souls who welcome hard-fought competition, it's more a case of "Let the games begin!" Proof of the pudding ultimately lies in how well the diffusion process works and how *practitioner* adoption is facilitated by the new entry.

FUTURE APPLICATIONS OF RESEARCH AND MODELING APPROACHES

The interplay between theory and practice is also helping to draw together different approaches to marketing research and focus them on specific

marketing decisions. The different approaches to marketing research discussed in this book – including Bayesian approaches, multivariate analysis, multidimensional scaling and clustering, and conjoint analysis – have been developed as independent streams, each with its own evolution. Individual researchers and practitioners often specialize in one approach, which has deepened the sophistication of these tools. As shown in Table 14-5, each of these tools is used to address specific types of marketing decisions.

Table 14-5. Applications of Key Research and Modeling Approaches

Marketing Decisions	Approaches					
	Bayesian	Multi-variate Analysis	MDS & Clustering	Conjoint Analysis	Decision Support Models	Multi Methods
Understanding Customers		x	x	x		x
Marketing Strategy		x	x	x		x
Market Segmentation		x	x	x	x	x
Positioning			x	x	x	x
New Product	x			x	x	x
Pricing	x	x		x	x	x
Distribution	x	x		x	x	x
Adv. & Communication	x	x		x		x
Competitive Strategies		x		x		x
Customer Satisfaction				x		x
Relationship Marketing				x		x
Business Strategy				x		x

As evident in practice and in much of Paul Green's applied work, we expect to see much greater focus on multi-method approaches. As marketing challenges become more complex and marketing researchers become more sophisticated, there is tremendous power in combining different approaches to address a broader range of decisions. Instead of focusing on the methods – picking up a hammer so that every problem looks like a nail – the focus is shifting more toward the marketing decisions that need to be made. Researchers and practitioners can then select the tools that are best suited to addressing those specific decisions.

This use of multiple methods to address real-world marketing decisions is part of the tradition established by Wroe Alderson and Paul Green. Through four decades of marketing research, we have created a powerful set of sophisticated approaches to marketing challenges. These have slowly moved into practice through publication in journals and direct applications to corporate challenges. Now we have an opportunity to draw these together and

creatively combine them to develop innovative research designs that incorporate the best approaches and tailor them to the particular marketing challenge to be addressed. While each of the streams of marketing research will continue to be refined, this central ground of multi-methods is one of the rich areas for future study and practice.

In examining the diffusion process of methodologies, we cannot ignore developments in related fields. For example, while developments in areas such as Total Quality Management (TQM) – with its emphasis on customer satisfaction – data mining initiatives, and Customer Relationship Management (CRM), did not originate as marketing research initiatives, they do contribute to the development and diffusion of marketing research methodologies.

This discussion highlights another divide that must be bridged for marketing research to achieve its greatest impact: cutting across different disciplines and functions in the organization. We need to consider expanding the scope of our applications of the tools and approaches of marketing research. Marketing has often been left out of key initiatives such as TQM or data mining, which have been spearheaded by operations and IT. Marketing research approaches have the potential to contribute to these types of strategic initiatives if researchers can think more broadly about applications. Even initiatives such as Customer Relationship Management (CRM) that have involved marketing often have broader applications. For example, CRM approaches are now being extended by Siebel to Employee Relationship Management (ERM) and Partner Relationship Management (PRM). Similarly, marketing research tools and approaches that are applied to external customers can also be used effectively with internal “customers” and other stakeholders. This suggests that if we expand our thinking beyond the narrow confines of strictly functional marketing challenges, we can find many other ways to use these valuable and sophisticated tools to address other strategic issues in our enterprises.

CLOSING THE GAP

How can researchers and practitioners work more closely together? We need to move away from the model of letting an academic researcher or research institution do the research and merely hoping that a marketing research firm will pick it up and start applying it. In the tradition of Wroe Alderson and Paul Green, we need to think about applications at the same time we are designing research projects. There are a variety of ways that we can increase the real-world orientation of research, including:

- Addressing the increased concern of management about the ROI of marketing expenditures,

- Assuring that the research designs and methods used address important management issues and concerns and lend themselves to the needed integration of research and modeling; the two should not be viewed as separate domains,
- Ensuring that the methods developed capture the latest developments in related disciplines such as statistics, mathematical psychology, decision processes, computer science, econometrics,
- Assuring that the new methods developed offer a better solution than the currently used approaches. This requires that Ph.D students and other researchers familiarize themselves with current practice and not only with the published articles in the field,
- Appraising the value of the new approaches to practitioners,
- To the extent possible, validating the newer research approaches on relevant samples. (Research based on Marketing 101 students can go only so far.)

Increasing real-world orientation would make our research more relevant to practitioners and put the results into their hands more quickly. On the research side, closer ties with practitioners can also provide robust data sets and offer a rich set of research problems for researchers to tackle in the years ahead. This is not to say that research should be limited to the questions raised by practitioners or that managers should be involved in every future research project. It means that we need to increase the awareness of both researchers and practitioners of one another so that they can most effectively work together to advance the theory and practice of the field.

NOTES

¹ Academics were also sampled. Here we focus only on industry practitioners and research suppliers.

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