Chapter 4

A Short History of Conjoint Analysis

The genesis of new statistical models has rarely been within the field of marketing research. Marketing researchers have mainly borrowed from other fields. Conjoint analysis and the more recent discrete choice or choice-based conjoint methods are no exception. Conjoint methods were based on work in the sixties by mathematical psychologists and statisticians Luce and Tukey (1964), and discrete choice methods came from econometrics, building upon the work of McFadden (1974), 2000 Nobel Prize winner in economics.

Marketers sometimes have thought (or been taught) that the word "conjoint" refers to respondents evaluating features of products or services "CONsidered JOINTly." In reality, the adjective "conjoint" derives from the verb "to conjoin," meaning "joined together." The key characteristic of conjoint analysis is that respondents evaluate product profiles composed of multiple conjoined elements (attributes or features). Based on how respondents evaluate the combined elements (the product concepts), we deduce the preference scores that they might have assigned to individual components of the product that would have resulted in those overall evaluations. Essentially, it is a back-door, decompositional approach to estimating people's preferences for features rather than an explicit, compositional approach of simply asking respondents to rate the various features. The fundamental premise is that people cannot reliably express how they weight separate features of the product, but we can tease these out using the more realistic approach of asking for evaluations of product concepts through conjoint analysis.

Let us not deceive ourselves. Human decision making and the formation of preferences is complex, capricious, and ephemeral. Traditional conjoint analysis makes some heroic assumptions, including the proposition that the value of a product is equal to the sum of the values of its parts (i.e., simple additivity), and that complex decision making can be explained using a limited number of dimensions. Despite the leaps of faith, conjoint analysis tends to work well in practice, and gives managers, engineers, and marketers the insight they need to reduce un-

This chapter is based upon an article first published in *Quirk's Market Research Review*, July/August 2004.

Reprinted from Orme, B. (2010, 2019) *Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research*. Fourth Edition, Madison, Wis.: Research Publishers LLC.

Exhibit 4.1. Conjoint card for automobiles

certainty when facing important decisions. Conjoint analysis is not perfect, but we do not need it to be. With all its assumptions and imperfections, it still trumps other methods.

4.1 Early Conjoint Analysis (1960s and 1970s)

Just prior to 1970, marketing professor Paul Green recognized that Luce and Tukey's (1964) article on conjoint measurement, published in a non-marketing journal, might be applied to marketing problems: to understand how buyers made complex purchase decisions, to estimate preferences and importances for product features, and to predict buyer behavior. Green could not have envisioned the profound impact his work on full-profile card-sort conjoint analysis would eventually achieve when he and coauthor Rao published their historic article "Conjoint Measurement for Quantifying Judgmental Data" in the *Journal of Marketing Research (JMR)* (Green and Rao 1971).

With early full-profile conjoint analysis, researchers carefully constructed a deck of conjoint cards based on published catalogs of orthogonal design plans. Each card described a product profile, such as shown in exhibit 4.1 for automobiles.

Respondents evaluated each of perhaps eighteen separate cards and sorted them in order from best to worst. Based on the observed orderings, researchers could statistically deduce, for each individual, which attributes were most important and which levels were most preferred. The card-sort approach seemed to work quite well as long as the number of attributes studied did not become too large. And researchers soon found that better data could be obtained by asking respondents to rate each card (say, on a ten-point scale of desirability) and using

	Made in USA	Made in Europe	Made in Far East
Front-wheel drive	7	6	3
Rear-wheel drive	9	8	5
All-wheel drive	4	2	1

Exhibit 4.2. Johnson's trade-off matrix with rank-order data

ordinary least squares regression analysis to derive the respondent preferences. In 1975 Green and Wind published an article in *Harvard Business Review* on measuring consumer judgments for carpet cleaners, and business leaders soon took notice of this new method.

Also just prior to 1970, a practitioner named Richard Johnson at Market Facts was working independently to solve a difficult client problem involving a durable goods product and trade-offs among twenty-eight separate product features, each having about five different realizations or levels. The problem was much more complex than those being solved by Green and coauthors with full-profile card-sort conjoint analysis, and Johnson invented a clever method of pairwise trade-offs. His paper on trade-off matrices was published in *JMR* (Johnson 1974). Rather than asking respondents to evaluate all attributes at the same time in full profile, Johnson broke the problem down into focused trade-offs involving just two attributes at a time. Respondents were asked to rank-order the cells within each table in terms of preference for the conjoined levels.

In exhibit 4.2 we see a respondent who liked the all-wheel drive vehicle made in the Far East best and the rear-wheel drive vehicle made in the United States least. With Johnson's trade-off matrices, respondents would complete a number of these pairwise tables, covering all attributes in the study (but not all possible combinations of attributes). By observing the rank-ordered judgments across trade-off matrices, Johnson was able to estimate a set of preference scores and attribute importances across the entire list of attributes for each individual. Because the method only asked about two attributes at a time, a larger number of attributes could be studied than was generally thought prudent with full-profile conjoint methods.

Near the end of the 1970s, academics Paul Green and Seenu Srinivasan published an influential paper in the *Journal of Consumer Research* summarizing the use of conjoint analysis in industry, outlining new developments, and giving advice regarding best practices (Green and Srinivasan 1978).

4.2 Conjoint Analysis in the 1980s

By the early 1980s, conjoint analysis was gaining in popularity, at least among leading researchers and academics possessing considerable statistical knowledge and computer programming skills. When commercial software became available in 1985, the floodgates were opened. Based on Green's work with full-profile conjoint analysis, Steve Herman and Bretton-Clark Software released a software system for IBM personal computers.

Also in 1985, Johnson and his new company, Sawtooth Software, released a software system (also for the IBM personal computer) called Adaptive Conjoint Analysis (ACA). Over many years of working with trade-off matrices, Johnson had discovered that respondents had difficulty dealing with the numerous tables and in providing realistic answers. He discovered that he could program a computer to administer the survey and collect the data. The computer could adapt the survey to each individual in real time, asking only the most relevant trade-offs in an abbreviated, more user-friendly way that encouraged more realistic responses. Respondents seemed to enjoy taking computer surveys, and some even commented that taking an ACA survey was like playing a game of chess with the computer.

One of the most exciting aspects of these commercial conjoint analysis programs for traditional full-profile conjoint and ACA was the inclusion of what-if market simulators. Once the preferences of typically hundreds of respondents for an array of product features and levels had been captured, researchers or business managers could test the market acceptance of competitive products in a simulated competitive environment. One simply scored the various product offerings for each individual by summing the preference scores associated with each product alternative. Respondents were projected to choose the alternative with the highest preference score. The results reflected the percent of respondents in the sample that preferred each product alternative, which was called share of preference. Managers could make any number of slight modifications to their products and immediately test the likely market response by pressing a button. Under the proper conditions, these shares of preference were fairly predictive of actual market shares. The market simulator took esoteric preference scores (part-worth utilities) and converted them into something much more meaningful and actionable for managers (product shares).

Conjoint analysis quickly became the most broadly used and powerful survey-based technique for measuring and predicting consumer preference. Helping to fuel this interest was an influential case study published by Green and Wind (1989) regarding a successful application of conjoint analysis to help Marriott design its new Courtyard hotels. But the mainstreaming of conjoint analysis was not without its critics, who argued that making conjoint analysis available to the masses through user-friendly software was akin to "giving dynamite to babies."

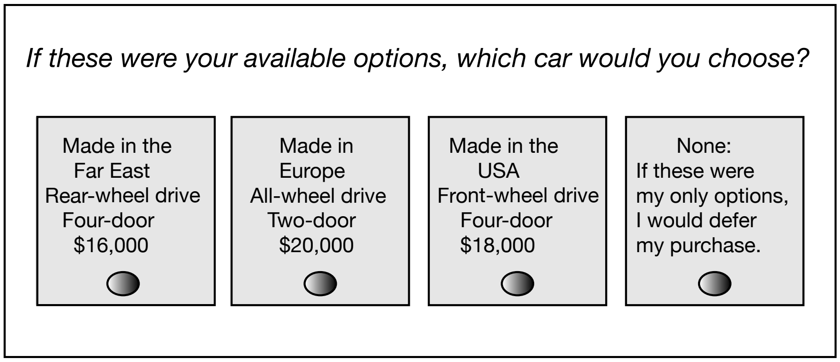

Exhibit 4.3. A choice set for automobiles

Prior to the release of the first two commercial conjoint analysis systems in 1985, Jordan Louviere and colleagues were adapting the idea of choice analysis among available alternatives and multinomial logit to, among other things, transportation and marketing problems. The groundwork for modeling choice among multiple alternatives had been laid by McFadden in the early 1970s. The concept of choice analysis was attractive: buyers did not rank or rate a series of products prior to purchase, they simply observed a set of available alternatives (again described in terms of conjoined features) and made a choice. From a theoretical and statistical standpoint, choice analysis was more defensible than ratings-based conjoint. But, from a practical standpoint, there were some challenges. A representative discrete choice question involving automobiles is shown in exhibit 4.3.

Discrete choice analysis seemed more realistic and natural for respondents. It offered powerful benefits, including the ability to do a better job of modeling interactions (i.e., brand-specific demand curves), availability effects, and cross-elasticities. Discrete choice analysis also had the flexibility to incorporate alternative-specific attributes and multiple constant alternatives. But the benefits came at considerable cost: discrete choice questions were an inefficient way to ask respondents questions. Respondents needed to read quite a bit of information before making a choice, and a choice only indicated which alternative was preferred rather than strength of preference.

With discrete choice there typically was not enough information to model each respondent's preferences. Rather, aggregate or summary models of preference were developed across groups of respondents. Aggregate models were subject to various problems such as independence from irrelevant alternatives (IIA or the red bus/blue bus problem) and ignorance of the separate preference functions for latent subgroups. Overcoming the problems of aggregation required building ever-more-complex models to account for attribute availability and cross-effects.

These models, called mother logit models, were used by a relatively small and elite group of conjoint specialists throughout the 1980s. Given the lack of easy-to-use commercial software for fitting discrete choice models, most marketing researchers had neither the tools nor the stomach for building them.

4.3 Conjoint Analysis in the 1990s

Researchers in the 1990s came to recognize that no one conjoint method was the best approach for every problem, and expanded their repertoires. Sawtooth Software facilitated the discussion by publishing research from its users and hosting the Sawtooth Software Conference. User case studies demonstrated under what conditions various conjoint methods performed best. Sawtooth Software promoted the use of various conjoint methods by developing additional commercial software systems for full-profile conjoint analysis and discrete choice.

Based on industry usage studies conducted by leading academics (Vriens, Huber, and Wittink 1997), ACA was the most widely used conjoint technique and software system worldwide. By the end of the decade, ACA would yield that position to discrete choice analysis. Two main factors were responsible for discrete choice analysis overtaking ACA and other ratings-based conjoint methods by the turn of the century: (1) the release of commercial software for discrete choice modeling (CBC for choice-based conjoint) by Sawtooth Software in 1993 and (2) the application of hierarchical Bayes (HB) methods to estimate individual-level models from discrete choice data (principally due to articles and tutorials led by Greg Allenby of Ohio State University).

Discrete choice experiments are typically more difficult to design and analyze than traditional full-profile conjoint or ACA. Commercial software made it much easier to design and conduct CBC studies, while easy-to-use HB software made the analysis of choice data seem nearly as straightforward and familiar as the analysis of ratings-based conjoint. With individual-level models under HB, IIA and other problems due to aggregation were controlled or mostly solved. This has helped immensely with CBC studies, especially for those designed to investigate the incremental value of line extensions or me-too imitation products. While HB transformed the way discrete choice studies were analyzed, it also provided incremental benefits for traditional ratings-based conjoint methods. Traditional conjoint methods had always estimated part-worth utilities at the individual level, but HB offered the prospect of more accurate estimation and shorter questionnaires. Other important developments during the 1990s included the following:

- Latent class models for segmenting respondents into relatively homogeneous groups, based on preferences
- Web-based data collection for all main flavors of conjoint and choice analysis
- Improvements in computer technology for presenting graphics

- Dramatic increases in computing speed and memory, making techniques such as HB feasible for common data sets
- Greater understanding of efficient conjoint and choice designs using concepts of level balance, level overlap, orthogonality, and utility balance
- Statistical Analysis System (SAS) routines for the design of discrete choice plans using computerized searches (Kuhfeld, Tobias, and Garratt 1994)
- Advances in the power and ease of use of market simulators offered both by commercial software developers and by consultants working with spreadsheet applications

The 1990s represented a decade of strong growth for conjoint analysis and its application in a fascinating variety of areas. Conjoint analysis had traditionally been applied to fast-moving consumer goods, technology products and electronics, durables (especially automotive), and a variety of service-based products such as cell phones, credit cards, and banking services. Other interesting areas of growth for conjoint analysis included design of Web sites, litigation and damages assessment, human resources and employee research, and Web-based sales agents for helping buyers search and make decisions about complex products and services. By the end of the decade, analysts had become so trusting of the technique that some used conjoint analysis to help them personally decide among cars to buy or members of the opposite sex to date.

4.4 Year 2000 and Beyond

Much recent research and development in conjoint analysis has focused on doing more with less: stretching the research dollar using IT-based initiatives, reducing the number of questions required of any one respondent with more efficient design plans and HB estimation, and reducing the complexity of conjoint questions using partial-profile designs.

Researchers have recently gone to great lengths to make conjoint analysis interviews more closely mimic reality: using animated three-dimensional renditions of product concepts rather than static two-dimensional graphics or pure text descriptions, and designing virtual shopping environments with realistic store aisles and shelves. In some cases the added expense of virtual reality has paid off in better data, in other cases it has not.

Since 2000, academics have been using HB-related methods to develop more complex models of consumer preference, relaxing the assumptions of additivity by incorporating noncompensatory effects, incorporating descriptive and motivational variables, modeling the interlinking web of multiple influencers and decision makers, and linking survey-based discrete choice data with sales data. Additional research includes efforts to customize discrete choice interviews so that they adapt to individual respondents in real time.

Interactive, customized discrete choice interviews can engage respondents in a dialog that probes their relevant decision space and reveals both compensatory (trade-off) and non-compensatory behavior (such as screening rules). It has long been held that buyers first screen available products to form consideration sets and then make choices within consideration sets. New research in adaptive CBC interviews has shown that staging the interview as a screening task (to select a consideration set) followed by focused trade-offs among considered products may lead to more accurate market simulation models, especially for high-involvement products and services described by many attributes (Gaskin, Evgeniou, Bailiff, and Hauser 2007; Johnson and Orme 2007).

Firms are becoming more nimble in the way they can customize products and services for consumers. Mass customization has become pervasive, as buyers can regularly design the product or service they wish to buy. Think of the Dell model for selling laptops a la carte, triple-play bundling of telecom services, restaurant menus, new car sales, banking and insurance options—these allow you the buyer to build your own product and then purchase it. The traditional conjoint approach does not mimic this buying process very well, so a new kind of conjoint called Menu-Based Conjoint or Menu-Based Choice (MBC) was created. The notion of MBC was envisioned and published nearly two decades ago (Liechty, Ramaswamy, and Cohen 2001; Bakken and Bayer 2001). Only in the last decade have practitioners begun to more widely apply this newest conjoint-based methodology (Orme 2010; Orme 2012).

Software developers continue to make conjoint analysis more flexible, as well as faster and less expensive to carry out. Software systems often support multiple formats, including paper-based, PC-based, Web-based, and mobile device interviewing. Developers keep a watchful eye on the academic world for new ideas and methods that appear to be reliable and useful in practice. Commercially available market simulators offer more actionable information as they incorporate price and cost data, leading to market simulations of revenues and profitability rather than just shares of preference.

To reduce the amount of manual effort involved in specifying successive market simulations to find better products, automated search routines are now available. These find optimal or near-optimal solutions when dealing with millions of possible product configurations and dozens of competitors—usually within seconds or minutes. This has expanded opportunities for academics working in the area of game theory. These academics can study the evolution of markets as they achieve equilibrium, given a series of optimization moves by dueling competitors.

Importantly, more people are becoming proficient in conjoint analysis as the trade is being taught to new analysts. Academics are including more units on conjoint analysis in business school curricula. A growing number of seminars and conferences are promoting conjoint training and best practices. And research is being published and shared more readily over the Internet.

On the horizon, advances in the fields of neuromarketing and neuroeconomics seem particularly relevant to conjoint analysis. Rather than directly ask respondents to rate or choose among product concepts, the response to conjoint stimuli may be simultaneously measured on multiple dimensions using brain imaging technology. Rather than building a single model of part-worth utilities to predict choice, researchers might develop different utility functions related to the ability of product characteristics to "light up" different areas of the brain associated with (for example) euphoria, memories, risks, rational decision making, and fears. Such studies could help marketers gain insight into the key drivers operating within the psyche that lead respondents to choose what they do. While this area seems promising, imaging technology is currently expensive and time-consuming, and the interpretation of brain image scans involves many assumptions and uncertainties (Page and Raymond 2006; Green and Holbert 2012).

Yes, conjoint analysis is nearly fifty years old. But rather than stagnating in middle-age, it continues to evolve—transformed by new technology and methodologies, infused by new intellectual talent, and championed by business leaders. It is very much in the robust growth stage of its life cycle. In retrospect, very few would disagree that conjoint analysis represents one of the great success stories in quantitative marketing research.