PART VII

CASE STUDIES AND APPLICATIONS IN MARKETING MANAGEMENT

15. Industry applications of conjoint analysis

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While conjoint analysis was originally developed to estimate utility values for attribute levels, it quickly became clear how versatile and useful the methodology is for marketing decision making (Green and Rao 1971). It has been applied with significant benefit to a large array of marketing decision problems such as product and service design, market segmentation, competitive analysis, pricing decisions, and sales/distribution analysis. Table 15.1 shows a selection of such applications. Appendix A to this chapter provides a brief description of the conjoint analysis method.

This chapter reviews five applications to provide the unique flavor and demonstrate the versatility of the conjoint analysis method. The following applications are discussed: store location selection, bidding for contracts, evaluating the market value of a change in a product attribute (MVAI), push marketing strategy in a B2B context, and choice of a distribution channel.[1]

STORE LOCATION

Retailers expand their business by expanding their presence in new geographic areas. They evaluate the potential of several new store locations using estimates of expected sales (or profits) and select a few locations for their geographic expansion. The estimate of expected sales in any location is simply the product of total market potential in the area and expected

Table 15.1 A selection of domain areas of applications

Application Domain	Products	Services
Product design	Electric car	Hotels (courtyard by Marriott)
	Carpet cleaners	Electronic toll systems (E-Z Pass)
	Personal computers	Consumer discount cards
Market segmentation	Copying machines	Car rental agencies
Product positioning	Ethical drugs	Banking services
Competitive analysis	Ethical drugs	Transcontinental airlines
Pricing	Gasoline pricing	Telephone services pricing
		Health insurance policies

market share of the new store. The estimate of market potential needs to include the likely market expansion due to the presence of the new store. The expected market share for the new store depends on the strength of competing stores in the area. While historical data can provide estimates of the current market potential and market shares of existing stores, judgment is called for estimating market expansion and market share. Conjoint methods have been applied in this context. One model in the franchising context (Ghosh and Craig 1991) considers both the potential to take market share from existing competitors and the market expansion potential in the geographic area due to the new store. We will first describe a mathematical model to estimate expected market share and then show how judgment is used for estimating its components as described in Durvasula, Jain, and Andrews (1992).

Let us consider a geographic area with n existing stores and introduction of another store (n+1). Let M_i, denote the market share of the i-th store. Let ME denote the market expansion due to the presence of the new store. Let k_i denote the proportion of the market expansion potential captured by i-th store (i=1, . . ., n+1) and $\sum_{i=1}^{i=n+1} k_i = 1$. All the k_i values are non-negative.

The new store will capture some market share of each of the existing stores, and PMS_i is the proportion of current market share of i-th store (M_i) captured by the new store. With these symbols, an estimate of the market share of the (n + 1)-th store can be derived as: $MS_{n+1} = \sum_{i=1}^{i=n} (PMS_i * M_i + k_{n+1} * ME)/(1 + ME)$, and the revised market shares of the existing stores are given by: $MS_i = (M_i - PMS * M_i + k_i * ME)/(1 + ME)$. Here, market shares of the n existing stores are typically known and the other quantities (*PMSs, ks,* and *ME*) need to be estimated by another model or judged by the decision makers.

One model used for estimating the PMS quantities is: PMS_i = PMIN + (PMAX- PMIN) (1- f (S_i)); i = 1, . . ., n, where PMIN (≥ 0) and PMAX (≤ 1) are the minimum and maximum share an outlet can obtain and S_i is the relative strength of the existing stores in the area. Typically, f (S_i) is modeled as a logistic function in S_i. PMIN and PMAX are judgmentally obtained. The relative strength construct (S_i) depends on various store attributes and can be modeled using conjoint analysis.

Durvasula, Jain, and Andrews (1992) applied this model for the case of banks and showed how conjoint analysis can be used in estimation. The context is that of a firm, called ABC Commerce, evaluating the potential of four locations, L1, L2, L3, and L4 in a certain geographic region. The firm currently has 16 branches in the region. In order to evaluate relative strength, the authors identified five attributes (by an exploratory study).

The attributes are: competitor's market share, growth of competitor's deposits, aggressiveness of the competitor in attracting deposits, age of the competitor's branch, and type of financial institution. The first three attributes were each at three levels described as "below," "about," and "above average of the ABC firm"; the fourth attribute was described by two levels as "relatively new" and "relatively established." The fifth attribute, type of financial institution, was described by two levels of "statewide" and "local." Using these five attributes, 16 descriptions of the competitive situation were developed using a fractional factorial design and four experienced managers rank ordered the sixteen profiles on the relative competitor strength. Based on these judgments, partworth values were computed for each of the five attributes for each manager separately. There was some heterogeneity among the partworths across managers.

The authors used these results to evaluate the market potential for the four locations using the models described earlier; the conjoint results for competitor's strength were the major input into the analysis. Managers also provided additional inputs (e.g., PMIN, PMAX etc.) judgmentally. The logistic functions, f(S), were estimated individually from the estimates of competitive strength obtained for the competitive branches in each location calculated using the partworth values. There was a reasonable agreement among the managers in their site evaluation. The market expansion (ME) was assumed to be zero in this application and the values of k_is were not estimated. The average market share potential for the proposed branches at locations L1, L2, L3, and L4 were 27.3, 11.1, 17.0, and 23.6, respectively. Based on this analysis, locations L1 and L4 were judged as offering higher potential. One should note that this analysis was conducted at one particular point in time, and expected growth factors were not included in these assessments. A dynamic conjoint study is called for to assess growth as well. Nevertheless, this illustration shows how conjoint analysis can be employed for retail location decisions.

A BIDDING APPLICATION

The Alpha catering firm located in Scandinavia was experiencing a decline in market share. The Alpha firm faces competition from four other firms in this market; we call these Beta, Gamma, Delta, and Phi; all but one of these are large firms and the fifth one (Phi) is a small entrepreneurial firm. These catering firms set up cafeterias on customers' (or client companies') premises and runs these cafeterias. They set prices for each item sold in cafeteria meals[2] at the company facility, and the client firms offer some subsidy to employees for lunch.

Pricing mechanisms in this catering supplier market are very complicated. Potential suppliers submit competitive bids that propose a fixed (one-time) payment for set-up costs for a cafeteria at the customer firm's location. These set-up costs are to be borne by the customer firm for the contract and are the basis for choosing a catering supplier. In order to understand the clients' trade-offs, the research firm conducted marketing research using conjoint analysis as the main technique for understanding the various trade-offs involved among the bids presented by the suppliers.

The attributes in the conjoint study were the setup costs specific to each supplier. The research firm used prior knowledge of the setup costs of the five competing firms to come up with a range of set-up costs. Rather than using actual possible values of set-up costs for each supplier, an index was used to describe the set-up costs (excluding the costs of catering and banquets) of each catering firm. These indexes varied from a low of 85 to a high of 120. For each supplier, five levels of the index were developed; for example, the levels for one catering firm, Gamma, were 85, 90, 95, 100, and 110. For a different supplier, Alpha, the levels were 90, 95,100, 110, and 120. Using an orthogonal fractional factorial design from a 5^5 factorial design, the researchers constructed 25 profiles of bid costs for each of the five competing firms; one profile was repeated three times, resulting in a total of 27 profiles; these were divided into three rotation sets A, B, and C of nine each. Each respondent received one of these rotation sets in a random order; the nine profiles within the rotation set also were administered randomly to each respondent. A respondent in a client company indicated the catering firm he or she will offer the contract for the cafeteria business for each choice set.

The researchers in this study first conducted preliminary interviews and focus groups to identify the factors that decision makers in the customer companies paid attention to. These variables fall into three groups: (1) customer characteristics (size, percent managerial and white- collar personnel, etc.) and preferences for menu and frequency of repetition; (2) restaurant factors (food quality, ambiance and service offered); and (3) pricing variables (lunch price and company subsidy). These data were collected from each client company in addition to the choice data. In all a sample of 207 respondents were contacted in the study; each respondent was chosen to represent his or her company and was responsible for making the decision on the choice of a catering firm for his company.

An aggregated logit model was developed to describe the choices made by the respondents. In this model, the bid price indexes and other variables were used as predictors. The model was estimated using maximum likelihood methods. The fit was quite good (model chi square was 286.44 with 34 degrees of freedom, with a p-value close to zero); several of the

Table 15.2 Predictions for three competitive bid profiles

Catering company	Competitive bid profile Set 1		Competitive bid profile Set 2		Competitive bid profile Set 3	
	Bid index	Predicted probability of winning the contract	Bid index	Predicted probability of winning the contract	Bid index	Predicted probability of winning the contract
Alpha	110	0.10	115	0.04	105	0.15
Beta	100	0.78	95	0.81	100	0.75
Gamma	95	0.005	95	0.005	95	0.005
Delta	102	0	100	0	102	0
Phi	100	0.115	100	0.145	100	0.095

variables turned out to be significant, as expected. The partworth values for the bid price attribute were in the expected direction; i.e., the probability of winning a bid decreased with increases in bid price. But, these relationships differed across the five suppliers. The analysis revealed the impact on the probability of winning a contract for the Alpha Company for changes in the three sets of variables noted above. The impact on the probability of choosing the Alpha firm decreases with an increase in the number of managerial and white-collar employees in the customer firm and when the customer firm prefers a dining room environment relative to a cafeteria. Similarly, the probability increases with changes in the weekly menus and lower lunch prices.

A decision support system was developed using the estimated logit model to predict the probability of winning a contract for the Alpha Company for a potential client under the assumptions of potential bids by the competing firms. The Alpha Company manager simply had to input the characteristics of the potential client and his or her assumptions about the possible competitive bids. Table 15.2 is an example of such a prediction for one client company, Omega. In this example, it is clear that the entrepreneurial firm will not be able to win the contract unless it drastically reduces its costs. Also, the chances of the Alpha Company winning fall when its bid goes up and rise when its bid goes down.

The Alpha Company used this decision support system in its bids and experienced great success in landing new contracts.

MARKET VALUE OF AN ATTRIBUTE IMPROVEMENT (MVAI)

As firms improve the attributes of their products, a question arises whether the attribute improvement measured in terms of profitability is worth the cost. This question can be answered with the help of conjoint analysis, as shown by Ofek and Srinivasan (2002). We now describe their approach.[3]

It is possible to derive a mathematical expression for the market value of an attribute improvement. For this purpose, we consider a market consisting of J firms, each offering one product in a category. Each product has K attributes in addition to its price. Let x_{jk} be the value of the k-th attribute for the j-th product and let p_j be the price of the j-th product. Consumers have the choice of buying any one of the J products or not buying at all. Let m_j denote the market share for the j-th product (j= 1, . . ., J) and m_0 be the market share of the no-purchase option. Further, let c_{jk} be the change in the cost of the j-th product for a unit change in the k-th attribute. The authors consider the ratio of the positive change in market share due to the improvement in an attribute to the negative change in market share due to an increase in price as the market value of an attribute improvement. Mathematically,

$$\text{MVAI} = -(\partial m_j / \partial x_{jk}) / (\partial m_j / \partial p_j)$$

It would be worthwhile for the firm to undertake the attribute improvement if this quantity exceeds the cost of attribute improvement (c_{jk}). Naturally, the market share of a brand depends upon the choice set, competitive reactions, heterogeneity of the sample of individuals whose responses are used to calibrate the conjoint model, and the particular specification used for the conjoint model, and the rule used to translate utilities into probabilities of choice. The changes in market share can be estimated using a conjoint study. This is what Ofek and Srinivasan used to empirically evaluate attribute improvements in a product under two scenarios: (1) no reaction by competition and (2) competitors react by making appropriate changes in their own products. They used a logit model to specify the probabilities of choice at the individual level and aggregated them to obtain market shares at the aggregate level.

We use the authors' example to illustrate the approach. The product category for this example is portable camera mount products. The set of competing products consists of UltraPod, Q-Pod, GorillaPod, Camera Critter, and Half Dome; the third product is a hypothetical one under development. These products are described on five attributes: weight, size, set-up time in minutes, stability, and positioning flexibility for adaptation to different terrains and angles. In the conjoint study, each attribute was varied at three levels and 302 subjects ranked 18 full profiles. The authors estimated the MVAI for each of the five attributes when changes are made in each of the three products. Their results show that the benefits from improving all attributes except set-up time exceed the cost of making the improvement. The authors found that the MVAI values calculated using a commonly used approach of averaging the ratio of weights of attribute and price across the individuals in the sample to be considerably upward biased and possibly incorrect. Further, the profitability of different attribute improvements is much lower when competitive reactions are considered in the computations. Note that such reaction calculations are possible with simulations in conjoint studies.

MARKETING INITIATIVES IN A B2B CONTEXT

This application will describe how conjoint analysis was applied in setting marketing initiatives (largely push marketing strategies) in a B2B context using the published article by Levy, Webster, and Kerin (1983), who applied conjoint analysis to the problem of determining profit functions for alternative push strategies for a margarine manufacturer. They described each push strategy in terms of four marketing mix variables: cooperative advertising (3 levels described as 3 times at 15 cents/lb.; 4 times at 10 cents/lb.; and 6 times at 7 cents/lb.), coupons in local newspapers (3 levels described as 2 times at 25 cents/lb., 4 times at 10 cents/lb. and 3 times at 15 cents/lb), financial terms of sale (2 levels described as 2 percent/10 days/net 30 and 2 percent/30 days), and service level defined in terms of percentage of items shipped that were ordered by the retailer (3 levels described as 96 percent, 98 percent, and 99.5 percent). While the costs for a push strategy could be computed from internal records of the firm, sales response could not be estimated from past data. The authors utilized conjoint analysis to determine the retailers' sales response to different push strategies. For this purpose, nine profiles, developed using a partial factorial orthogonal design, were presented to a sample of 68 buyers and merchandising managers. The judgment by the respondent was the expected change from last year's sales due to the push marketing mix defined by each profile. All the retail buyers were classified into small, medium, and large buyers, with respective levels of past purchases of 5,000, 15,000, and 30,000 cases. The sales level used in the questionnaires was changed according to the size of past buying by the retail buyer. The judged sales changes were used in computing the expected sales revenues and profits from each marketing mix and average partworth values were computed as dollar sales.

Based on this analysis, the authors concluded that the least profitable marketing mix is cooperative advertising offered three times a year at 15 cents per pound, coupons in newspapers offered two times a year at 25 cents per pound, terms of sale 2 percent/10 days/ net 30, and 96 percent level of service. The most profitable marketing mix consisted of cooperative advertising six times a year at 7 cents per pound, coupons four times a year at 10 cents per pound, 2 percent/30 day terms and a 98 percent service level. Although the particular results are specific to the situation considered, the application shows how conjoint analysis can be employed to determine the allocation of a marketing mix budget for a brand.

CHOICE OF A DISTRIBUTION CHANNEL FOR PURCHASE OF A DURABLE ITEM

This is based on an empirical study conducted by Foutz, Rao, and Yang (2002); while the authors' purpose was to test some behavioral decision theories, we use it simply to show an application of choice-based conjoint analysis to the problem of an individual choosing an outlet (conventional bricks-and-mortar, catalog, and an internet store) for purchasing a computer monitor. The choice context given to respondents of the study was as follows:

> Place yourself in a situation where you have just settled down in a new city, and you are thinking of purchasing a new 17"" computer monitor for yourself, since you sold the old one when you moved. You have a budget of *three hundred U.S. dollars* for this purchase, and you have other uses for any funds left over. You also wish to get the monitor soon due to the need of some work at hand. After some initial information search, you have narrowed down to your most favorite model. Your search has also identified three retailers, each of which is the best in each of the three channels from which you may consider purchasing the monitor, *bricks & mortar*, *print catalog*, and the *Internet/online*. Fortunately, all of them carry the model you want.

All three retailers are described on five attributes of average price, product trial/evaluation, sales assistance, speed of acquiring purchased monitor, and convenience of acquisition and return, described on 3, 2, 3, 3, and 3 levels respectively. The definitions of the levels were as shown in Table 15.3.

This study was conducted among 146 graduate and senior undergraduate students (78 males and 68 females) in a major Northeastern university; respondents were compensated for their participation in the study. Each survey took about half an hour and consisted of 11 conjoint choice tasks on channel choices for the purchase of a computer monitor and respondents were asked to choose the one option from which he/she would

Table 15.3 Attributes and levels for the computer monitor conjoint study

Attribute	Levels
Average price	1. around \$230 2. around \$250 3. around \$270
Product trial/evaluation	1. display only 2. display AND physical/virtual trial
Sales assistance	1. not available 2. only minimal technical support 3. very helpful with rich technical information
Speed of acquiring purchased monitor	1. same day 2. within 2–7 days 3. longer than 7 days
Acquisition and return	1. in store only 2. mail only 3. in store OR mail

Table 15.4 Attributes and levels for the competitive options in the computer monitor study

	Bricks and mortar	Print catalog	Internet/online
Average price	Around \$270	Around \$250	Around \$230
Product trial/evaluation	Display AND physical/virtual trial	Display AND physical/virtual trial	Display AND physical/virtual trial
Sales assistance	Very helpful with rich technical information	Very helpful with rich technical information	Only minimal technical support
Speed of acquiring purchased monitor	Same day	Within 2–7 days	Same day
Acquisition and return	Mail only	In store only	Mail only

actually purchase a monitor. An example of a purchase situation is shown in Table 15.4.

In addition a short questionnaire was used to collect information on demographics and other important individual characteristics. The

Table 15.5 Logit estimates for the choice-based conjoint study of channel choice

Attribute and levels	Coefficient	Standard Error	t-value	p-level
Channel:				
Bricks and mortar	0.112	0.882	1.27	0.20
Catalog	−0.221	0.096	−2.29	0.02
Internet	0			
Price:				
\$230	2.702	0.138	19.57	0.00
\$250	1.598	0.129	12.37	0.00
\$270	0			
Trial and evaluation:				
Display only	−0.730	0.095	−7.70	0.00
Display and physical trial	0			
Sales assistance:				
Not available	−1.692	0.119	−14.23	0.00
Only minimal technical support	−0.763	0.113	−6.71	0.00
Very helpful rich technical information	0			
Speed of acquisition:				
Same day	2.000	0.121	16.48	0.00
Within 2–7 days	1.564	0.125	12.46	0.00
Longer than 7 days	0			
Acquisition and return:				
In store only	−0.136	0.106	−1.28	0.20
Mail only	−0.873	0.113	−7.70	0.00
In store or mail	0			
Likelihood of the model	−901.15			
Rho-square	0.37			
Number of observations	1,305			

majority of the respondents had more than three years of online experience (93.8 percent of the 146 respondents) and spent less than 20 hours per week online (72.4 percent). One-third (32.4 percent) of the respondents spent less than \$200 per year online; another third (37.9 percent) spent between \$200 and \$1,000 annually online; the rest of them spent more than

$1000. 64.8 percent of the respondents had purchased computer monitors before, however only 20.7 percent claimed that they had adequate technical knowledge about computer monitors. In addition, 71 percent of the respondents had purchased from catalogs before.

The choice data were analyzed using a simple multinomial logit model. The fit of the model as described by the Rho-square (a measure analogous to R-square for the multinomial logit analysis) was 0.37; this indicates heterogeneity among the respondents. The estimates for the sample as a whole, shown in Table 15.5, represent average partworth values for the attributes used in the study; there were few surprises in the partworth values. After appropriate validation, these estimates can be employed in identifying the attribute levels deemed important in a new store on any one of the three distribution channels. We should note that the attribute levels implied different resource commitments in the design of a store.

CONCLUSION

This chapter has summarized a set of five applications of conjoint analysis to show the versatility of the method. In general, the methodology of conjoint analysis is extremely useful in conceptualizing and implementing research for a variety of marketing decision problems. It is the imagination of researchers that may limit the usefulness of conjoint methods.

NOTES

1. This material is drawn from Chapter 9 and Section 8.6.1 of Vithala R. Rao, *Applied Conjoint Analysis*, Berlin Heidelberg: Springer Verlag, 2014; used with the permission of Springer.
2. The catering company also sets fixed fees for setting up the catering arrangement and arranging special banquets, but these were outside the scope of this study.
3. While the authors developed their theory using continuous changes in the attributes, we use discrete changes for the purpose of exposition.

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