

Understanding Customer Choices:

A Key to Successful Management of Hospitality Services

Discrete choice analysis gives managers an effective way to determine which product and service attributes have the greatest effect on consumers' purchase decisions.

BY ROHIT VERMA, GERHARD PLASCHKA, AND JORDAN J. LOUVIERE

We know that hospitality customers usually make purchases by simultaneously evaluating several criteria. A typical buying decision might take into account service quality, delivery speed, price, and any special buying incentives, for instance. It is imperative that businesses take into account customer preferences and choices when making decisions regarding product and service attributes. Managers need to understand how customers integrate, value, and trade off different product and service attributes. By the same token, information about customer demands and preferences must be incorporated into the design and day-to-day management of service-delivery processes.

In this paper we describe a particularly effective way to determine those customer preferences and to assess the trade-offs that customers make in considering various product and

service bundles. The methodology we describe is discrete-choice analysis (DCA).¹ After explaining DCA, we provide guidelines for incorporating customer-preference information into the design and management of business processes. The DCA approach provides a robust and systematic way to identify the implied relative weights and attribute trade-offs revealed by decision makers' choices (whether customers or managers).

To be sure, DCA is not the only approach that has been used to understand and model consumer decision making, but it has proved particularly valuable in many hundreds of applications since its introduction by Daniel L. McFadden

¹ For an earlier application of DCA, see: Rohit Verma and Gary M. Thompson, "Basing Service Management on Customer Determinants: The Importance of Hot Pizza," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 37, No. 3 (June 1996), pp. 18–23.

(winner of the Nobel Prize for economics in 2000).² More important, DCA is one of only a few modeling approaches based on a sound, well-tested, and relatively comprehensive behavioral theory (known as random-utility theory—RUT) that leads to a wide variety of testable and tractable models of choice behavior. Indeed, RUT provides a sound theoretical link between behavior observed in experiments, surveys, or other forms of stated preferences and the behavior observed in real-life situations.

Discrete-choice analysis is one of only a few choice-modeling approaches that connect surveys to real life.

As a disclaimer, we must note that all models are abstractions of reality, and the applicability of a particular choice model depends on the assumptions, theoretical foundations, and scientific methods used in modeling, data collection, and analysis, as well as one's understanding of customer demands and firms' resources by the managerial decision makers.³

Close, but not conjoint. DCA is often compared to and confused with another (strategic) marketing-research method known as conjoint analysis.⁴ The two bear superficial resemblance to each other insofar as they both analyze customer responses to experimentally designed profiles of products or services. Conjoint-analysis data are obtained in the form of ratings or rankings based on comparisons of experimentally designed product-and-service descriptions or pro-

files (that is, customers do not select particular alternatives, but instead rate or rank them). More rarely, conjoint analysis involves binary responses (yes or no) regarding particular attribute packages.

DCA distinguished. In contrast, DCA places a respondent in simulated choice-making situations derived from realistic variations of the product and service offerings that one might find in the market. DCA is used to identify the relative weights that customers accord to product or service features and attributes. The weights are derived from consumers' responses to experimentally designed descriptions of product and service options. DCA results can lead to many managerially useful conclusions, such as identification of optimum product-and-service bundles, identification of market segments, measurement of brand equity, and development of process-improvement action plans. With that in mind, we present an overview of the DCA approach followed by a discussion of the managerial implications of DCA results.

Meta-choice: Possibilities Are Endless

The purpose of meta-choice is to assess and challenge management preconceptions of business and market conditions and to uncover customers' decision-making patterns using available market information. The first step in this framework-building process is to identify the relevant choice drivers, using qualitative market assessment, in-depth interviews, case studies, focus groups, and analysis of secondary information. Great care must be taken to ensure that all (or at least as many as possible) of the determinant demand-choice drivers are identified and expressed in terms understood by customers. One should consider the following two questions when building a list of market-choice drivers: (1) Is it necessary to include an exhaustive list of all salient product and service drivers?; and (2) How can product and service attributes be configured so that the critical choice drivers are identified while the choice experiment is at once realistic and small enough to be tractable?

The next step is to identify the range of variability, or the levels of the demand-choice drivers. Although the range of variability should span the actual values of product attributes observed

² For example, see: D. McFadden, "The Choice-theory Approach to Marketing Research," *Marketing Science*, Vol. 5, No. 4D (1986), pp. 275–297.

³ Good discussions of the theoretical and statistical background to DCA can be found in: *Ibid.*; and J.J. Louviere, D.A. Hensher, and J.D. Swait, *Stated Preference Methods: Analysis and Application* (Cambridge, UK: Cambridge University Press, 2001).

⁴ For a discussion of conjoint analysis, see: Leo M. Renaghan and Michael Z. Kay, "What Meeting Planners Want: The Conjoint-Analysis Approach," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 28, No. 1 (May 1987), pp. 66–76.

in the market and encompass the entire range of possible options, it should also be small enough to keep the experiment to a realistic and practical size, so as not to overwhelm the respondents with too many scenarios from which to choose. Once the range is determined, it must be divided into two or more discrete levels for experimental-design purposes. Two levels are sufficient to estimate the linear effect that the attributes have on choice, but more than two levels are needed to estimate non-linear effects for quantitative attributes. As well, several levels of qualitative demand drivers like check-in times or room color are often required.

For the sake of illustration, we present a constructed example for dine-in restaurants that serve pizza as the main dinner entrée (operations such as Pizza Hut and California Pizza Kitchen). The illustration presented in Exhibit 1 is based on an actual study conducted by the lead author—although the exact nature of the study is disguised for confidentiality reasons. Two previous articles in *Cornell Quarterly* contain real examples of choice drivers for pizza establishments.⁵

Say that we are interested in modeling the choice processes of customers who visit such establishments primarily for pizza, although they may order other items listed on the menu. Exhibit 1 presents a list of potential choice drivers for dine-in pizza restaurants. The list of choice drivers is constructed after collecting in-depth qualitative data from the marketplace, business managers, and reliable published information. Our illustration categorizes choice drivers into the following groups: cost, product quality, service quality, delivery performance, flexibility, and brand name. Those broad categories are further subdivided into a total of 13 specific choice drivers.

Constructing a choice-driver list can be an intensive process. It requires consensus building and using both creative and analytical techniques.

⁵ See: Rohit Verma, Madeleine E. Pullman, and John C. Goodale, "Designing and Positioning Food Services for Multicultural Markets," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 40, No. 6 (December 1999), pp. 76–87; and Rohit Verma and Gary M. Thompson, "Basing Service Management On Customer Determinants: The Importance of Hot Pizza," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 37, No. 3 (June 1996), pp. 18–23.

EXHIBIT 1

Sample choice drivers for dine-in pizza restaurants

Choice drivers	Levels
Cost	
1. Price of a small pizza	1. \$5 2. \$6 3. \$7 4. \$8
2. Price of a medium pizza	1. \$9 2. \$10 3. \$11 4. \$12
3. Price of a large pizza	1. \$13 2. \$14 3. \$15 4. \$16
Product quality	
4. Type of toppings	1. Only traditional toppings 2. A variety of traditional and gourmet toppings
5. Amount of toppings	1. Little 2. Average 3. Plentiful
6. Type of cheese	1. Mozzarella cheese only 2. Mozzarella and cheddar cheese 3. Mozzarella and other standard cheeses 4. A variety of standard and gourmet cheeses
7. Type of pizza crust	1. Only one type of crust 2. Hand-tossed, thin crust, or pan-fried crusts
Service quality	
8. Aesthetics of the restaurant	1. Décor resembles an economy restaurant 2. Décor resembles a mid-range restaurant 3. Décor resembles an upscale restaurant
9. Employees' knowledge	1. Server appears very knowledgeable 2. Server does not appear to be very knowledgeable
10. Employee interpersonal skills	1. Employee behaves in extremely polite and friendly manner 2. Employee behaves in a matter-of-fact manner
Delivery performance	
11. Speed	1. Order prepared within 10 mins. 2. Order prepared within 20 mins. 3. Order prepared within 30 mins. 4. Order prepared in more than 30 mins.
Flexibility	
12. Reservations	1. Reservations are not accepted 2. Reservations accepted only during non-peak periods 3. Reservations accepted all the time
13. Brand name	1. Brand name A, B, C, D (specific names)

EXHIBIT 2

Sample DCA exercise

Choice drivers	Restaurant #1	Restaurant #2
1. Price of a small pizza	\$8	\$6
2. Price of a medium pizza	\$11	\$10
3. Price of a large pizza	\$15	\$13
4. Type of toppings	Traditional and gourmet toppings	Traditional toppings only
5. Amount of toppings	Plentiful	Average
6. Type of cheese	Variety of standard and gourmet cheeses	Mozzarella and cheddar cheese
7. Type of pizza crust	Hand-tossed, thin crust, or pan-fried crusts	Only one type of crust
8. Aesthetics	Décor resembles an up-scale restaurant	Décor resembles a mid-range restaurant
9. Employee knowledge	Server appears very knowledgeable	Server appears very knowledgeable
10. Employee interpersonal skills	Employee behaves in a matter-of-fact manner	Employee behaves in extremely polite and friendly manner
11. Speed	Order prepared within 30 mins.	Order prepared within 20 mins.
12. Reservations	Take reservations all the time	Reservations are not accepted
13. Restaurant brand	Italian Village	Pizza R Us

Some options for choice questions:

A. If the above two restaurants were your only alternatives, which one will you choose:

___ Restaurant #1 ___ Restaurant #2 ___ Neither

B1. If Restaurant #1 were your only option, would you choose to go there? (Y or N)

B2. If Restaurant #2 were your only option, would you choose to go there? (Y or N)

C. List the *most* attractive and *least* attractive features of the two restaurants:

Restaurant #1 ___ most attractive feature ___ least attractive feature

Restaurant #2 ___ most attractive feature ___ least attractive feature

Depending on the exact nature of the study, the process of finalizing the list of choice drivers may take a few days or several weeks of fact finding, discussions, and profile iterations.

To Choose or Not to Choose

After identifying the demand-choice drivers, a systematic procedure is used to construct the choice experiments. A typical choice experiment consists of a series of choice exercises in which respondents are asked to choose a bundle of product and service attributes from a set of options. A simple example of a choice exercise is shown in Exhibit 2. One can frame choice exercises in any of several ways. For example, one can show the respondents two restaurant profiles and ask them to choose restaurant number one, restaurant number two, or neither one. A second approach is to show respondents one restaurant profile at a time and ask them either to accept or reject the restaurant represented by each profile. A third option is to ask respondents to identify the most desirable and the least desirable features for each of the restaurants presented. Yet a fourth approach would be to ask respondents to indicate how often (say, in a six-month period) they might choose to visit each establishment presented in a profile. Finally, in some applications we have asked respondents to compare a hypothetical restaurant profile with a real restaurant (e.g., the last pizza restaurant that the respondent visited).

However the DCA exercise is designed, researchers should strive for realistic descriptions of products or services. We suggest a multimedia approach that supplements sentences, short phrases, or paragraphs with any combination of pictures, drawings, photographs, computer images, videos, and models. The idea is to build the choice exercises in such a way that they represent the actual decision situation as closely as possible.

Advances in information technology have made it possible to assemble web-based multimedia presentations to realistically describe and present customer-choice scenarios. In cases when it was not possible to present choice exercises via the web, we have used touch-screen data-collection devices, networked computers, or even created realistic prototypes of choice options. To gain verisimilitude in pre-web days (only about three

years ago!), we once created over 20 versions of supermarket aisles and then asked each respondent to walk around and pick the products they wanted to purchase from each aisle. In another pre-web study we created several versions of a home appliance to realistically communicate the appliance's potential sizes, shapes, and related sensory images to respondents.

The nature of each customer-choice exercise depends on the choice drivers and their possible values (again, refer to Exhibit 1). To successfully assess each choice driver's effect on customer preferences, respondents are presented with several different choice scenarios generated by means of sophisticated experimental-design procedures (similar to Exhibit 2, but with different combinations of choice-driver values). Such design procedures typically generate many possible alternatives. The total number of possible options that can be created by choice drivers in Exhibit 1, for instance, is 1,769,472.⁶ We think it self-evident that it would be unrealistic to ask respondents to evaluate that many restaurant options in a survey.

Main effects. Fortunately it is not necessary to ask respondents to evaluate all possible options. In fact, respondents typically evaluate no more than 32 scenarios in a given choice experiment, although they might examine as few as four or eight and as many as 64. This seemingly miraculous reduction in numbers is made possible by the fact that respondents base their choices on certain "primary" attributes that matter most (e.g., price or location). The effects of these primary attributes on decisions are called main effects, because they account for most of the variability in responses. Beyond those main effects, two-way interaction effects (e.g., price interacting with delivery speed) account for an additional, but typically small proportion of response variability.

We make use of two statistical techniques—fractional factorial design and blocking—to reduce the number of choice options presented to each respondent. Fractional factorial design allows us to reduce the number of combinations of choice drivers while still capturing the main

effects and interaction effects. In the case of Exhibit 1, we might be able to reduce the number of options from 1,769,472 to, say, 64. Blocking techniques are used to further divide the experimentally designed choice exercises into several

With advanced statistical methods, one can estimate individuals' or market segments' preferences, rather than work with aggregates.

statistically equivalent sub-groups. Taking Exhibit 1's pizza study, for instance, if we employ the fractional factorial design process to generate 64 restaurant scenarios, we can then use blocking to reduce the number of scenarios for each individual respondent. We could, for example, create eight blocks of eight choice exercises. However, it should be noted that subdividing a fractional factorial design requires fairly large sample sizes for statistically reliable results.⁷

Where Is Value?

Once the experimental design is implemented in the form of a set of choice scenarios, response data are collected from a sample that represents the population of interest. Discrete-choice responses are categorical, because respondents choose one option from each set of options. As a consequence, several hundred observations are needed to satisfy the asymptotic conditions specified for estimating the model's parameters and obtaining reliable statistical tests. Hence, responses from multiple individuals are aggregated in estimating the choice model. However, more recently, advanced statistical methods have been used to estimate distributions of individual-preference effects or segment-level choice models (e.g., latent-market segmentation; Bayesian estimation methods). It is important to note that when one combines the responses of many individuals to estimate choice models, differences in

⁶ Calculated as follows: $4 \times 4 \times 4 \times 4 \times 2 \times 3 \times 4 \times 2 \times 3 \times 2 \times 2 \times 4 \times 3 \times 4 = 1,769,472$.

⁷ For references on fractional factorial designs, please refer to: R. Verma, M.E. Pullman, and J.C. Goodale, "Designing and Positioning Services for Multicultural Markets," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 40, No. 6 (1999), pp. 76–87.

EXHIBIT 3

Discrete-choice-analysis equations

Equation 1:
Multinomial logit
(MNL) model

$$P_{ij} = \frac{e^{\mu V_{ij}}}{\sum_{k=1}^K e^{\mu V_{ik}}}$$

Equation 2:
Utility function
(value of a choice driver)

$$V_{ij} = \sum_{l=1}^L \beta_l x_{ijl}$$

individual preferences become an issue (i.e., so-called “preference heterogeneity”). Both choice sets and respondents in choice experiments are randomly assigned to blocks, with the purpose of that randomization being to ensure that the resulting data are orthogonal (that is, mutually exclusive or mathematically independent).⁸

The most common form of the econometric model based on discrete-choice analysis is known as the multinomial logit (MNL) model,⁹ as expressed in Equation 1 in Exhibit 3. In this equation, P_{ij} represents the probability of someone selecting option i during the j^{th} choice exercise which contains K different alternatives. V_{ij} represents the systematic utility of option i in choice exercise j . The parameter μ is a relative scale for the error associated with the model.¹⁰ The utility function V_{ij} in its simplest form can be represented as shown in Equation 2 in Exhibit 3, where x_{ijl} represents the value of choice-driver l of option i in choice exercise j . The parameter β_l is the relative utility associated with choice driver l , and L represents the total number of attributes.

Estimated-choice models include the following information:

- (1) Relative weights (β or utility) for each choice-driver (e.g. price, speed) on individual, segment, or aggregate choices stated in the experiment.
- (2) Relative weights for interactions among choice-drivers—as specified in the estimated model.
- (3) Several statistical goodness-of-fit measures for the estimated model(s).¹¹

⁸ For statistical details, please refer to: Louviere, Hensher, and Swait, *op.cit.* See also: Robert C. Lewis, “Isolating Differences in Hotel Attributes,” *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 25, No. 3 (November 1984), pp. 64–77.

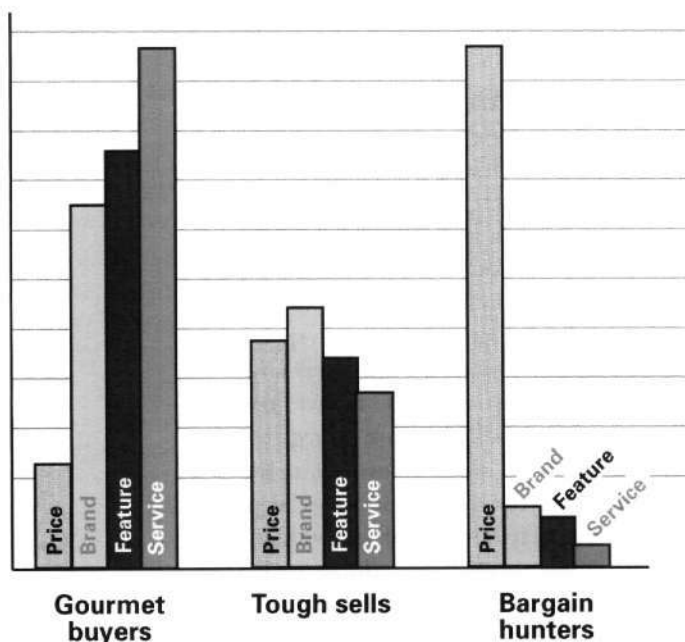
⁹ As explained in: R. Verma, G.M. Thompson, and J.J. Louviere, “Configuring Service Operations in Accordance with Customers’ Needs and Preferences,” *Journal of Service Research*, Vol. 1, No. 3 (1999), pp. 262–274.

¹⁰ For details, see: Louviere, Hensher, and Swait, *op. cit.*

¹¹ For examples of estimated-multinomial-choice models for hospitality services, see: Verma and Thompson, pp. 18–23; and Verma, Pullman, and Goodale, pp. 76–87. For statistical details on estimating choice models, refer to: M. Ben-Akiva and S.R. Lerman, *Discrete Choice Analysis* (Cambridge, MA: MIT Press, 1991); or Louviere, Hensher, and Swait, *op. cit.*

EXHIBIT 4

Relative preferences for various customer groups



By analyzing the outcome of discrete-choice tests, one can isolate the choice drivers for given market segments. In the hypothetical example shown here, “gourmet buyers” respond most strongly to service offered with a product, but price does not move them as much. In contrast, price is almost the only factor that moves the “bargain hunters,” while the “tough sells” live up to their name by responding only modestly to any of the four factors being tested.

Managerial Implications of Customer-choice Modeling

By understanding consumer choices, senior managers can effectively develop and position product and service offerings to better suit their customers' needs. In addition, mathematical models representing customer choice can be linked to operating decisions (e.g., budgets, labor scheduling, special-activities planning, service offerings), and optimal service configurations can be identified for further improvement.

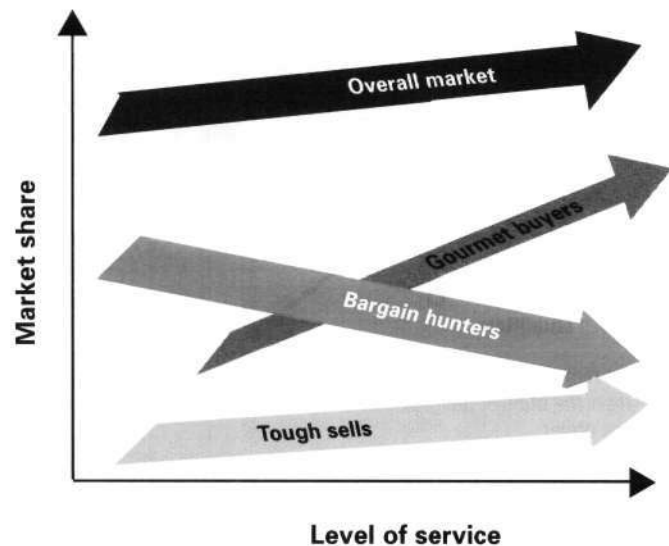
The statistical models developed from discrete-choice experiments can be easily incorporated in spreadsheet-based decision-support systems (DSSs)¹² to create a model for strategy development. Although designing choice experiments and estimating models requires sophisticated training and skills, implementing the estimated model(s) in a spreadsheet-based DSS is fairly straightforward. Once the DSS is set up, a manager has only to input the attributes of the desired product-service offering and the available competitors' products to predict expected market shares for all. The DSS captures the dynamic nature of the market, allowing managers to evaluate multiple businesses, operating and marketing strategies, and the effects of changing strategies in the competitive marketplace. In addition, the predictive power of DCA-based models can be further improved by market-segmentation techniques such as latent-segment analysis.

Beyond pizza. The following sections discuss various analyses that can be conducted by a DSS developed from discrete-choice experiments. For the sake of clarity, we have kept our discussion general.

Relative weights of various choice drivers (β s, or utility estimates) can be used to identify the similarities in a firm's user base and assess how those commonalities affect the current and future value of firm offerings. Choice models also can identify key features that drive market share in different customer-preference clusters. We offer examples in Exhibit 4 of several customer-preference clusters (Gourmet Buyers, Tough Sells, and Bargain Hunters) along with the corresponding relative utilities for the main choice drivers.

EXHIBIT 5

Market-share effects of choice drivers

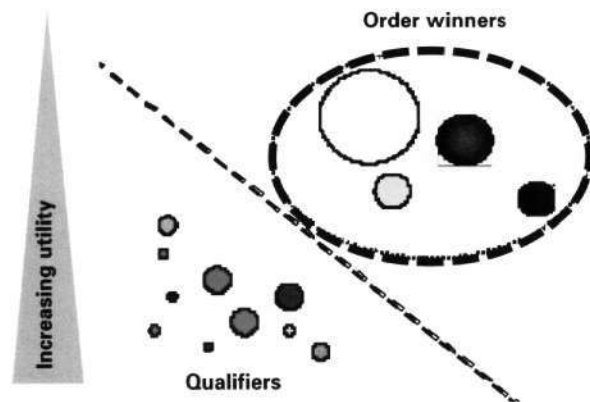


This hypothetical example demonstrates that gourmet buyers respond to increasing service levels, but bargain hunters are actually put off by more service.

¹² For an example, see: Verma and Thompson, pp. 18–23.

EXHIBIT 6

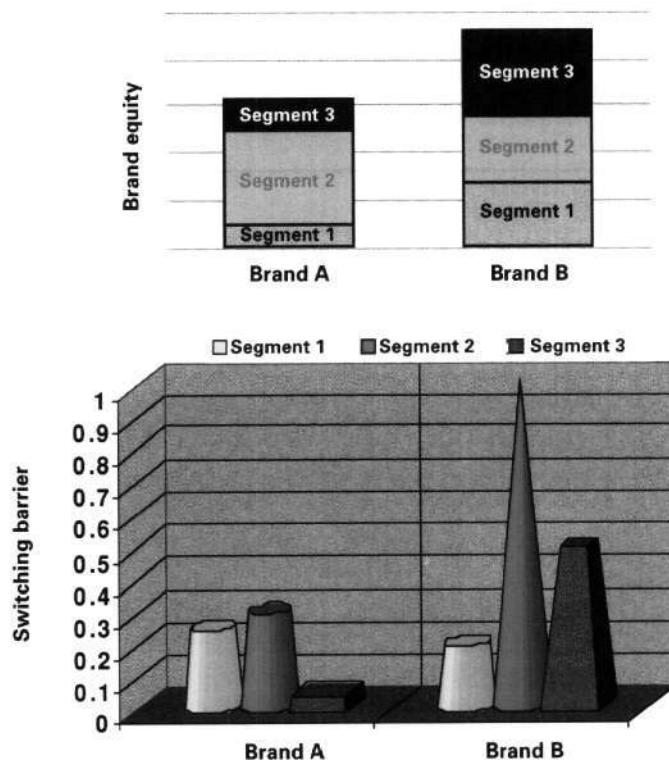
Conceptual order winners and qualifiers



Each "bubble" represents a distinct choice driver (e.g., brand, feature, or service). The larger the bubble, the greater management's flexibility in manipulating that choice driver.

EXHIBIT 7

Brand equity and switching barriers



Although Brand B has the greatest overall equity, as shown at top in this hypothetical example, Brand A has the greatest equity for customer segment two. On the other hand, the lower graph shows that segment two sees the greatest switching costs in leaving Brand B. Brand B also enjoys much higher switching costs for segment three than does Brand A.

The group labeled Gourmet Buyers, for example, carries relatively high utilities for all choice drivers except price. Members of the Tough Sells group, on the other hand, consider each of the four choice drivers to be of roughly equal importance, whereas the Bargain Hunters seem by nature to be the most price sensitive.

Identifying such preference differences across customer groups can help a firm improve the effectiveness of its marketing campaign for each cluster. In addition to identifying the overall relative effects of customer preferences, choice-modeling results can also be used to assess the implications for overall market share resulting from changes in the value of one or more choice drivers (see Equation 1). For example, choice models can be used to assess how the market share of one firm will be affected by a competitor's change in one or more choice drivers. Assuming that the competitor profile stays the same, the market-share effects of changing service levels for the three preference clusters are shown by the arrows in Exhibit 5, on the previous page. Although the overall market share is shown to increase modestly with enhanced service levels, the effect of that change is largest for Gourmet Buyers, but only moderate for Tough Sells—and negative for Bargain Hunters.

By assessing the relative weights of various market drivers to identify order-winning features, firms can further optimize product and service offerings. This analysis allows firms to focus on a few selected choice drivers when developing new products and services or when changing selected features of existing offerings. The choice drivers represented by the circles on the upper right-hand side of Exhibit 6 are primary order winners, while the lower left half of the figure is composed of qualifiers. The size of each bubble in this figure represents the allowable flexibility for a specific choice driver that managers can exercise without seriously compromising that driver's market power.

Barriers and switching. Two potentially important analyses that can be conducted from the choice-modeling results are assessment of brand equity (as related to customer choices) and determination of barriers to switching products.

As illustrated in Exhibit 7, the relative equity of Brand B is higher for all segments combined

than is Brand A's equity. However, when Segment 2 is considered independently, Brand A carries far more value than does Brand B. A complementary analysis, shown in the lower left quadrant of Exhibit 7, identifies the relative switching barriers for the two brands. As indicated in Exhibit 7, the high switching barrier for Brand A among customers in Segment 2 indicates that the customers in Segment 2 are least likely to switch to another brand. The analysis also shows that customers in Segment 3 are more likely to switch to Brand A than are the customers in the other two segments. Similar analyses can be conducted to evaluate the effects of brand names on various customer groups.

DCA's results can also be used to develop effective implementation guidelines or to prioritize various initiatives to maximize the net gain from any chosen strategic plan. The illustration in Exhibit 8 shows that in the case of our hypothetical example, a firm obtains maximum value growth in the market by improving service levels. Exhibit 8 shows both individual and cumulative consequences of changes in values of various market drivers on overall gains in the marketplace.

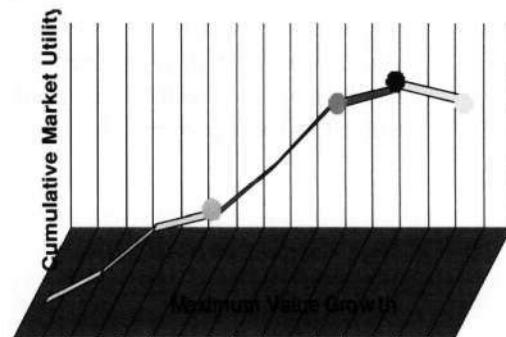
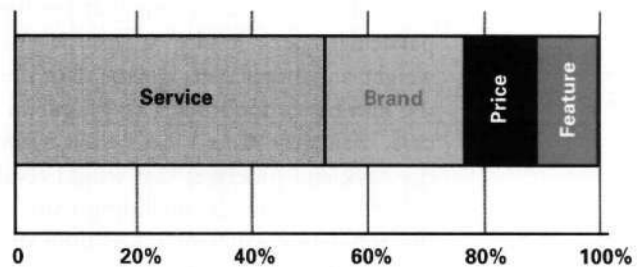
Education and training. In addition to the applications described above, choice models and associated decision-support spreadsheets also can be used as education and training tools and to help managers better align their decisions with what customers want and are willing to pay for. Often managers of large service organizations (including hotels and resorts) are busy managing day-to-day operations, so that gaps may exist between customers' needs and managers' perceptions of those needs. Comparing two choice models—one representing customer choices and another one representing the managers' beliefs about customer choices—can identify such perception-choice gaps.

We would like to emphasize that a number of past studies have shown that, in general, market-share predictions generated from carefully developed choice models are reasonably accurate. That observation is subject, however, to the further note that the accuracy of predictions arising from a specific study will depend on the robustness of the experimental design, levels, and attributes; the appropriateness of the sample selection; and

EXHIBIT 8

Implementation guidelines

Choice drivers



Based on the bar graph at top for a hypothetical product, the brand managers can see that improving service levels provides the greatest market leverage, followed by emphasizing the brand name. Price and features take a back seat for this particular product. The line graph above summarized the cumulative effect of manipulating each choice driver.

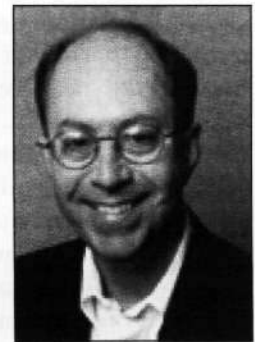
the changes in market conditions that might occur between data collection and analysis and predictions.

Furthermore, customer-choice information obtained from DCA can be used to design services and improve management of operating processes. For example, assume that customers of a particular quick-service restaurant place more weight on (short) waiting time than they do on the number of food items on the menu. In that case, managers should focus their attention on the back-end processes that would result in reduced waiting times, including some or all of the following: efficient scheduling of the appropriate labor force, streamlining operations and minimizing redundancies, and limiting the number of menu items to speed up the order-preparation cycle. Choice models can predict the effects of each of these alternative action plans on the market, as will be discussed in a future issue of *Cornell Quarterly*. ■

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