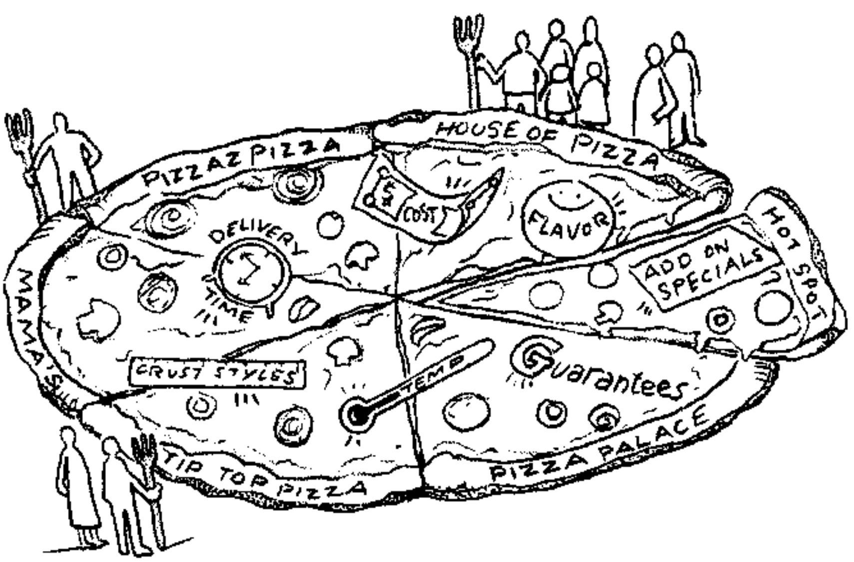
Basing Service Management on Customer Determinants

The Importance of Hot Pizza

Before tinkering with product and service attributes (such as product price and service speed), it helps to know what's most important to your customers. Discrete-choice analysis can provide that information.

by Rohit Verma and Gary M. Thompson



Integrating the voice of the customer into service management is an important concern in the hospitality industry. A number of management scholars have emphasized the need for customer-based operations management in service businesses, advocated an integrated approach to service-operations

***Rohit Verma,** Ph.D., is a visiting assistant professor of operations management in the department of management at DePaul University. **Gary M. Thompson,** Ph.D., is an associate professor of operations management at the Cornell University School of Hotel Administration.*

management, and suggested that managers use marketing constructs and techniques to manage services well.[1] James Heskett's "strategic service vision," for instance, consists of identifying a target market segment, developing a service concept to address customers' needs, codifying an operating strategy to support the service concept, and designing a service-delivery system to support the operating strategy.[2] Christopher Hart advocates using unconditional service guarantees and suggests that such guarantees push the entire company to focus on the customers' definition of good service, rather than on any executive's assumptions.[3] A large number of other published articles and books highlight the importance of customer-based operations management in improving the competitive position of service businesses. Broadly speaking, these publications stress the multidisciplinary nature of service-operations management and emphasize the need for positioning operating capabilities according to customer needs.

Incorporating customer preferences and choices into operating decisions is essential for hospitality businesses because their customers evaluate them on more than one criterion at a time. A customer might consider, for example, the following attributes in choosing a particular fast-food establishment: cost, service quality, food quality, food variety, and speed of delivery. Past research in marketing shows that after acquiring information and learning about the possible alternatives, consumers define a set of determinant attributes, which they use in deciding on a restaurant.[4] They then form impressions of different restaurants' positions with regard to those determinant attributes, make value judgments, and combine information to form overall impressions of the alternative restaurants. In forming their overall impressions, customers make mental tradeoffs among the restaurants' attributes.[5] That is, a customer may accept the fact that a quick-service restaurant isn't really as quick as its competitors because that restaurant is offering a lower price or greater value than other restaurants. By understanding customer-choice patterns such as this, managers can design service operations to best meet market demands.

This article presents an approach for positioning hospitality services according to customer tastes and preferences known as discrete-choice analysis (DCA), which has been successfully used for a variety of applications in marketing, consumer research, transportation, recreation and leisure research, and sociology.[6] We present an overview of DCA and show how it can be implemented for operations management by pizza-delivery firms. The results demonstrate how customers choose pizza-delivery chains by evaluating their different attributes. We also explain how managers of pizza-delivery units can use the results as a decision-support system for evaluating the effect on market share of changing one or more attributes.

Discrete-Choice Analysis

Discrete-choice analysis is a systematic approach for identifying the relative weights of attributes applied when a decision-maker (in this instance, a customer) makes a selection from a set of possible choices (e.g., where to order pizza). The DCA approach is based on the decision-maker's response to experimentally designed profiles of possible alternatives, in which each alternative has a different combination of product-and-service attributes. The analysis is conducted by applying a statistical procedure known as "maximum-likelihood estimation" to approximate each attribute's relative importance for the alternatives, based on empirical data collected from a random sample of customers. For our purpose, DCA involves designing several experimental profiles of pizza-delivery establishments with different levels of food quality, cost, delivery time, and other attributes, and then asking the decision-makers to choose their preferred set of attributes from pairs of alternatives. Since the alternatives are developed according to a specific experimental design procedure, the researchers control the independent variables, or, in this case, the different combi-

[1] For example, see: D.E. Bowen and T.G. Cummings, "Suppose We Took Service Seriously," in *Service Management Effectiveness* (San Francisco: Jossey-Bass Publishers, 1990), pp. 1–4; C.H. Lovelock, "*Managing Services: Marketing, Operations, and Human Resources*, Second Edition (Englewood Cliffs, NJ: Prentice-Hall, 1992), pp. 17–30; R.S. Sullivan, "The Service Sector: Challenges and Imperatives for Research in Operations Management," *Journal of Operations Management*, Vol. 2 (1981), pp. 211–214.

[2] J.L. Heskett, "Lessons in the Service Sector," *Harvard Business Review*, Vol. 65, No. 2 (March–April 1987), pp. 118–126.

[3] Christopher W.L. Hart, "The Power of Unconditional Service Guarantees," *Harvard Business Review*, Vol. 66, No. 4 (July–August 1988), pp. 54–62.

[4] For an examination of determinant attributes in hotels, see: Robert C. Lewis, "Isolating Differences in Hotel Attributes," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 25, No. 3 (November 1984), pp. 64–77.

[5] M. Ben-Akiva and S.R. Lerman, *Discrete Choice Analysis* (Cambridge, MA: MIT Press, 1991), pp. 31–58.

[6] For instance, see: D. McFadden, "The Choice Theory Approach to Market Research," *Marketing Science*, Vol. 5 (1986), pp. 275–297; and J.J. Louviere and H. Timmermans, "Stated Preference and Choice Models Applied to Recreation Research: A Review," *Leisure Science*, Vol. 12, No. 1 (1990), pp. 9–32. Discrete-choice analysis (DCA) resembles conjoint analysis (CA), but DCA examines actual choices while CA considers stated choices. For applications of conjoint analysis, see: Leo M. Renaghan, "What Meeting Planners Want: The Conjoint-Analysis Approach," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 28, No. 1 (May 1987), pp. 66–76.

nations of food features and service levels.

To develop a discrete-choice experiment, one starts by identifying determinant attributes used in the decision-maker's evaluation process. Qualitative market surveys, interviews, case studies, and focus groups can help a researcher identify a broad set of attributes. By conducting a small number of informal interviews the researcher can refine the broad set to a list comprising the most relevant attributes. Qualitative data collection is important for DCA because qualitative data provide information regarding the realistic numerical or categorical values of the attributes (e.g., reasonable waiting time or price points). After identifying the relevant attributes and their possible numerical or categorical values, the researcher applies an experimental procedure to generate a set of alternatives.

In a typical discrete-choice experiment, the researcher simultaneously shows the decision-maker two or more alternative sets of various attribute levels and asks him or her to choose one of them. Each alternative contains a different combination of the attributes, or independent variables. This selection process is repeated several times with different combinations of attributes (independent variables) arranged by the researcher. One can hypothesize that the decision-maker's choice (dependent variable) is driven by the determinant attributes among the independent variables. Next, multinomial-logit (MNL) regression is used to identify the weights and statistical significance of the determinant attributes. An MNL model represents the probability of a person's selecting a particular alternative from a set of alternatives. The MNL model assumes that the probability of selecting an alternative depends on the decision-maker's perceptions of the relative attractiveness, or utility, of the alternatives. Utility can be defined as "judgments, impressions, or evaluations that decision-makers form of products or services, taking all the determinant-attribute information into account."[7] The customer-based utility of a product can be found by summing the product's attributes weighted by the MNL-regression values of each attribute. The utility of the product can be used to calculate the expected market share of a company. Later in this article we present a simple example that shows how an MNL-regression model can be used to calculate the utility of a product and its corresponding expected market share.

Discrete Choice in Pizza Delivery

Our study of pizza-delivery companies demonstrates the usefulness of DCA and, incidentally, offers pizza-chain operators some clues to customer attributes. We chose to examine pizza delivery because we anticipated that customers' choice patterns would be influenced by several identifiable operating variables (e.g., waiting time, service reliability) combined with specific product attributes (e.g., cost, types of pizza crust, food temperature). Similar studies can easily be conducted for other hospitality businesses.

Data collection. We collected our data in two phases. First, we interviewed a small, random sample of pizza customers. We collected this form of qualitative data to determine the number and levels of attributes to use in our experimental design. The academic literature in operations management and marketing provided a general list of possible attributes that customers consider when choosing products (e.g., product quality, service quality, cost, delivery speed, and flexibility). We wanted to ensure that those attributes were relevant for pizza delivery. We also wanted to identify any characteristics unique to pizza delivery that were not represented in the variables identified by previous research.

We randomly selected 15 customers from a large metropolitan area in the western United States for informal interviews. We asked them to list the attributes they consider when choosing a pizza-delivery company. Based on their comments, we selected the seven most relevant attributes for the experimental design. These attributes are pizza price, discount on second pizza, promised delivery time, late-delivery time, types of pizza crust, pizza temperature, and money-back guarantee. Next, we asked the managers of three large pizza-delivery establishments to identify realistic levels for those seven attributes. We used CONSERV, an experiment-design procedure, to generate profiles of 16 hypothetical pizza-delivery companies based on the seven attributes.[8] The profiles comprised 16 discrete sets of variables, each of which had two levels. For instance, the promised delivery time might be either 20 minutes or 40 minutes, while the price might be either $12 or $18. Our survey would ask respondents to choose repeatedly between different combinations of two profiles. A sample paired-choice set based on our seven pizza attributes is shown in Exhibit 1. In addition to the paired experimental profiles, the survey instrument included a number of demographic questions (e.g., age, gender, income) and asked the customers to list the pizza-delivery chains they patronized within the last six months.

[7] J.J. Louviere, *Analyzing Decision Making: Metric Conjoint Analysis* (Newbury Park, CA: Sage Publications, 1988), p. 12.

[8] *CONSERV* is a computer application developed in 1992 by Intelligent Marketing Systems, Edmonton, Alberta, Canada.

Time to choose. Phase two consisted of collecting customers' responses to a set of discrete-choice experiments by a self-administered mail survey. We sent surveys to 500 randomly selected residents of a large metropolitan area in the western United States. A total of 145 surveys were returned, of which 17 were less than 25-percent complete and had to be discarded. The 128 usable responses constitute an effective response rate of 31 percent.

Results. Exhibit 2 presents the results of the MNL regression for customer-choice data.[9] The regression coefficients represent the relative weights (part-worth utilities) of the attributes. The exhibit shows that all the attributes are statistically significant at the $p \leq .05$ level. Exhibit 2 also shows that McFadden's r^2 for the MNL model is 0.871 and the adjusted r^2 is 0.858.[10] These results show that the MNL model fits the customer-choice data well, explaining 87 percent of variation in the dependent variable (customer choice).

The numerical signs for price, promised delivery time, and late-delivery time are negative, which means that the probability of a customer's selecting a pizza-delivery company decreases as pizza price, promised delivery time, or late-delivery time increase. On the other hand, the numerical signs for the other attributes are positive, indicating that the probability of a customer's selecting a company increases when the company offers a discount on a second pizza, more variety, steaming-hot pizza, or a money-back guarantee.

Each attribute has a different weight in the customer's decision.

Exhibit 1
Sample discrete-choice set

Assuming that you are in the mood for pizza and that you want your pizza delivered, please choose the company from which you would like to order pizza. For the sake of simplicity, the choice sets contain information about only some of the attributes of the companies. Assume that all other attributes (not specified) are the same for both companies. For example, even though the choice sets show the price of large pizza only, you can assume that both companies also offer small and medium size pizzas at prices lower than those for their large pizzas.

Choice Set #1	Company #1	Company #2
Price of first large pizza	$18	$12
Discount on second pizza	none	1/2 price
Promised delivery time	20 mins	40 mins
Late-delivery time	15 mins late	as promised
Types of pizza crust	3 types	1 type
Pizza temperature when delivered	steaming hot	warm
Unconditional money-back guarantee	yes	no

Note: Each customer responded to 16 choice sets such as this.

Exhibit 2
MNL-regression model for all customers (n=128)

Inverse attributes	Regression weight
Price of a large pizza	-0.614*
Promised delivery time	-0.179*
Late-delivery time	-0.125*
Direct attributes	
Pizza temperature	0.341*
Types of pizza crust	0.273*
Money-back guarantee	0.236*
Half-price for second pizza	0.222*

Statistical test	Value
Intercept	0.726*
McFadden's r^2	0.871
r^2 (adjusted)	0.858

*Significant at $p < 0.05$

Note: As the values of inverse attributes increase, the likelihood of a person's ordering a pizza decreases. A person is more likely to order a pizza as the direct attributes increase.

The relative weight for price is highest, followed by pizza temperature, pizza variety, money-back guarantee, discount, and delivery time. A high weight for price and low weight for discount suggests that a chain might be able to induce more purchases (and increase profit) by reducing price and discount simultaneously.

It is interesting to note that pizza temperature has the second-highest weight, because most of the chains' systems are not set up to deliver steaming-hot pizza. This result suggests that there is an opportunity to increase market share and profit by improving operations so that customers receive steaming-hot pizza.

[9] Generated by *NTELOGIT*, Intelligent Marketing Systems, 1992.

[10] Analogous to the r^2 applied to ordinary-least-squares regression, McFadden's r^2 is the appropriate statistics for multinomial logit regression.

Exhibit 3

MNL-regression values for pizza-chain customers

Indirect attributes	Ambassador	Domino's	Godfather's	Pizza Hut
Price of first large pizza	-0.7603*	**-0.3176***	-0.3666*	-0.5201*
Promised delivery time	-0.1332*	0.0324	-0.2551*	-0.2016*
Late-delivery time	-0.1629*	0.0403	-0.0816	-0.1356*
Direct attributes				
Types of pizza crusts	**0.5251***	0.1311*	**0.3411***	0.3046*
Pizza temperature	0.1295	0.1975*	0.2583*	**0.3999 ***
Money-back guarantee	0.3497*	0.3557*	0.2095*	0.2395*
Discount on second pizza	0.2124*	0.0091	0.1997*	0.2484*
Sample size	*31*	*56*	*30*	*76*
Statistical values				
Intercept	0.7447*	0.9219*	0.9690*	0.7210*
McFadden's r^2	0.7520	0.5500	0.6710	0.8150
r^2 (adjusted)	0.7170	0.5240	0.6250	0.7940

*Significant at $p < 0.05$ COLOR = most important; **BOLD** = second-most important

By using customers' responses regarding the chains from which they had recently ordered, we were able to segment the customers. We then examined the segments, looking for similarities and differences. Exhibit 3 shows customers' choice patterns for the four largest pizza-delivery chains operating in the area. All four models are statistically significant at the $p \leq .05$ level. High values of McFadden's r^2 for Pizza Hut (0.81) and Ambassador Pizza (0.75) lead us to conclude that these chains' customers have relatively homogeneous choice patterns. In contrast, the comparatively low r^2 for Domino's Pizza (0.55) and Godfather's Pizza (0.67) customers indicates less homogeneity in those customers' choice patterns.

In addition to the r^2 values, Exhibit 3 shows a number of differences in the choice patterns of various chains' customers. We can summarize these differences in terms of statistical significance and relative weights of attributes in the MNL model. For example, all attributes except pizza temperature are statistically significant in determining purchase for Ambassador Pizza customers, while all attributes except late-delivery time are statistically significant for Godfather's Pizza customers. All seven attributes are statistically significant for Pizza Hut customers. For Domino's Pizza customers all attributes except the discount on second pizza and delivery time are statistically significant as determinant attributes.

The most-important attributes for customers of the various pizza-delivery chains are highlighted in Exhibit 3.

Price is the most-important attribute for customers of Ambassador Pizza, Godfather's Pizza, and Pizza Hut. Ambassador Pizza and Godfather's Pizza customers consider types of pizza crusts to be the second-most-important attribute, while pizza temperature holds second place for Pizza Hut customers. Domino's Pizza customers consider the money-back guarantee to be the most-important attribute, followed by price. It is important to note that some customers probably order pizza from more than one chain and their choice patterns are reflected in more than one chain's values presented in Exhibit 3.

Managerial Implications

Many current articles and books emphasize the need for customer-based operations management in the hospitality industry. In this article we have presented an effective approach for positioning operations based on customer tastes and preferences. Discrete-choice analysis can be used to identify relative weights for product attributes from the customer's point of view. The discrete-choice weights show the probable impact of a change in a particular attribute level on market share.

The MNL model presented in Exhibit 2 can be easily incorporated into a spreadsheet as a decision-support system. Managers can use this model to evaluate the expected change in market share if one or more attributes are changed by them or their competitors. This application is illustrated by the following example, depicted in Exhibit 4.

Assume that there are only three pizza-delivery chains, Cheep 'N Cheese Pizza (CNC), Pizza to Go (PTG), and Hot 'N Spicy Pizza (HNS) in the geographic area from which discrete-choice data were collected. The attributes for the three chains and their corresponding design codes (listed in Exhibit 4) are as follows. Cheep 'N Cheese charges $12 for a delivered pizza; gives a 50-percent discount on the second pizza; offers only one type of pizza crust; promises to deliver pizza in 40 minutes; usually delivers the pizza 10 minutes late; and does not offer a money-back guarantee. On the other hand ordering from Hot 'N Spicy is relatively expensive ($18 per pie) but HNS delivers in 20 minutes and offers three types of crusts. Pizza to Go is between the

Exhibit 4

Sample multinomial-logit model

	Pizza-Delivery Chain								
	Cheep 'N Cheese Pizza (CNC)			Pizza to Go (PTG)			Hot 'N Spicy Pizza (HNS)		
Attribute	Value	Design Code (X1)	X1 * *b*	Attribute Value	Design Code (X2)	X2 * *b*	Attribute Value	Design Code (X3)	X3 * *b*
Price of first large pizza	$12	–1	0.614	$15	0	0 .000	$18	1	–0.614
Discount on second pizza	yes	1	0.222	yes	1	0.222	no	–1	–0.222
Promised delivery time	40 mins	1	–0.179	30 mins	0	-0.179	20 mins	–1	0.179
Late-delivery time	10 mins	0.33	–0.063	5 mins	-0.33	0.125	0 mins	–1	0.125
Types of crusts	1	–1	–0.273	2	0	0.273	3	1	0.273
Pizza temperature	warm	–1	–0.341	warm	–1	0.341	steaming	1	0.341
Money-back guarantee	no	–1	–0.236	yes	1	0.236	yes	1	0.236
Intercept	—	1	0.726	—	1	0.726	—	1	0.726
Utility ($V = \Sigma x \beta$)			0.491			0.885			1.044
e^V			1.635			2.422			2.841
Market Share ($e^V / \Sigma e^V$)			23.70%			35.12%			41.18%

other two chains in price, delivery time, and typical late time.

Exhibit 4 also shows that the design codes for the attributes can be multiplied by their respective MNL weights (from Exhibit 2) to calculate each chain's overall utility. Expected market share for the three chains can be calculated by using the MNL model as shown in Exhibit 4. Expected market shares with the attribute levels shown are CNC, 23.7 percent; PTG, 35.1 percent; and HNS, 41.2 percent.

The MNL model can also be used to evaluate the expected change in market share if any chain changes one or more attribute levels. For instance, if CNC starts offering two types of pizza crust, the change can be easily incorporated into the MNL model by changing the code for "types of crusts" from -1 to 0 (second column). All other things being equal, the change would be a good one for Cheep 'N Cheese, because the resulting recalculated market shares will be CNC, 29.0 percent; PTG, 32.7 percent; and HNS, 38.3 percent. Thus, by adding a choice of crusts Cheep 'N Cheese gains 5.3 percent in market share at the expense of Pizza to Go (losing 2.4 percent) and Hot 'N Spicy (losing 2.9 percent).

Needless to say, our example is simplified and real pizza chains would constantly be jockeying for market share by changing their product and service attributes. The MNL model can readjust market-share projections as the various attributes change. Once an MNL model has been set up it can be easily used as a decision-support system for evaluating, from the customers' points of view, the features of new products or changes in existing products' attributes. For example, assume a proposed change in a given product attribute increases a chain's market share by 5 percent. This information can be used to calculate expected net revenue. By comparing the expected revenue with the costs associated with actually changing the attribute, hospitality managers can make a sound decision regarding whether to make that change or to consider other changes in product or service design and delivery. We believe that the use of customer-based approaches such as discrete-choice analysis can significantly improve the financial and market position of hospitality chains. **CQ**