marketing research

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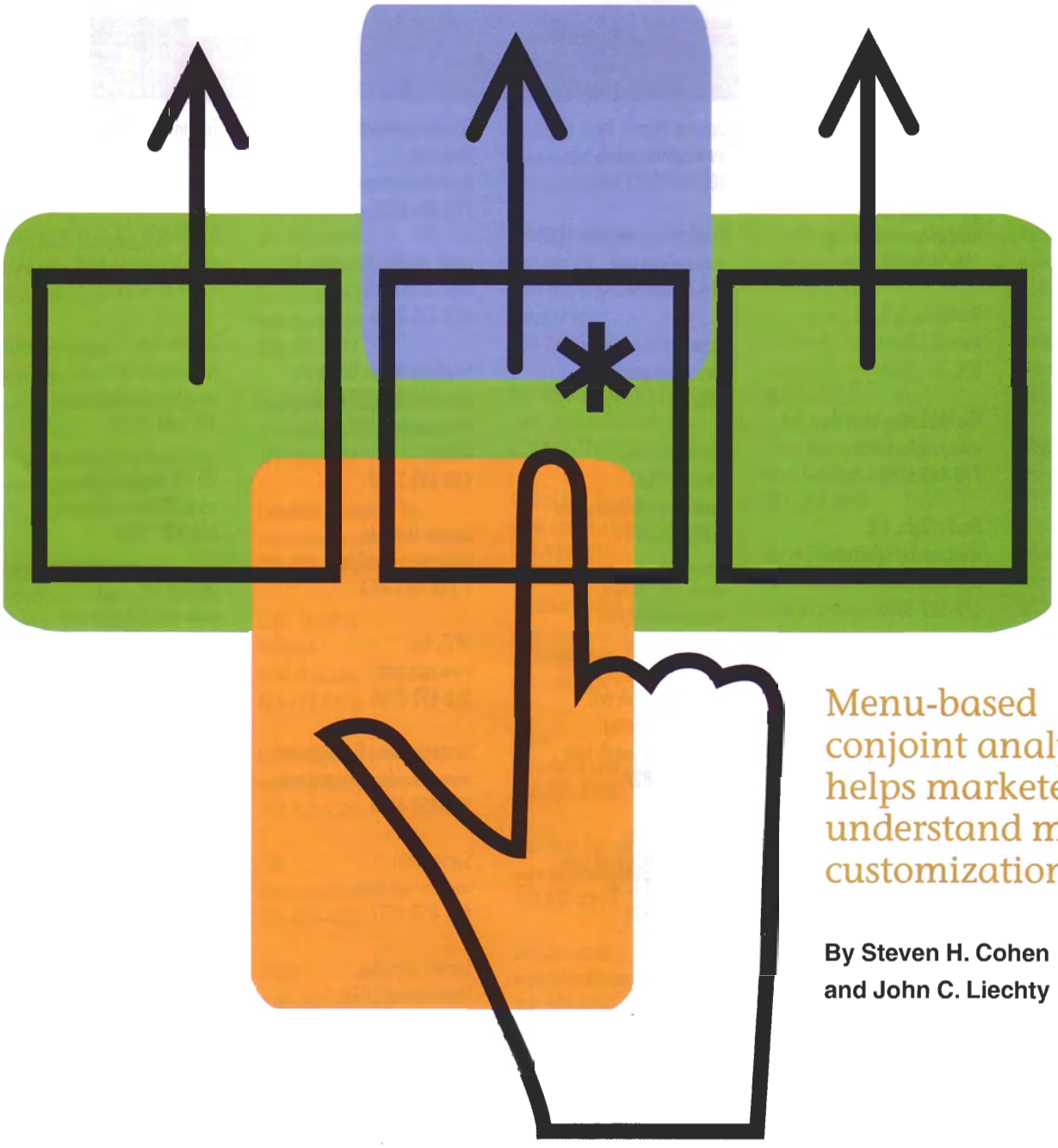

Menu-based conjoint analysis helps marketers understand mass customization.

By Steven H. Cohen and John C. Liechty

If anything is true of the relationship between companies and customers, it's that companies need to know more about what customers want. How else do we explain the high failure rate of new products? How else do we account for the frequent and ongoing use of factory incentives, rebates, discounts, and markdown sales? Clearly there is a disconnect between what customers want and what companies sell to them.

The development of the Internet has accelerated the ability of companies to deliver mass customized products and services to consumers and businesses. Mass customization promises the buyer the ability to design an offering that is tailored to the customer's own precise needs. Marketers of mass customized products and services certainly believe that consumers will purchase—and perhaps even pay more for—products and services that are targeted directly to them. A major benefit of mass customization should be the elimination of (1) the low- or no-profit tactics associated with having to unload unwanted goods at lower than optimal prices or (2) introducing yet another product failure.

To truly implement mass customization, the competitive game for companies must shift from having a portfolio of products that satisfy the needs of potential buyers to having a full portfolio of features that the buyer can pick and choose from to design his own product. So instead of introducing preassembled products that the manufacturer thinks the customer will purchase, the company that engages in mass customization inserts the customer as a cocreator of the product—offering the buyer the flexibility to choose from a menu of features, resulting in a product that he wants.

Build Your Own Product

In a seminal *Journal of Marketing Research* article in 1997, on new-product development, Jerry Wind and Vijay Mahajan recognize the importance of researching mass customized products: "From a new product design perspective, organizations are no longer searching for the best optimal product, nor even for a product line of optimal products (against a target of market segments), but for the development of capabilities to allow customers to customize a desired product from thousands or millions of possible products.

"From a marketing research point of view, the focus is no longer on conjoint analysis studies leading to the identification of an optimal product or product line, but rather on the following:

1. The identification of the set of features and levels that typically constitute the conjoint analysis tasks;
2. The way consumers want to customize their products; and,
3. The premium, if any, customers are willing to pay for a customized design versus an off-the-shelf product."

In addition, Wind and Mahajan see the value of this type of research so that manufacturers can use "customer input not only for designing customized products but also as a response (to a conjoint analysis-type task) that provides operational guidelines for the design of products to inventory for the segment that is not willing to pay the premium required for customized products."

Hence, the key marketing challenges are to (1) identify the features that should be offered; (2) understand how customers want to build customized products and which customers want to customize and which they do not; and (3) uncover how to price each feature to simultaneously increase customer value, revenues, and profits.

Executive Summary

How must researchers craft studies and analyze the data to get a deeper grasp of mass customization? How must researchers investigate picking from a menu, and how must they examine the results to best expose the behavioral underpinnings of the build-your-own situation? One might think that traditional conjoint analysis is appropriate and effective for understanding how people want to construct product bundles, but the menu situation's additional complexity makes that approach entirely inadequate. Enter menu-based conjoint analysis—expressly designed for handling a build-your-own, select-from-a-menu, mass customization situation.

Although Wind and Mahajan do not specify what the "conjoint analysis-type task" looks like, we suggest that it looks like choices from a menu.

Menus are Everywhere

We encounter menus all the time. Consider how a restaurant serves meals. The diner exactly chooses the starter, main dish, dessert, and beverage that satisfy his hunger and thirst. The problem for the restaurant owner is what to put on the menu, how much of each raw ingredient to stock, and how to price each item to deliver a good meal to the diner and still make a profit in the process. Perhaps the restaurant owner also wants to have price-fixed options on the menu. Which menu items to bundle into the price-fixed options and how many bundles to have versus a la carte choices becomes a very difficult decision—especially without a marketing scientist on staff!

Adrian J. Slywotzky writes about the menu scenario in a 2000 *Harvard Business Review* article: "I call these systems choiceboards—the sort of interactive online system popularized by Dell Computer Corp. that allows a customer to design a personal computer. They choose from a menu of attributes, components, prices, and delivery options. Those choices send directions to the supplier's manufacturing system that set in motion the wheels of procurement, assembly, and delivery. The result is a purchasing process that involves fewer price comparisons of commodities and creates more active customers."

Obviously choiceboards and menus are not limited to just restaurants or Dell. Employee benefits packages (interestingly, often called "cafeteria plans"), cable television, telephone calling plans, and maintenance and service agreements have all been mass customized using a menu.

The use of menus has even been extended to consumer products. Procter & Gamble's Reflect Web site promises women the opportunity to purchase cosmetics mass-customized to each woman's unique needs. Timbuk2 allows the customer to custom-build a bicycle bag. Build-a-Bear shops allow the buyer to custom-build a stuffed toy bear.

Even auto companies have gotten in on the action. General Motors' Web site says, "In six easy steps you'll pinpoint a vehicle that is perfect for you. Research, build your own, and locate your choice in a dealer's inventory near you." Not exactly mass customization, but General Motors certainly wants to give the customer that impression.

Menu-based Conjoint Analysis

While choiceboards and menus have become more attractive, how should the practicing researcher design studies and analyze the data to better understand mass customization with menus? What is the task that we should ask respondents to do, and how should we analyze the results from that task to best reflect the behavioral underpinnings of the menu situation?

At first glance, understanding product bundles—which consist of discrete features—seems like something that conjoint analysis should be able to handle. But the complexity of the menu situation renders traditional conjoint analysis wholly inadequate.

Menu-based conjoint analysis (MBCA) extends choice-based conjoint analysis (CBCA), so as to handle the mass customized, build-your-own-from-a-menu situation. The differences between traditional analysis and MBCA are shown in Exhibits 1 and 2.

CBCA asks respondents to react to several buying situations or simulated shopping trips, each of which is composed of a few competitive alternatives. In each task, the respondent is asked to choose one single most favored alternative, which may include "none of the above." An experimental design is used to construct the choice alternatives, such that they differ systematically on features and price.

In MBCA, the respondent also sees buying situations or simulated shopping trips. However, rather than a few complete products, the buying situation consists of a menu of feature alternatives. Across menus, the experimental design sets up a systematic variation of the prices of each feature, the overall menu characteristics (e.g., incentives for multiple purchases, constraints on choices), and perhaps even which features are offered in each menu. Rather than choosing a single most favored alternative, the respondent's task is to choose one, several, or even all of the alternatives on the menu.

In conjoint analysis, the levels of each feature are varied independently of the price of the whole product and typically are not priced individually. When using MBCA, each feature is priced separately, and the total price to be paid is the sum of the prices of the individual features that are chosen.

The traditional conjoint task requires the respondent to evaluate each product profile or choice situation and then provide just one overall reaction. In contrast, MBCA will ask the respondent to examine each menu and provide a "buy/not buy" reaction to each feature on the menu. The number of responses to an MBCA task is not a single overall response, as in traditional conjoint, but a series of responses.

A simple example clearly illustrates the complexity of the

Exhibit 1 Choice-based vs. menu-based

	Choice-based conjoint analysis	Menu-based conjoint analysis
Problem	Understand and predict the consumer's choice of a single alternative from competing alternatives. There is one total price for each alternative.	Understand and predict the consumer's customization of products and services, entailing the selection of as many features and options as he desires from a menu of features and options, which might or might not be individually priced.
Illustrative research applications	Customer chooses a single hotel room from competing brands of hotels. The hotel has pre-configured features and a brand with a total price for each night.	Customer chooses multiple features and options of Web-based information services, telecommunications services, and so on. There might be menu-specific characteristics such as a discount structure, minimum time commitment, and constraints on choice combinations. The constraints might be firm (e.g., manufacturing) or consumer (e.g., budget) driven.
Typical data	Single choice from pre-configured whole products in a choice set. There is a common alternative across all choice sets that scales the utility levels between choice sets—usually "none."	Multiple simultaneous choices of features and options from each menu. Each feature might or might not be individually priced.
Design of models	Given characteristics of alternatives, the model is designed to explain which single option is chosen from the set of alternatives.	Given characteristics and prices of each feature, the model is designed to explain which collection of features is chosen.
Theoretical basis of models	Maximizing the utility of a single alternative from a set of competing alternatives yields the classic multinomial choice formulation.	If the utility of each feature is above a threshold, then it is chosen. The utility of all features is maximized simultaneously, yielding multiple chosen alternatives.

menu situation. Let's say a restaurant offers four starters, five main dishes, three desserts, and four beverages. Let's not concern ourselves about the prices of those items just yet. If every person ordered at least one of each, there would be 4*5*3*4 = 240 possible meals. This would be the set of menus that a CBCA would test.

However, there are meals that consist of less than all four choices. Because some people might not want dessert, there are an additional 60 possible dessertless meals. Similarly, if some people do not want a starter or dessert, then 20 additional meals would consist of just a main dish plus a beverage. A light eater might want just a starter and a beverage (16). Others might want a starter and a beverage followed by dessert (48). Yet others might want to skip dessert (80). And others might not want something to drink (60). Thus, instead of there being one "full" meal, as in a CBCA task, each person is really (1) engaging in a task that could be described as "choose any from many" and (2) selecting one of those meals—having it his way—from the 524 possibilities.

Imagine that now we are interested in testing three prices for each item, and we systematically vary the prices across menus. Those 240 potential full meals are represented by $3^4*3^5*3^3*3^4$ = 43,046,721 possible price combinations across all full menus; this is the full factorial that would be tested in a CBCA. However, the remainder of our less-than-full meals requires an additional 2.8 million possibilities to be tested.

Analyzing Menu Data

Upon analysis of traditional conjoint data, the analyst works with one equation, which decomposes the respondents' overall reactions—to the brands, features, levels, and prices—into the utilities that are attributable to each level of each feature. Because the MBCA task obtains K reactions to each menu (where K is the number of features on the menu), the analyst must simultaneously estimate the coefficients of a series of K-linked equations—rather than analyzing just one equation. Each equation in the series estimates the attractiveness and price elasticity of each feature along with the correlations among the errors of the equations.

Exhibit 2 describes three competing ways to analyze menu data. The first way analyzes the binary "buy/not buy" choices from the menu, without regard to how they might be chosen together. The second way enumerates all possible sets of choices from the menu, and then it uses a multinomial choice model to predict the choice of the single chosen array from all possible ones. The third way is MBCA.

The MBCA approach has some very desirable characteristics. First of all, we obtain a unique utility for each feature: net of its price. This tells us the intrinsic attraction of each feature on the menu. Next we obtain an estimate of the price sensitivity to each feature. Most importantly, the linked system of equations accounts for the interrelationships among menu choices.

For example, we know that people often choose certain products in combination (e.g., a cheeseburger is frequently bought with french fries). Accounting for combinations tells us which features are complements: good candidates for being marketed in a bundle. Certain features might also be bought to the detriment of others; buyers think they are substitutes. This might indicate that the menu is too fully featured or perhaps that there exists segmentation in the patterns of choices. We diagnose those complements and substitutes from the matrix of correlations among the errors of the equations: Complementary features will have positive correlations and substitutes will have negative ones.

Estimating the series of MBCA equations can incorporate menu constraints. Those can occur when the marketer wants to:

Exhibit 2 Comparison of alternate approaches

	Analyze as a series of binary choices without regard to combinations	Traditional single choice modeling (pick one from many)	Menu modeling (pick any from many)
Analysis setup	Convert menu choices into a series of K binary choice models.	Convert menu choices to a single choice array from 2^k possible arrays	Preserve the individual menu choices.
Modeling approach and theoretical basis	Estimate each binary choice model separately.	Use a multinomial choice model to analyze the chosen array as a choice from all possible arrays.	Statistical formulation that models the choices in terms of the probability of choosing a collection of features. A utility is specified for each feature (as a function of its characteristics, price, and other scenario-specific attributes), which might be correlated with the utilities of other features. These correlations capture unobserved cross-dependencies in the items chosen.
	Utility is at the level of each item in the menu. The objective is to find the parameter values that maximize the choice of each item separately.	Utility is conceptualized and specified at the level of an "array of chosen features." The probability of choosing a single array (from the 2^N possible arrays) is specified as a function of its features and prices.	If the utility of each feature is above an estimated threshold, then it is chosen. The utility of all features is maximized, simultaneously yielding multiple chosen alternatives.
Model design	Given characteristics and prices of each feature, the model is designed to predict whether each feature is chosen—without regard to whether it might have been chosen in combination with other features.	Given characteristics of alternatives, the model is designed to predict which single array is chosen from all possible arrays.	Given characteristics and prices of each feature, the model is designed to predict which collection of features is chosen.
Comments	As long as menu choices are uncorrelated, this approach will work well. When menu choices are positively correlated (complements) or negatively correlated (substitutes), estimates obtained from this approach will be incorrect.	Gives the ability to evaluate "predetermined bundles" easily.	In addition to providing an evaluation of predetermined bundles, this approach will reveal "natural bundles." Using a random effects formulation, we can assess the intrinsic worth of each feature and the price sensitivity of an individual to that feature. The model also yields the correlations between the errors in estimating the utilities of these features, net of price, and other effects.
	To the extent that there are constraints on choice combinations (either manufacturer-driven or based on the consumer's budget), this approach will not work correctly.	However, as the number of features increases, the size of the exploded choice set becomes very large and unwieldy, and one must resort to "sampling of alternatives." For identification purposes, correlations between errors in estimating the utilities, net of price, and intrinsic effects have to be set to a constant value—typically zero.	Accommodating and preserving menu constraints requires additional programming and computation.

- limit the number of features that the consumer can choose ("pick any three premium channels from our lineup");
- require that the consumer buy certain features in combination ("you can get a high-end graphics card only if you purchase a 21-inch monitor");
- or require that the consumer stay within a budget ("choose the health benefits you want but stay under a total of $250 per month").

Although one could estimate the utilities of MBCA by a series of equations that are not linked to one another, the linked equations explicitly account for the interrelationships among the features. Ignoring the interrelationships will misrepresent the demand for feature combinations. If there are explicit constraints on menu choice, then separate and unlinked equations will give even worse results.

An Example

We have applied MBCA in several commercial applications since developing this methodology. We discuss our first application of MBCA because it is relatively small and includes constraints on consumer choice.

A content-based site, such as the Internet Yellow Pages (IYP), could offer advertisers the option to customize their online listings. For many years, the paper version of the Yellow Pages has used a business model wherein the advertiser can choose the size, color, page placement, and detail of its listing. IYP

Exhibit 3 (Disguised) menu of service options

Minimum commitment:
12 months

Discount on monthly fee:
Choose at least two services and receive an X% discount for up to one year of monthly fees

Optional services:	**SERVICE OPTIONS** Monthly fee ▼
ENHANCED LISTING	**$10** ☐
PAGE OPTIONS *(If you pick any of the three do NOT pick Special Page)*	
Option 1	**$5** ☐
OR	*OR*
Option 2	**$10** ☐
OR	*OR*
Option 3	**$25** ☐
ENHANCED PAGE	**$25** ☐
SPECIAL PAGE *(If you pick the Special Page do NOT pick any Page Options)*	**$75** ☐
	OR check the box below ▼
I would choose NOT to enhance my basic listing on the Internet	☐

was envisioned to offer the same buying flexibility, but the challenge was how to price the listings.

The study, originally undertaken in the late 1990s, involved in-person interviews with potential small- and medium-sized business advertisers—just the target for the soon-to-be-started online listings. The company had designed a pricing scheme that offered discounts for the selection of multiple features and/or longer time commitments. Online listings could be customized by size, with images, and/or with links to other information.

The key question was whether and how advertisers would be interested in customizing a free, standard IYP listing. And if so, how should IYP set its pricing to increase customer value and revenues?

The information needed to answer those questions: (1) the advertisers' preferences for the features that could be used to enhance their listings, (2) their price sensitivity to each of the features, (3) the relationship between pricing and preference for multiple features, and (4) the influence of contract commitments and discounts on overall market demand.

As the customized enhancements are proprietary, we present the features in disguised form:

- enhanced listing (EL—three levels tested)
- Web page options (P1—three levels; P2—nine levels; or P3—12 levels)
- enhanced Web page (EP—three levels)
- special Web page (SP—three levels)

In addition, three levels of time commitment and three levels of discounts for choosing multiple features were tested.

Exhibit 3 shows a sample of a disguised menu scenario. The special page incorporated the three Web page options while offering additional customized benefits. From the enhanced listing through the special page, those services are ordered in increasing customer benefits, complexity, and monthly fee. Note that within each service feature, the customer has flexibility to customize according to his own business needs. As part of the pricing structure, the company wished to investigate different monthly price levels for each of the four key customized services, taking into account cost considerations and the potential added value.

A master design of 81 menu scenarios was developed and then blocked into nine sets of nine menus each. Each respondent was randomly assigned to one of the nine blocks. A tenth menu task, which the client considered a base case, was administered to all respondents. Time to complete the interview lasted about 30 minutes and included a thorough description of how to complete the menu task. For the purpose of estimation, we randomly selected seven of the 10 menu tasks per person and reserved the remaining three as holdouts.

We did not analyze those data using a series of independent binary choices because it was clear that this model would yield biased estimates, owing to the fact that it does not take into account multiple choices and choice constraints. We analyzed the data using the second and third methods described in Exhibit 2.

To implement the second method, for each menu for each person we (1) created an array of the chosen items, (2) completed the full choice set by adding all of the unchosen arrays, and (3) used a multinomial probit model to predict the one array that was chosen. Because of the menu constraints, there

Ignoring the interrelationships will misrepresent the demand for feature combinations.

are actually only 20 possible combinations of the six features—rather than $2^6 = 64$ combinations that would seem to exist at first glance. This method of estimating the results is described in Moshe Ben-Akiva and Shari Gershenfeld's 1998 *Journal of Forecasting* article.

We then used our linked multiequation MBCA model. With this, we estimated the desired effects using both an aggregate model and a Bayesian framework that allowed for individual-level coefficients. In addition, the MBCA model was estimated with and without correlations among the errors in the equations.

In general, the Bayesian specification outperformed the aggregate model in correctly predicting choices in the hold out tasks. Those results are shown in Exhibit 4. The first row of this exhibit displays the percent of time (hit rate) that we correctly predicted combinations of features; the subsequent rows are the hit rates for predicting the choice of each

Exhibit 4 Performance of alternate approaches

	Aggregate multinomial probit	Bayesian multinomial probit	Aggregate MBCA model (no correlations)	Bayesian MBCA model (no correlations)	Aggregate MBCA model (with correlations)	Bayesian MBCA model (with correlations)
Percent correct combinations	7.7%	9.3%	12.5%	35.2%	15.1%	36.3%
Feature 1 only	50%	50%	51%	69%	50%	70%
Feature 2 only	74	82	72	80	72	80
Feature 3 only	85	90	85	89	85	89
Feature 4 only	79	86	79	86	79	86
Feature 5 only	66	48	69	82	71	82
Feature 6 only	68	86	80	89	79	88

individual feature (rows 2 through 7). The first thing to notice is that when predicting the choice of individual features, the MBCA model slightly outperforms its multinomial probit counterparts.

However, when predicting combinations of features, the MBCA model performs much better than the multinomial model (as shown in row 1). The probit model predicts, at best, 9.3% of the combinations of features in the holdout data; MBCA predicts, at worst, 12.5% of the combinations. More interesting still is the improved performance of the MBCA model—in predicting combinations of features even at the aggregate level—over the traditional multinomial probit when estimated with a Bayesian model. This alone demonstrates the superiority of the MBCA model over alternative ways of estimating the desired effects.

The MBCA model that also estimates the correlations among the errors of the features performs better than a similar model that assumes no correlations. The improvement is not dramatic (36% versus 35%). However, in other studies in which the correlations are stronger than found here (those correlations ranged from -.46 to .42), the model with correlations performed much better than the one without.

With the MBCA model, we were able to say which potential advertisers were more willing to customize and which were more willing to take the "plain vanilla" listing. And we were able to diagnose the differential attractiveness of each feature to different advertiser groups. Space considerations preclude us from discussing those results.

Final Considerations

Now that companies can mass customize their portfolios of features or services, a major challenge for them is to set prices to increase customer value and revenues. The Web allows companies to compete on the basis of benefits sought, effectively allowing the marketer to engage in value-based pricing. Carl Shapiro and Hal R. Varian, in *Information Rules* (Harvard Business School Press, 1999), note that although companies can attempt to develop and exploit information obtained from customer-provided profiles, online behavior, and marketing data, they could learn more about their customers by offering them a menu of products, services, or information and seeing which ones they choose. The menu situation can also be used by manufacturers to fully understand the choice of components when there is a need to reduce operational complexity.

The astute reader will realize that mass customization is just one of several choice problems in which the consumer engages in building his own product. Others include (1) the selection of optional features to add to a base product, (2) the choice of system components from several vendors, and (3) the choice of bundles versus á la carte selections. The latter case is mentioned by Wind and Mahajan, in which the manufacturer is looking to offer consumers both the option of mass customization and the choice of a prepackaged bundle. Our research design for IYP did not investigate the choice between those two possibilities, but one could imagine a research design to do so.

Here we have introduced the marketing research audience to a new way to design and analyze studies that allow the customer to choose from a menu, to select from a choiceboard, to "build his own." Our proposed model, MBCA, employs a linked Bayesian multiequation approach. That approach allows the marketer to understand (1) how his customers want to customize, (2) which customers want to customize, (3) how attractive each feature is, and (4) how price sensitive they are to individual features. ●

Additional Reading

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