The Hard Impact of the Soft Touch
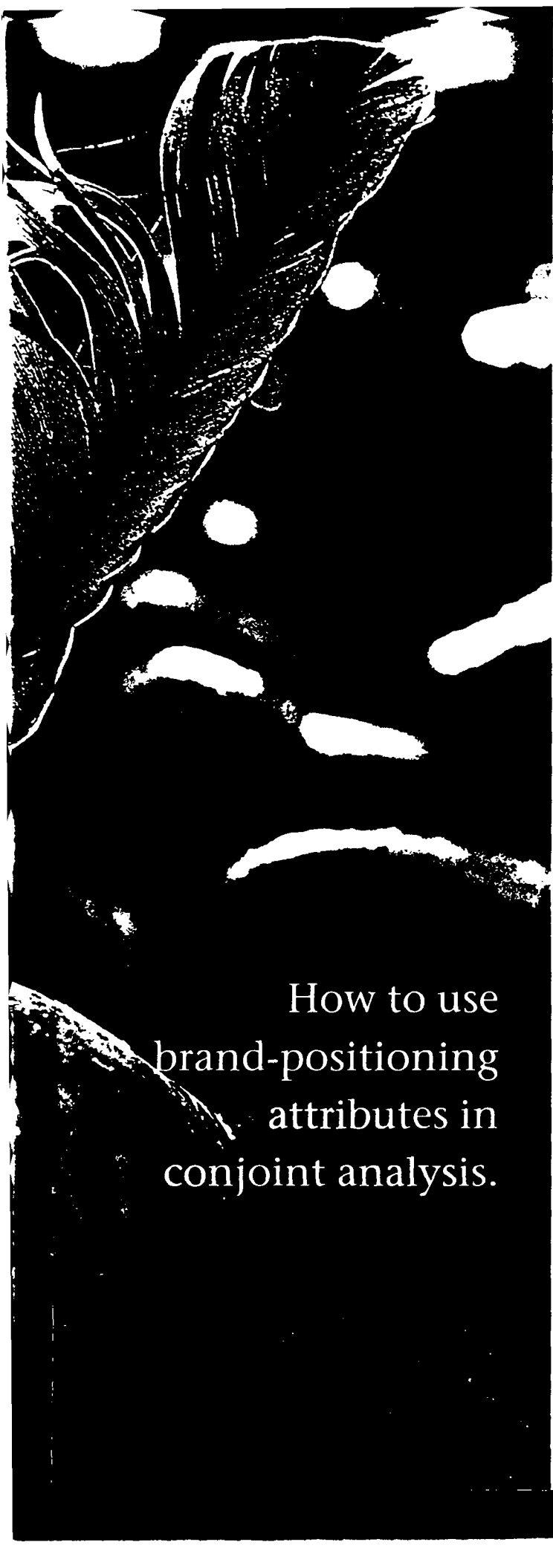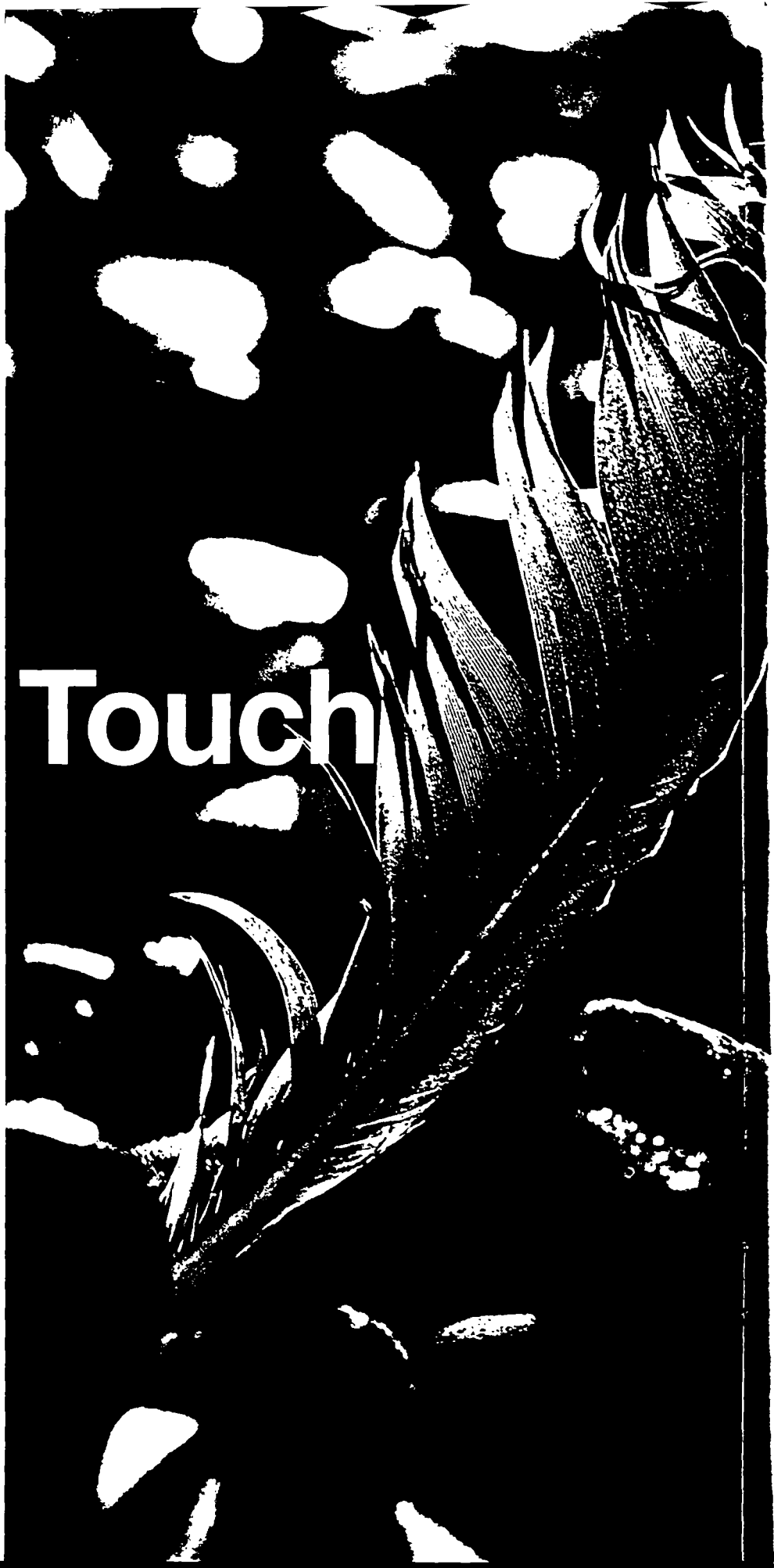
How to use brand-positioning attributes in conjoint analysis.

By Marco Vriens and Curtis Frazier

C onjoint analysis is probably the most popular tool in marketing research today for assessing and quantifying consumer preferences and choices. The conjoint approach can be used for a variety of marketing problems including product optimization, product line optimization, market segmentation, and pricing. Usually market simulations are performed to facilitate decision making based on the conjoint results. Recent developments have expanded the set of problems that can be tackled with conjoint analysis. For example, discrete choice modeling has made it possible to study trade-offs when different product categories are involved, latent class methods and hierarchical Bayes (HB) methods have increased the ability to identify market segments, and the development of efficient experimental design has increased the number of attributes and levels that can be dealt with in a conjoint study. One problem, however, has remained rather elusive: the integration of soft brand positioning attributes in a conjoint framework that aims to predict hard consumer choices.

Executive Summary

Brand-positioning attributes play an important role in consumer choice behavior, but can't be included in a conjoint study directly because it's difficult to define such attributes in terms of concrete attribute levels. Consumers may already have perceptions of how brands perform on such positioning dimensions, which makes it difficult for them to engage in a task where they need to ignore their own perceptions. This article describes a practical approach to tackling this problem.

An important attribute in consumer trade-offs is brand. A typical conjoint study will include a series of alternatives that are defined on a number of concrete attributes and price. From such a design we can assess the value (utility) of the included brand names. Hence, conjoint can be used to measure brand equity. Concrete attributes are often the basis for product modification or optimization, while more abstract attributes are often the basis for brand positioning. However, including more abstract brand-positioning attributes in a conjoint study so they can become part of predicting preference shares of hypothetical market situations has been more complicated and hasn't been typically pursued.

In many product categories it's difficult to position a brand and maintain a strategic advantage based on concrete attributes alone. Any customer-perceived advantage that's the result of specific concrete attributes can often be copied fairly easily or imitated by the competition unless a patent exists to prevent this. Brand-positioning attributes are much better suited for creating a sustainable advantage, and they play an important role in consumer choice behavior.

We encounter brand-positioning attributes in consumer markets. For example, when considering a car purchase, concrete attributes like price, power of the engine, extras, trunk volume, warranty, and design will have an impact on consumers' choices, but perceptions of the brand in terms of "reliability," "safety," "sporty," or "luxurious" will also play a role. We also encounter brand-positioning attributes in many business-to-business technology markets for products such as servers, enterprise software, and storage solutions. For example, for buyers of business/enterprise software, concrete attributes like price, total cost of ownership, and licensing terms will play a role, but so will brand-related attributes such as "This is a brand that knows me," "This is a pro-active brand," and "This is a brand that is innovative." Concrete attributes can be evaluated in the choice situation, be it in a hypothetical choice situation in a survey or in a real-life choice situation in a store comparing alternatives. Brand-positioning (abstract) attributes are more likely to be retrieved from memory. Prior to the choice situation, a consumer may have been exposed to brand-attribute information because they used the brand, heard about it from others, or saw it in advertising.

Such exposures will lead to brand information stored in memory as abstract attributes.

Hence, there are three reasons why brand-positioning attributes can't be included in a conjoint study directly and why the integration of brand positioning attributes in conjoint analysis is problematic:

1. It's difficult to define such attributes (or perceptual dimensions) in terms of concrete attribute levels, which is needed in order to design the conjoint experiments.

2. Consumers may already have perceptions of how the various brands perform on such positioning dimensions as a result of previous exposures. This makes it difficult for them to engage in a conjoint task where they need to ignore their own perceptions.

3. Often, by including both concrete and more abstract attributes the sheer number of attributes becomes a problem in itself. The conjoint task would become prohibitively difficult or fatiguing.

These factors have prevented the conjoint approach from being fully leveraged for the purposes of brand equity and brand-positioning research. As a result, the research literature has developed a separate class of techniques to deal with brand-positioning attributes such as multidimensional scaling or tree structure analysis. However, such methods don't allow the researcher to understand the joint impact of changes in both concrete attributes and brand-positioning dimensions upon consumer brand choices. For their impact to become clear, brand-positioning attributes need to be a part of a trade-off methodology.

A 1993 paper by Swait and colleagues demonstrated that discrete choice conjoint is a powerful method for measuring brand equity in terms of what consumers are willing to pay extra for a brand relative to competing brands. In 1994, Park and Srinivasan discussed how a self-explicated approach could be used to measure brand equity and to understand the sources of brand equity using attribute-based and non-attribute-based sources. Neither paper, however, discusses how to assess the impact of changes in performance on soft attributes or hard measures such as preference and choice. We have discovered a practical approach to dealing with the issue that has worked very well in practice.

Taking the Steps

Our approach is conceptually shown in Exhibit 1 and involves the following steps:

First, identify the key decision attributes that can be defined concretely (e.g., brand, price). Using this set of concrete attributes, a conjoint experiment is designed to derive individual-level brand utilities. In its simplest form, we could design a brand-price trade-off exercise. A more complicated design, involving more attributes, can be used so long as it includes brand name. Key here is that the data must be analyzed in such a way as to achieve individual-level brand utilities. When a traditional ratings-based conjoint is used, it's easy to estimate directly at the individual level. When a choice-based conjoint is used, we need to apply HB techniques to obtain the required individual-level utilities.

Exhibit 1 Brand-positioning conjoint
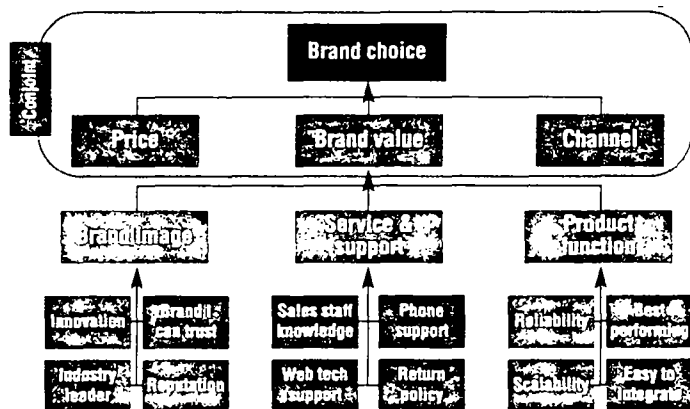
Second, identify the attributes that are potentially important for positioning the brands and that are expected to play a role in consumer decision making. The respondents evaluate all potentially relevant brands on these more abstract dimensions.

Third, use the individual-level brand utilities as the dependent variable in a linear or non-linear regression model with the performance perceptions of the abstract brand-positioning attributes as independent variables. Essentially, the brand utilities become a dependent variable and are modeled as a function of brand-positioning attributes. By asking respondents to evaluate each of the brands tested in the conjoint on a series of brand performance questions, we can construct a common key drivers model. The difference from a standard key drivers model is that, rather than modeling overall brand value from a stated brand preference/value question, we are modeling derived brand value from the conjoint stage. The conjoint analysis and regression analysis can be executed simultaneously by specifying an HB model where the brand parameters are a function of the brand-positioning perceptions and where a normal distribution is assumed for the non-brand conjoint parameters.

Fourth, use the relative regression weights to calculate pseudo-utilities for the different levels of the brand positioning attributes. For example, if a 5-point rating scale was used to evaluate the brands, we would assign utility values to the five levels of the rating scale. Finally, utilize the comprehensive consumer choice model to build a simulator that allows the manager to evaluate different scenarios, including those that involve anticipated or planned changes in the brand-positioning perceptions.

Put It to the Test

We have tested this approach in a variety of situations including consumer and B2B markets and on hardware and software technology products. Our illustration is derived from a recent study where respondents did a Web-based interview that included 14 discrete choice tasks presented in random order. In each of these tasks, respondents were shown profiles

defined on only brand and price. Respondents were asked which, if any, of the options shown they would actually purchase. The "none of these" option is important because it allows estimation of the minimum requirements for a product to become considered. The conjoint exercise was followed by a series of brand-positioning and relationship attributes. Respondents were asked familiarity with each of the brands tested in the conjoint. For brands with sufficient familiarity, they were asked to indicate how they perceived the brands on these soft-touch attributes. These attributes included questions about brand reliability and performance as well as less tangible attributes, such as "a brand I trust." The full list of brand positioning attributes is presented in Exhibit 2.

The analyses comprised three stages. In the first stage the conjoint choice data are analyzed using HB methods. This methodology enables us to obtain unique conjoint utilities for each respondent in our sample. These unique utilities are what allow us to estimate the second piece of our model. In the second stage we first need to merge the brand utilities back into the survey data. At this point the analysis can take two different directions. Stage two can be done either at the market level or can be brand-specific. Analysis at the market level means we estimate the relationships between brand-positioning perceptions and brand utilities across all brands. In other words, we assume the importance of brand-positioning attributes is the same for all brands. The model for this data format would specify that brand utility is a function of brand-positioning attributes such as "trust," "performance," or "reliability."
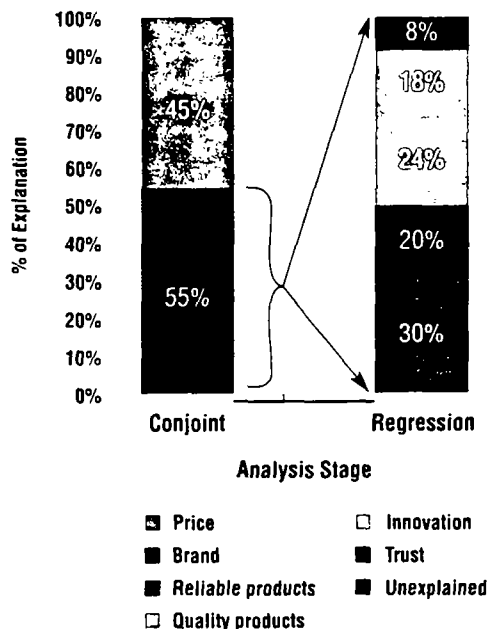
The alternative strategy is analysis at the brand level. There is no need for stacking the data because the individual is the

Exhibit 2 Importance of brand-positioning attributes

Example Results Based on Studies of Three Products in B2B and Consumer Spaces (Six Studies Total)

Brand-Positioning Attributes	Minimum Importance Found	
Brand	29%	58%
Reliability	4%	12%
Performance	1%	11%
Service and support	6%	14%
Value for the price	5%	15%
Products with latest technology	0%	14%
Is a market leader	10%	19%
Product meets my needs	8%	38%
Is a brand that I trust	9%	16%
Stable, long-term player	9%	19%
Easy to use	3%	11%
Appealing design/style	3%	14%

Exhibit 3 Integrating models

Legend:
- ■ Price
- □ Innovation
- ■ Brand
- ■ Trust
- ■ Reliable products
- ■ Unexplained
- □ Quality products

appropriate level of analysis. Rather than a single equation that applies equally well to each brand, we create unique equations for each brand. Hence the brand utility for brand 1 is modeled as a function of brand-positioning attributes or the brand utility of brand 2 is modeled this way.

Analysis at the market level has several advantages. The most important of these involve sample size and reporting. In terms of sample size, the stacking process essentially replicates the data so that our final regression analysis has k x N cases, where k equals our number of brands and N equals our number of respondents. Analysis at the market level also has the advantage of being easier to report/interpret. Rather than having attributes with differential importances, depending on which brand is being discussed, the analysis at the market level illustrates the importance across brands.

Although analyzed using a smaller effective base size, analysis at the brand level has some important advantages. Foremost among these is that it doesn't impose the assumption that the equations are equal across brands. This assumption, while valid in some markets, is tenuous, at best, in others. For example, the utility of Apple/Macintosh may be driven more by the fact that it fulfills a need or is compatible with other systems, whereas the utility of Gateway may be more driven by reliability or performance. Alternatively, the brand equity of smaller brands might be driven largely by awareness and familiarity, while larger brands may be driven by brand image.

In the third stage of the analysis we integrate the results from the first two stages. The basic process for model integration has already been discussed, using conjoint results as inputs into the hierarchical regression models. In this stage we

rescale the regression coefficients to the same scale as the conjoint utilities. The process of rescaling is relatively simple. Attribute importances for the conjoint stage are calculated in the standard way. The importances in the regression stage are calculated in the standard way, except they're scaled to sum up to equal the adjusted R^2. Once the model integration is complete we have a set of (pseudo) utilities that can be used as input for an integrated decision support tool. We note that the brand-positioning perceptions don't predict brand utility completely (i.e., the regression equation has an explained variance of less than 100%). We have found that the predictive power can range from high (e.g., more than 80% explained variance) to low (e.g., 20% explained variance). (See Exhibit 3.)

Decision support tools are fairly common in conjoint studies because they enhance and facilitate how the product/market managers can study and work with the results. An example of how a simulator tool looks when brand-positioning attributes are included is shown in Exhibit 4. However, allowing the user of the tool to manipulate not only the tangible product features, but also brand positioning and relationship attributes, creates a more complete marketing picture. As the user manipulates the brand-positioning attributes, these changes are adding, or subtracting, value from the utility for the brand(s). This rescored brand utility value is then used in the share of preference calculations.

We have applied our approach in both consumer and B2B markets. We can't present the results of individual studies because of their proprietary nature. However, Exhibit 2 illustrates the ranges we've found for the relative importance estimates of a series of commonly used brand-positioning attributes.

The technique described here extends conjoint analysis by allowing for a second set of research questions to be asked. Through conjoint, we know the answers to questions like "What do respondents want?" The technique described here allows answers to questions like "Why do they prefer it?" and "What can we do to make the brand more attractive?"

Our approach is useful for assessing the impact of softer attributes and can be used when a large number of attributes exists that can't all be included in the trade-off exercise. It can be extended in several useful ways. First, variables other than brand could be used to make the integration between conjoint and non-conjoint variables. In our illustration we used brand as a variable that connects the two stages, but we also used channel (retail vs. Web), technology type (CD vs. DVD vs. tape), and other attributes as a link between conjoint and non-conjoint attributes. Second, we only have one non-conjoint level in our illustration (using simple OLS). This model simplicity does not have to be the case. The second stage can be a set of hierarchical regressions in which brand attributes are regressed on attribute subcomponents. (This is actually the situation shown in Exhibit 1.)

For example, brand equity may be a function of service and image, while service is modeled as a function of Web tech support and phone tech support. By creating this hierarchical model, the results of the second stage move toward being more actionable. The second stage could also entail a factor analysis

Exhibit 4 Decision support tool
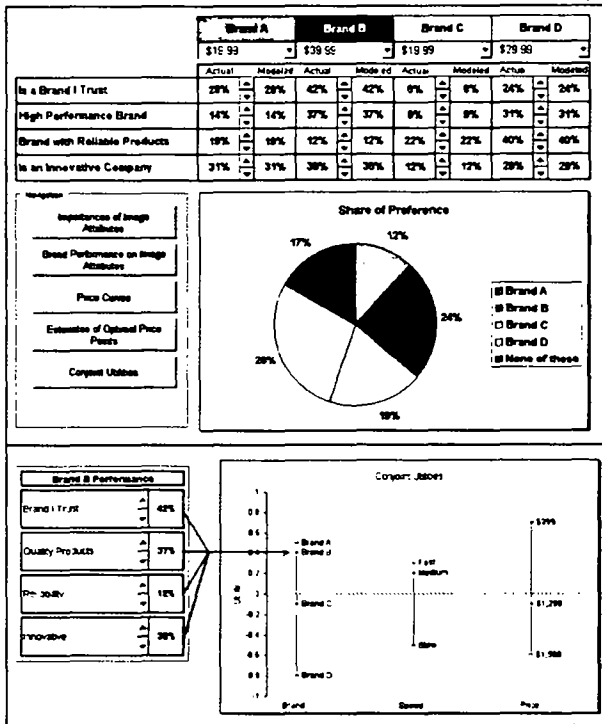
or structural equations approach to model brand equity. One could also apply latent class methods or HB techniques to allow for heterogeneity in the importance of brand-positioning attributes. With any of these designs, the basic framework remains the same—utilities derived from a conjoint are used as dependent variables in a second-stage regression-based analysis. However, by applying latent-class or HB techniques we could use our approach for segmentation purposes. It's very likely that different groups of consumers are looking for different things, not only at the level of concrete attributes but also at the level of brand-positioning attributes.

Finally, we could apply our approach to study consideration set issues. In complex markets, consumers often screen out alternatives they don't wish to evaluate in detail. We believe that for consumers the most efficient way of screening out alternatives is using perceptions they already have in their mind, instead of looking at concrete attributes, since it requires less mental searching costs than going out and finding information on concrete attributes.

In a lot of branding research the focus is on "just" measuring a brand's position on identified branding variables, such as image attributes, brand personality, and brand relationship attributes, without explicit empirical links to how people make choices and trade-offs. By linking brand perceptions to brand choices, a researcher is able to develop a framework that enables a return on investment analysis. Hence, we believe any brand approach can benefit from the basic notions outlined here. ●

Additional Reading

Park, C.S. and V. Srinivasan (1994), "A Survey-Based Method for Measuring and Understanding Brand Equity and Its Extendibility," *Journal of Marketing Research*, 31, 271-288.

Swait, J., T. Erdem, J. Louviere, and C. Dubelaar (1993), "The Equalization Price: A Measure of Consumer-Perceived Brand Equity," *International Journal of Research in Marketing*, 10, 23-45.

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Wedel, M., M. Vriens, T. Bijmolt, W. Krijnen, and P.S.H. Leeflang (1998), "Assessing the Effects of Abstract Attributes and Brand Familiarity in Conjoint Choice Experiments," *International Journal of Research in Marketing*, 15, 71-78.

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