LAN LUO, P.K. KANNAN, and BRIAN T. RATCHFORD*

Consumers often use both objective and subjective criteria to evaluate a product. For example, power tool users may evaluate a power tool on the basis of not only its objective attributes, such as price and switch type, but also its subjective characteristics, such as ease of use and feel of the tool. This research emphasizes incorporating subjective characteristics in new product design. The authors propose a model in which consumers' purchase intentions can be affected by both the objective attributes and the subjective characteristics. This model has the form of a hierarchical Bayesian structural equation model, in which the subjective characteristics are treated as latent constructs. The authors also propose a Bayesian forecasting procedure in which the estimated relationships are used to improve the out-of-sample prediction. They illustrate the proposed approach in two empirical studies. The results indicate that by collecting additional information about consumers' perceptions of the subjective characteristics, the proposed model provides the product designer with a better understanding and a more accurate prediction of consumers' product preferences than the traditional conjoint models.

Keywords: new product design, subjective product characteristics, qualitative product perceptions, hierarchical Bayesian structural equation model, Bayesian forecasting

Incorporating Subjective Characteristics in Product Design and Evaluations

In general, the existing literature in new product design has focused only on objective attributes, such as price and features. However, focusing only on these objective attributes can be insufficient. For example, in addition to price and features, the determinant factors of a power tool purchase may include qualitative characteristics, such as whether the tool is perceived as powerful and comfortable to use. We refer to these qualitative perceptions as subjective characteristics. In many purchase situations, both groups of factors contribute to the overall attractiveness of a product.

Industrial designers and marketing researchers have long recognized that consumers' perceptions of subjective characteristics exert an important influence on their product evaluations (e.g., Srinivasan, Lovejoy, and Beach 1997; Yamamoto and Lambert 1994). In the consumer electronics market, many consumers prefer to touch and feel an electronic product before purchasing it (Lawton 2006). A case study by Design Management Institute (1997) showed that one of the main reasons for the DeWalt Compact Power Drill's significant market success was that its design team focused on improving the ergonomic comfort of the product. Introduced by Black & Decker in 1994, the product was an instant success in the market and was soon the winner of numerous design awards.

Although subjective characteristics have been informally considered at the product design stage, currently, no formal model accounts for the impact of subjective characteristics in new product design. A particular challenge is that consumers' perceptions of the subjective characteristics often depend on a complex set of factors that can be quite different for different people. For example, people may have dif-

*Lan Luo is Assistant Professor of Marketing, Marshall School of Business, University of Southern California (e-mail: lluo@marshall.usc.edu). P.K. Kannan is Harvey Sanders Associate Professor of Marketing, Robert H. Smith School of Business, University of Maryland (e-mail: pkannan@rhsmith.umd.edu). Brian T. Ratchford is Charles and Nancy Davidson Professor of Marketing, School of Management, University of Texas at Dallas (e-mail: btr051000@utdallas.edu). This article is based on Essay 2 of the first author's doctoral dissertation, submitted to the University of Maryland. The authors thank the two anonymous *JMR* reviewers for their helpful comments and guidance. This research was supported in part by the U.S. National Science Foundation through Grant No. DMI 0200029. Such support does not constitute an endorsement by the funding agency of the opinions expressed in this article.

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ferent views as to what is emotionally appealing, comfortable, or easy to use. In general, the levels of these subjective characteristics are inferred by consumers, and their values on the measurement scales can vary substantially across consumers. Dealing with this complexity requires an additional modeling effort.

The objective of this article is to provide an effective way to incorporate subjective characteristics into new product design. In particular, we develop a formal model that helps the product designer better understand the impact of the subjective characteristics on consumers' product preferences and to incorporate this impact into the selection of an optimal product design. The model we propose has the form of a hierarchical Bayesian (HB) structural equation model, in which the subjective characteristics are treated as latent constructs that are determined partly by objective attributes and partly by consumers' idiosyncratic evaluations. In this model, overall product evaluations are a function of both objective attributes and latent subjective characteristics. Unlike most existing research in new product design (for exceptions, see Dahan and Srinivasan 2000; Srinivasan, Lovejoy, and Beach 1997), we present customer-ready prototypes to consumers and incorporate their ratings for the subjective product characteristics into the estimation procedure. We also propose a Bayesian forecasting procedure in which the estimated relationships are used to improve the out-of-sample prediction.

We apply our approach to the data collected in two empirical studies. We conducted the first study jointly with a U.S. manufacturer in the development project of a new power tool, for which subjective characteristics tend to influence consumers' purchase intentions strongly (Design Management Institute 1997). To explore the validity and generality of our model further, we conducted a second study in the toothbrush category. The results from both studies indicate that our model provides the product designer with (1) a better understanding of the causal relationships between the objective attributes and the subjective characteristics, (2) insights into how the objective attributes and the subjective characteristics jointly contribute to consumers' purchase decisions, and (3) an improvement in out-of-sample prediction when the model is used to forecast consumers' purchase likelihood and choice compared with using the traditional conjoint models. Therefore, our model proves to be valuable in both providing diagnostics and improving prediction.

We organize the rest of this article as follows: First, we discuss our view of consumer product evaluation. Second, we present the mathematical representation of our model. Third, we compare our proposed model with several alternative models in two empirical applications. We conclude by summarizing results, discussing limitations, and providing directions for further research.

OUR PERSPECTIVE OF PRODUCT EVALUATION

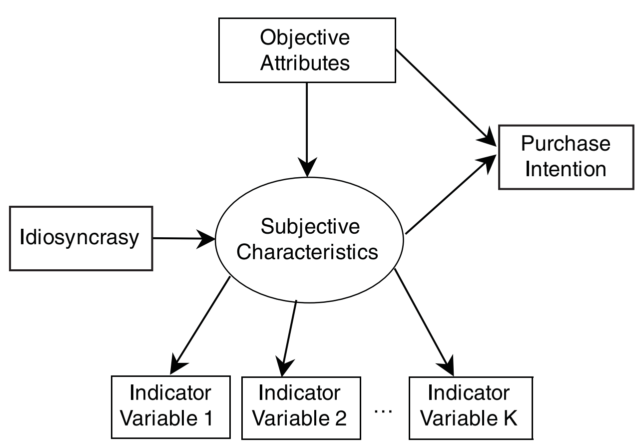
Traditionally, most consumer preference elicitation models, such as conjoint models, view a product as a bundle of objective attributes (e.g., price, features). The implicit assumption is that consumer preference is solely a function of these attributes. The advantage of considering only the objective attributes is that the values of these attributes are the same for everyone. As a result, firms can collect consumers' responses to a set of hypothetical product concepts quantified by these attributes. However, several researchers have questioned this view of product evaluation. For example, Srinivasan, Lovejoy, and Beach (1997) argue that consumer preference for a product is only partially captured by the objective attributes. Tybout and Hauser (1981) find that a combination of the objective attributes and the subjective characteristics (called "physical attributes" and "consumer perceptions" in their study) better explains consumer preference than using just the objective attributes.

Our view of consumer product evaluation (see Figure 1) includes both objective and subjective criteria. Following the suggestion of Srinivasan, Lovejoy, and Beach (1997), we propose that for firms to understand the impact of the subjective characteristics on consumers' purchase intentions, customer-ready prototypes are necessary at the product evaluation stage.[1] Our model views each prototype as a specific combination of several objective attributes (e.g., shape, switch type, and weight in the power tool example), with price included as an additional attribute. The complete set of product designs is defined by all the possible combinations of the objective attribute levels. As the combination varies, consumers' perceptions of the subjective product characteristics (e.g., perceived power, perceived comfort) change accordingly.

As Figure 1 shows, we view the subjective characteristics as latent constructs, with consumers' ratings of their perceptions of these characteristics treated as indicator variables. Modeling the subjective characteristics as latent constructs (1) avoids the direct use of consumer perception ratings in the utility function, which may provide misleading results given the presence of the measurement errors (Ashok, Dillon, and Yuan 2002), and (2) allows for differences in precision of ratings among individuals. For example, experts may provide more precise ratings (i.e., lower measurement error variances) and possess a more refined knowledge structure to distinguish different latent con-

[1]As Gerald M. Mulenburg (chief of Aeronautics and Spaceflight Hardware Development Division at NASA) pointed out, "it is far easier for clients to articulate what they want by playing with prototypes than by enumerating requirements" (Mulenberg 2004, p. 9).

Figure 1
VIEW OF PRODUCT EVALUATION



structs (i.e., lower factor covariances) than novices (Ansari, Jedidi, and Jagpal 2000). Accordingly, we allow the measurement error variances and the factor covariances to vary across individuals.

We define the subjective characteristics as a function of (1) the objective attributes and (2) consumer idiosyncrasy. The former has received significant support in the literature (e.g., Griffin and Hauser 1993; Gupta and Lord 1995; Hauser and Clausing 1988; Narasimhan and Sen 1992; Neslin 1981; Tybout and Hauser 1981), and the latter captures additional variation in consumers' subjective perceptions. Consider the example of power tools; although a consumer with a smaller hand size may have relative preferences among different switch types, he or she may rate the entire design space toward the low end on the scale of perceived comfort.

Finally, we hypothesize that a consumer's purchase intention can be affected by both the objective attributes and the subjective characteristics. Because the objective attributes affect consumers' perceptions of the subjective characteristics, a simple model with both the objective attributes and the subjective characteristics as explanatory variables of consumer preference is subject to the problem of multicollinearity (Tybout and Hauser 1981). To address this issue, we examine all the causal relationships in Figure 1 simultaneously using an HB structural equation model (Bollen 1989). This hypothesis derives its support from Huber and McCann's (1982) study, which shows that consumers spontaneously use the visible attributes as cues to make inferences about the unobservable product attributes or characteristics. The imputed values are then integrated with the available attribute information to form preferences. Rather than imputing the unobservable values, we show that consumer perceptions of the subjective characteristics can be measured and incorporated into a model of product evaluation.

The general framework in Figure 1 subsumes various models as special cases. For example, the traditional conjoint model is obtained when the subjective characteristics have zero impact on purchase intention. Alternatively, we can have a model in which the subjective characteristics completely mediate the influence of the objective attributes on purchase intention (i.e., the direct link from objective attributes to purchase intention in Figure 1 disappears). In addition, consumers' perceptions of the subjective characteristics can be driven by a subset of the objective attributes in the design space. Furthermore, different consumers can make inferences on the subjective characteristics from different subsets of the objective attributes. The relative importance of consumer heterogeneity in evaluating these attributes may also vary across product categories.

The merit of our proposed model lies not only in its flexibility to accommodate the various possibilities but also in its ability to provide the product designer with valuable answers to these empirical questions. For example, the empirical results from our model may suggest that subjective characteristics do not play an important role in a laptop purchase. This may imply that marketers should promote the objective attributes (e.g., a high-resolution monitor, a long battery life) when launching new laptops. Alternatively, researchers using our model may find that the purchase of sunglasses is driven purely by consumers' perceptions of the subjective characteristics, such as perceived comfort and aesthetics. That is, these subjective characteristics completely mediate the impact of the objective attributes on purchase intention. Under such a scenario, marketers may need to communicate the aesthetics and comfort of the sunglasses to the consumers. Even when both the objective attributes and the subjective characteristics affect consumers' purchase decisions (this is probably the case for most purchases), it is useful to understand the underlying causal relationships. For example, without accounting for the subjective characteristics, a traditional conjoint analysis may suggest that consumers are more likely to purchase an office chair when it is offered at a high price. However, our model may suggest that consumers perceive a high-priced office chair as more durable, which leads to a higher purchase intention, and that the direct impact of price on purchase intention is actually negative. If the marketers ignore the role of the subjective characteristics, they may position their products as "luxurious" office chairs rather than "durable" office chairs.

Finally, it is likely that the most important application of this model is for predictive purposes in estimating potential demand for new design concepts. Given the design space defined by all the possible combinations of the objective attribute levels, we posit that firms need to develop only a subset of the product concepts into prototypes. Using the estimated relationships between the objective attributes and the subjective characteristics, we can forecast the values of the subjective characteristics for the out-of-sample product alternatives. Such predictions, along with the other estimated relationships in the model, can be used to forecast the purchase likelihood of these alternatives and thus determine the optimal design.

Ashok, Dillon, and Yuan (2002) also consider a model that incorporates latent attitudes and perceptions. However, our approach is different in focus and execution. Whereas Ashok, Dillon, and Yuan make an important contribution by demonstrating how to incorporate latent attitudes into discrete choice models, their focus is mainly on perceptions of satisfaction and other latent attitudes of existing products. Because these attitudes might exist independently of the objective product attributes, Ashok, Dillon, and Yuan do not explore relationships between objective attributes and latent attitudes. In contrast, our primary focus is on product design and the relationship between objective attributes and subjective characteristics. Thus, we model subjective characteristics as a function of objective attributes and individual-specific effects and purchase intent as a function of both objective attributes and subjective characteristics.

MODEL DEVELOPMENT

The HB Structural Equation Model

We use an HB structural equation system to form the basis of our model. We specify the relationships outlined in Figure 1 for each individual. At the population level, we specify population distributions to model variations in individual-level parameters.

Let $i = 1, \ldots, N$ represent the individuals, and let $s = 1, \ldots, S$ index the product profiles used in the calibration sample. Suppose that these product profiles are constructed in a fractional factorial design using the orthogonal design criterion (Addelman 1962) and developed into prototypes. Each individual provides the following information: (1) purchase likelihood of each prototype (denoted as pr_{is}) and (2) answers to a series of questions that assess his or her perceptions of the subjective product characteristic (denoted as a $[K \times 1]$ vector v_{is}). Let x_s denote the $(M \times 1)$ vector of objective attributes. Let z_{is} be the $(J \times 1)$ vector of latent constructs representing individual i's perceptions of the subjective characteristics of prototype s, and let the $(K \times 1)$ vector v_{is} be the observed indicator variables.

For individual i, we can write the mapping between the observed indicator variables, v_{is}, and the latent constructs, z_{is}, in the form of measurement equations as follows:

$$v_{is} = \Lambda_i z_{is} + \varepsilon_{is}. \tag{1}$$

In Equation 1, the $(K \times J)$ matrix, Λ_i, contains the factor loadings that map the indicator variables onto the latent constructs. The term $\varepsilon_{is} \sim MVN(0, \Theta_i)$ represents the vector of measurement errors. To make the factor scores comparable across individuals and to preserve the interpretability of the constructs (Ansari, Jedidi, and Jagpal 2000; Yung 1997), we assume that the factor-loading matrices are invariant across individuals; that is, $\Lambda_i = \Lambda$, for $i = 1, \ldots, N$. Following the tradition in confirmatory factor models, we also set the appropriate elements in the loading matrix Λ to be unity for identification.[2] Finally, the $(K \times K)$ matrix, Θ_i, is diagonal, with the measurement error variances varying across individuals. Specifically, we assume that each measurement error variance comes from an independent inverse gamma population distribution.

The structural equation relating consumer idiosyncrasy and the objective attributes to the subjective characteristics for each individual is as follows:

$$z_{is} = \delta_i + B_i x_s + \mu_{is}. \tag{2}$$

In Equation 2, δ_i represents the $(J \times 1)$ vector of idiosyncratic terms, B_i is a $(J \times M)$ coefficient matrix denoting the effects of x_s on z_{is}, and the $(J \times 1)$ vector of $\mu_{is} \sim MVN(0, \Delta_i)$ represents the disturbance terms. We fix δ_1 to be zero for identification. This is similar to fixing the intercept of one group to zero in a multigroup analysis (Sörbom 1982). We also assume that the jth row vector (denoted as b_{ij}) in the coefficient matrix $B_i = (b'_{i1}, b'_{i2}, \ldots, b'_{iJ})'$ is distributed multivariate normal from a population distribution. Finally, we allow the $(J \times J)$ variance–covariance matrix Δ_i to vary across individuals with an inverse Wishart population distribution.

We now consider the structural equation of purchase intention. For individual i, the indicated purchase likelihood for product profile s is pr_{is}. Following the common practice in conjoint studies (Mahajan, Green, and Goldberg 1982; Moore, Gary-Lee, and Louviere 1998; Sawtooth Software 2002), we employ a logit transformation on pr_{is} to ensure that the predicted purchase likelihood for each profile in the design space is bounded between 0 and 1. Therefore, we have the following:

$$\ln\left(\frac{pr_{is}}{1 - pr_{is}}\right) = y_{is} = A_i x_s + \gamma_i z_{is} + e_{is}. \tag{3}$$

In Equation 3, A_i is a $(1 \times M)$ vector reflecting the direct impact of the objective attributes on purchase intention, γ_i is a $(1 \times J)$ vector denoting the influence of the subjective characteristics on purchase intention, and $e_{is} \sim N(0, \sigma_e^2)$ denotes the error term. Specially, we assume that the row vector of $\eta_i = \{A_i, \gamma_i\}$ is distributed from a multivariate normal population distribution.

In summary, after accounting for the individual-level model and the heterogeneity specifications, we can write the complete HB model as follows:

Individual-level model:

$$\begin{aligned} v_{is} &= \Lambda z_{is} + \varepsilon_{is} \\ z_{is} &= \delta_i + B_i x_s + \mu_{is} \\ y_{is} &= A_i x_s + \gamma_i z_{is} + e_{is} \\ \varepsilon_{is} &\sim MVN(0, \Theta_i) \\ \mu_{is} &\sim MVN(0, \Delta_i) \\ e_{is} &\sim N(0, \sigma_e^2). \end{aligned} \tag{4}$$

Population-level model:

$$\begin{aligned} \theta_{ik} &= \mathrm{diag}(\Theta_i) \sim IG(\varsigma_k, \psi_k), \text{ for } k = 1, \ldots, K \\ \Delta_i^{-1} &\sim W(\rho, R) \\ \delta_i &\sim MVN(\kappa, \Sigma) \\ b_{ij} &\sim MVN(\beta_j, D_j), \text{ for } j = 1, \ldots, J \\ \eta_i &\sim MVN(\varphi, \Omega). \end{aligned} \tag{5}$$

Given our model setup, an alternative model would be a traditional conjoint model using prototypes as stimulus presentation (i.e., a model directly relating y_{is} to x_s). The key difference between our model and a traditional conjoint model is that we collect consumers' ratings on the subjective characteristics as augmented data. As long as these subjective perceptions (z_{is}) contain information about the individual (i) that is independent of the objective attributes (x_s), it is possible for our model to explain purchase intent (y_{is}) better than the traditional conjoint model. The separate individual-level intercepts (δ_i) allow this relationship between subjective perceptions and personal characteristics to be captured. However, even if δ_i were the same across individuals, B_i and γ_i in Equation 4 could vary across individuals. To replicate the results implied by our model from estimating the relationship between y_{is} and x_s, it would be necessary to capture the resultant distribution of the product of B_i and γ_i. Therefore, because our model incorporates additional information on subjective characteristics (z_{is}) that can influence purchase intent (y_{is}), we expect the pro-

[2]Although this structural approach explicitly accounts for measurement errors in v_{is}, we acknowledge that our model could possibly become overparameterized. An alternative approach would be to use the average ratings of v_{is} to represent the subjective characteristics, which would result in an HB path analysis model. We present a summary comparison between these two modeling approaches in our empirical application section; details of this comparison are contained in the Web Appendix (see www.marketingpower.com/jmrapril08).

posed model to have incremental in-sample fit over the traditional conjoint model.[3]

The estimation of this model is carried out in a Markov chain Monte Carlo procedure. In particular, the unknown parameters in our model are given by $\{\Lambda, \sigma_e^2, \{\varsigma_k\}, \{\psi_k\}, \rho, R, \kappa, \Sigma, \{\beta_j\}, \{D_j\}, \varphi, \Omega\}$. We can express the joint density of all model parameters as follows:

$$(6)\quad f(\{\Lambda, \sigma_e^2, \{\varsigma_k\}, \{\psi_k\}, \rho, R, \kappa, \Sigma, \{\beta_j\}, \{\Delta_j\}, \varphi, \Omega\} | \{y_{is}\},\{v_{is}\})$$
$$\propto \prod_{i=1}^{N}\prod_{s=1}^{S} f(y_{is}|x_s, z_{is}, \eta_i, e_{is}) f(v_{is}|z_{is}, \Lambda, \varepsilon_{is})$$
$$f(z_{is}|x_s, \delta_i, \{b_{ij}\}, \mu_{is}) f(\eta_i|\varphi, \Omega) f(e_{is}|\sigma_e^2)$$
$$f(\varepsilon_{is}|\{\theta_{ik}\}) f(\delta_i|\kappa, \Sigma) f(\{b_{ij}\}|\{\beta_j\}, \{D_j\}) f(\mu_{is}|\Delta_i)$$
$$f(\{\theta_{ik}\}|\{\varsigma_k\}, \{\psi_k\}) f(\Delta_i|\rho, R)$$
$$f(\Lambda, \sigma_e^2, \{\varsigma_k\}, \{\psi_k\}, \rho, R, \kappa, \Sigma, \{\beta_j\}, \{D_j\}, \varphi, \Omega).$$

We use the Gibbs sampler and the Metropolis–Hastings algorithm to sample draws from the full conditional distribution of each block of the parameters.[4] The outputs of our Bayesian estimation are the posterior distributions of these parameters, with all the underlying relationships in the model accounted for simultaneously.

Prediction Procedure for Out-of-Sample Product Alternatives

In this section, we discuss how to use these posterior distributions to predict the values of the subjective characteristics and purchase likelihood for product concepts not included in the calibration sample. Our main premise is that for these out-of-sample product alternatives, the latent measures of the subjective characteristics can be predicted from the estimated links between the objective attributes and the subjective characteristics. Such predictions, along with the other estimated relationships in the model, can be used to predict the purchase likelihood of these products.

We first describe the procedure of estimating the posterior predictive distribution of the latent factor scores. In our calibration sample, we estimate the posterior distribution of the factor scores z_{is} on the basis of the priors and information from two data sources. The first data source is the measurement equation $v_{is} = \Lambda z_{is} + \varepsilon_{is}$. The second data source is from the structural equation $z_{is} = \delta_i + B_i x_s + \mu_{is}$. Therefore, we can write the full conditional distribution of z_{is} as $MVN(\omega_{z_{is}}, \Delta_{z_i})$, where $\omega_{z_{is}} = \Delta_{z_i}[\Delta_i^{-1}(\delta_i + B_i x_s) + \Lambda'\Theta_i^{-1}v_{is}]$ and $\Delta_{z_i}^{-1} = \Delta_i^{-1} + \Lambda'\Theta_i^{-1}\Lambda$. Let g = 1, …, G represent the index of the out-of-sample product alternatives, x_g denote the vector of the objective attribute combination for product g, and z_{ig}^p be the vector of predicted factor scores. We can express the posterior predictive distribution of z_{ig}^p as $MVN(\omega_{z_{ig}}, \Delta_{z_i})$, where $\omega_{z_{ig}} = \Delta_{z_i}[\Delta_i^{-1}(\delta_i + B_i x_g) + \Lambda'\Theta_i^{-1}v_{is}]$ and Δ_{z_i} is as defined previously. The basic idea is that when the combination of the objective attribute levels changes from x_s (in-sample) to x_g (out-of-sample), we can use the posterior distribution of the model parameters to forecast the individual-level subjective perceptions (i.e., z_{ig}^p) for the out-of-sample product alternatives.

We now explain the procedure of estimating the posterior predictive distribution of purchase likelihood. Let $\xi = \{\Lambda, \sigma_e^2, \{\varsigma_k\}, \{\psi_k\}, \rho, R, \kappa, \Sigma, \{\beta_j\}, \{D_j\}, \varphi, \Omega\}$ denote all the parameters in our model, y_{ig}^p be the predicted purchase intention of individual i for product alternative g, and Pr_g^p be the expected purchase likelihood of product g over the entire sample of respondents. Given a particular objective attribute combination (i.e., x_g), we can calculate the posterior predictive distribution of purchase likelihood (i.e., Pr_g^p) from random draws of the parameters from the posterior distribution (Equation 7):

$$(7)\quad f(Pr_g^p | x_g, \{y_{is}\}, \{v_{is}\}) = \int \prod_{i=1}^{N} \frac{\exp(y_{ig}^p)}{[1 + \exp(y_{ig}^p)]^2}$$
$$f(y_{ig}^p|x_g, z_{ig}^p, \xi) f(z_{ig}^p|x_g, \xi) f(\xi|\{y_{is}\}, \{v_{is}\}) d\xi.$$

In Equation 7, the first component in the integral is the conditional predictive density distribution of the purchase likelihood, the second component is the conditional predictive distribution of purchase intention, the third component is the conditional predictive distribution of the individual-level factor scores (discussed previously), and the last component is the posterior distribution of model parameters ξ. As Rossi and Allenby (2003) point out, an advantage of this full Bayesian prediction approach is that the uncertainties in the model parameters are factored into the managerial decision itself.

Given the procedure summarized in Equation 7, the product designer can predict the purchase likelihood of the out-of-sample product alternatives given their objective attribute values and the estimated relationships in the model. Because the values of the subjective characteristics are predicted from the objective attributes and because these predictions are used to limit the error in the prediction of purchase likelihood, we expect our model to do better in out-of-sample prediction than the traditional conjoint model. An optimal design from the entire design space can then be selected according to the posterior means of the predicted purchase likelihood.

EMPIRICAL APPLICATIONS

In this section, we illustrate the proposed model in two empirical applications. We also compare the in-sample fit and predictive power of this model with several benchmark models.

[3]The proposed model can be identified as long as z_{is} and x_s are not perfectly correlated. When independent variation in z_{is} is not explained by x_s and this helps explain y_{is}, the proposed model remains valid. This identification becomes more precise as the independent variation in z_{is} increases. If z_{is} were perfectly collinear with x_s, Equation 4 would not be identified. However, a reduced-form relationship between y_{is} and x_s (the traditional conjoint model) could still be estimated.

[4]The prior distributions, the conditional distribution for each block of the model parameters, and the simulation steps involved in the Markov chain Monte Carlo procedure appear in the Web Appendix (see www.marketingpower.com/jmrapril08).

Study 1: The Design of a Handheld Power Tool

Data. The study context was the design of a handheld power tool by a U.S. manufacturer. On the basis of exploratory research and field studies, we identified four objective attributes (shape, switch type, weight, and price) and two subjective characteristics (perceived power and perceived comfort) as the important objective and subjective criteria for the users of this power tool.[5] We did not include brand as an objective attribute, because its impact on purchase intention is identical across all the design candidates. Given the various combinations of the objective attribute levels, ten product profiles were constructed in a fractional factorial design using orthogonal design criterion (Addelman 1962). These product profiles were developed into customer-ready prototypes.

The data for this study were collected from 51 construction and metal workers recruited from various job and construction sites in a large metropolitan area. Ten customer-ready prototypes were presented for evaluation. Each prototype was painted gray and had an attached price tag. Our experiment consisted of two stages.

In Stage 1, we asked the participants to imagine that they were shopping for the power tool in a retail store. The participants had an opportunity to touch and feel each prototype before providing their purchase likelihood ratings on an 11-point scale anchored by "extremely unlikely" and "extremely likely." We purposely did not ask the participants about their opinions on any of the subjective characteristics at this stage, because previous research has indicated that prompting inferences may significantly alter consumers' preferences (Huber and McCann 1982).

In Stage 2, we collected additional information on the participants' subjective perceptions. We used a three-item measure and a seven-point scale anchored by "strongly disagree" and "strongly agree" to assess perceived power (i.e., "I expect this tool to be powerful," "This tool feels weak" [reverse coded], and "This tool may not be powerful enough to do my job" [reverse coded]). We used a four-item measurement scale to assess perceived comfort (i.e., "The grip of this tool feels comfortable," "This tool feels balanced," "This tool is difficult to use" [reverse coded], and "The configuration of this tool will allow me to do my job without any kind of obstruction"). We conducted a pretest with 80 observations across eight participants to assess the validity and reliability of these measurement scales. We tested the convergent and discriminant validities through confirmatory factor analysis (Bollen 1989). Cronbach's alpha for perceived power was .778, and for perceived comfort, it was .747. We used standardized values of the subjective measures in our analysis.

Models. We used data from the first nine prototypes for calibration. We estimated the following models on the calibration sample: Model 1 is the proposed model. Model 2 used only the latent constructs of the subjective characteristics as explanatory variables of purchase likelihood.[6] In Model 3, purchase likelihood is solely a function of the objective attribute values.[7] We kept the HB method as the common denominator for all three models so that the comparisons of model fits could be purely ascribed to the underlying relationships in the models and not to improvement from the use of a Bayesian technique. In particular, Model 3 is identical to a prototype-based conjoint model estimated by an HB technique.[8]

Measures of in-sample fit. We use three measures to assess the in-sample fits of these models. First, we estimate the percentage of variance acounted for as follows:

$$\text{(8)} \qquad \text{Pseudo } R^2 = \frac{\sum_{i=1}^{N}\sum_{s=1}^{N}(\hat{y}_{is} - \bar{y})^2}{\sum_{i=1}^{N}\sum_{s=1}^{N}(y_{is} - \bar{y})^2},$$

where $\hat{y}_{is}$ is the predicted purchase likelihood and $\bar{y}$ is the average of all observations.

Second, we calculate the deviance information criterion (DIC) (Spiegelhalter et al. 2002) as follows:

$$\text{(9)} \qquad \text{DIC} = D(\bar{\xi}) + 2p_D,$$

where $D(\bar{\xi}) = -2\log[f(y|\bar{\xi})]$ is the deviance obtained by substituting the posterior means of the model parameters into the log-likelihood function of the observed $y = \{y_{is}\}$ and $p_D = E_{\xi|y}\{-2\log[f(y|\xi)]\} + 2\log[f(y|\bar{\xi})]$ represents the effective number of model parameters. A smaller DIC value indicates a better model–data fit after the complexity of the model is penalized.

Third, we provide a posterior predictive check of internal validity (Gelman, Meng, and Stern 1996; Jedidi, Jagpal, and Manchanda 2003). We begin by generating a replicated data set of $\{y_{is}^{rep}\}$ using the observed values of the explanatory variables and the posterior distribution of the model parameters (denoted as ξ). We can express the posterior predictive distribution of $\{y_{is}^{rep}\}$ as follows:

$$\text{(10)} \qquad f(y_{is}^{rep}|y_{is}) = \int f(y_{is}^{rep}|\xi)f(\xi|y_{is})d\xi.$$

We then compare the replicated data set and the actual data set using a discrepancy variable, RMSD (root mean square discrepancy), which is defined as follows:

[5]Some supplemental information related to both empirical studies (e.g., experimental design, stimulus description, auxiliary estimation results) appear in the Web Appendix (see www.marketingpower.com/jmrapril08).

[6]Mathematically, we can express the individual-level model as follows: $v_{is} = \Lambda z_{is} + \varepsilon_{is}$, and $y_{is} = \alpha_i + \gamma_i z_{is} + e_{is}$. The heterogeneity specifications and the population-level distributions are similar to the specifications in the proposed model. We kept the mathematical representation of this model similar to that of the proposed model so that the difference in model fits could be ascribed purely to the exclusion of the objective attributes.

[7]The individual-level model can be presented as $y_{is} = \beta_i + \pi_i x_s + \varpi_{is}$. The heterogeneity specifications and the population-level distributions are similar to the specifications in the proposed model.

[8]We also conducted an ordinary least square (OLS) conjoint estimation at the individual level. Because the number of observations per respondent equals the number of parameters, our individual OLS estimation did not provide satisfactory results. Therefore, we do not report the individual OLS estimation results here.

$$\text{(11)} \qquad \text{RMSD} = \sqrt{\frac{\sum_{i=1}^{N}\sum_{s=1}^{S}(y_{is}^{rep} - y_{is})^2}{N \times S}}.$$

The advantage of this internal validity check is that it considers both the mean and the variance of the prediction and is free of asymptotic definitions.

Results of in-sample fit comparisons. The results of the in-sample fit comparisons appear in the top panel of Table 1. With regard to the pseudo-R-square measure, the proposed model explained more variance in the observed purchase likelihood than the other models. Because the key difference between the proposed model and the subjective-only model is the exclusion of objective attributes, we observed that the addition of the objective attributes explained an extra 5% (i.e., .615 – .565) of the variance in purchase likelihood. Similarly, a comparison between the proposed model and the HB conjoint model suggests that the subjective characteristics contributed to an extra 9.2% (i.e., .615 – .523) of the variance in purchase likelihood in the proposed model. When both the objective attributes and the subjective characteristics influence purchase likelihood, dropping either group of data from the explanatory variables of purchase likelihood results in a loss of model fit. In the power tool application, the loss due to the exclusion of the subjective characteristics is relatively larger than the loss due to the exclusion of the objective attributes (i.e., 9.2% versus 5%). Even with the use of a DIC measure, which penalizes the more complex model, we found that the proposed model provided the smallest DIC value, followed by the subjective-only model and the HB conjoint model. We found a similar pattern for the discrepancy measure, RMSD.

Measures of predictive power. Next, we examine the predictive power of these models. In practice, researchers often need to predict the purchase likelihood of the out-of-sample products on the basis of their physical configurations (i.e., the values of the objective attributes). Therefore, in the holdout sample, only the values of the objective attributes are used to predict purchase likelihood.[9] We summarize the prediction procedure for Model 1 in Equation 7. The prediction procedure for Model 3 follows the convention of conjoint models. Specifically, we use two measures to assess the predictive power. First, we calculate the mean absolute error (MAE) between the true (Pr_{ih}) and the estimated ($\hat{P}r_{ih}$) purchase likelihoods in the holdout sample (h is the index for holdout profile):

$$\text{(12)} \qquad \text{MAE} = \frac{\sum_{i=1}^{N}\sum_{h=1}^{H}\left(\left|Pr_{ih} - \hat{P}r_{ih}\right|\right)}{N \times H}.$$

Second, we calculate the root mean square error (RMSE) between the true (Pr_{ih}) and the estimated ($\hat{P}r_{ih}$) purchase likelihoods in the holdout sample (h is the index for holdout profile):

$$\text{(13)} \qquad \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}\sum_{h=1}^{H}\left(Pr_{ih} - \hat{P}r_{ih}\right)^2}{N \times H}}.$$

Results of predictive power comparisons. We first compared the actual purchase likelihood data collected on Prototype 10 with the predicted purchase likelihood. As evident in the second panel of Table 1, the proposed model predicted the actual purchase likelihood better than the HB conjoint model (smaller MAE and RMSE).

Because we collected purchase likelihood data and the subjective characteristic ratings from all ten prototypes, we further investigated the predictive power of the proposed model and the HB conjoint model in a robustness check. We conducted a hold-one-out validation iteratively. First, we chose one prototype among the ten prototypes as the holdout prototype. Second, we calibrated the model on the remaining nine prototypes. Finally, we used the model estimates to predict the purchase likelihood of the holdout prototype. We repeated this procedure until each of the ten prototypes had been selected as the holdout prototype. In each prediction scenario, we used only the values of the objective attributes to predict the purchase likelihood of the holdout prototype.

Table 2 provides the average MAE and the RMSE measures of both the proposed model and the HB conjoint model over the ten prediction scenarios. For each prediction scenario, we also calculated the percentage of improvement in the MAE and RMSE measures when the proposed model was compared with the HB conjoint model. For example, when Prototype 10 was the holdout prototype (Table 1), we calculated the percentage of improvement in MAE as 13.05% (i.e., [12.41% – 10.79%]/12.41%). The ranges of the percentage improvement appear in the last column of Table 2. Overall, our model comparisons and robustness

[9]Model 2 lacks predictive power because the objective attributes are not included in the model.

Table 1
MODEL COMPARISONS: POWER TOOL STUDY

	Proposed Model (Model 1)	*Subjective Only (Model 2)*	*HB Conjoint (Model 3)*
In-Sample Fit			
Pseudo-R^2	.615	.565	.523
DIC	1658.270	1669.337	1770.040
RMSD	.330	.358	.405
Predictive Power			
MAE	10.79%	—	12.41%
RMSE	12.13%	—	15.58%

Table 2
ROBUSTNESS CHECK IN PREDICTIVE VALIDITY: POWER TOOL STUDY

Predictive Power	*Proposed Model: Average (%)*	*HB Conjoint: Average (%)*	*Range of Improvement (%)*
MAE	11.45	13.39	10.23–17.65
RMSE	12.53	15.52	14.69–22.14

check indicate that the proposed model outperforms the benchmark models in goodness-of-fit and out-of-sample prediction.

Parameter estimates of models. Table 3 reports the parameter estimates from the proposed model and the HB conjoint model. The population posterior standard deviations appear in parentheses as an indication of heterogeneity in preferences within the population. Columns 2–4 in Table 3 provide the estimates from the proposed model. As evident, there is a large dispersion in the idiosyncratic terms of perceived power and perceived comfort. This indicates that the idiosyncratic characteristics play an important role in determining the heterogeneous subjective perceptions across individuals. With respect to perceived power, our model estimates indicate that, in general, switch types did not have a large influence on consumers' perceptions of whether the tool is powerful. Among the other product attributes, a larger-than-ultimate body-grip shape, heavy weight, and a high price were perceived as being powerful. This is consistent with previous research on price–quality inference (e.g., Rao and Monroe 1989, 1996). In terms of perceived comfort, consumers did not seem to relate price levels to comfort. In contrast to perceived power, a lightweight power tool was considered comfortable to use. In addition, a trigger switch was perceived as the most comfortable at the population level, though the heterogeneity across individuals was relatively high. With regard to purchase intentions, consumers valued perceived comfort more than perceived power when making purchase decisions. These subjective characteristics partially mediated the influences of the objective attributes on purchase intention. In particular, the direct effect of higher prices on purchase intention was negative. The last column in Table 3 gives the model estimates from the HB conjoint model. This model suggests that consumers preferred a high-priced power tool. According to what we observed in the proposed model, the consumers preferred such a power tool because they perceived it as powerful, not because they liked to pay more.

Given our model estimates, we can calculate the total effects of changing an objective attribute (direct effect on purchase intention plus indirect effect on subjective perceptions). Consider the effects of paddle and trigger switches in Table 3. At the population level, we could obtain the total effect of the paddle on purchase intention as follows:

$$\text{Paddle effect} = .065 + .207 \times .011 + .726 \times .130 = .162,$$

Table 3

PARAMETER ESTIMATES AND OPTIMAL DESIGN SPECIFICATIONS: POWER TOOL STUDY

	Parameter Estimates			
	Proposed Model			*HB Conjoint Model*
Parameter	*Perceived Power*	*Perceived Comfort*	*Purchase Intention*	*Purchase Intention*
Constant	.053 (.162)	.169 (.123)	—	.187 (.172)
Shape				
Rear motor	–.159 (.109)	.051 (.097)	–.255 (.096)	–.253 (.113)
Ultimate body grip	–.120 (.109)	–.008 (.092)	–.037 (.090)	–.056 (.100)
Larger-than-ultimate body grip	.279 (.107)	–.043 (.132)	.292 (.128)	.309 (.151)
Switch Type				
Top slider	–.070 (.096)	–.294 (.097)	–.039 (.094)	–.188 (.106)
Side slider	–.017 (.096)	–.292 (.100)	–.011 (.101)	–.226 (.112)
Paddle	.011 (.093)	.130 (.095)	.065 (.096)	.234 (.105)
Trigger	.076 (.181)	.456 (.183)	–.015 (.183)	.180 (.181)
Weight				
4.5 lbs.	–.145 (.109)	.109 (.090)	.068 (.091)	.106 (.109)
5.5 lbs.	.145 (.109)	–.109 (.090)	–.068 (.091)	–.106 (.109)
Price				
\$79	–.134 (.092)	–.001 (.094)	.105 (.091)	–.101 (.101)
\$99	.013 (.090)	.016 (.089)	–.018 (.094)	–.105 (.100)
\$129	.120 (.082)	–.015 (.076)	–.087 (.130)	.206 (.135)
Perceived Power	—	—	.207 (.095)	—
Perceived Comfort	—	—	.726 (.094)	—

	Optimal Design	
Parameter	*Proposed Model*	*HB Conjoint Model*
Shape	Larger-than-ultimate body grip	Larger-than-ultimate body grip
Switch type	**Trigger**	**Paddle**
Weight	4.5 lbs.	4.5 lbs.
Price	\$129	\$129

Notes: Population posterior standard deviations appear in parentheses. The bold text highlights the differences in the optimal designs when the proposed model and the benchmark models were used.

where .065 is the direct effect, .207 × .011 is the power effect times the effect of the paddle on power, and .726 × .130 is the effect of comfort times the effect of the paddle on comfort. A similarly calculated average effect of the trigger would be as follows:

$$\text{Trigger effect} = -.015 + .207 \times .076 + .726 \times .456 = .332.$$

Because it is viewed as more comfortable and because comfort is an important characteristic, the trigger effect is considerably larger than the paddle effect, even though its direct effect is negligible. In contrast, the standard conjoint model indicates that the paddle switch is more attractive. Incorporating perceptions of comfort into the analysis revealed that the trigger switch is the better design alternative.

Finally, we used the procedure summarized in Equation 7 to predict the purchase likelihood of the out-of-sample product alternatives. The optimal design was the one with the highest overall purchase likelihood (i.e., highest posterior mean) in the design space. A comparison in the optimal design specifications reveals that the optimal product designs identified by the two models differ in switch types (Table 3). Defining consumers' purchase intentions as a function of only the objective attributes, the HB conjoint model did not provide a prediction of purchase likelihood as accurate as the proposed model. As a result, the HB conjoint model identified a suboptimal switch type in the optimal design selection.

We also estimated an HB path analysis model in which the average ratings of perceived power and perceived comfort represented the values of the subjective characteristics. There is considerable similarity in the parameter estimates from the proposed model and the path model, except that the subjective characteristics have a relatively smaller impact on purchase likelihood in the path model than in the proposed model. This is consistent with the findings in Ashok, Dillon, and Yuan (2002). Our conjecture is that because the path model does not account for the measurement errors in the subjective characteristic ratings, the impact of these subjective characteristics appears to be smaller in the path model than in the proposed structural model. Regarding in-sample fit and out-of-sample prediction, the proposed model demonstrates better in-sample fit (in terms of pseudo-R^2 and RMSD) and out-of-sample prediction (in terms of MAE and RMSE) than the path model.[10]

Study 2: The Design of a Toothbrush

Data. In practice, the majority of conjoint experiments are paper-and-pencil or Web-based studies. Therefore, in Study 2, we further investigated the performance of the proposed model compared with both verbal and prototype-based conjoint models. In addition, by simulating a realistic retail environment, we assessed the ability of the competing models to predict actual choice behavior.

We collected the data for Study 2 from undergraduate marketing students in a large mid-Atlantic university. In the exploratory stage, we collected different designs of toothbrushes through field visits to retail outlets. We then conducted pretests to identify the set of objective attributes (i.e., price, softness of bristles, head size, bristle design, angle of head, and grip design) and subjective characteristics (i.e., perceived effectiveness and perceived comfort) used in this study. Brand was not selected for the same reason we discussed in the power tool study. Among the toothbrushes collected in the field, we chose 14 toothbrushes with various combinations of attribute levels for our study.

We included two experimental conditions in this application. The experimental setup in Condition 1 is similar to that of the power tool study. We masked the brand name and attached a tag to each toothbrush that indicated its price and the softness of the bristles.[11] In Condition 2, we conducted a verbal conjoint survey using Media Lab. Pictures of the toothbrushes were taken to depict their bristle and grip designs. Other attributes were described verbally. The participants were asked to rate their purchase likelihood on an 11-point scale for each of the toothbrushes. Condition 1 consisted of 1176 observations across 84 participants, and Condition 2 consisted of 896 observations across 64 participants.

In Condition 1, after providing the purchase likelihood ratings (Stage 1), the participants rated each toothbrush on whether they perceived it as effective or comfortable to use (Stage 2). We used a four-item measure on a seven-point scale ranging from "strongly disagree" to "strongly agree" to assess the perceived effectiveness (i.e., "I expect this toothbrush to work well," "I expect this toothbrush to be very effective in cleaning my teeth," "This toothbrush will perform better than an average toothbrush," and "This toothbrush will do a good job in preventing tooth decay"). We used a three-item measurement scale to assess the perceived comfort (i.e., "I expect this toothbrush to be more comfortable than an average toothbrush," "This toothbrush is difficult to use" [reverse coded], and "The design of this toothbrush is awkward" [reverse coded]). We conducted a pretest study with 140 observations across ten participants to assess the validity and reliability of these measurement scales. We examined the convergent and discriminant validity of these scales through confirmatory factor analysis. Cronbach's alpha for perceived effectiveness was .937, and for perceived comfort, it was .713. We used standardized values of the subjective measures in our analysis.

In both conditions, we offered each respondent $5 at the beginning of the study to purchase one toothbrush from a set of five toothbrushes. The toothbrushes available for purchase were chosen to represent five out-of-sample product alternatives in the design space (i.e., their product specifications differed from the 14 toothbrushes we used in the main study). Because this choice experiment simulates a realistic retail environment in which consumers choose among several competing products, it helps us examine how well each of the competing models can predict actual choice behavior. At the end, the chosen toothbrush and the amount remaining from the $5 were given to each participant.

Model comparisons. We used data from the first 12 toothbrushes for calibration. In Condition 1, we examined

[10]Details appear in the Web Appendix (see www.marketingpower.com/jmrapril08).

[11]Our pilot study revealed that the respondents could not identify the brand names of the masked toothbrushes by just observing their attributes.

the in-sample fit of three models (i.e., the proposed model, the subjective-only model, and the HB conjoint model). In Condition 2, we estimated an HB conjoint model.[12]

The results of the in-sample fit comparisons shown in the top panel of Table 4 indicate that the proposed model was superior to the alternatives on all measures.[13] The predictive power of the models appears in the second panel of Table 4. Similar to the prediction procedures described in the power tool application, we used only the values of the objective attributes in the out-of-sample predictions. In the hit-rate prediction, we used the first-choice rule (i.e., the respondent chooses the product with the highest overall utility) to predict the actual choice behavior of each participant under each model. A hit occurs when the model correctly predicts which of the five toothbrushes the respondent chose. Among the four models under comparison, the hit rate of the proposed model is superior to both the prototype-based (Model 3) and the verbal (Model 4) conjoint models. Using Toothbrushes 13 and 14 as holdout profiles, we also employed procedures similar to those used in the power tool application to compare the actual and predicted purchase likelihood using MAE and RMSE measures. Table 4 indicates that the relative performance of the models in terms of MAE and RMSE is similar to their relative performance on hit rates.

[12]We also estimated an HB path analysis model for the toothbrush study. The comparisons between the path model and the structural model are highly similar to the comparisons in the power tool study. Details appear in the Web Appendix (see www.marketingpower.com/jmrapril08).

[13]In Table 4, we do not report the DIC value of Model 4 because we could not directly compare the DIC values across different data sets of purchase likelihood. Model 2 does not have predictive power, because only the values of the objective attributes are used for out-of-sample prediction.

Finally, we conducted a robustness check to examine further the predictive power of the proposed model, the prototype-based HB conjoint model, and the verbal HB conjoint model. With the purchase likelihood data and the subjective ratings collected on all the 14 toothbrushes, we carried out an iterative procedure of hold-two-out validations. We first chose 2 toothbrushes from the 14 toothbrushes as the holdout products. We then calibrated each of the three models on the remaining 12 toothbrushes. We used the model estimates and the values of the objective attributes to predict the purchase likelihood of the holdout products. Table 5 presents the results of this robustness check over a total of 91 prediction scenarios. We report the average MAE and RMSE measures as well as the ranges of improvement in percentage when the proposed model is compared with the prototype-based and verbal HB conjoint models. In general, we found that the proposed model provided a considerable amount of improvement in predictive validity compared with the two HB conjoint models. To summarize, our model comparisons indicate that the proposed model is superior to all the benchmark models across both conditions regarding in-sample fit and out-of-sample prediction.

Parameter estimates. In Table 6, we provide the parameter estimates from the proposed model, the prototype-based HB conjoint model, and the verbal HB conjoint model. Notably, the proposed model estimates suggest that at the population level, price does not play an important role in consumers' perceptions of whether a toothbrush is effective or comfortable to use. In contrast, price has a strong direct impact on purchase intention such that a higher price is less preferred. The individual-specific intercepts seem to explain more variance in perceived effectiveness than perceived comfort. At the population level, consumers perceive a medium-, full-, angled-head toothbrush with a two-

Table 4

MODEL COMPARISONS: TOOTHBRUSH STUDY

	Condition 1: Prototype Based			*Condition 2: Verbal*
	Proposed Model (Model 1)	*Subjective Only (Model 2)*	*HB Conjoint (Model 3)*	*HB Conjoint (Model 4)*
In-Sample Fit				
Pseudo-R^2	.658	.449	.587	.541
DIC	3151.030	3681.814	3279.380	—
RMSD	.329	.497	.410	.469
Predictive Power				
Hit rate	75.00%	—	65.48%	60.94%
MAE	9.26%	—	11.03%	14.94%
RMSE	11.74%	—	13.31%	16.55%

Table 5

ROBUSTNESS CHECK IN PREDICTIVE VALIDITY: TOOTHBRUSH STUDY

	Condition 1: Prototype Based			*Condition 2: Verbal*	
Predictive Power	*Proposed Model: Average (%)*	*HB Conjoint: Average (%)*	*Range of Improvement (%)*	*HB Conjoint: Average (%)*	*Range of Improvement (%)*
MAE	10.15	12.28	13.46–21.99	14.85	24.23–38.05
RMSE	12.39	14.56	10.92–18.43	17.76	23.16–36.43

Table 6
PARAMETER ESTIMATES AND OPTIMAL DESIGN SPECIFICATIONS: TOOTHBRUSH STUDY

Parameter Estimates					
	Proposed Model			*HB Conjoint (Prototype)*	*HB Conjoint (Verbal)*
Parameter	*Perceived Effectiveness*	*Perceived Comfort*	*Purchase Intention*	*Purchase Intention*	*Purchase Intention*
Constant	.106 (.135)	.013 (.098)	—	.123 (.114)	.135 (.120)
Price					
$1.99	.045 (.075)	.010 (.076)	.357 (.105)	.434 (.119)	.160 (.103)
$3.39	.018 (.074)	–.028 (.075)	.103 (.075)	.092 (.078)	–.007 (.078)
$4.59	–.063 (.071)	.018 (.086)	–.460 (.129)	–.526 (.135)	–.153 (.136)
Softness of Bristles					
Soft	–.114 (.107)	–.022 (.071)	–.081 (.099)	–.103 (.116)	–.108 (.086)
Medium	.114 (.107)	.022 (.071)	.081 (.099)	.103 (.116)	.108 (.086)
Head Size					
Compact	–.108 (.107)	–.032 (.072)	–.039 (.071)	–.108 (.074)	–.109 (.076)
Full	.108 (.107)	.032 (.072)	.039 (.071)	.108 (.074)	.109 (.076)
Bristle Design					
Plain	–.909 (.126)	–.773 (.130)	–.848 (.112)	–1.347 (.165)	–1.155 (.134)
Middle indicators	–.200 (.083)	–.042 (.083)	.062 (.079)	.030 (.085)	–.298 (.095)
Three layers	.309 (.081)	.262 (.084)	.225 (.083)	.373 (.092)	.746 (.110)
Four separate groups	.149 (.091)	.135 (.089)	.124 (.084)	.239 (.096)	.140 (.091)
Two circulars	.650 (.160)	.418 (.144)	.407 (.121)	.704 (.200)	.568 (.183)
Angle of Head					
Straight head	–.109 (.071)	.017 (.073)	–.048 (.075)	–.104 (.079)	–.130 (.080)
Angled head	.109 (.071)	–.017 (.073)	.048 (.075)	.104 (.079)	.130 (.080)
Grip Design					
Plain grip	.079 (.108)	–.309 (.082)	–.249 (.080)	–.208 (.125)	–.222 (.117)
Concave without thumb grip	–.060 (.078)	.152 (.075)	.168 (.072)	.129 (.082)	.105 (.085)
Concave with thumb grip	–.019 (.117)	.157 (.079)	.081 (.040)	.079 (.136)	.117 (.122)
Perceived Effectiveness	—	—	.309 (.082)	—	—
Perceived Comfort	—	—	.250 (.095)	—	—

Optimal Design			
	Proposed Model	*HB Conjoint (Prototype)*	*HB Conjoint (Verbal)*
Price	$1.99	$1.99	$1.99
Softness of bristles	Medium	Medium	Medium
Head size	Full	Full	Full
Bristle design	**Two circulars**	Two circulars	**Three layers**
Angle of head	Angled	Angled	Angled
Grip design	**Concave with thumb grip**	**Concaved without thumb grip**	Concave with thumb grip

Notes: Population posterior standard deviations appear in parentheses. The bold text highlights the differences in the optimal designs when the proposed model and the benchmark models were used.

circular-bristle design as effective. With regard to perceived comfort, it is clear that a two-circular-bristle design and a concave handle with thumb grip are considered the most comfortable to use. Partially mediating the effects of the objective attributes on purchase intention, both subjective characteristics play an important role in consumers' purchase decisions, with perceived effectiveness valued slightly more than perceived comfort. The last two columns in Table 6 provide the model estimates from the prototype-based HB conjoint model in Condition 1 and the verbal HB conjoint model in Condition 2.

Next, we compare the optimal designs predicted by the three models (Table 6). These optimal designs vary in bristle designs and grip designs. This is intuitive because the bristle and grip design of a toothbrush exerts an indirect influence on purchase likelihood through perceived effectiveness and comfort. The absence of such effects in the traditional conjoint models led to the selection of possibly suboptimal product designs. It is not surprising that the optimal products suggested by the three models are all low priced. Because price does not have any impact on perceived effectiveness or comfort of the toothbrush, consumers always prefer a cheaper toothbrush, all else being equal.

CONCLUSIONS

In this article, we developed a formal model to incorporate the impact of the subjective characteristics in new product design. Through two empirical applications, we demonstrated that the traditional conjoint models may not be sufficiently information rich for product designers. With the creation of several customer-ready prototypes and the collection of additional data on subjective characteristics, our proposed model can help the product designer better understand (1) the causal relationships between the objective attributes and the subjective characteristics at the individual and aggregate levels and (2) how the objective attributes and the subjective characteristics jointly influence consumers' purchase decisions. Such diagnostic information can be useful for managers to position and promote the new product properly in the marketplace. Furthermore, our model provides an actionable procedure so that the product designers can account for the subjective characteristics in predicting consumers' purchase intentions for out-of-sample product alternatives. As a result, our model offers the product designer a more accurate out-of-sample prediction than the traditional conjoint models.

Historically, the qualitative aspects of the products have not received much attention in the quantitative modeling of new product design literature. From a theoretical perspective, a particular obstacle is that consumers' perceptions of the subjective characteristics often depend on a complex set of factors that can be different for different people. An additional modeling effort is needed to address this complexity. Our HB structural equation model provides a feasible solution to this problem. From the perspective of implementation, the cost of developing customer-ready prototypes has been the main concern of using prototypes in product development (Srinivasan, Lovejoy, and Beach 1997). We suggest that there are effective ways of producing the prototype stimuli. A collection of the existing products on the market can be used to form the basis of the prototype pool. Products with new features can be generated at a relatively low cost as alterations of existing products. Consequently, we believe that our methodology is amenable to practical application.

A limitation of our research is that the highly fractionated main-effects designs that we employed limited our ability to address potential interaction effects among the objective attributes. Specifically, several simulation studies employing our fractional main-effects designs indicated that our model could not uncover interaction effects after main effects were removed. This limitation could be overcome by employing other designs, which would involve presenting consumers with more prototypes. Another limitation of our proposed data collection approach is that it may not be feasible when there are large numbers of attributes or when prototypes are expensive to produce. In such situations, virtual-reality representations (Dahan and Srinivasan 2000) might be considered substitutes for physical prototypes. Finally, if prototypes or virtual-reality representations are used in various choice scenarios, a discrete choice model could be built into our conceptual framework. In this case, the general model would be similar to the model in the work of Ashok, Dillon, and Yuan (2002), which defines the subjective characteristics as functions of the objective attributes and individual-specific effects. Further research might also investigate the applicability of our approach to cases with interaction effects, high numbers of attributes, and choice-based designs.

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