Separating Brand from Category Personality

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Abstract

Consumers often describe brands by using adjectival descriptors of personality traits, and marketers often create or reinforce these perceptions by their brand positioning. Successfully positioning a brand's personality within a product category requires measurement models that are able to disentangle a brand's unique personality traits from those traits that are common to all brands in the product category. This paper proposes a factor model that separates the two by using category-level and brand-level random effects. It illustrates the model on a data-set about brand personalities in three categories (Jeans, Magazines and Cars), and investigates the marketing implications of the results obtained with the model, through analysis of the parameter estimates. The analyses provide support for our conjecture that entire product categories (or sub-categories), not simply brands within them, are perceived to possess personality characteristics, which can be leveraged for marketing strategy.

Introduction

Over forty years of research in marketing (Levy 1959; Martineau 1958) has shown that the perceptions and associations consumers have about brands go beyond their functional attributes and benefits, and include non-functional, symbolic qualities, often referred to as "brand image." Among these aspects of brand image are perceptions and associations about the brand's "personality," the "set of human-like characteristics associated with a brand" (Aaker 1997, p. 347). For instance, among soft drinks, Pepsi is often perceived by consumers as more "young," Coke as more "real and honest," Dr. Pepper as more "non-conformist and fun" (Aaker 1997, p. 348).

Not surprisingly, marketers attempt to differentiate and build preference for their brands not only on the basis of how consumers perceive them functionally but also on the basis of these brand personality perceptions (Aaker 1997; Keller 1993). It is believed that consumers prefer those brands which, in addition to satisfying their functional needs and wants, also symbolize those personality aspects that they find most congruent with their own actual or desired ("aspired to") personality associations (Belk 1988; Dolich 1969). The perceived personality of a brand can be shaped by marketers via "transferring cultural meaning" into it in various ways, such as by associating the brand in communications with an endorser or place that already possesses the personality or meaning considered strategically desirable for that brand (McCracken 1986).

In assessing the strategic desirability of creating or reinforcing a particular kind of brand personality association for a specific brand, marketers need to study both (1) the existing brand personality that consumers associate with the focal brand and its competition, and (2) the extent to which a target consumer segment desires that particular kind of brand

personality association, for that brand. The first of these analyses allows the marketer to assess how "differentiating" that particular kind of brand association will be; the second, how "relevant" and "value-creating" it will be. Both such "differentiation" and "relevance" are necessary for such a brand personality association to create consumer value (Batra and Homer 2004; Aufreiter, Elzinga and Gordon 2003).

We show below that current methods of measuring a brand's personality, and of strategically altering it (to make it more differentiating and value-creating) ignore that portion of a brand's personality perceptions that are shared by all brands in a particular product category, because they are intrinsic to that category itself. We therefore develop and illustrate a model that separates the two, thus allowing for improved strategic assessment and targeting of a brand's personality-based differentiation. The model we present also makes certain other technical contributions (modeling of individual variations in scale usage and imputation of data missing due to the design of the questionnaire).

Measuring Brand Personality

The appropriate measurement of existing brand personality imagery has been studied for over twenty years (Plummer 1984-85). Researchers have quite naturally sought to develop a valid and reliable measurement (survey) instrument of brand personality that is generalizable enough to be usable across various product categories and consumer segments, drawing on the extensive literature on human personality (Digman 1990; McCrae and Costa 1987), but going beyond it where necessary (Batra, Lehmann and Singh 1993). The measurement instrument used most often recently is the one developed by Aaker (1997). In her extensive development of this instrument, she sought to develop scales "generalizable across product categories" (Aaker 1997, p. 348), by having 631 respondents rate each of 37 brands on 114 personality traits - with these brands being carefully selected to represent a

broad array of product/service categories, a few brands per category. She factor analyzed the between-brand variance after averaging the scores of each brand on each personality trait across multiple respondents. In other words, the data matrix she factor-analyzed was based on pooled data from 37 brands across multiple product categories. Using this aggregated category/brand matrix, she found five factors, labeled Sincerity (sample item: honest), Excitement (daring), Competence (reliable), Sophistication (upper-class), and Ruggedness (tough); her scale is described in more detail below.

Two Explanations of Category Influence

It is widely acknowledged that "most of the research papers on brand personality are now based on Aaker's scale" (Azoulay and Kapferer 2003, p. 144), though her scale is not without its critics. It has been criticized on conceptual grounds, with some critics questioning whether the aspects being measured truly represent "personality" (Azoulay and Kapferer 2003; Caprara, Barbaranelli and Guido 2001). Empirically, some others have complained that it does not replicate well in other countries and consumer samples, especially when it is used to gauge within-category brand personality differences (e.g., Austin, Siguaw and Mattila 2003). Importantly for present purposes, it has also been pointed out that some brand personality scale items (those of Aaker 1997, but also others) appear, depending on the category, to pick up functional product category characteristics rather than brand personality ones. Thus in one study the brands rated highest on "energetic" were energizer drinks, while the item "sensuous" was most associated with ice cream brands (Romaniuk and Ehrenberg 2003). Given the well-known phenomenon of "concept × scale interaction" in the literature on measurement by scales such as semantic differentials (Osgood, Suci and Tannenbaum 1957; Komorita and Bass 1967), it is not surprising that certain brand

personality measurement items (in Aaker's scales, or others) might mean different things in different product categories (Caprara, Barbaranelli, and Guido 2001).

There is, however, another intriguing and important possible substantive explanation for these "category interaction" results: that entire product categories such as alcoholic beverages (or sub-categories such as beer or wine), not simply brands within them, also are perceived to possess a "personality." This explanation may in fact complement the measurement explanation provided above. Levy (1986, p. 216-217) wrote "a primary source of meaning is the product (category) itself," pointing out that within the beverage category liqueurs connote discrimination, while wine symbolizes snobbism, beer sociability and democracy, soup tradition, and juices virtue. Coffee is seen as stronger and more masculine, tea as weaker and more feminine. Consistent with his ideas, Domzal and Kernan (1992) found that ads for most beers typically highlighted friendship and social consumption, while liquor ads stressed solitude, relaxation, extroverted festivity, as well as status communication. Levy (1981, p. 55) highlighted how user stereotypes - a common source of brand personality (Keller 1993) - differ for specific food categories: chunky peanut butter for boys, but smooth peanut butter for girls; lamb chops and salads for women, steaks for men. Other researchers such as Lautman (1991) have also noted that consumers appear to have a "schema" for different categories, clusters of inter-connected emotions, facts and perceptions stored in memory as a unit. Durgee and Stuart (1987) found that consumers associate "fun" with the entire ice-cream category. Batra and Homer (2004, p. 321) report finding potato chips rated more "fun" than expensive cookies, which were rated as more "sophisticated and classy."

The Importance of studying Brand Personality Across Categories

In this paper, we maintain that entire product (sub)categories, not just brands, possess characteristic personalities, as will be demonstrated with an illustrative example.

Several consequences, which are important to marketing managers, flow from this thesis. First, market leaders often need to modify an entire category's personality, to make its consumption more attractive to a broader target market. Thus in recent years Coca-Cola sought to make diet Colas more appealing to men by making these drinks seem less "feminine," just as beer companies have tried to increase consumption by women by making them seem less "masculine." Marketers of scotch and cognac liquors run campaigns to make these drinks seem more "hip/cool" and less "formal" (Lawton 2004), while the Milk Board attempts to portray milk consumption as "adult," not just for children (Keller 2003a). Such attempts clearly call for the systematic, empirical study of the personality of various product categories.

Second, a major avenue for revenue growth in companies today is the extension of their existing brands into new categories, requiring the systematic study of many candidate categories on "personality" and "image" dimensions to see which ones best "fit" and "match" the personality of the brand being extended (Keller 2003b, p.602). Many companies also seek to leverage their existing brand assets via licensing deals to other manufacturers in other categories (such as Caterpillar and Harley into shoes and boots, both made by Wolverine Footwear); or via co-branding promotions and arrangements (such as Coach with Lexus, or Harley-Davidson and Eddie Bauer with Ford trucks). In all these cases, the company that owns the high-equity brand needs to explore which of many candidate product categories represents the highest-potential licensing or co-branding opportunities, by studying the personality characteristics of these categories in depth.

Third, even when the object of study is one particular category, there are many occasions when a researcher might wish to collect and analyze the personality data of brands coming from multiple categories. Such data analysis can often offer substantial strategic

insight into the "meanings" of a particular brand, by showing which brands in other categories are seen by consumers as being similar to it in a personality sense (see, for example, the correspondence analyses discussed by Collins 2002). Recently, for instance, an analysis showed that presidential candidate John Kerry was perceived as similar to Starbucks and Heineken, while George Bush was seen as similar to brands Dunkin Donuts and Bud Light (Landor Associates 2004). Such cross-category analogies are frequently used as sources of insight into brand personality (Plummer 1984-5). Brands from multiple categories are also often compared and ranked on their personality strengths and weaknesses, as is done by the well-known Young and Rubicam Global Brand Asset Valuator (Agres and Dubitsky 1996), which collects data on brands from a large number of categories and analyzes them jointly. And research seeking to create a generalizable brand personality measurement inventory (such as Aaker 1997) naturally collects and analyzes personality data on many brands from multiple categories.

In all these cases, any factor analysis of a pooled brand × category data matrix must partial out the "category personality" from the "brand's personality," for otherwise it could confound the two. It could be argued, of course, that most analyses of brand personality are conducted entirely within one relevant category, and do not need to utilize data from several product categories. Even here, however, when these single-category brand personality data are analyzed to assess the differentiation of one brand from another, and used to help explain differences in brand preference data, it is important to partial-out those aspects of brand personality which are category-generic ("points of parity," cf. Keller 2003b, p.133), to identify those which are truly differentiating ("points-of-difference"). It could be argued that the latter ought to be possibly more predictive of brand preference, if the "category-generic" aspects are not drivers of final brand choice because they are common to all brands in that

category. It could also be the case, however, that brands which best capture a category's mythic "desired" personality might gain in preference, since their brand personality is now most "relevant" to consumer choice criteria in that category (Batra and Homer 2004). In either case, it is critical to obtain and understand the "category personality" context within which the personality of the various brands within it must be studied.

Intended Contribution of this Study

There is thus a clear need to be able to separately measure "category personality" (CP) and "brand personality" (BP) and separate these as distinct dimensions from brand personality evaluations provided by individuals. To our knowledge, no such methodology exists, and no prior quantitative empirical study of CP has been published, despite the qualitative evidence of its importance described earlier (e.g., Levy 1986; Batra and Homer 2004). This paper will develop such a method, demonstrate an illustrative application as hinted on above, and discuss insights into the "category personality" of the three different categories that emerge from using our method. These insights are illustrative, and we make no claim at this stage that our substantive findings are necessarily generalizable. We will test whether the separation via our method of category from brand personality helps in predicting the preference scores of the brands in our illustrative data.

In summary, there exists a need for the development of research methodologies that tease apart product category influences from brand personality perceptions. Such a research methodology would have potential importance for the development of marketing strategy, in particular for advertising and brand image management. Such a methodology is developed and applied here, based on a conceptual model of the brand and category personality constructs. In addition to allowing for the extraction of category-specific factor structures and brand scores on those factors, it also presents other methodological contributions that

alleviate problems commonly encountered in collecting data for brand personality research, such as the use of individual-specific scale cut-points to accommodate differential scale usage by respondents. Section 2 describes the empirical data used in the analysis. Section 3 presents the random effects, hierarchical factor model for brand and category personality, and Section 4 discusses the results of the study. Section 5 ends with a discussion.

Preliminary Evidence of Category Personality

This section will describe the survey and data used in our study and will present the results from preliminary, standard analyses that provide face validity for the thesis of category personality. This standard analysis ignores the structure of the survey data, which is why a more involved model is developed in the next section.

Data

Data were collected on brand personality perceptions using a subject pool at a large Midwestern U.S. University. 119 respondents completed the questionnaire. The three categories were Cars, Jeans and Magazines, with ten brands in each category, as shown in Table 1. The three categories were selected because we thought they would vary meaningfully on Ratchford's (1987) think-versus-feel dimensions (i.e, in the utilitarian, symbolic, and emotional benefits they provide).

[TABLE 1 ABOUT HERE]

A major challenge in developing the questionnaire was its length and the resulting burden for respondents. Assessing a large number of brand personality items for 30 brands presents an insurmountable burden to respondents. Two solutions to this problem were adopted. First, a split questionnaire design was used. The questions were split across four groups of respondents, with each respondent evaluating approximately a quarter of the

brands for each category. The splits were assigned at random. Table 1 shows the numbers of respondents that answered the questions on each of the brands¹.

Second, for each of the brands, brand personality was assessed on only fifteen items selected from Aaker (1997). She derived 5 factors, with a total of 15 facets, and used multiple (2-3) items for each facet. We used the first (highest loading) item she gave for each of her 15 facets (See Figure 1, Aaker 1997, p. 352). The items were selected to represent the five personality dimensions identified. Table 2 presents the personality items that we used in each of the five personality dimensions. In addition to the brand personality items, the survey included two items – Overall Feelings and Overall Quality – to measure brand preference. Overall Preference is the average² of the two to obtain a measure for Brand Preference.

[TABLE 2 ABOUT HERE]

Respondents responded to the personality items on a 9-point, ordinal scale with one anchored with "[brand] is not at all like this [personality item]" and 9 described as "[brand] is very much like this [personality item]." The items and their means and standard deviations across brands within each category are also shown in Table 2. Looking across categories, given the mix of specific brands on which we have data, Cars are rated *relatively* high on Upper Class, Charming, and Spirited; Jeans are *relatively* highly rated on Out-of-Doors and Tough; and Magazines are rated *relatively* high on Up-to-Date, Honest, and Down-to-Earth. This between-category dispersion in mean ratings provides prima facie evidence that personality may vary across categories. Preferences also systematically vary across categories, with Cars scoring highest and Jeans scoring lowest.

Preliminary Analysis

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¹ Two brands, Porsche and Mercedes were used as common, first-listed "anchors" for all respondents.

² A factor analysis of these preference items indicated one factor accounting for 86% of the variance with equal loading of 0.93 and the coefficient alpha was 0.83.

A simple approach to extracting factor structures from our data would be to replicate Aakers' procedure of factor analyzing the mean scores of the brands on the personality items. This analysis ignores important features of the survey and the data: brands are nested within categories; subjects evaluate more than one brand possibly leading to correlations among brand evaluations; subjects may be heterogeneous and have different scale usage behavior; and not all subjects evaluate all brands. Inadequate modeling of these features can distort brand and category personality. For example, if the model does not account for intra-subject correlation of brand evaluations, the resulting brand and category structure may be misleading because it confounds multiple sources of correlation.

Table 3 presents the estimated factor loadings using Aaker's procedure. The presented loadings are normalized Varimax rotated factor loadings from the solution with four extracted factors. Only the first four factors have Eigenvalues greater than one. The four factor solution accounts for 80.2% of the variation in the data. Large loadings are indicated in bold face. The factors for Sincerity and Excitement are mixed, as are Competence and Sophistication. The first factor seems contrasts Sincerity and Excitement, while the second factor combines Competence and Sophistication. The third factor cleanly corresponds to Ruggedness. The fourth factor picks up the items Cheerful and Charming and does not seem to correspond to a factor in Aaker's model.

[TABLE 3 ABOUT HERE]

The estimated factor scores across all brands are uncorrelated with mean zero and variance 1 by design. Table 4 presents the means and standard deviations of the factor scores by category. The ordering of categories based on these means depends on the personality factor³. For example, Cars are more Sincere-Exciting than Magazines and Jeans,

³ A multivariate analysis of variance indicates that the category effects are very significant.

while Jeans are more Rugged than Cars and then Magazines. This result again implies significant personality difference in the categories.

[TABLE 4 ABOUT HERE]

Next, we will demonstrate interactions between categories and personality factors in their relation with Overall Preference. Table 5 presents the results from regressing Overall Preference onto the factor scores, category effects, and category by factor interactions. The main effects for category, Sincere/Excitement, and Competence/Sophistication are significant. The other factors were not significant. There are interaction effects among category and the factors. In particular, Rugged Jeans tend to be less preferred, while Cheerful/Charming Jeans tend to be more preferred in our illustrative sample data

[TABLE 5 ABOUT HERE]

Taken together, these results are consistent with our thesis that the relation between brand preference and brand personality is moderated by the category of the brand. The analyses in this section, though rather standard, ignore much of the structure of the data. The next section develops a model that alleviates these limitations.

The BP/CP Factor Model

Figure 1 presents our conceptual view of the Brand Personality construct. It presumes that the brand-personality scores (BP1, BP2,...) have a unique (idiosyncratic) component due to the specific person providing the ratings, and a common component driven by commonalities between brands within a category. A portion of this common component derives from the contribution of the different categories being rated (not just the particular brand being rated), reflecting the fact that the personality rating is derived from the individual's views of both the brand and the category, as will become clear below. The proposed model to quantify this consists of two parts.

The first part deals with the *scale measurement* of the personality construct for both brands and categories. All observed variables are ordinal, and we use a cut-point model (Congdon 2001, p. 154) to relate the ordinal data to underlying, continuous, latent variables. The cut-point model assumes that the respondent's ordinal response occurs if the continuous latent variable falls between two consecutive cut-points. Each respondent has his or her own set of cut-points that she uses in responding to all survey items, and in addition has a random effect that determines her tendency to use the scale endpoints. Accounting for such scale usage heterogeneity is of eminent importance in brand personality research, since a respondent's current or aspired-to self-personality may well idiosyncratically bias the way in which he or she rates brand personality characteristics. Our model thus effectively accounts for respondents' scale usage and can accommodate ordinal data that is highly skewed or multi-modal. Rossi, Gilula, and Allenby (2001) demonstrate that cut-point models effectively accommodate unwanted scale-usage heterogeneity. More importantly, as Figure 1 illustrates, within a category, measured brand personality items (i1,..,i15) relate uniquely to brand personality through a set of category-specific loadings (denoted by L below). These category specific loadings capture the possibly differential meaning of the items in every category, based on the theories of concept × scale interaction (Osgood et al 1957; Capara et al. 2001) outlined above.

The second model component represents the personality *dimensions* for both brands and categories. The brand personality items follow a factor model that has a hierarchical structure. This constitutes a core component of our model, since it allows us to derive both the BP and CP factor structure, where the BP structure is free of CP influence and measurement issues. The model we propose is in line with recent work on mixed outcome and hierarchical factor models by Ansari and Jedidi (2000), Wedel and Kamakura (2001), and

Ansari, Jedidi and Dube (2002). This specific structure of the brand personality factor scores will be represented by a random effects specification below (factor scores are denoted by A below), where these factor scores are decomposed into three random components contributing to the ratings of the items: 1) a unique contribution of every respondent, independent of brands and categories, 2) a contribution of a specific brand in a category, 3) the contribution of the category. These components capture the notion that the personality constructs derives from individual's views of both the brands and the category (Keller 1993; Batra and Homer 2004). Thus, the model outlined below captures both possible mechanisms – measurement, and category/brand schemata - for BP and CP structures. We now proceed with providing the details of the model. We begin with the exposition of our scale usage cutpoint model. While in some ways tangential to our main model, we need to present it here to introduce the notation used in our central model.

[INSERT FIGURE 1 ABOUT HERE]

Cut-Point Specification for Response Scale Usage

The cut-point model relates the ordinal responses to an underlying, normally distributed random variable. Figure 2 illustrates the cut-point model for an ordinal item measured on a five-point scale. In this study, all questions were on a nine point scale. $Q_{i,m}$ is the ordinal response for respondent i to question or item m. There are n respondents in the study and a total of M items. The index m will be used here in a generic sense. Personality items are crossed with brands, which are nested within product categories.

[INSERT FIGURE 2 ABOUT HERE]

The cut-point model assumes that respondent i selects scale point k for item m if a latent variable $U_{i,m}$ falls between two consecutive cut-points $\eta_i(k-1) < \eta_i(k)$:

(1)
$$Q_{i,m} = k \quad \text{if and only if } \eta_i(k-1) < U_{i,m} < \eta_i(k),$$

where there are K categories; the cut-points are specific to the respondent; and

$$\eta_i(0) = -\infty \text{ and } \eta_i(1) = -1$$
 $\eta_i(k-1) < \eta_i(k) \text{ for } k = 2,..., K-1.$
 $\eta_i(K-1) = 1 \text{ and } \eta_i(K) = \infty$

To identify the model, $\eta_i(1) = -1$ and $\eta_i(K-1) = 1$, so there are K-3 unknown cut-points per respondent, and these are estimated from the data. The choice of the value of these cut-points is arbitrary, for example, $\eta_i(1) = 0$ would be equally possible. The model accounts for individual differences in the cut-points to accommodate idiosyncratic scale use. But, since we consider the cut-points incidental parameters, we will not impose a hierarchical structure on them. The distribution of the ordinal data is derived from the latent variable and the cut-points:

$$P[Q_{i,m} = k] = P[\eta_i(k-1) < U_{i,m} < \eta_i(k)] \text{ for } k = 1,..., K$$
$$= \int_{\eta_i(k-1)}^{\eta_i(k)} dF_{i,m}(u)$$

where $F_{i,m}$ is the distribution of $U_{i,m}$, which is taken to be the normal distribution in this paper. The model for $U_{i,m}$ is:

(2)
$$U_{i,m} = \phi_i + \mu_m + V_{i,m},$$

where ϕ_i is a random effect that accounts for scale usage. The random effects are assumed to arise as a random sample from a normal distribution with standard deviation τ^4 . The mean of $U_{i,m}$ over respondents for item m is μ_m . The random term $V_{i,m}$ is normally distributed with mean zero and will be represented through various model components,

⁴ These scale usage effects are respondent-specific, and we will assume that the same effect applies to all ordinal responses in our data. We did fit a model with brand-specific scale usage random effects and found that the estimated parameters for the two models were similar and that fit statistics indicated the smaller model performed as well as the larger one

depending on the item.⁵ The next subsection provides the model for $V_{i,m}$ for a personality item, and the following subsection gives the model for the dependent variable.

Hierarchical Factor Structure for Brand Personality

There are B brands in each of the C categories. Brands within a category will be indexed sequentially from 1 to B. In our study, brands are unique to their product categories, and we will use " $b \mid i$ " to specify that brand b is nested in product category c. Respondents responded to J = 15 personality items for subsets of the brands in three categories. The model for the latent variable $V_{i,m}$ in Equation (2) for respondent i, personality item j, and brand b nested in category c is:

$$(3) V_{i,j,b|c} = L'_{j,c} A_{i,b|c} + \varepsilon_{i,j,b|c}$$

The error terms $\varepsilon_{i,j,b|c}$ are, conforming to standard assumption in factor analysis models, mutually independent, normally distributed with mean 0 and standard deviation $\sigma_{j,b|c}$. The latent factor scores contained in the $(P\times 1)$ vector $A_{i,b|c}$ are respondent-specific and follow a multivariate normal distribution with mean zero. They capture the brand personality construct, as detailed further below. The parameters in the $(P\times 1)$ vector $L_{j,c}$ are factor loadings for each personality item per brand and category. They capture the category/context effect on the measurement of the category/brand personality construct. The model is identified by setting an arbitrary $(P\times P)$ sub-matrix of the loadings matrices to be lower-triangular with ones along the diagonal. There are P loadings for each personality item within a category, and each category has a unique set of loadings, which allows for different interpretations of personality items across categories.

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⁵ These random terms are independent across respondents but correlated within respondents. Because the cutpoints and scale usage effects are specific to a respondent, this model accommodates a wide variety of distributions for ordinal data, including skewed and bimodal.

Our formulation thus extends the original work of Aaker (1997), since there the personality structure in terms of the factor loadings is assumed invariant across categories. For example in our formulation, "Reliable" may have different connotations for Cars, Jeans, and Magazines. Our formulation allows respondents to assign category specific meanings to the personality items through the loadings. In addition, our formulation recognizes person, brand and category sources of brand personality, and accommodates individual differences.

The factor scores $A_{i,b|e}$ are scaled to have mean zero and express respondent, brand and category influences on the latent personality dimensions. Respondent i's perceptions of brand b's personality is represented by the vector $A_{i,b|e}$, and personality item j is represented by the vector $L_{j,e}$. We now represent the structure of the personality data - brands nested within product categories - through a random components decomposition of the factor scores:

$$A_{i,b|c} = \alpha_i + \alpha_{i,c} + \alpha_{i,b|c}.$$

 α_i are random coefficients that reflect common personality traits across the C product categories for subject *i*. These coefficients are common to all brands. The $\alpha_{i,c}$'s are random coefficients that reflect a common personality trait across all brands within category c after removing traits common to all product categories. The same random coefficients appear for all brands within a product category, and they vary from category to category. Lastly, $\alpha_{i,b|c}$ reflect personality traits that are specific to the brand b in product category c after adjusting for category specific and common personality traits. In this way, the model disentangles brand from product category personality. The relative dispersion of the category and brand random coefficients reflects the extent to which a brand's personality is determined by the

product category. The α_i , $\alpha_{i,c}$, and $\alpha_{i,b|c}$, are $(P\times 1)$ vectors. The complete hierarchical factor model is thus:

$$V_{i,b|c} = L'_{i|c} \left(\alpha_i + \alpha_{i,c} + \alpha_{i,b|c} \right) + \varepsilon_{i,i,b|c}.$$

The random coefficients in Equation (5) are mutually independent and normally distributed with mean of zero and the following standard $(P \times P)$ covariance matrices:

$$Var(\alpha_i) = \Lambda$$
; $Var(\alpha_{i,c}) = \Lambda_c$, and $Var(\alpha_{i,b|c}) = \Lambda_{b|c}$

The off-diagonal elements are zero, so that the personality random effects are uncorrelated.

The prior distributions for all means and regression coefficients are normal with mean zero and large variances. All variance parameters come from an inverse gamma distribution. In the cut-point model, the free parameters are uniformly distributed on $\eta_i(2) < ... < \eta_i(K-2)$. As mention above, we refrain from imposing a hierarchical structure on these incidental parameters.

A final feature of our approach is that it enables imputation of missing data (if any), arising due to the structure of the questionnaire. Brand personality data, in particular when collected for several categories as proposed here, pose a substantial burden on respondents. To ensure the quality of the data and reduce the effects of fatigue and boredom, the questionnaire can (but need not) be split such that respondents only respond to part of the questions (Ragunathan and Grizzle 1995). In our empirical application we chose to split the questionnaire, by randomly assigning blocks of questions to subjects. This, however, creates missing data, hindering the application of traditional factor models. Therefore, we impute the missing data at the same time as we estimate the model, by drawing from the "predictive distribution" of the data, an approach that is made possible by the application of the Gibbs sampler (Gelfand and Smith 1990).

Brand-Category Personality Illustration

We fitted the model in Section 3 to the data that is described in Section 2 with Markov chain Monte Carlo (MCMC) methods. The MCMC algorithm ran for 30,000 iterations. The initial transition period consisted of 20,000 iterations, which were not used in estimation. Of the next 10,000 iterations, every tenth iterate was used in the analysis for a total of 1000. Traces of the iterations indicate that the chain reached the stable distribution well before the 20,000 iteration, and simulation studies using artificial data indicated that 30,000 iterations were more than sufficient: the chains using simulated data frequently converged within 3000 iterations and remained stable at the true parameters thereafter. The algorithm simultaneously imputed the data for brands that a respondent did not evaluate (Raghunathan and Grizzle 1995), thus simplifying the analysis.

Table 6 presents two fit statistics, the log marginal density of the data (LMD) and the Brier scores, for 1 to 10 factors. In Bayesian comparisons, we choose the model with the best LMD, since that measure accounts for posterior uncertainty in the parameter estimates. However, we also compute the Brier score, which we believe provides a preferable measure of fit for the data at hand, since it is tailored to discrete data and counter to the LMD we can compute its posterior standard deviation (see the Appendix for details). The Table reveals that both fit statistics decrease with the number of factors. However, the decrease in the Brier score when going from 5 to 6 factors is not "significant", i.e. the posterior credible intervals, defined as the posterior mean plus or minus three times the posterior standard deviation, do not overlap. The same holds for more than six factors; i.e. there is no improvement in fit as measured by the Brier score after five factors. In addition, looking at the interpretation of the factor solutions for 4-6 factors made us decide

to choose the five-factor solution for presentation. Note that Aaker (1997) also found five factors to underlie brand personality.

[TABLE 6 ABOUT HERE]

The individual-level cut-points in Equation (1) and the grand means and error standard deviations in Equation (2) are nuisance parameters and will not be discussed extensively here. The aggregate cut-point estimates, anchored at minus and plus one, are: (-1.000, -0.702, -0.449, -0.235, 0.033, 0.278, 0.587, 1.000). The standard errors of the heterogeneity distribution on them indicate some heterogeneity (0.000, 0.072, 0.077, 0.075, 0.074, 0.072, 0.067, 0.000; note that the first and last cut-points are fixed for reasons of identification). The random effect for scale usage ϕ_i has a posterior standard deviation, of τ = 0.233 (compare this to the range of the cut-points provided above), which presents evidence for differential usage by respondents of the nine-point scale and testifies to the importance of including this model component.

We will present below the estimated five factor model, which derived category-specific factor structures as discussed earlier. For reasons of comparison, we also estimated a model without the category specific factor structure, i.e. estimating one set of loadings across the three pooled categories. This model is comparable of that of Aaker (1997), but goes beyond it to also accommodate heterogeneity across respondents, scale usage and missing data. Whereas our five factor model with a category-specific factor structure has a log marginal density of -19813, the pooled model has a log marginal density of -20197, which is substantially smaller, supporting the value of the category-specific model. The Brier scores also point to the model with category-specific factor structure: while it has a posterior mean Brier score of 0.0673 (SD=0.0003), the pooled categories model has a Brier score of 0.0682

(SD=0.0003), which is significantly worse. Thus, there is substantial evidence of a category influence on the structure of brand personality, which we will explore in more detail below.

Brand and Category Personality Results

Table 7 displays the posterior means of the category-specific weights for the brand personality items. For comparison, Table 3, which was discussed in Section 2, presents the estimated weights for the pooled-categories, Aaker-like analysis. The presented loadings are normalized Varimax rotated factor loadings from the solution with five extracted factors. In each of these tables, the brand personality dimensions and items shown (Columns 1 and 2) are as identified by Aaker (1997), and relatively large loadings are marked in boldface.

[TABLE 7 ABOUT HERE]

Table 7 shows that there are several interesting differences with the pooled solution and across the three different category-specific factor structures, capturing the category/context effects on the measurement of personality. Our comparison proceeds by factor (using Aaker's factor names), starting with *Sincerity*. In the pooled solution, the loadings match Aaker's pattern very well, with very high loadings (above 0.76) for Wholesome (0.94), Down-to-Earth (0.95), Honest (0.0.89) and Cheerful (0.76). However in the category-specific results there are differences in how Cheerful loads, depending upon the category. For Cars, it loads not only on this Sincerity factor (at 0.79) but also on the Excitement factor (0.51). For Magazines, it loads much higher on Excitement (0.63) than on Sincerity (0.31). For Jeans, it loads about equally on both Sincerity (0.65), and Excitement (0.69).

Moving to the *Excitement* factor, we see that Aaker's factor structure again appears in the pooled data, with high loadings from Spirited (0.99), Daring (0.99), Imaginative (0.96) and Up-to-Date (0.68). However across the within-category loadings, there are important

and interesting differences in how the Up-to-Date item loads. For Cars, this item loads highly not only on Excitement (0.70) but also on Competent (0.58). For Jeans, it loads highly both on Excitement (0.65) and on Sophisticated (0.60). For Magazines, it does not load highly on Excitement at all (0.39), but does very highly load on the Competence factor (0.96).

Aaker's *Competence* factor structure does emerge, but not as cleanly, in our pooled solution: loadings are high for the Reliable (0.92) and Intelligent (0.79) items, but not from Successful (0.48), which instead loads much more highly (0.84) on the Sophistication factor. This aberrant loadings pattern for the Successful item also shows up in the category-specific solutions for Cars (0.18 with Competence, 0.96 with Sophistication), for Jeans (0.10, 0.96 respectively), and also in Magazines, though less so (0.75, 0.61 respectively). In addition, for Jeans, even the intelligent-item loads not on Competence (0.17), but instead on Sophistication (0.86).

For Aaker's *Sophistication* factor, in our pooled loadings table (Table 5), the predicted high loadings do emerge for Upper-Class (0.96) and Charming (0.82), but they are also unexpectedly high for Successful (0.84) and even for Intelligent (0.53) and slightly for Cheerful (0.42). The successful item loads on this Sophistication factor in all three within-category solutions (0.96 for Cars, 0.96 for Jeans, 0.61 for Magazines). In addition, Intelligent loads highly on this Sophistication factor for Cars (0.71; which also has reliable loading on it at 0.42) and Jeans (0.86; which also has Up-to-date loading on it at 0.60 and Reliable at 0.43). Ruggedness emerges strongly, conforming with Aaker in both the pooled and each within-category solutions.

Overall, Aakers' factors of Sincerity, Excitement, Ruggedness and to a somewhat lesser extent Competence show up quite convincingly in the pooled analysis of the data. Of

these four factors, only Ruggedness is convincingly present for all three categories in the category-specific solution. At minimum, these results indicate that the dimensions of brand personality vary in their markers and measurement in different product categories, and that part of Aaker's solution — as does our pooled solution — confounds differences between categories. Recall here our earlier results that whereas our five factor model with a category-specific factor structure has a log marginal density of -19813, the pooled model has a log marginal density of -20197, which is substantially smaller, supporting the value of our category-specific model. Given the previously-cited literature on concept × scale interactions (Komorita and Bass 1967), this is not an unexpected finding.

Brand and Category Personality Insights from the Model Estimates

Our model is fairly complex with three sets of loadings (one for each category) and random personality factors for subject, category, and brands nested within category, for a total of 170 personality factor⁶ scores for each subject. Instead of displaying large tables of estimates, in this section we derive brand and category personality positions from the estimated parameters to summarize the model and to develop managerial insights. Note that these results cannot be obtained by simply applying these methods to Aakers' original scales. While such post-hoc analyses are not an integral part of our model, we believe they provide useful insights into the category structure of brand personality, especially since we use them to provide additional graphical displays of the factor structure; for these purposes we can use standard statistical packages (SPSS). We present these post-hoc analyses not as statistical tests, but as convenient ways to summarize the posterior estimates of our model, and to present them graphically to facilitate managerial interpretation.

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⁶ See Equation (5). There are five dimensional vectors for person, category, and brand nested in category or (5)(1+3+30) = 170. By construction these scores have mean zero and are uncorrelated.

For these analyses, brand and category positions are derived using a method footnoted below.⁷ Therefore, instead of 170 measures per subject, these projections result in 5 measures per brand and category. These personality projections will be used in the following analyses.

Figure 3 plots the category positions for each category and personality factor and shows the extent to which these category locations are above or below the pooled all-category mean.

[INSERT FIGURE 3 HERE]

It is apparent from this Figure that the Cars category is higher on the Sophistication Factor (Upper-Class, Successful, Charming, Intelligent); (2) the Magazine category is higher on the Competence Factor (Reliable, Up-to-Date, Intelligent, Successful) and lower on the Ruggedness Factor (Out-of-Doors, Tough); (3) the Jeans category is higher on the Ruggedness factor (Out-of-Doors, Tough) and lower on the Competence factor (Successful, Intelligent). These results may not be generalizable, limited as they are to our specific mix of ten brands per category, but they appear to make much intuitive sense, and could well be interpreted as the "relative salience" of the different personality factors across these three categories.

In a second analysis, we use the brands' personality positions to predict category membership using discriminant analysis. In predicting membership in these 3 category groups, the 2 discriminant functions explained 93.5 and 6.7% of the variance. The

factor loading for the three categories from Table 7. Third, compute brand and category positions by projecting the brand and category effects into the space defined by the loadings.

⁷ First, use the estimated item means $\mu_{j,b|c}$ for item j and brand b nested within category c from Equation (2) to compute category and brand effects: a. compute brand effects for each item by subtracting the grand mean across all brands from each of means, and b. compute category effects for each item by subtracting the grand mean across all brands from the average of the brands within the category. Second, obtain the normed, rotated

coefficients show that the first discriminant function is negatively related to Ruggedness and positively to Competence and Excitement, while the second function relates positively to Sincerity and Sophistication. The two functions correctly classified 77% of the brands, which drops to 60% in a cross-validation. Figure 4 shows the location of all the 30 brands and the three category centroids, in this two-function discriminant space.

[INSERT FIGURE 4 ABOUT HERE]

The centriod for Cars is next to Saturn, Volvo, and Gap; the centriod for Jeans is next to Guess?, and the centriod for Magazines is between People and Money. The Car category centroid is slightly above average on dimension 2, which implies it is somewhat higher on Sophistication and very slightly lower on Ruggedness. The Jeans category centroid, however, is about at the middle on Dimension 2, but very much below average on dimension 1, implying it is significantly higher-than-average on ruggedness. The Magazine category centroid is only slightly below the average on dimension 2, but significantly above average on dimension, implying it is significantly above average on Competence (but lower on Ruggedness). Figure 4 is very consistent with the results discussed earlier from Figure 2 and, again, appears to be intuitively comfortable.

It was argued earlier that examination of these Category Personality structures could potentially give companies ideas for, and help in their evaluation of, possible brand extensions and licensing and co-branding opportunities in other (new) categories. To explore how brands of one category "fit" with brands of another category in the perceptions of our sample of consumers, we performed a hierarchical cluster analysis (using the average linkage method) of our 30 brands' personality positions. Results of these are shown in Figure 5.

[INSERT FIGURE 5 ABOUT HERE]

The cluster analysis in Figure 5 yielded some extremely interesting "brand constellations" (Solomon 1983), brands in different categories perceived to be very similar in "personality space." Thus Volvo cars are seen as contiguous to Readers Digest and Parent magazines, perhaps reflecting the family/safety equities of this car brand (and adding insight into one's understanding of the perceived personality of each of these brands). Luxury cars Mercedes-Benz, Lexus and Jaguar appear contiguous to Money and GQ magazines, and to Calvin Klein Jeans: clearly, status, elegance and a sense of high fashion are shared personality attributes. Levi's jeans are very close to Chevy cars, likely reflecting the "everyman/American-ness" of both; and Guess Jeans is close to Rolling Stone magazine, reflecting perhaps the celebrity-following nature of both.

Using these results as fodder, one can brainstorm on extension and licensing and cobranding opportunities. Should Mercedes-Benz start a lifestyle magazine? Could Jaguar and Cosmopolitan magazine co-promote and co-brand? Should Gap license its brand name to Saturn or Honda, just as Harley and Eddie Bauer have done to Ford trucks and SUVs? We believe that the types of results presented by our approach may provide useful input to help answering these questions. More mundane results would suggest that Reader's Digest and Parenting are better advertising outlets than GQ or Rolling Stone, in terms of personality fit, for Volvo.

Finally, we wished to obtain an indication of the predictive value of the derived personality factor solution, by assessing its relation to a measure of preference based on Overall Feeling and Overall Quality (see Section 2). We averaged subjects' response within brands to obtain an aggregate measure of preference that can be related to the brands' personality positions. The correlation among these two items was 0.94; scores on these two were thus averaged into a unidimensional multi-item brand preference scale, which had a

coefficient alpha reliability of 0.97. These brand preference scores (for the 30 brands) were then first related to the category-specific factor brand personality scores, which led to an adjusted R² of .71, with all but the Sincerity brand personality factor scores significant. We then created interaction terms of each of factor scores with dummy variables for the categories, to see if any of them would increase R². We used stepwise regression to settle on an equation which included the two category dummies, the five factors and two selected interaction terms (Magazines × Sophistication, and Jeans × Sophistication). This raised the adjusted R² to 0.89. Details of these regression analyses appear in Table 8. The results illustrate that the factor scores derived from our model relate significantly to a measure of the overall attractiveness of the brands, but also that these effects vary across categories. Although these results are illustrative, we do find them supportive of our basic conjectures.

[INSERT TABLE 8 ABOUT HERE]

Discussion and Implications

Where functional brand benefits are nowadays being matched quickly by competitors, it is becoming more and more clear that brand marketers need to differentiate their brands, and add perceived consumer value, on the basis of brand personality imagery (Aaker 1997). Therefore, brand strategy planners need to be able to study the perceived personality characteristics of their brand and those of competitive brands, to find ways to shape their brand's imagery-building communications to better tap into the needs of their customers. However, brand personality characteristics are inevitably influenced by the nature of the product category itself (Durgee and Stuart 1987; Domzal and Kernan 1992). Thus, in studying brand personality one needs to separate category-level and brand-level determinants of a brand's perceived personality characteristics, which is especially important in situations where brand strategists look to brands in other product categories for strategic inspiration.

Category-level personality characteristics become particularly salient for brand extensions to new categories and cross-branding between brands in different categories.

The methodology developed and illustrated in this paper should prove helpful in meeting this need, and our results quite clearly show the value of partialling-out category personality in meaningful analysis of brand personalities. They make clear that the meaning of brand personality descriptors can be significantly influenced by the category context. For example, a "Reliable" magazine may have a different connotation than a "Reliable" car. We therefore believe that the category specific personality representation that we provide enables deeper insights and improved brand management strategy than have been possible heretofore. An additional benefit of the proposed methodology is that it accounts for two important features of many brand personality datasets. The first is the rank order nature of the personality scales and idiosyncratic scale usage (Rossi, Gilula and Allenby 2001). This disentangles respondents' behavior with respect to the measurement scales and their underlying brand personality perceptions. The second is the absence of blocks of data (resulting in abundant missing data) due the use of split questionnaires (Ragunathan and Grizzle 1995), which seems common or even desirable in large questionnaires on brand personality to reduce respondent fatigue and boredom.

The three categories - Cars, Magazines, and Jeans - used in our study had clearly distinct baseline category personality characteristics. While such category differences had previously been qualitatively discussed by researchers such as Levy (1959), our method enables a level of empirical quantification and precision heretofore missing from the literature. Such analysis ought to be particularly useful in cases where brands originating in one category are stretched or leveraged into other categories, via brand extensions. In such cases, brand planners need to assess which other product categories fit an existing brand, so

being able to gauge how similar different product categories are, in a personality structure sense, is critical for implementing those brand extensions. The same results allow us to identify the archetypical brands of specific categories with respect to their personalities; this is potentially important in improving the personality positioning for these brands, involving potential modification of their brand personality though advertising, amongst other tactics.

A criticism of existing inventories of brand personality descriptors and dimensions (such as that developed by Aaker 1997) is that they are often used uniformly across very different products and categories. Since it is likely that not all these descriptors are equally salient to and relevant for every category, this complete listing forces survey respondents to provide some perception ratings that may appear inapplicable to the category being rated. However, this undesirable state of affairs is caused by the current lack of ways for the researcher to systematically decide which perceptions are relevant and should be attended to in a particular category, and which ones could be ignored. Our approach gives us a way to assess which particular brand personality traits most appear to drive preference in each category. For example, respondents who believe that brand selection is informative about one's personality respond most to traits such as Upper-Class, Up-to-Date and Successful (Aaker's "Sophistication") for Jeans and Cars. Thus, our approach allows one to further tailor brand personality questionnaires to the category in question, in future research.

Our results of brand personality differences, once the category personality has been partialled-out, show an intuitively appealing characterization of the differences of personalities of brands within the categories and also reveal the characteristic personalities of the categories. The fact that these personality perceptions significantly shape overall evaluations of brands provides further support and enables us to study the extent to which

brand personality affects outcome measures of predictive and managerial relevance. This enhances the predictive validity of the brand personality construct.

The ability to separate category personality measurement and structure from those of brand personality is the major contribution of the model developed and illustrated in the present research, with the important strategic marketing research applications discussed above. It is also possible that these ideas and this model may even contribute to the literature on human personality, by allowing personality psychologists to tease out the influence of gender, race, culture and occupation on the personality perceptions of a particular individual.

Several limitations remain, suggesting avenues for future research. We did not collect the respondent's personality self-evaluation, so we were unable to confirm Aaker's (1999) result that self-schematic traits lead to stronger brand preferences. Such a study would be informative about brand personality segmentation and, as previously mentioned, may indicate respondent and brand interactions. Second, the data used in our illustrative application came from just three product categories, thirty brands, and a convenience sample, which obviously limits the generalizability of the personality structures we obtained. Future research should extend the data collection to more categories, with more and different brands, and a larger, probabilistic respondent sample, for enhanced generalizability. Whereas such an extension would yield a close to insurmountable burden to respondents, the use of a split questionnaire design in combination with the feature of our approach that enables one to impute of the resulting missing data would greatly help to reduce that burden. Finally, there might exist the need and potential to apply our model to include cultures or sub-cultures in the extraction of category personality. Some prior research (e.g. Aaker, Martinez, and Gariolera 2001) has shown that consumers in different cultures (in their study, Japan, Spain and the U.S.) evaluate brands on somewhat different personality dimensions.

Since our model can be used to separate out cultural and category structures from brand personality ratings and enables one to remove the effect of culture-specific response scale usage (Ter Hofstede, Steenkamp and Wedel 1999), it may prove to be of great value in an era where more and more brands are being marketed on a global basis (cf., Steenkamp, Batra and Alden 2003).

Appendix: Model Selection

In order to select the number of factors, we consider two fit statistics: the marginal distribution of the data given the model, P(Q|Model) (Kass and Raftery 1995) and the Brier score. Gelfand and Dey's (1994) method is used to approximate the marginal distribution from the MCMC draws. Our choice of the density to normalize the joint distribution is the prior so that the marginal density is estimated as the geometric average of the distribution of the data across the iterations of the Gibbs sampler. The distribution of the data is:

$$P(\Omega \mid Q) = \prod_{i}^{n} \prod_{m}^{M} \prod_{k}^{K} P(Q_{i,m} = K \mid \Omega)^{\epsilon_{i,m,k}}$$

where the probabilities on the right-hand-side for the ordinal data are given above, where Q is the ordinal data; Ω contains the parameters given the model; and $z_{i,m,k}=1$ if $Q_{i,m}=k$ is observed and $z_{i,m,k}=0$, otherwise.

Brier (1950) proposed a squared error loss statistic that compares predictive probabilities and random outcomes (see also Gordon and Lenk 1991, 1992). Let z_i be n uncertain events where $z_i = 1$ if the event occurs and $z_i = 0$ otherwise. The Brier score is defined as $BS = \sum_i (z_i - p_i)^2 / n$, where p_i is the predictive probability for z_i . The Brier score can be decomposed into two components, called "calibration" and "refinement". Calibration is related to bias and is zero when the predictive probability and relative frequencies are equal. The second component, refinement, is similar to variance, and measures the propensity of the prediction model to produce values close to zero or one: in a well-calibrated system, forecasts closer to zero or one are more useful. Our fit measure is based on a modification of the Brier score. Instead of using the predictive probabilities given the data, we compute the predictive probabilities given the parameters Ω and the data and use these to compute a Brier score at each iteration of the Markov chain:

$$BS^{(r)} = \frac{1}{NH} \sum_{i}^{n} \sum_{m}^{M} \sum_{k}^{K} \delta_{i,m} \left[z_{i,m,k} - P(Q_{i,m} = k \mid \Omega^{(r)}) \right]^{2}$$

where N is the total number of observations; $z_{i,m,k} = 1$ if person i responded k to variable m, and 0 otherwise; and $\delta_{i,m} = 1$ if the variable is observed and 0 if it is missing. That is, missing observations are excluded from the Brier score. The $BS^{(r)}$ are then used in computing posterior means and standard deviations. This approach extends the Brier score to include calibration, refinement, and uncertainty in the predictive probabilities. For testing the number of factors, we look at the marginal distribution of the data given the model P(Q|Model), and the posterior mean of the Brier score and its posterior standard deviation. In particular, we will search for that number of factors where the decrease in the Brier score is smaller than twice its posterior standard error.

TABLE 1

Brands Nested Within Categories, and the Numbers of Respondents that Answered the Questions on Each of the Brands

Cars	Number	Jeans	Number	Magazines	Number	
Porsche	119	Levi's	27	Readers	30	
				Digest		
Mercedes	119	Lee	31	Cosmopolitan	28	
Lexus	30	Guess?	28	National	31	
	•		•	Geographic	•	
Saturn	28	Fubu	29	Time	30	
Chevrolet	29	Polo	29	Money	27	
Pontiac	28	Tommy	32	People	32	
		Hilfiger				
Honda	31	Calvin Klein	28	Parenting	30	
Volvo	29	Gap	29	GQ	27	
Jaguar	30	Diesel	28	Rolling Stone	27	
VW	28	Abercrombie and Fitch	32	Consumer Reports	27	

TABLE 2
Personality Dimensions and Items

		Number		Mean		Standard Deviation				
Dimension	Item	Cars	Jeans	Magz	Cars	Jeans	Magz	Cars	Jeans	Magz
Sincerity	Down-to-earth	476	299	295	4.83	5.14	5.73	2.54	2.29	2.36
	Honest	476	299	295	5.65	5.18	6.15	2.11	2.13	2.20
	Wholesome	476	299	295	5.29	5.15	5.76	2.26	2.21	2.39
	Cheerful	476	299	295	5.51	5.19	5.40	1.94	1.90	1.98
Excitement	Daring	476	299	295	5.63	5.03	5.25	2.32	2.07	2.35
	Spirited	476	299	295	6.21	5.51	5.79	2.02	2.01	2.17
	Imaginative	475	299	295	6.02	5.25	5.95	2.13	2.10	2.20
	Up-to-date	476	298	295	7.12	6.20	7.67	1.84	2.06	1.39
Competence	Reliable	476	299	295	6.98	6.14	6.79	1.84	1.94	1.93
	Intelligent	476	299	295	6.84	5.23	6.77	1.91	1.87	2.07
	Successful	476	299	295	7.23	5.63	7.01	2.10	2.06	1.76
Sophistication	Upper class	476	299	294	7.02	5.36	6.06	2.51	2.21	2.00
	Charming	474	298	295	5.99	4.81	4.85	2.05	1.88	1.96
Ruggedness	Out-of-Doors	476	299	295	3.82	4.90	3.56	2.09	2.36	2.51
	Tough	476	298	294	4.19	5.27	3.64	2.16	2.22	2.33
Preferences	Feelings	475	298	295	6.65	5.07	5.94	2.09	2.30	1.95
	Quality	472	295	293	7.35	5.98	6.52	1.89	1.96	1.74
	Average	471	294	293	7.01	5.51	6.23	1.86	1.94	1.66

TABLE 3
Loadings for the Brand-Means of Personality Items,
Four Factor Brand Personality Model¹

Dimension	Item	F1	F2	F3	F4
Sincerity	Down-to-earth	0.969	-0.170	0.266	0.153
	Honest	0.991	0.135	0.218	0.138
	Wholesome	0.955	0.036	0.261	0.184
	Cheerful	0.291	-0.158	-0.047	0.963
Excitement	Daring	-0.950	0.361	0.269	0.068
	Spirited	-0.806	0.325	0.184	0.517
	Imaginative	-0.814	0.561	0.122	0.370
	Up-to-date	-0.525	0.937	-0.265	0.109
Competence	Reliable	0.656	0.781	0.147	0.053
	Intelligent	0.269	0.974	-0.061	-0.040
	Successful	-0.224	0.980	-0.165	0.026
Sophistication	Upper Class	-0.426	0.950	-0.219	-0.062
	Charming	-0.508	0.713	-0.038	0.753
Ruggedness	Out-of-doors	0.266	-0.108	0.984	0.124
	Tough	-0.055	-0.230	1.005	-0.150

¹ Loadings have been normalized and rotated.

TABLE 4
Category Specific Means and Standard Deviations of Personality Factor Scores
Using Brand-Means of Personality Items

		Means		Standard Deviations			
	Cars	Jeans	Magz	Cars	Jeans	Magz	
Sincere-Exciting	0.187	-0.293	0.106	0.981	0.810	1.207	
Comp & Soph	0.161	-0.615	0.454	1.230	0.551	0.852	
Rugged	-0.083	0.454	-0.371	0.497	0.886	1.342	
Cheerful&Charming	0.288	-0.321	0.033	0.693	0.878	1.328	

TABLE 5
Brand Preferences Regressed on Brand Personality Factor Scores^{1,3}

Variable ²	Coefficient	SE
Intercept	6.477	0.104
JEANS	-0.195	0.174
MAGZ	-0.703	0.147
Sincere-Excite	-0.269	0.066
Comp&Soph	0.784	0.071
JEANS*rugged	-0.262	0.130
JEANS*cheer&charm	0.553	0.138

¹Brand Preference is the average of Feeling for Brand and Brand Quality. Adjusted R-Squared is 0.89, and Error Standard Deviation is 0.33.

JEANS and MAGZ are dummy indicator variables for jeans and magazines

F1 is factor score for Sincerity

F2 is factor score for Excitement

F3 is the factor score for Competence and Sophistication

³Note:

- 1. F1 was retained in the model despite a large p-value because its interactions with categories were significant.
- 2. MAGZ interactions with F1 and F2 were retained because of significant interactions with JEANS.

²Variable definition:

TABLE 6
Log Marginal Density (LMD) and Brier Scores for 1-10 Factors

		Brier	95% Cre	edible
Factors	LMD	Score	Interval Bri	er Score
2	-23184	0.0757	0.0752	0.0762
3	-21819	0.0722	0.0716	0.0728
4	-20644	0.0696	0.0689	0.0704
5	-19874	0.0673	0.0665	0.0682
6	-19568	0.0668	0.0658	0.0678
7	-18895	0.0648	0.0635	0.0661
8	-18568	0.0637	0.0624	0.0651
9	-17930	0.0627	0.0616	0.0637
10	-17439	0.0614	0.0601	0.0626

TABLE 7
Item Loadings for 5 Factor Brand-Category Personality Model¹

		Pooled					Cars				
Dimension	Item	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
Sincerity	Down-to-	0.946	0.035	-0.130	-0.225	0.193	0.948	-0.064	0.045	-0.252	0.176
	earth Honest	0.885	0.006	0.399	0.225	-0.082	0.917	0.026	0.221	0.326	0.054
	Wholesome	0.940	-0.122	0.201	0.246	0.027	0.970	0.001	0.110	0.189	0.107
	Cheerful	0.762	0.435	0.228	0.419	-0.038	0.785	0.514	0.062	0.313	0.134
Excitement	Daring	-0.033	0.986	-0.054	0.137	0.077	-0.053	0.973	-0.087	0.177	0.105
	Spirited	0.044	0.991	0.073	0.102	0.032	0.033	0.979	0.069	0.126	0.138
	Imaginative	0.058	0.961	0.196	0.183	0.016	0.106	0.939	0.159	0.246	0.143
	Up-to-date	0.017	0.682	0.647	0.340	-0.024	0.130	0.700	0.576	0.372	0.151
Competence	Reliable	0.238	0.035	0.922	0.260	0.156	0.218	0.032	0.861	0.416	0.191
	Intelligent	0.248	0.193	0.789	0.525	0.053	0.261	0.164	0.614	0.708	0.165
	Successful	0.136	0.205	0.482	0.839	0.049	0.106	0.209	0.177	0.955	0.030
Sophistication	Upper Class	0.068	0.098	0.243	0.962	0.030	0.044	0.198	0.214	0.953	0.062
	Charming	0.204	0.449	0.153	0.823	0.240	0.209	0.465	0.193	0.799	0.253
Ruggedness	Out-of-	0.051	0.014	-0.014	0.070	0.996	0.136	0.148	0.013	0.048	0.978
	doors Tough	0.034	0.077	0.155	0.088	0.980	0.219	0.265	0.353	0.223	0.841
		Jeans					Magazi	nes			
Dimension	Item	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
Sincerity	Down-to-	0.952	-0.030	0.039	-0.193	0.231	0.971	-0.060	-0.063	-0.090	0.202
	earth Honest	0.990	0.110	0.029	0.086	-0.005	0.832	0.156	0.515	0.137	0.001
	Wholesome	0.979	-0.001	0.008	0.168	0.119	0.957	-0.078	0.215	0.145	0.099
	Cheerful	0.648	0.686	0.050	0.327	0.023	0.312	0.627	0.191	0.480	0.492
Excitement	Daring	0.013	0.989	-0.089	0.096	0.069	-0.128	0.947	0.139	0.181	0.186
	Spirited	0.087	0.965	0.103	0.227	-0.003	0.005	0.960	0.179	0.094	0.196
	Imaginative	0.012	0.943	0.112	0.314	0.007	0.013	0.928	0.274	0.171	0.186
	Up-to-date	-0.194	0.653	0.393	0.595	0.167	-0.015	0.392	0.915	-0.091	-0.028
Competence	Reliable	0.123	0.101	0.803	0.427	0.384	0.334	0.054	0.910	0.202	0.132
	Intelligent	0.246	0.411	0.173	0.860	-0.013	0.235	0.168	0.865	0.380	0.155
	Successful	0.063	0.261	0.096	0.956	0.069	0.067	0.236	0.750	0.611	0.065
Sophistication	Upper Class	-0.100	0.065	0.184	0.972	-0.083	-0.038	0.190	0.476	0.841	0.171
	Charming	0.194	0.591	-0.084	0.768	0.131	0.214	0.445	0.013	0.714	0.496
Ruggedness	Out-of-	0.192	0.019	0.081	0.037	0.977	0.145	0.172	-0.009	0.205	0.952
	doors Tough	0.069	0.071	0.144	-0.006	0.985	0.105	0.332	0.196	0.085	0.913

¹ Loadings have been normalized and rotated.

TABLE 8
Estimates of Regression of Preference on Brand Personality Locations¹.

	Coefficient	SE
(Constant)	6.383	0.110
Jeans	0.164	0.180
Magazines	-0.656	0.180
Excitement	0.702	0.304
Competence	1.724	0.333
Sophistication	1.574	0.190
Jeans × Sophistication	1.251	0.449
Magz × Sophistication	-1.510	0.417

Adjusted R-Squared is 0.888, and error standard deviation is 0.330.

FIGURE 1
Conceptual Representation of Brand Personality Construct
(BP denote Brand Personality Factors, i1...i15 items)

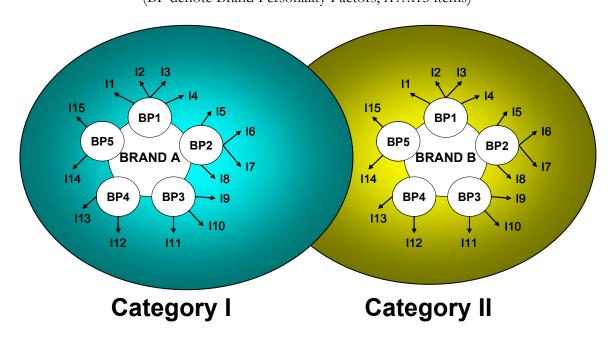


FIGURE 2
The Cutpoint Representation of Ordinal Items

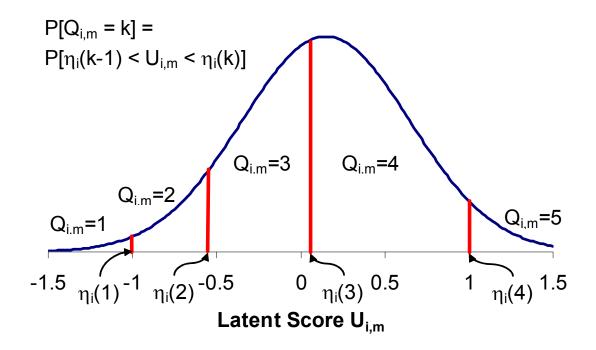


FIGURE 3
Category Positions on Personality Dimensions

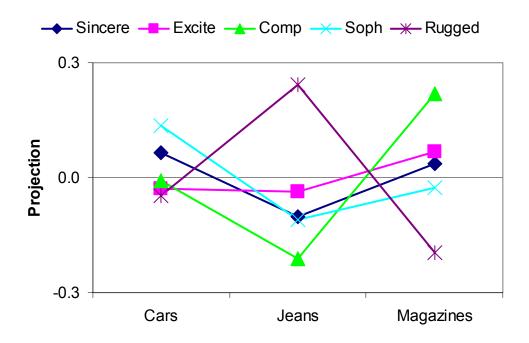
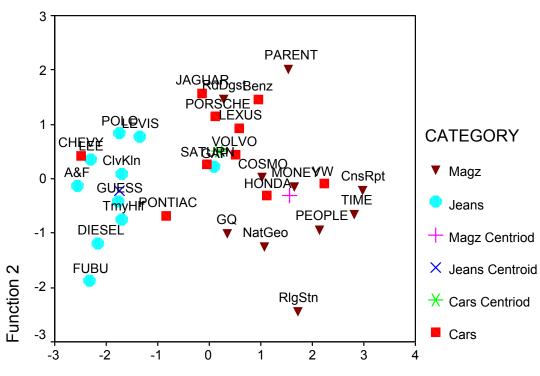


FIGURE 4
Category and Brand Positions in Discriminant Space

Discriminant Space



Function 1

FIGURE 5
Brand Dendrogram from Average Linkage, Based on z-Scores Within Brands

C A S E 5 10 15 20 25 Label Num Benz 3 LEXUS JAGUAR ClvKln 17 PORSCHE 1 GQ 28 MONEY 25 COSMO 22 PEOPLE 26 GUESS 13 RlgStn 29 TmyHlf 16 DIESEL 19 A&F 20 FUBU 14 POLO 15 CHEVY 5 LEVIS 11 LEE GAP 18 NatGeo 23 PONTIAC 6 HONDA 7 SATURN 4 10 24 TIME CnsRpt 30 VOLVO 8 RdDgst 21 PARENT 27

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