



Marketing Science

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To cite this article:

Ralf van der Lans, Joseph A. Cote, Catherine A. Cole, Siew Meng Leong, Ale Smidts, Pamela W. Henderson, Christian Bluemelhuber, Paul A. Bottomley, John R. Doyle, Alexander Fedorikhin, Janakiraman Moorthy, B. Ramaseshan, Bernd H. Schmitt, (2009) Cross-National Logo Evaluation Analysis: An Individual-Level Approach. Marketing Science 28(5):968-985.
<https://doi.org/10.1287/mksc.1080.0462>

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Cross-National Logo Evaluation Analysis: An Individual-Level Approach

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The universality of design perception and response is tested using data collected from 10 countries: Argentina, Australia, China, Germany, Great Britain, India, The Netherlands, Russia, Singapore, and the United States. A Bayesian, finite-mixture, structural equation model is developed that identifies latent logo clusters while accounting for heterogeneity in evaluations. The concomitant variable approach allows cluster probabilities to be country specific. Rather than a priori defined clusters, our procedure provides a posteriori cross-national logo clusters based on consumer response similarity. Our model reduces the 10 countries to three cross-national clusters that respond differently to logo design dimensions: the West, Asia, and Russia. The dimensions underlying design are found to be similar across countries, suggesting that elaborateness, naturalness, and harmony are universal design dimensions. Responses (affect, shared meaning, subjective familiarity, and true and false recognition) to logo design dimensions (elaborateness, naturalness, and harmony) and elements (repetition, proportion, and parallelism) are also relatively consistent, although we find minor differences across clusters. Our results suggest that managers can implement a global logo strategy, but they also can optimize logos for specific countries if desired.

Key words: design; logos; international marketing; standardization; adaptation; structural equation models; Gibbs sampling; concomitant variable; Bayesian; mixture models

History: Received: August 2, 2007; accepted: July 30, 2008; processed by Wayne DeSarbo. Published online in *Articles in Advance* June 19, 2009.

1. Introduction

Design is a language that communicates to consumers and others, independent of verbal information. Hence, it is critical that marketing managers and scholars understand design's impact on viewers. In general, visual information is processed differently from, faster than, and independent of verbal information (Edell and Staelin 1983). In addition, visual information can trigger affect prior to cognitive processing (Lutz and Lutz 1977).

Most marketing research has examined how individual design elements such as color, symmetry, proportion, and angularity affect consumers' reactions (e.g., Pittard et al. 2007). Although such research is useful, it is like studying alphabets—critical to understanding but offering limited insight into word or sentence meaning. Henderson and Cote (1998), in an early attempt to understand broader design characteristics, uncovered three basic design dimensions: elaborateness, naturalness, and harmony. *Elaborateness* refers to a design's richness and its ability to capture the essence of an object, *natural* designs depict commonly experienced objects, and *harmony* refers to the congruency of the patterns and parts of a design. Extending our analogy, these design dimensions act as words instead of letters. Preliminary evidence indicates that these design dimensions are important for understanding reactions to a variety of marketing stimuli such as typeface (Henderson et al. 2004) and wine bottle design (Orth and Malkewitz 2008).

Although the evidence suggests that elaborateness, naturalness, and harmony are universal words that are useful for understanding visual marketing stimuli, we have limited evidence about whether these design dimensions exist across cultures. We also do not know if people from different cultures respond in the same way to these design dimensions. Evolutionary psychology suggests that human response to visual stimuli is genetically programmed and relatively immune from cultural influence (Adams et al. 2003). For example, we have an innate ability to determine what stimulus features provide information across several domains, including evaluations of landscapes (Orians and Heerwagen 1992), facial expressions of emotion (Ekman 1998), and physical attractiveness (Jones 1996). However, some research on reactions to individual design elements find cultural differences (e.g., Perfetti et al. 2005, Zhang et al. 2006), whereas others such as Pittard (2007) report similarities across cultures.

Given the literature's conflicting findings, our study examines whether the design dimensions uncovered by Henderson and Cote (1998) and Henderson et al. (2003) underlie reactions to logos in 10 different countries: Argentina, Australia, China, Germany,

Great Britain, India, The Netherlands, Russia, Singapore, and the United States. Using consumer and designer ratings of 195 stimuli, we apply a Bayesian, finite-mixture, structural equation model using an Markov chain Monte Carlo (MCMC) algorithm to uncover latent differences in cultural perceptions of and responses to designs. This will provide the most comprehensive and rigorous test to date of such cultural variations on design dimensions (as opposed to individual design elements¹). Specifically, we build on Henderson and Cote (1998) to examine the following research questions:

- (1) Do the design dimensions of elaborateness, naturalness, and harmony exist cross-nationally?
- (2) Are consumers' responses to these design dimensions stable cross-nationally?

Beyond studying the theoretical questions of design dimension universality and consumer response stability, our paper also makes a methodological contribution. Research in experimental aesthetics typically analyzes data at the stimulus level by averaging individual judgments for each stimulus (e.g., Henderson and Cote 1998). However, such an approach does not consider heterogeneity in individual responses, which will mask information contained in individual response variation. This may bias correlations between judgments about different stimuli (DeShon 1998). Thus we extend finite-mixture structural equation models (DeSarbo et al. 2006) to simultaneously analyze responses at the stimuli level while accounting for individual judgment heterogeneity through an additional hierarchical layer. Our model also uses a concomitant variable specification (Ter Hofstede et al. 1999) to allow the probabilities of stimuli's latent clusters membership to vary across countries. We then use the country-specific cluster probabilities to interpret the latent clusters. Last, we assess measurement invariance (Steenkamp and Baumgartner 1998) across clusters rather than across countries. This offers two advantages. First, the number of cross-national clusters is usually smaller than the number of countries if many countries are studied—so fewer computations are required and invariance testing is more tractable (invariance tests grow exponentially with the number of countries). Second, Steenkamp and Baumgartner's (1998) framework usually selects countries a priori, whereas our approach is not restricted to country.² A priori allocations may not be realistic because "consumers in different countries often have more in common with one another than with other consumers in the same country" (Ter Hofstede et al. 1999, p. 1).

¹ A design element is a single characteristic, whereas a design dimension is a combination of elements.

² The constrained finite mixture does not require that all stimuli within a country be part of the same cluster. Any cluster may contain only a portion of stimuli from a given country.

We use logos as a context to examine the research questions. As a key component of corporate visual identity, managers use logos to create positive emotions, convey meaning, or enhance recognition about the company and brand. However, managers have expressed uncertainty about how to manage corporate visual identity systems globally (e.g., see Alashban et al. 2002). The literature suggests that logos are most often used in an unaltered form when going abroad (Kapferer 1992). Does using unaltered logos in new markets accomplish their communication goals, or would it be necessary to modify logos for individual countries? Depending on our findings, managers can either feel secure using standardized logos and other visual material or, if cross-cultural differences exist, we can provide guidelines for adapting logos to specific countries or regions.

2. Conceptual Framework

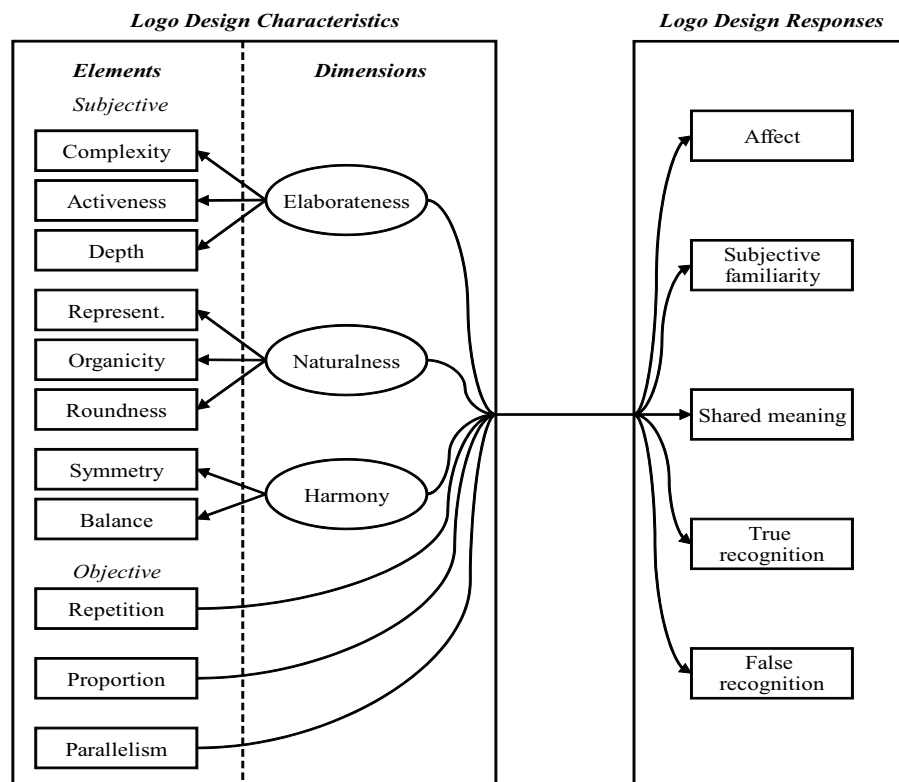
Consistent with Henderson and Cote (1998), our framework is specified at the logo level and proposes that consumers perceive logo designs along three objective design elements and three design dimensions (see Figure 1). The three objective design elements include (1) repetition (number of times identical shapes are repeated), (2) proportion (the ratio

of a logo's width to its height), and (3) parallelism (number of parallel lines). As discussed earlier, the design dimensions are elaborateness, naturalness, and harmony. The design dimensions consist of eight design elements (complexity, activeness, depth, representativeness, organicity, roundness, symmetry, and balance) measured subjectively by designers (see Appendix A). Although these six characteristics (i.e., three dimensions plus three objective design elements) do not capture all aspects of design, they appear to represent a fundamental core for logo design.

We use positive affect, shared meaning, subjective familiarity, and true and false recognition to assess responses to logo designs. *Positive affect* is important because feelings can transfer to the product or company, especially in low-involvement decision making, where affective reactions can guide choice. Prior work suggests that increasing a design's harmony, elaborateness, and naturalness creates positive affect primarily because these design changes facilitate perception (Anand and Sternthal 1991, Martindale et al. 1988) and stimulate arousal (Raymond et al. 2003). Natural designs may also be more pleasing, because they are more prototypical (Seifert 1992).

Shared meaning exists when there is a consensus among respondents about the first meaning or association that comes to mind when they see a logo

Figure 1 Conceptual Framework of Logo Design Evaluation



Note. Logo design dimensions (consisting of subjective elements) and objective elements are on the left, and consumer responses to logos are depicted on the right.

(Ellis et al. 1974). Logos with high shared meaning are valuable because they are perceived, interpreted, and remembered better than stimuli with varied meaning (Rodewald and Bosma 1972). Naturalness, harmony, and, to a lesser extent, elaborateness may increase shared meaning because universally experienced objects are more easily interpreted and recognized than abstract objects (Seifert 1992, Shinar et al. 2003).

Previous studies have not examined the relationship between logo design and *subjective familiarity* (feeling of having seen a logo before, regardless of prior exposure). Subjective familiarity can increase positive affect (Zajonc 1968) and even enhance brand choice (Henderson and Cote 1998). Because shared meaning and subjective familiarity are closely related, the rationale behind the relationships between the design characteristics and subjective familiarity are similar to those for shared meaning.

Logo *recognition* means consumers remember seeing the logo before. Because consumers recognize pictures more quickly than words, a company can communicate quickly by using a logo in the brand name (Edell and Staelin 1983). We distinguish between two types of recognition: (1) *true recognition* is the correct assertion that one has seen the logo before, and (2) *false recognition* is the incorrect assertion that one has seen the logo before. False recognition is not necessarily a bad outcome as companies may deliberately create new logos that seem familiar. According to Gestalt, motivational, and cognitive theories, consumers are likely to exhibit true recognition for stimuli that are easily encoded and command attention. Natural logos are easily encoded and should increase true recognition and decrease false recognition. However, other design dimensions should have little effect on either type of recognition.

This conceptual framework does not propose any cross-cultural differences. Rather, we expect that the same underlying design structure, and relationships between design characteristics and consumer responses, exist independent of where the consumer lives. We start with the framework in Figure 1 and use a latent-class methodology to test whether different logo clusters exist across cultures.

3. Method

3.1. Overview

Our conceptual model (Figure 1) is defined at the logo level. We follow previous studies on aesthetics (Berlyne 1974, Henderson and Cote 1998) to derive scores for design and responses and asked different designers and consumers to rate subjective logo design elements and responses for each logo. In addition, to test if perception of and response to design is

invariant across cultures, we collected these data from consumers and designers in 10 countries: Argentina, Australia, China, Germany, Great Britain, India, The Netherlands, Russia, Singapore, and the United States. These countries, on five continents, represent an array of geographic, economic, political, language, and cultural backgrounds (see Table 1). This data set allows a rigorous test of perceptions of and responses to logo designs. By comparison, recent international marketing research has generally involved two (e.g., Gurhan-Canli and Maheswaran 2000) or three countries (e.g., Erdem et al. 2004), or a limited region (Baumgartner and Steenkamp 2001, Ter Hofstede et al. 1999).

We used 195 unfamiliar logos used by Henderson and Cote (1998) that were originally obtained from a book of foreign logos (Kuwayama 1973) and from advertisements in the *Yellow Pages*. To minimize the effects of past exposure and to prevent confounding of symbolic with verbal processing, the logos contained no verbal material. Standard back-translation methods were used on all questionnaires—a bilingual native speaker translated the questionnaires written in English into each country's language, and then a different bilingual native speaker translated the questionnaires back into English.

3.2. Ratings of Logo Design Elements

Consistent with experimental aesthetics research (Berlyne 1974), data were collected on a large number of stimuli and variables, across multiple samples. Two or three professional logo designers in each country evaluated the degree of activeness, balance, depth, organicity, representativeness, roundness, and symmetry each logo possessed. The designers had formal training and extensive experience with commercial clients and logo design. Before rating the logos, the evaluators received a short description of each characteristic. Consistent with Henderson and Cote (1998), for each country five groups of approximately 40 undergraduates evaluated the design element of complexity for a different subset of 39 logos.³ Finally, data from Henderson and Cote (1998) provided the three objectively measured logo design elements of parallelism, proportion, and repetition.

In summary, the 11 design elements were each measured with a single indicator. Eight of the design elements (activeness, balance, depth, organicity, representativeness, roundness, symmetry, and complexity) are country specific and measured by different raters (either designers or students) in each country. Repetition, proportion, and parallelism are identical across countries. Appendix A defines these design elements and contains examples of logos scoring high and low on them.

³ This furnishes evaluations for 5×39 , or 195, logos in total.

Table 1 Characteristics of the Countries Studied

Nation/ Characteristic	Argentina	Australia	China	Germany	Great Britain	India	The Netherlands	Russia	Singapore	United States
Geography	South America	Oceania	East Asia	Western Europe	Western Europe	South Asia	Western Europe	Eastern Europe	East Asia	North America
Economics: ¹	\$5,528	\$37,924	\$2,055	\$34,955	\$39,207	\$784	\$40,535	\$6,877	\$30,159	\$43,562
Gross national income/capita										
Government ²	Republic	Commonwealth	Socialist	Federal Republic	Constitutional monarchy	Federal Republic	Constitutional monarchy	Federalist	Republic	Federal Republic
Culture: ³	49	36	80	35	35	77	38	93	74	40
Power distance	86	51	30	65	35	40	53	95	8	46
Uncertainty avoidance	46	90	20	67	89	48	80	39	20	91
Individualism/collectivism	56	61	66	66	66	56	14	36	48	62
Masculinity/femininity										
Language/writing system ⁴	Spanish/alphabetic 26 + 3	English/alphabetic 26	Mandarin/logographic 47,035	German/alphabetic 26 + 4	English/alphabetic 26	English and Hindi/alphabetic and Abugida 64	Dutch and Frisian/alphabetic 26 + 1	Cyrillic/alphabetic 33	English and Mandarin/alphabetic and logographic	English/alphabetic 26

¹ United Nations (2006).² Source: CIA (2004).³ Source: Hofstede (1983). Higher scores reflect greater power distance, uncertainty avoidance, individualism, and masculinity, respectively. Statistics for China and Russia were not in the original IBM data set but were collected later and reported in Hofstede (2001, Exhibit A5.3, p. 502).⁴ The first value is the number of basic symbols in the writing system. The second is the number of diacritics and ligatures.

3.3. Responses to Logo Design

Affect and Subjective Familiarity. To minimize fatigue, each respondent rated only 39 logos on the five affective items (like/dislike, good/bad, high/low quality, distinctive/not distinctive, and interesting/uninteresting) as well as subjective familiarity (familiar/unfamiliar). Each logo appeared on a separate page with the 7-point rating scales and was evaluated by 20–70 respondents (about 40 on average).

Shared Meaning. Shared meaning exists when respondents agree about the first meaning or association that comes to mind when they see a logo (Ellis et al. 1974). The same respondents for the affect and subjective familiarity questions listed the first meaning or association that came to mind when they looked at each logo (collected in the second half of the booklet). A trained research assistant from each country grouped similar associations. For each logo in each country, we calculated the Hirschman-Herfindahl index score by squaring and then summing across the probabilities of each response (Henderson and Lafontaine 1996).⁴ A high-concentration index indicates that a logo evokes shared meaning.

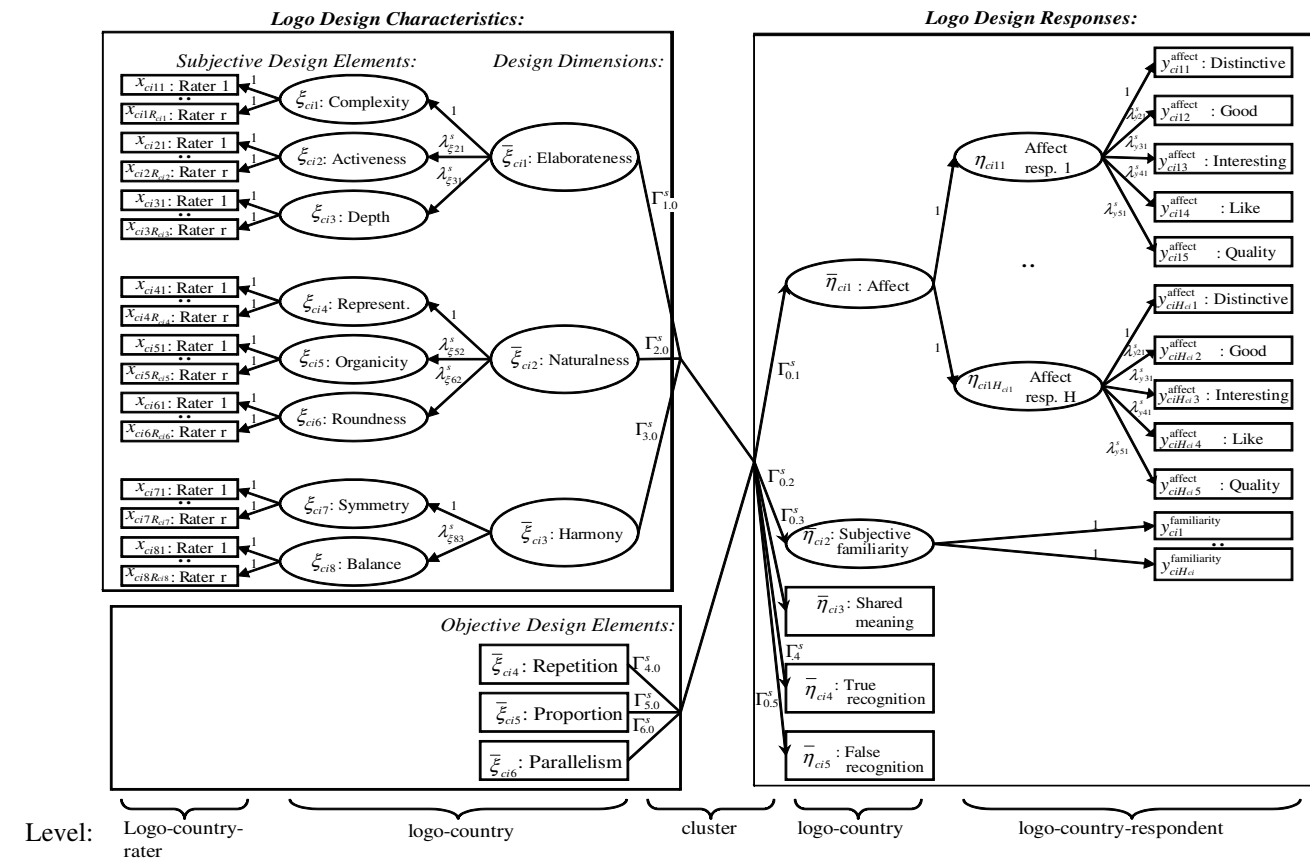
Recognition. For each country, five groups of approximately 30 business undergraduates (different from the groups used to collect the affect, familiarity, and meaning ratings) viewed a subset of 39 logos in a slide show, with each logo appearing for two seconds. Respondents next participated in a distracter task for about 10 minutes. Then they viewed a booklet with 78 logos—(39 target logos from the slide presentation and 39 distracter logos that were not presented earlier). The students then indicated whether they had seen the logo in the slide show. True recognition is the percentage of respondents who correctly recognize a target logo, whereas false recognition is the percentage of respondents who claimed to recognize a distracter logo.

4. The Model

Following previous aesthetics research, our model uses logos as the primary unit of analysis. The structural relationships between logo design characteristics and consumer responses are specified using logo-level data (see Figures 1 and 2). Previous research averages individual ratings and responses to compute each logo's design and response scores (e.g., Henderson et al. 2003). In contrast, our model (Figure 2) includes an additional hierarchy to analyze individual-level data, thus minimizing potential aggregation bias

⁴ For example, if 50% of respondents said a logo reminded them of a sun, 30% said wheel, and 20% said star, the Hirschman-Herfindahl index would be $0.5^2 + 0.3^2 + 0.2^2 = 0.38$.

Figure 2 Model Specification at the Cluster and Individual Response Levels



Note. All intercepts and errors are omitted for clarity.

(DeShon 1998).⁵ To test whether perceptions and evaluations of logos are similar cross-nationally, we specify a concomitant variable, finite-mixture, structural equation model that allocates logos to clusters. With fewer clusters than countries, our approach reduces the number of invariance tests relative to Steenkamp and Baumgartner (1998), who define clusters a priori at the country level. If logos are evaluated similarly across cultures, we will find a one-cluster solution.

We estimate our model in a Bayesian framework using an MCMC algorithm, which has several advantages over traditional methods, including no asymptotic assumptions, suitability for smaller sample sizes, incorporation of prior information (Rossi and Allenby 2003), and avoidance of Heywood cases (negative variances). Most important, Bayesian inference estimates individual-specific effects. Thus we can obtain each logo's country-specific posterior distribution of factor scores and cluster probabilities. Managers can use this information to optimize individual logos on specific dimensions of interest, as shown in §6.1.

⁵ We estimated a model without taking into account individual response differences and found a significant aggregation bias.

4.1. Model Specification

Before introducing our model, we present some notation that defines the sets and (latent) variables. Let

$i = 1, \dots, I$ denote the set of logos. In this study, $I = 195$.

$c = 1, \dots, C$ denote the set of countries. In this study, $C = 10$.

$s = 1, \dots, S$ denote the a priori unknown set of cross-national clusters to be determined empirically.

$q = 1, \dots, Q$ denote the set of subjective logo design elements related to the design dimensions. In this study, $Q = 8$ (i.e., complexity, activeness, depth, representativeness, organicity, roundness, symmetry, and balance).

$n = 1, \dots, N$ denote the set of logo design characteristics. In this study, $N = 6$ and consists of two subsets: $N_{\text{dimension}} = 3$ design dimensions (i.e., elaborateness, naturalness, and harmony), and $N_{\text{element}} = 3$ objective design elements (i.e., repetition, proportion, and parallelism).

$p = 1, \dots, P$ denote the set of affect response items. In this study, $P = 5$ (i.e., distinctive, good, interesting, like, and quality).

$m = 1, \dots, M$ denote the set of logo response variables. In this study, $M = 5$ (i.e., affect, subjective familiarity, shared meaning, true recognition, and false recognition).

$r = 1, \dots, R_{ciq}$ denote the raters in country c that evaluated subjective design element q of logo i .

$h = 1, \dots, H_{ci}$ denote the respondents in country c that responded to logo i on affect and subjective familiarity.

x_{cirq} denote the evaluation of subjective design element q of logo i in country c by rater r .

ξ_{ciq} denote the latent score of subjective design element q of logo i in country c .

$\bar{\xi}_{cin}$ denote the (latent) value of design dimension or objective element n of logo i in country c .

y_{cih}^{affect} denote the $(P \times 1)$ vector containing the value of the affect items of logo i in country c by respondent h .

$y_{cih}^{\text{familiarity}}$ denote the value of the subjective familiarity item of logo i evaluated in country c by respondent h .

η_{cimh} denote the latent score on logo variable m by respondent h in country c on logo i . In this study, this score is only computed for affect and subjective familiarity (i.e., $m = 1, 2$, respectively).

$\bar{\eta}_{cim}$ denote the (latent) scores on logo response variable m in country c on logo i .

Based on our conceptual framework, Figure 2 summarizes our model specification for a given cluster s and incorporates both individual rater and logo-level data. The $Q = 8$ design elements are measured at the individual level and capture the first $N_{\text{dimension}} = 3$ logo design dimensions: elaborateness (complexity, activeness, and depth), naturalness (representativeness, organicity, and roundness), and harmony (symmetry and balance). The $N_{\text{element}} = 3$ logo objective design elements (repetition, proportion, and parallelism) are measured at the logo level and are equal across countries. These $N = 6$ logo design characteristics influence $M = 5$ response variables (affect, subjective familiarity, shared meaning, and true and false recognition). Affect is assessed by $P = 5$ items measured at the individual level. Subjective familiarity is also measured at the individual level using a single item for each respondent. Shared meaning, true recognition, and false recognition are measured at the logo level and are an aggregate of the individual-level responses as described previously. Because these aggregated responses are proportions, we applied a logit transformation to obtain continuous dependent variables.

Previous research on aesthetics assumes that the subjective logo design scores, ξ , are observed and therefore computes these values by averaging over the rater scores x ; i.e., $\xi_{ciq} = (1/R_{ciq}) \sum_{r=1}^{R_{ciq}} x_{cirq}$ (Henderson and Cote 1998). In contrast, our approach recognizes

heterogeneity of individual ratings and directly models these, given cluster membership s , as follows:

$$x_{cirq} | s = \xi_{ciq} + \delta_{cirq}^s, \quad (1)$$

where δ_{cirq}^s is assumed to be normally distributed with mean zero and standard deviation σ_{xq}^s .

To derive the latent scores of the subjective logo design elements, ξ , we assume the following measurement model, given cluster membership s :

$$\xi_{ci} | s = \tau_{\xi}^s + \Lambda_{\xi}^s (\bar{\xi}_{ci1} \quad \bar{\xi}_{ci2} \quad \bar{\xi}_{ci3})' + \epsilon_{\xi ci}^s. \quad (2)$$

In (2), Λ_{ξ}^s ($Q \times N_{\text{dimension}}$) is a factor loading matrix and τ_{ξ}^s is a $(Q \times 1)$ vector containing measurement intercepts. The $(Q \times 1)$ vector of disturbance terms $\epsilon_{\xi ci}^s$ is multivariate normally distributed with mean vector zero and diagonal covariance matrix Σ_{ξ}^s ($Q \times Q$), given cluster s . Note that (2) is the standard measurement model used in a structural equation modeling approach in which ξ_{ci} is observed, whereas in our approach, it is a vector of latent scores depending on (1).

In addition, we specify

$$(\bar{\xi}_{ci1} \quad \bar{\xi}_{ci2} \quad \bar{\xi}_{ci3})' | s = \mu^s + \psi_{ci}^s, \quad (3)$$

with μ^s ($N_{\text{dimension}} \times 1$) containing the design dimension intercepts. The disturbance terms ψ_{ci}^s are assumed to be normally distributed with mean zero and diagonal covariance matrix Ω_{ξ}^s ($N_{\text{dimension}} \times N_{\text{dimension}}$). Note that each country c has the same scores for the logo objective design elements (i.e., $\bar{\xi}_{cin}$ with $n \in N_{\text{element}}$) as these are measured directly (see §3.2).

Aesthetics research generally uses average scores across individuals to measure affect and subjective familiarity, which ignores individual differences. We compute a separate affect and subjective familiarity score for each respondent. Because subjective familiarity is measured with only one item (see Figure 2), its score is equal to the observed item: $\eta_{ci2h} = y_{cih}^{\text{familiarity}}$ for all countries c , logos i , and individuals h .

For affect, we assume the following measurement model at the respondent level, given that the logo belongs to cluster s in country c :

$$y_{cih}^{\text{affect}} | s = \tau_y^s + \Lambda_y^s \eta_{ci1h} + \epsilon_{y ci h}^s. \quad (4)$$

In (4), Λ_y^s is a $(P \times 1)$ vector containing the factor loadings, and τ_y^s is a $(P \times 1)$ vector containing measurement intercepts. The $(P \times 1)$ error vector $\epsilon_{y ci h}^s$ is assumed to be normally distributed with mean zero and diagonal covariance matrix Σ_y^s ($P \times P$), given cluster s .

Similar to Equation (1), we assume the following measurement model to derive the latent affect and subjective familiarity scores at the logo level:

$$(\eta_{ci1h} \quad \eta_{ci2h})' | s = (\bar{\eta}_{ci1} \quad \bar{\eta}_{ci2})' + \epsilon_{\eta ci h}^s. \quad (5)$$

In (5), $\epsilon_{\eta cih}^s$ is a (2×1) vector that is assumed to be normally distributed with mean zero and (2×2) diagonal covariance matrix Σ_{η}^s , given cluster s .

Given the measurement model in Equations (1)–(5), we now specify the structural relationships among the exogenous design characteristics and the responses at the logo level. Henderson and Cote (1998) found the effects of the response variables on each other were nominal. Thus we did not include any response variables as predictors to avoid multicollinearity problems (Grewal et al. 2004). This leads to the following structural relationships, given cluster s :

$$\bar{\eta}_{ci} | s = \alpha^s + \Gamma^s \bar{\xi}_{ci} + \zeta_{ci}^s. \quad (6)$$

In (6), the vector α^s ($M \times 1$) contains the intercepts for the endogenous logo responses $\bar{\eta}_{ci}$. The coefficient matrix Γ^s incorporates the effects of the exogenous logo design dimensions and objective design elements, $\bar{\xi}_{ci}$, on the endogenous logo responses $\bar{\eta}_{ci}$ (see Figure 2). It is assumed that the disturbance term ζ_{ci}^s is normally distributed with mean zero and diagonal covariance matrices Ω_{η}^s ($M \times M$).

The model is tested on logos that may belong to an unknown group of cross-national clusters. Thus we propose a constrained, finite-mixture, structural equation approach to allow for heterogeneity in both measurement and structural relationships (DeSarbo et al. 2006, Jedidi et al. 1997). Because structural relationships are cluster specific and defined at the logo level, our constrained finite-mixture approach assigns logos to clusters. Using a concomitant variable specification (Ter Hofstede et al. 1999), we allow mixture probabilities for country-specific logo cluster membership. We therefore introduce parameter π_{cs} that specifies the probability that a logo evaluated in country c is assigned to cluster s . This concomitant variable specification simultaneously derives clusters of logos and profiles these clusters based on country membership (i.e., the concomitant variable that indicates in which country a logo is evaluated). Similar to DeSarbo et al. (2006), response and structural parameters are flexibly constrained across clusters to test for nested versions of the model. These nested model versions are needed to assess measurement invariance and our two research questions. Using the country-specific cluster proportions π_{cs} in combination with the measurement Equations (1)–(5) and structural Equation (6), we obtain the following model likelihood:

$$\begin{aligned} L(\mathbf{y}, \mathbf{x}, \mathbf{z}, \boldsymbol{\eta}, \bar{\boldsymbol{\eta}}, \bar{\boldsymbol{\xi}}, \boldsymbol{\Theta}, \boldsymbol{\pi}) \\ = \prod_{c=1}^C \prod_{i=1}^{I_c} \sum_{s=1}^S \pi_{cs} \left\{ \left(\prod_{h=1}^{H_{ci}} N_p(\mathbf{y}_{cih}^{\text{affect}}; \boldsymbol{\tau}_y^s + \Lambda_y^s \eta_{ci1h}, \Sigma_y^s) \right) \right. \\ \left. \cdot \left(\prod_{h=1}^{H_{ci}} N_2((\eta_{ci1h} \quad \eta_{ci2h})'; (\bar{\eta}_{ci1} \quad \bar{\eta}_{ci2})', \Sigma_{\eta}^s) \right) \right\} \end{aligned}$$

$$\begin{aligned} \cdot \left(\prod_{q=1}^Q \prod_{r=1}^{R_{ciq}} N(x_{cirq}; \xi_{ciq}, \Sigma_{xqq}^s) \right) \\ \cdot N_Q(\bar{\xi}_{ci}; \boldsymbol{\tau}_{\xi}^s + \Lambda_{\xi}^s (\bar{\xi}_{ci1} \quad \bar{\xi}_{ci2} \quad \bar{\xi}_{ci3})', \Sigma_{\xi}^s) \\ \cdot N_M(\bar{\boldsymbol{\eta}}_{ci}; \boldsymbol{\alpha}^s + \Gamma^s \bar{\boldsymbol{\xi}}_{ci}, \Omega_{\eta}^s) \\ \cdot N_{N_{\text{Dimension}}}((\bar{\xi}_{ci1} \quad \bar{\xi}_{ci2} \quad \bar{\xi}_{ci3})'; \boldsymbol{\mu}^s, \Omega_{\xi}^s) \Big\}, \quad (7) \end{aligned}$$

where $\boldsymbol{\Theta} = \{\boldsymbol{\Theta}^1, \dots, \boldsymbol{\Theta}^S\}$ contains the set of cluster-specific structural equation parameters $\boldsymbol{\Theta}^s = (\alpha^s, \Gamma^s, \boldsymbol{\tau}_{\xi}^s, \boldsymbol{\tau}_y^s, \Lambda_{\xi}^s, \Lambda_y^s, \Sigma_x^s, \Sigma_y^s, \Sigma_{\xi}^s, \Sigma_{\eta}^s, \Omega_{\xi}^s, \Omega_{\eta}^s)$.

4.2. Model Identification and Estimation

To ensure identification, one item's factor loading was set to unity (and intercept to zero) for all cross-national clusters s . As noted by Jedidi et al. (1997), the finite mixture of a structural equation model (with unknown groups) is identified when the corresponding multigroup model with known groups is identified and the data are multivariate normal.

Using these identification restrictions, the model was estimated using the Gibbs sampler (Diebolt and Robert 1994, Rossi and Allenby 2003). For the estimation of cross-national cluster membership, an auxiliary variable, $z_{ci} \in \{1, 2, \dots, S\}$, was introduced for each logo i evaluated in country c (Diebolt and Robert 1994). This auxiliary variable indicates to which cluster s logo i in country c is allocated. After introducing the auxiliary variables (z_{ci}), the likelihood (7) can be rewritten as follows:

$$\begin{aligned} L(\mathbf{y}, \mathbf{x}, \mathbf{z}, \boldsymbol{\eta}, \bar{\boldsymbol{\eta}}, \bar{\boldsymbol{\xi}}, \boldsymbol{\Theta}, \boldsymbol{\pi}) \\ = \prod_{c=1}^C \prod_{s=1}^S \prod_{i: z_{ci}=s} \left\{ \left(\prod_{h=1}^{H_{ci}} N_p(\mathbf{y}_{cih}^{\text{affect}}; \boldsymbol{\tau}_y^s + \Lambda_y^s \eta_{ci1h}, \Sigma_y^s) \right) \right. \\ \cdot \left(\prod_{h=1}^{H_{ci}} N_2((\eta_{ci1h} \quad \eta_{ci2h})'; (\bar{\eta}_{ci1} \quad \bar{\eta}_{ci2})', \Sigma_{\eta}^s) \right) \\ \cdot \left(\prod_{q=1}^Q \prod_{r=1}^{R_{ciq}} N(x_{cirq}; \xi_{ciq}, \Sigma_{xqq}^s) \right) \\ \cdot N_Q(\bar{\xi}_{ci}; \boldsymbol{\tau}_{\xi}^s + \Lambda_{\xi}^s (\bar{\xi}_{ci1} \quad \bar{\xi}_{ci2} \quad \bar{\xi}_{ci3})', \Sigma_{\xi}^s) \\ \cdot N_M(\bar{\boldsymbol{\eta}}_{ci}; \boldsymbol{\alpha}^s + \Gamma^s \bar{\boldsymbol{\xi}}_{ci}, \Omega_{\eta}^s) \\ \cdot N_{N_{\text{Dimension}}}((\bar{\xi}_{ci1} \quad \bar{\xi}_{ci2} \quad \bar{\xi}_{ci3})'; \boldsymbol{\mu}^s, \Omega_{\xi}^s) \Big\}, \quad (8) \end{aligned}$$

where $i: z_{ci} = s$ under the third product indicates that this index runs over all logos i in country c that belong to cluster s . Given the unobserved values for z_{ci} , specification (8) leads to standard posterior distributions for $\boldsymbol{\Theta}$, $\boldsymbol{\eta}$, $\bar{\boldsymbol{\eta}}$, $\bar{\boldsymbol{\xi}}$, and $\boldsymbol{\pi}$. We used flat prior distributions specified in Technical Appendix A (available at <http://mktsci.pubs.informs.org>) to estimate the model using the MCMC algorithm as specified in Appendix B.

To address possible label switching, a well-known problem during Bayesian inference for mixture models (Frühwirth-Schnatter 2006, Rossi et al. 2005), we relabeled cluster memberships by postprocessing the posterior draws using Richardson and Green's (1997) approach.⁶ In all runs, we used 2,000 draws, thinned 1 in 10, with a burn-in of 100,000 iterations. We examined convergence using diagnostics proposed by Raftery and Lewis (1992) and Geweke (1992) and found that all runs converged well before burn-in (see Technical Appendix C, available at <http://mktsci.pubs.informs.org>). Synthetic data analysis revealed that the model recovered all parameter values well within the corresponding 95% confidence intervals.

4.3. Model Selection and Investigation of Research Questions

Because the number of cross-national clusters is a priori unknown, we estimated several models with different numbers of clusters and selected the model with the largest posterior probability (Lenk and DeSarbo 2000). We implemented Chib's (1995) procedure to compute the log-marginal density (LMD) for each model and obtained the number of cross-national clusters represented in the data a posteriori.

Research question 1 (i.e., whether logo design characteristics are captured by the same design dimensions across cross-national clusters) corresponds to testing for configural invariance (Steenkamp and Baumgartner 1998). In the configural model, each cross-national cluster has the same factor structure. Hence, configural invariance is satisfied when the pattern of the unrestricted (nonzero) factor loadings of Λ_ξ^s and Λ_y^s is the same across clusters. To test for configural invariance, we investigated whether all factor loadings are significantly and substantially different from zero. In addition, we compared our model with a model without any factor structure (i.e., a simultaneous equation model, where Λ_ξ^s corresponds to the $(Q \times Q)$ identity matrix). A more stringent test is the metric model, which constrains the factor loadings $\Lambda_\xi^1 = \Lambda_\xi^2 = \dots = \Lambda_\xi^S$ and $\Lambda_y^1 = \Lambda_y^2 = \dots = \Lambda_y^S$ to be equal across all S cross-national clusters. If the metric model provides similar or better fit based on LMD, metric invariance also exists; not only do the clusters have similar factor structures, but the size of the factor loadings are also similar. If the two models are not equivalent, Steenkamp and Baumgartner (1998) suggest relaxing constraints for some factor loadings. If at least two equal factor loadings per factor (including the marker) are observed, we have partial metric invariance and are allowed to test the second

Table 2 Median Cluster Probabilities and Summary Characteristics

Country/cluster	West	Asia	Russia
Argentina	0.41 (0.31 to 0.51)	0.43 (0.34 to 0.52)	0.16 (0.11 to 0.23)
Australia	0.76 (0.67 to 0.84)	0.08 (0.04 to 0.14)	0.15 (0.08 to 0.23)
Great Britain	0.97 (0.93 to 0.99)	0.02 (0.00 to 0.06)	0.01 (0.00 to 0.03)
China	0.19 (0.13 to 0.26)	0.76 (0.69 to 0.82)	0.04 (0.02 to 0.08)
Germany	0.60 (0.51 to 0.69)	0.37 (0.29 to 0.46)	0.02 (0.01 to 0.05)
India	0.30 (0.22 to 0.38)	0.62 (0.53 to 0.69)	0.08 (0.04 to 0.14)
The Netherlands	0.75 (0.66 to 0.82)	0.22 (0.16 to 0.30)	0.03 (0.01 to 0.06)
Russia	0.01 (0.00 to 0.03)	0.01 (0.00 to 0.03)	0.98 (0.95 to 1.00)
Singapore	0.08 (0.05 to 0.13)	0.91 (0.86 to 0.95)	0.00 (0.00 to 0.02)
United States	0.85 (0.77 to 0.91)	0.12 (0.06 to 0.19)	0.03 (0.01 to 0.07)
Characteristic weighted averages*			
Income	\$25,763	\$17,551	\$11,136
Power distance	42.7	64.3	77.8
Uncertainty avoidance	49.8	39.2	76.8
Individualism/collectivism	75.5	41.1	45.4
Masculinity/femininity	54.8	54.8	43.5

Notes. Confidence intervals (95%) are in parentheses. Bold percentages indicate the cluster category with the highest value.

*All characteristic values are statistically different except masculinity/femininity for the West and Asia.

research question (i.e., whether consumers' responses to design dimensions are stable cross-nationally) by testing for invariance of structural relationships across clusters; i.e., $\Gamma_1 = \Gamma_2 = \dots = \Gamma_S$.

Results

4.4. Number of Cross-National Clusters

The LMD indicates that a three-cluster model fits best (LMD = −891,508 versus −896,328 for the one-cluster; −891,879 for the two-cluster; and −891,894 for the four-cluster models). The country-specific cluster probabilities displayed in Table 2 indicate that each country (except Argentina) clearly belongs to a single cluster. The clusters are labeled as follows: *West*, which includes Australia, Great Britain, Germany, The Netherlands, and the United States; *Asia*, which includes China, India, and Singapore; and *Russia*, which includes only Russia. Argentina straddles the West and Asia, which means that logo evaluations in Argentina are somewhat ambiguous.

These three clusters vary by cultural characteristics (except masculinity/femininity for the West and Asia) and writing systems. The Asian cultures use a more complex writing system and have lower individualism scores than either the West or Russia. Interestingly,

⁶ In our analysis, we did not observe label switching in any of the runs, indicating that the clusters are well separated (Rossi et al. 2005); see Technical Appendix B, available at <http://mktsci.pubs.informs.org>, for some posterior draws.

Table 3 Median Factor Loadings of Design Dimension and Affect

Design dimension	Design characteristic	Factor loading
Elaborateness	Complexity	1.00
	Activeness	1.29
	Depth	(1.13 to 1.47)
		1.34
Naturalness	Organic	(1.18 to 1.50)
		1.00
	Representativeness	0.82
		(0.74 to 0.91)
Harmony	Roundness	0.76
		(0.67 to 0.86)
	Symmetry	1.00
		0.62
Affect	Balance	(0.57 to 0.66)
		1.00
	Distinctive	0.62
		(0.57 to 0.66)
	Good	1.00
		1.07
	Interest	(1.06 to 1.08)
		1.25
	Like	(1.24 to 1.26)
		1.23
	Quality	(1.22 to 1.25)
		1.08

Notes. Confidence intervals (95%) are between parentheses. Factor loadings are equal across clusters because of metric invariance.

Argentina shares the simpler writing system with the West and a relatively low individualism score with Asia. Russia has a higher uncertainty avoidance score than the West and Asia. For the remainder of the analysis, we focus on the three-cluster solution.

4.5. Similarity of Design Factor Structures Across Clusters

Inspection of the factor loadings (see Table 3) reveals that all estimates are significantly and substantially different from zero. The proposed factor structure also strongly outperforms a simultaneous equation model in which no factor structure is assumed for logo design (LMD = −1,055,170). These results confirm Henderson and Cote's (1998) design factor structure with three dimensions: elaborateness (complexity, activeness, and depth), naturalness (organicity, representativeness, and roundness), and harmony (symmetry and balance). We tested for metric invariance using the LMD and found the metric invariance model (LMD = −891,403) fits better than the configural model (LMD = −891,508). This indicates that logo design characteristics are captured by the same factor structure and loadings across clusters.

4.6. Similarity of Design Response Relationships Across Clusters

Because we found metric invariance, we can now test whether the structural paths are invariant across the three clusters. As indicated by the LMD of structural relationship invariance (LMD = −891,510), this model

is rejected. Table 4 presents the results of the metric invariance model where structural paths are different across clusters. As suggested by Gelman and Pardoe (2006), the last column contains the explained variance for each dependent factor. Table 4 shows that the explained variance for each response variable varies substantially across clusters. Although there is a high degree of similarity to the pattern of relationships between design dimensions and response variables, the structural parameters have slight differences across clusters. We consider reasons for these patterns in the summary at the end of this section.

Affect. Overall, logo design dimensions and objective elements explain 84% of the variance in affect for Asia, 62% for the West, and 28% for Russia. In all clusters, affect increases as the design dimensions (harmony, elaborateness, and naturalness) increase as seen in the positive and significant structural path coefficients. However, the importance of elaborateness varies across the three clusters—the Russian cluster puts significantly less emphasis on it (0.19) than the Asian (0.70) and Western clusters (0.54). The effects of parallelism, proportion, and repetition on affect are small and statistically equivalent across the three clusters.

Subjective Familiarity. Logo design characteristics explain 24% of subjective familiarity for the West, 35% for Russia, and 41% for Asia. The relationships for harmony and naturalness are positive and statistically significant in all three clusters. Additionally, the effects of parallelism, repetition, and proportion are not significant across the clusters. However, the relationship between elaborateness and subjective familiarity varies across clusters—the path for Russia (−0.22) is negative and significant, whereas those of the West (0.26) and Asia (0.41) are positive and significant.

Shared Meaning. Logo design characteristics explained about the same amount of variance for all three clusters (19% for Asia, 22% for the West, and 23% for Russia). Naturalness increases shared meaning, while elaborateness reduces shared meaning in all three clusters. Harmony and the objective design elements do not influence shared meaning.

True Recognition. Logo design dimensions and objective elements explain 10% of true recognition for Asia, 6% for Russia, and 3% for the West. Naturalness has a positive influence and is equivalent across the clusters (Asia 0.10, the West 0.07, and Russia 0.06). Harmony, parallelism, and repetition have nonsignificant effects on true recognition in all three clusters. Two cluster differences emerge in the relationships between elaborateness, proportion, and true recognition. Elaborateness has a positive influence in Asia but no influence in Russia or the West (Asia 0.07 versus

Table 4 Median Estimates: Structural Paths

Response	Cluster	Elaborateness	Naturalness	Harmony	Parallelism	Proportion	Repetition	Intercept	Variance explained
Affect	West	0.54 (0.41 to 0.77)	0.12 (0.08 to 0.17)	0.06 (0.03 to 0.09)	0.00 (-0.02 to 0.03)	-0.06 (-0.12 to 0.01)	0.01 (-0.01 to 0.04)	1.75 (1.01 to 2.22)	0.62
	Asia	0.70 (0.59 to 0.82)	0.17 (0.12 to 0.24)	0.03 (0.01 to 0.05)	-0.04 (-0.06 to -0.01)	-0.02 (-0.11 to 0.07)	0.02 (-0.01 to 0.05)	0.87 (0.48 to 1.21)	0.84
	Russia	0.19 (0.05 to 0.34)	0.14 (0.09 to 0.19)	0.09 (0.04 to 0.16)	0.04 (-0.01 to 0.08)	-0.08 (-0.25 to 0.08)	0.06 (0.01 to 0.12)	2.40 (1.69 to 3.05)	0.28
Subjective familiarity	West	0.26 (0.02 to 0.61)	0.22 (0.13 to 0.30)	0.17 (0.11 to 0.23)	0.02 (-0.03 to 0.06)	0.14 (0.00 to 0.28)	-0.01 (-0.06 to 0.04)	0.93 (-0.13 to 1.71)	0.24
	Asia	0.41 (0.21 to 0.61)	0.26 (0.16 to 0.38)	0.07 (0.04 to 0.11)	-0.04 (-0.08 to -0.00)	0.04 (-0.12 to 0.21)	0.03 (-0.01 to 0.08)	0.93 (0.33 to 1.44)	0.41
	Russia	-0.22 (-0.46 to -0.02)	0.29 (0.21 to 0.36)	0.12 (0.03 to 0.22)	0.05 (-0.02 to 0.11)	-0.01 (-0.25 to 0.23)	0.04 (-0.04 to 0.12)	3.04 (2.08 to 4.11)	0.35
Shared meaning	West	-0.07 (-0.10 to -0.02)	0.08 (0.06 to 0.09)	0.00 (-0.01 to 0.01)	0.00 (-0.01 to 0.01)	0.02 (-0.01 to 0.05)	0.00 (-0.01 to 0.01)	0.18 (0.03 to 0.31)	0.22
	Asia	-0.05 (-0.08 to -0.01)	0.06 (0.04 to 0.08)	-0.00 (-0.01 to 0.00)	0.00 (-0.01 to 0.01)	0.01 (-0.03 to 0.05)	-0.00 (-0.02 to 0.01)	0.16 (0.04 to 0.27)	0.19
	Russia	-0.11 (-0.18 to -0.05)	0.06 (0.04 to 0.08)	-0.00 (-0.03 to 0.02)	-0.00 (-0.02 to 0.01)	-0.00 (-0.07 to 0.07)	-0.01 (-0.03 to 0.01)	0.67 (0.40 to 0.96)	0.23
True recognition	West	-0.04 (-0.12 to 0.06)	0.07 (0.03 to 0.10)	0.01 (-0.02 to 0.04)	0.02 (0.00 to 0.05)	-0.01 (-0.08 to 0.07)	0.02 (-0.00 to 0.05)	0.27 (-0.07 to 0.59)	0.03
	Asia	0.07 (0.00 to 0.16)	0.10 (0.07 to 0.14)	0.00 (-0.02 to 0.02)	0.00 (-0.02 to 0.03)	0.03 (-0.07 to 0.13)	0.01 (-0.02 to 0.04)	-0.13 (0.41 to 0.14)	0.10
	Russia	-0.02 (-0.14 to 0.09)	0.06 (0.03 to 0.10)	-0.03 (-0.07 to 0.02)	0.01 (-0.03 to 0.04)	-0.17 (-0.31 to -0.03)	0.03 (-0.02 to -0.07)	0.75 (0.24 to 1.28)	0.06
False recognition	West	0.15 (0.05 to 0.24)	-0.06 (-0.10 to -0.02)	0.05 (0.02 to 0.09)	-0.01 (-0.04 to 0.02)	-0.08 (-0.17 to 0.00)	0.02 (-0.01 to 0.05)	-1.29 (-1.66 to -0.95)	0.07
	Asia	0.14 (0.05 to 0.23)	-0.07 (-0.12 to -0.03)	0.03 (0.00 to 0.05)	-0.01 (-0.03 to 0.02)	-0.01 (-0.12 to 0.09)	0.01 (-0.02 to 0.04)	-1.21 (-1.51 to -0.89)	0.06
	Russia	0.13 (0.03 to 0.26)	-0.13 (-0.16 to -0.09)	0.06 (0.01 to 0.11)	-0.02 (-0.05 to 0.02)	0.03 (-0.11 to 0.17)	0.00 (-0.04 to 0.05)	-1.31 (-1.86 to -0.79)	0.23

Notes. Confidence intervals (95%) are in parentheses. Bold values correspond to coefficients with a 95% confidence interval not containing zero.

Russia -0.02 versus West -0.04), although this difference is not statistically significant across clusters. The effect of proportion is not statistically different across clusters but has a negative influence in Russia (-0.17) and is insignificant in Asia (0.04) or the West (-0.01).

False Recognition. Logo design characteristics explain a small percentage of false recognition for Asia (6%) and the West (7%) but a larger percentage in Russia (23%). For all clusters, naturalness decreases false recognition, whereas elaborateness and harmony increase false recognition.

Summary. Overall, the results for the cross-national clusters were consistent with prior work (Henderson and Cote 1998, Henderson et al. 2003). This is especially true for naturalness and harmony, where the patterns of the path estimates are consistent across response variables and clusters. Natural designs universally increase positive affect, shared meaning, subjective familiarity, and true recognition and decrease false recognition. Designs high in harmony universally increase positive affect, subjective familiarity, and false recognition while not affecting shared meaning or true recognition. However, the effect of harmony on subjective familiarity was higher for the West than for Asia.

The largest cluster differences were for elaborate designs. In most cases, elaborate designs increased positive affect, subjective familiarity, and true and false recognition while decreasing shared meaning. However, the Russian cluster differed significantly from the other clusters, where the influence of elaborate designs on affect was much smaller and that on subjective familiarity was actually negative. Arrindell et al. (2004) offer a possible explanation for this result. They find that countries with low uncertainty avoidance scores have greater tolerance for uncertainty and complexity. Because consumers in the Asian and, to a lesser extent, Western clusters have lower uncertainty avoidance scores, they may like and feel more familiar with complex designs than their Russian counterparts.


5. Conclusion

The goals of our study were to (1) extend finite-mixture structural equation models to account for individual judgment in stimulus-level design responses, (2) assess the cross-cultural universality of design dimensions and the stability of responses to these dimensions, and (3) address managerial concerns about adapting logos for global markets.

5.1. Extending Finite-Mixture Structural Equation Models

The proposed constrained, finite-mixture, structural equation modeling approach using concomitant variables proved a valuable tool for identifying latent logo clusters that are evaluated similarly across countries.

Our approach does not assume that logo evaluations within countries belong to the same cluster a priori (although our findings resulted in country-based clusters). Because of our concomitant variable formulation, the identified cross-national clusters are easily interpreted. Furthermore, previous experimental research in aesthetics aggregates individual responses for each logo. In contrast, our approach addresses a potential aggregation bias by modeling response heterogeneity through a hierarchical structure. More generally, our constrained, finite-mixture, structural equation modeling procedure can be extended to analyze data sets with many subgroups, aggregating them into larger classes based on response similarity. For example, our procedure can answer such questions as the following: How would different stakeholders (stockholders, consumers, competitors, public policy makers) respond to different multidimensional stimuli such as a company's pricing practices? How would different industries or markets react to different types of research and design projects? In addition, the proposed approach is suitable for smaller sample sizes, allows the incorporation of available prior parameter information, and avoids obtaining negative variances or Heywood cases.

The constrained finite-mixture modeling procedure can also provide important logo optimization guidelines. For instance, the Western cluster seems to have difficulty recognizing the logo , as indicated by an average true recognition score of 0.57 (on a 0–1 scale), compared to 0.64 in Asia and 0.73 in Russia. In addition, this logo has a moderate affect score across cultures (average score of 3.9 on a 7-point scale). The low naturalness score (2.3) is probably why this logo performs poorly, because naturalness has a positive influence on both true recognition and affect. Using posterior draws of the parameters, a designer can determine the minimum required naturalness score for a given country, such that its expected affect and true recognition values are higher than a predetermined threshold.⁷ For instance, the score of naturalness should be at least 3.5 in Russia, 3.9 in China, and 5.7 in the United Kingdom to obtain true recognition and affect scores of at least 0.65 and 4.0, respectively. Similarly, the elaborateness score of logo 65 in Germany should be between 3.2 and 4.2 (current median score equals 3.0) to reach an expected score of at least 4.0 on affect and 0.15 on shared meaning (current median scores are 3.9 and 0.33, respectively). Such optimization is especially important for

⁷ In the optimization, we determined for each posterior draw what the minimum score of natural should be, given the scores of this logo on the other dimensions, such that prespecified values of affect and true recognition are reached. We chose the posterior median of the minimum expected score as the threshold for natural.

elaborateness because its effects are not positive on all responses for all clusters.

5.2. Design Dimension Universality and Stability of Consumer Responses

Previous research suggests that elaborateness, naturalness, and harmony are design dimensions that exist across stimuli. Even when the design elements are quite different, these three dimensions appear repeatedly. Our results show that these design dimensions also exist across cultures, suggesting that they may be universal. The existence of universal design dimensions has important implications for design research. Currently, when developing a design study, researchers must select which of innumerable elements should be used to describe the design. For example, Orth and Malkewitz (2008) included 62 design elements for wine labels, and Henderson et al. (2004) used 24 elements for typeface. Focusing on a reduced set of design dimensions should make design research more tractable.




Our results also support the contention of evolutionary psychology that design perceptions are innate and relatively immune from cultural influence. Not only do different cultures perceive design similarly, but they also appear to respond similarly as well. Of course, culture does have some influence. For example, our results suggest that higher uncertainty avoidance cultures may find elaborate designs less attractive than lower uncertainty avoidance ones.

Future research can extend our findings in several important ways. Most notably, future research should investigate the universality of other possible design dimensions, such as weight, flourish, compression, size, and color. Additionally, consumer responses to brands with established designs/logos may differ from reactions to unfamiliar logos. Future work might consider how brand familiarity moderates the relationships uncovered in this research. Future research might also study more countries and extend the concomitant variable approach to allow cluster proportions to vary along more dimensions (e.g., writing systems and uncertainty avoidance) than only country evaluations.

5.3. Managerial Guidelines for Adapting Global Logos

For the manager interested in maintaining a consistent brand image worldwide, our results suggest a standardized core logo can work globally. Logo perceptions and responses are similar enough across cultures that a given logo design will produce similar effects in many parts of the world. In addition, when evaluating logo designs, managers may want to focus on affective responses where design dimensions and elements appear to have the strongest influence.

Design appears less related to recognition and shared meaning, which are learned responses strongly influenced by other marketing investments.

This implies that managers should particularly focus on designing elaborate, natural, and harmonious logos that elicit positive affect because it may be difficult to rectify design problems by other marketing efforts. For example, Habitat for Humanity recently created a new logo, . It is more natural and elaborate, but it may be slightly less harmonious than the previous logo, . We predict that this new logo will increase positive affect and, to a lesser extent, shared meaning worldwide. Increasing harmony such as  might have been even more effective.

Although these guidelines seem intuitive, managers continue to create poor logos (Colman et al. 1995) as the 2012 London Olympics logo (which cost £400,000 to create) so vividly illustrates (Methven and McGurran 2007).

Elaborating on the suggestions of Kohli et al. (2002), we suggest managers do the following when designing or modifying a logo:

- (1) Choose the core logo image carefully and specify clear response objectives for various regions.
- (2) Communicate with logo designers using the design dimensions of elaborateness, naturalness, and harmony. Our results suggest that they provide a parsimonious vocabulary for design communication.
- (3) Design something effective before entering new markets. You often cannot change your brand name, but you can change your logo.
- (4) Do not go with the “flavor of the month” or “artistically interesting” logos. Stick to logos that simply and richly capture the essence of something (elaborateness), depict commonly experienced objects (naturalness), and represent congruent patterns or arrangements of parts (harmony).
- (5) Be systematic and objective and allow designers to modify the core logo for individual markets. However, use the results of Table 4 to guide logo selection rather than to rely solely on the opinion of a particular logo designer or committee.
- (6) Test new alternatives against existing logos, because there are multiple ways to create elaborate, natural, and harmonious logos.

As a company builds brand familiarity within a country, consumer responses to its logo may depend less on the actual design and more on the associations formed with the brand. However, there are several cases where our recommended guidelines will be important regardless of brand name and reputation, which include the following:


- (1) *New companies*. When you first create a logo and brand, they have no meaning.

(2) *New consumers*. New international markets will interpret a logo design before the brand's verbal information.

(3) *Changing logos*. A product may have a place in the mind, but a new logo triggers new thinking about the brand (which may be inconsistent with the original positioning). If a logo is not properly designed, it can interfere with the processing of brand information and interpretation of the new image.

(4) *Mergers or brand extensions*. Acquiring new companies may necessitate modifying a logo to better capture the full range of company products.

(5) *Marketing to children or the illiterate*. Children and the illiterate will learn by visuals before any processing of verbal information.









Last, for managers less concerned about having a single global logo, it may be possible to optimize a logo for specific countries or regions, as shown in the previous discussion of logo optimization. Because country differences are mostly in degree not direction, adding or deleting a design element or dimension should elicit better responses across cultures. If Habitat wanted to optimize their logo for Russia, it could be made less complex by removing the repetitive elements as in . Tide did something similar with its logo (left below). When the logo was used for packaging in China (right), it was much more elaborate and natural than in the United States (middle). Additional color and visual elements, plus arms added to the traditional circular logo make the image more active and representative—like a cyclone.























There are at least three caveats associated with our recommended approach to logo design in international markets. First, because our research was done in only 10 of 195 possible countries, managers need to be cautious about generalizing results beyond the 10 studied markets. If a manager needs to modify a design for markets not included in our study, we recommend that managers obtain the cultural characteristics of the country from a website such as <http://www.geert-hofstede.com/> and match the new market to the cultural characteristics of the markets described in Table 1. Then, select the most similar country and apply the optimization procedure discussed in §6.2 to obtain dimensional estimates of the optimal logo design. Second, student subjects were used to test consumer responses to consumer logos. Hence the observed relationships between logo characteristics and responses may have a different direction and strength in other groups. Our respondent homogeneity may underestimate the cultural effects of logo design characteristics. Third, our recommendations may not apply to brand/logo combinations. Future research could assess consumer familiarity with brands; expose them to different brand/logo combinations; and measure affect, subjective familiarity, shared meaning, and recognition.

In a limited experiment with U.S. student subjects, the logo used for the 2012 London Olympics application campaign (see <http://i43.photobucket.com/albums/e360/revcruz/Candidate.jpg>) generated a more positive attitude toward the Olympics brand than when using the final official logo (see <http://img.photobucket.com/albums/V181/bragin/DE/londonlogo.gif>). The alternative logo was rated as more natural, harmonious, and elaborate than the one selected (see Technical Appendix D, available at <http://mktsci.pubs.informs.org>). This result suggests that logos can have an effect even on an established brand. We are thus optimistic that future brand/logo research will replicate our findings.

Appendix A. Examples and Definitions of Design Elements and Dimensions (from Henderson and Cote 1998)

Design Characteristics	High	Low
<p>Elaborateness captures the concept of design richness and the ability to use plain lines to capture the essence of an object. It comprises the elements of complexity, activeness, and depth.</p> <p><i>Complexity</i> is created by irregularity in the arrangement of elements, increases in the number of elements, heterogeneity in the nature of elements, and ornateness of the design.</p> <p><i>Active</i> designs give the impression of motion or flow.</p> <p><i>Depth</i> gives the appearance of perspective or of being three-dimensional.</p>	   	   

Appendix A. (Cont'd.)

Design Characteristics	High	Low
Naturalness reflects the degree to which the design depicts commonly experienced objects. It comprises the elements of representativeness and organicity.		
<i>Representativeness</i> is the degree of realism in a design. This occurs when the elements of an object are distilled to its most typical features.		
<i>Organicity</i> refers to natural shapes as opposed to angular and abstract designs.		
<i>Round</i> designs are made of primarily curved lines and circular elements.		
Harmony is a congruent pattern or arrangement of parts that combines the elements of symmetry and balance.		
<i>Symmetric</i> designs appear as reflections along one (or more) axis.		
<i>Balance</i> captures the notion that there is a center of suspension between two weights or portions of the design.		
<i>Parallel</i> designs contain multiple lines or elements that appear adjacent to each other.		
<i>Repetition</i> is the iterative use of design parts that are similar or identical to each other—unless they are simply part of a larger whole (e.g., branches on a tree).		
<i>Proportion</i> is the relationship between the horizontal and vertical dimensions.		

Note. Design dimensions are in bold, whereas design elements are italic.

Appendix B

This appendix presents the posterior distributions we used to draw the model parameters in the MCMC sampler. Because we chose conjugate prior distributions,⁸ the derivations of these posterior distributions are relatively standard. However, for some of the derivations of conditional posteriors, we use the following well-known result in statistics to derive the conditional distribution of the free parameters in a multivariate normal vector in which some parameters are fixed to a prespecified number a . Let

$$\begin{pmatrix} \mathbf{X}_{\text{free}} \\ \mathbf{X}_{\text{fixed}} \end{pmatrix} \sim N \left(\begin{pmatrix} \boldsymbol{\mu}_{\text{free}} \\ \boldsymbol{\mu}_{\text{fixed}} \end{pmatrix}, \begin{pmatrix} \boldsymbol{\Sigma}_{\text{free, free}} & \boldsymbol{\Sigma}_{\text{fixed, free}} \\ \boldsymbol{\Sigma}_{\text{free, fixed}} & \boldsymbol{\Sigma}_{\text{fixed, fixed}} \end{pmatrix} \right);$$

then $\mathbf{X}_{\text{free}} | \mathbf{X}_{\text{fixed}} = a \sim N(\bar{\boldsymbol{\mu}}, \bar{\boldsymbol{\Sigma}})$, with

$$\bar{\boldsymbol{\mu}} = \boldsymbol{\mu}_{\text{free}} + \boldsymbol{\Sigma}_{\text{free, fixed}} \boldsymbol{\Sigma}_{\text{fixed, fixed}}^{-1} (a - \boldsymbol{\mu}_{\text{fixed}}),$$

and

$$\bar{\boldsymbol{\Sigma}} = \boldsymbol{\Sigma}_{\text{free, free}} - \boldsymbol{\Sigma}_{\text{free, fixed}} \boldsymbol{\Sigma}_{\text{fixed, fixed}}^{-1} \boldsymbol{\Sigma}_{\text{fixed, free}}$$

(see Arnold 1990, p. 214). In the derivations, we refer to this result as the *partitioning result*.

⁸ For the specifications of the prior distributions, see Technical Appendix A, available at <http://mktsci.pubs.informs.org>.

For the Gibbs sampler, we use cycles sequentially through the following conditional posteriors. In the first two steps, we followed (Diebolt and Robert 1994) to draw the augmented variables z_{ci} and the cluster probabilities π .

$$\text{Step 1. } z_{ci} | \dots \sim MN \left(\frac{L(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \bar{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \bar{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^{s=1})}{\sum_{s=1}^S L(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \bar{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \bar{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^s)}, \dots, \frac{L(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \bar{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \bar{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^{s=S})}{\sum_{s=1}^S L(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \bar{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \bar{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^s)} \right),$$

with $MN(\cdot)$ the multinomial distribution, and $L(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \bar{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \bar{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^s)$ the likelihood (8) of logo i in country c assigned to cluster s .

$$\text{Step 2. } \pi_{c\cdot} | \dots \sim D \left(r_{c1} + \sum_{i=2}^{I_c} I\{z_{ci} = 1\} \dots r_{cS} + \sum_{i=2}^{I_c} I\{z_{ci} = S\} \right)$$

for each country $c = 1, \dots, C$, with $D(\cdot)$ representing the Dirichlet distribution, and $I\{\cdot\}$ the indicator function that equals one when the expression between brackets holds, and zero otherwise.

$$\text{Step 3. } \begin{pmatrix} \tau_{\xi, \text{free}}^s \\ \text{vec}(\Lambda_{\xi, \text{free}}^s) \end{pmatrix} \sim N(\bar{U}_{\xi}^s, \bar{Q}_{\xi}^s) \quad \text{and} \\ \begin{pmatrix} \tau_{y, \text{free}}^s \\ \text{vec}(\Lambda_{y, \text{free}}^s) \end{pmatrix} \sim N(\bar{U}_y^s, \bar{Q}_y^s),$$

where subscripts *fix* and *free* refer, respectively, to the set of fixed and free parameters of the corresponding matrix (Arnold 1990). Using the *partitioning results* described earlier, we get for $\phi \in \{\xi, y\}$:

$$\bar{U}_{\phi}^s = U_{\phi, \text{free}}^s + Q_{\phi, \text{free}}^s (Q_{\phi, \text{fix}}^s)^{-1} \cdot \left(\begin{pmatrix} \tau_{\phi, \text{fix}}^s \\ \text{vec}(\Lambda_{\phi, \text{fix}}^s) \end{pmatrix} - U_{\phi, \text{fix}}^s \right),$$

and

$$\bar{Q}_{\phi}^s = Q_{\phi, \text{free}}^s - Q_{\phi, \text{free}}^s (Q_{\phi, \text{fix}}^s)^{-1} Q_{\phi, \text{fix}}^s,$$

with

$$U_{\xi}^s = Q_{\xi}^s \cdot \left(\sum_{c=1}^C \sum_{i: z_{ci}=s} \left\{ \begin{pmatrix} 1 & \bar{\xi}_{ci} \end{pmatrix} \otimes I_Q \right\}' \Sigma_{\xi}^{s-1} \bar{\xi}_{ci} \right\} \\ + \begin{pmatrix} H_{\xi}^s & 0 \\ 0 & V_{\xi}^s \end{pmatrix}^{-1} \begin{pmatrix} h_{\xi}^s \\ L_{\xi}^s \end{pmatrix} \Bigg), \\ U_y^s = Q_y^s \cdot \left(\sum_{c=1}^C \sum_{i: z_{ci}=s} \sum_{h=1}^{H_{ci}} \left\{ \begin{pmatrix} 1 & \eta_{cih} \end{pmatrix} \otimes I_P \right\}' \Sigma_y^{s-1} y_{cih}^{\text{affect}} \right\} \\ + \begin{pmatrix} H_y^s & 0 \\ 0 & V_y^s \end{pmatrix}^{-1} \begin{pmatrix} h_y^s \\ L_y^s \end{pmatrix} \Bigg), \\ Q_{\xi}^s = \left(\left(\sum_{c=1}^C \sum_{i: z_{ci}=s} \begin{pmatrix} 1 & \bar{\xi}_{ci} \end{pmatrix} \cdot \begin{pmatrix} 1 & \bar{\xi}_{ci} \end{pmatrix}' \right) \right. \\ \left. \otimes \Sigma_{\xi}^{s-1} + \begin{pmatrix} H_{\xi}^s & 0 \\ 0 & V_{\xi}^s \end{pmatrix}^{-1} \right)^{-1},$$

and

$$Q_y^s = \left(\left(\sum_{c=1}^C \sum_{i: z_{ci}=s} \sum_{h=1}^{H_{ci}} \begin{pmatrix} 1 & \eta_{cih} \end{pmatrix} \cdot \begin{pmatrix} 1 & \eta_{cih} \end{pmatrix}' \right) \right. \\ \left. \otimes \Sigma_y^{s-1} + \begin{pmatrix} H_y^s & 0 \\ 0 & V_y^s \end{pmatrix}^{-1} \right)^{-1}.$$

In the following four steps, we sequentially draw, respectively, the scores on the subjective logo design items (Step 4), logo design dimensions (Step 5), affect response items (Step 6), and affect and subjective familiarity response dimensions (Step 7). The derivations of these conditional posterior distributions are relatively straightforward using multiplication of normal distributions.

$$\text{Step 4. } \xi_{ciq} \sim N \left(\frac{\Sigma_{\xi qq}^s \sum_{r=1}^{R_{ciq}} x_{cirq} + (\tau_{\xi q}^s + \Lambda_{\xi q}^s \bar{\xi}_{ci}^r) \Sigma_{\xi qq}^s}{R_{ciq} \Sigma_{\xi qq}^s + \Sigma_{\xi qq}^s}, \right. \\ \left. \frac{\Sigma_{\xi qq}^s \Sigma_{\xi qq}^s}{R_{ciq} \Sigma_{\xi qq}^s + \Sigma_{\xi qq}^s} \right).$$

Step 5. $\bar{\xi}_{ci} \sim N(U_{\bar{\xi}_{ci}}, Q_{\bar{\xi}_{ci}})$, with

$$Q_{\bar{\xi}_{ci}} = \left(\Lambda_{\xi}^{z_{ci}} (\Sigma_{\xi}^{z_{ci}})^{-1} \Lambda_{\xi}^{z_{ci}} + \Gamma^{z_{ci}} (\Omega_{\bar{\eta}^{z_{ci}}}^{-1})^{-1} \Gamma^{z_{ci}} + (\Omega_{\bar{\xi}^{z_{ci}}}^{-1})^{-1} \right)^{-1},$$

and

$$U_{\bar{\xi}_{ci}} = Q_{\bar{\xi}_{ci}} \left(\Lambda_{\xi}^{z_{ci}} (\Sigma_{\xi}^{z_{ci}})^{-1} (\xi_{ci} - \tau_{\xi}^{z_{ci}})' \right. \\ \left. + \Gamma^{z_{ci}} (\Omega_{\bar{\eta}^{z_{ci}}}^{-1})^{-1} (\bar{\eta}_{ci} - \alpha^{z_{ci}})' + (\Omega_{\bar{\xi}^{z_{ci}}}^{-1})^{-1} \mu^{z_{ci}} \right).$$

Step 6. $\eta_{ci1h} \sim N(L_{\eta_{cih}}, Q_{\eta_{ci}})$, with

$$Q_{\eta_{ci}} = \left(\Lambda_y^{z_{ci}} (\Sigma_y^{z_{ci}})^{-1} \Lambda_y^{z_{ci}} + (\Sigma_{\eta}^{z_{ci}})^{-1} \right)^{-1},$$

and

$$L_{\eta_{cih}} = Q_{\eta_{ci}} \left(\Lambda_{z_{ci}}^{y'} (\Sigma_{z_{ci}}^y)^{-1} (y_{cih}^{\text{affect}} - \tau_y^{z_{ci}}) + (\Sigma_{\eta, 11}^{z_{ci}})^{-1} \bar{\eta}_{ci1} \right).$$

Step 7. $\eta_{ci} \sim N(U_{\eta_{ci}}, Q_{\eta_{ci}})$, with

$$U_{\eta_{ci}} = Q_{\eta_{ci}} \left((\Sigma_{\eta}^{z_{ci}})^{-1} \sum_{h=1}^{H_{ci}} \eta_{cih} + (\Omega_{\bar{\eta}^{z_{ci}}}^{-1})^{-1} (\alpha^{z_{ci}} + \Gamma^{z_{ci}} \bar{\xi}_{ci}') \right),$$

and

$$Q_{\eta_{ci}} = (H_{ci} (\Sigma_{\eta}^{z_{ci}})^{-1} + (\Omega_{\bar{\eta}^{z_{ci}}}^{-1})^{-1}).$$

In Step 8, we draw the means of the subjective logo design dimensions. The derivations are again relatively straightforward using multiplication of normal distributions.

Step 8. $\mu^s \sim N(U_{\mu}^s, Q_{\mu}^s)$, with

$$U_{\mu}^s = Q_{\mu}^s \left((\Omega_{\xi}^s)^{-1} \left(\sum_{c=1}^C \sum_{i: z_{ci}=s} \bar{\xi}_{ci} \right) + (H_{\xi}^s)^{-1} h_{\xi}^s \right),$$

and

$$Q_{\mu}^s = \left(\left(\sum_{c=1}^C \sum_{i=1}^{I_c} I\{z_{ci}=s\} \right) (\Omega_{\xi}^s)^{-1} + (H_{\xi}^s)^{-1} \right)^{-1}.$$

In the following six steps, we, respectively, draw the variances of the rater variance of the subjective logo design items (Step 9), the item variances of logo response items (Step 10), the item variances of the subjective logo design characteristics (Step 11), the variance of the individual-specific logo design responses (affect and subjective familiarity) (Step 12), the variances of the subjective logo design dimensions (Step 13), and the variances of the logo design responses (Step 14).

$$\text{Step 9. } \Sigma_{xqq}^s \sim IG \left(\frac{1}{2} \sum_{c=1}^C \sum_{i=1}^{I_c} I(z_{ci}=s) \cdot R_{ciq} + v_{x0}^s, \right. \\ \left. \frac{1}{2} \sum_{c=1}^C \sum_{i: z_{ci}=s} \sum_{r=1}^{R_{ciq}} (x_{cirq} - \xi_{ciq})^2 + v_{xp}^s \right).$$

$$\text{Step 10. } \Sigma_{ypp}^s \sim IG \left(\frac{1}{2} \sum_{c=1}^C \sum_{i=1}^{I_c} I(z_{ci}=s) \cdot H_{ci} + v_{y0}^s, \right. \\ \left. \frac{1}{2} \sum_{c=1}^C \sum_{i: z_{ci}=s} \sum_{h=1}^{H_{ci}} (y_{cihp}^{\text{affect}} - \tau_{yp}^s - \Lambda_{yp}^s \eta_{ci1h}')^2 \right. \\ \left. + v_{yp}^s \right).$$

$$\text{Step 11. } \Sigma_{\xi q q}^s \sim IG \left(\frac{1}{2} \sum_{c=1}^C \sum_{i=1}^{I_c} I(z_{ci} = s) + v_{\xi 0}^s, \frac{1}{2} \sum_{c=1}^C \sum_{i: z_{ci}=s} \sum_{r=1}^{R_{ciq}} \left(\xi_{ciq} - \tau_{\xi q}^s - \Lambda_{\xi q}^s \bar{\xi}_{ci}' \right)^2 + v_{\xi p}^s \right).$$

$$\text{Step 12. } \Sigma_{\eta p p}^s \sim IG \left(\frac{1}{2} \sum_{c=1}^C \sum_{i=1}^{I_c} I(z_{ci} = s) \cdot H_{ci} + v_{\eta 0}^s, \frac{1}{2} \sum_{c=1}^C \sum_{i: z_{ci}=s} \sum_{h=1}^{H_{ci}} (\eta_{cip h} - \bar{\eta}_{cip})^2 + v_{\eta p}^s \right) \quad \forall p \in \{1, 2\}.$$

$$\text{Step 13. } \Omega_{\xi n n}^s \sim IG \left(\frac{1}{2} \sum_{c=1}^C \sum_{i=1}^{I_c} I(z_{ci} = s) + v_{\xi 0}^s, \frac{1}{2} \sum_{c=1}^C \sum_{i: z_{ci}=s} (\bar{\xi}_{cin} - \mu_n^s)^2 + v_{\xi n}^s \right) \quad \forall n \in \{1, 2, 3\}.$$

$$\text{Step 14. } \Omega_{\eta m m}^s \sim IG \left(\frac{1}{2} \sum_{c=1}^C \sum_{i=1}^{I_c} I(z_{ci} = s) + v_{\eta 0}^s, \frac{1}{2} \sum_{c=1}^C \sum_{i: z_{ci}=s} (\bar{\eta}_{cim} - \alpha_m^s - \bar{\xi}_{ci} \Gamma_{\cdot m}^s)^2 + v_{\eta m}^s \right).$$

In the last step, we draw the intercepts and parameters of the structural relationships between the logo design characteristics and responses. The derivations are based on standard derivations for multivariate normal distributions.

$$\text{Step 15. } \begin{bmatrix} \text{vec}(\alpha^s) \\ \text{vec}(\Gamma^s) \end{bmatrix} \sim N(\bar{U}^s, \bar{Q}^s), \quad \text{with} \\ \bar{U}^s = \bar{Q}^s \cdot \left(([1 \quad \bar{\xi}_{ci:z_{ci}=s}] \otimes (\Omega_{\eta}^s)^{-1}) \text{vec}(\bar{\eta}_{ci:z_{ci}=s}) + \begin{pmatrix} \mathbf{A}^s & \mathbf{0} \\ \mathbf{0} & \mathbf{G}^s \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{a}^s \\ \mathbf{g}^s \end{pmatrix} \right), \\ \bar{Q}^s = \left(([1 \quad \bar{\xi}_{ci:z_{ci}=s}] [1 \quad \bar{\xi}_{ci:z_{ci}=s}] \otimes (\Omega_{\eta}^s)^{-1} + \begin{pmatrix} \mathbf{A}^s & \mathbf{0} \\ \mathbf{0} & \mathbf{G}^s \end{pmatrix}^{-1} \right)^{-1},$$

and $i: z_{ci} = s$ the logos assigned to cluster s .

Acknowledgments

The authors thank Berk Ataman for valuable suggestions and the National University of Singapore for project funding.

The Habitat for Humanity International logo is used with permission of the organization. Tide laundry detergent logo used with permission of the Procter & Gamble Company.

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