Does Matching Website Characteristics to Cognitive Styles Increase Online Sales?

by

Michael Braun

Clarence Lee

Glen Urban

and

John R. Hauser

December 2009

Michael Braun is the Homer A. Burnell Career Development Professor and Assistant Professor of Marketing, MIT Sloan School of Management, Massachusetts Institute of Technology, E40-169, 1 Amherst Street, Cambridge, MA 02142, (617) 253-3436, fax (617) 253-7597, braunm@mit.edu.

Clarence Lee is a doctoral student in the Marketing Department at the Harvard Business School, Soldiers Field, Boston, MA 02163, clee@hbs.edu.

Glen L. Urban is the David Austin Professor of Marketing, MIT Sloan School of Management, Massachusetts Institute of Technology, E40-159, 1 Amherst Street, Cambridge, MA 02142, (617) 253-6615, fax (617) 258-7597, glurban@mit.edu.

John R. Hauser is the Kirin Professor of Marketing, MIT Sloan School of Management, Massachusetts Institute of Technology, E40-179, 1 Amherst Street, Cambridge, MA 02142, (617) 252-2929, hauser@mit.edu.

This research was supported by the MIT Sloan School of Management, the Center for Digital Business at MIT (ebusiness.mit.edu), and the BT Group. We gratefully acknowledge the contributions of our industrial collaborators, research assistants, and faculty colleagues: Cinda Amyx, Theta Aye, Fabio Colacchio, Shane Frederick, Shirley Fung, Tilli Kalisky, Steven Kao, Robert Klein, Mangesh Kulkarni, Shelly Lau, Matthew Lawson, Guilherme Liberali, Antonio Lorenzon, Aman Narang, Gavin Patterson, Harold Salomann, Steven Stokols, Fareena Sultan, and Steven Whittaker.

Does Matching Website Characteristics to Cognitive Styles Increase Online Sales?

Abstract

This paper presents evidence that matching website characteristics to cognitive styles increases online sales. Such evidence tests the basic premise underlying industry trends toward consumer-specific website customization. A website characteristic describes the basic "look and feel" of an entire website and a cognitive style is a consumer's preferred method to process information. For example, webpages with graphical characteristics make extensive use of graphs and pictures rather than text. Such webpages may generate more sales when matched to a consumer with an analytical cognitive style while more-texted-based webpages may be more effective when matched to a consumer with an holistic cognitive style.

We use Bayesian methods to account for heterogeneity and for mixed data regimes so that we might examine the differential impact of website characteristics, cognitive styles, and their interactions on purchase intentions for broadband subscriptions. In the experiment, 835 respondents are assigned randomly to sets of website characteristics. Their cognitive styles and purchase intentions are measured with standard scales. Our analyses suggest that models with interactions fit the data better and do well on posterior predictive checks.

Keywords: *Cognitive styles, Bayesian methods, website design, Internet marketing, personalization, telecommunications*

1. Cognitive Styles and Website Characteristics

In this paper we examine whether consumer intentions can be improved if website characteristics are matched to cognitive styles. A website characteristic is a feature or set of features that affects the "look and feel" of a website. For example, if a page uses more figures and pictures rather than words, it said to be "graphics-intensive." A website that displays many alternatives, many features of those alternatives, and much other information is said to present a "large load." A cognitive style is a description of a consumers' preferred way of processing information. For example, a consumer with an impulsive cognitive style makes decisions quickly with little information or analysis. In contrast, the consumer with a deliberative cognitive style processes information carefully before making a decision.

Website characteristics affect website traffic and sales. For example, Google's minimalistic interface is credited, in part, with its rise to become the top search engine. This minimalism is in sharp contrast to the cluttered portals of the late 1990s such as Altavista, AOL, and Yahoo. However, one size does not fit all. iGoogle presents consumers with a chance to customize their home page and make it as cluttered or uncluttered as they would like.

While anecdotes abound to suggest that sales increase if website designs match cognitive styles, these anecdotes are not based on a systematic variation of website design, nor do they explicitly measure consumers' cognitive styles. If matching website characteristics to cognitive styles does, in fact, increase sales then firms can increase profits dramatically. Either they invest in ways that allow consumers to customize websites or, when websites are visited infrequently, they develop "engines" to match website characteristics to cognitive styles. For example, Hauser, et al. (2009) demonstrate increases of 20% with an inference engine that identifies consumers' cognitive styles from clickstreams before assigning website characteristics to consumer segments with similar cognitive styles.

Our paper differs from, but complements, Hauser, et al. Their analyses depend upon the conditional probabilities that consumers in a cognitive-style segment would make a purchase if shown a set of website characteristics. Their estimates were sufficient for illustrating their "website morphing" methodology, but were based on aggregate logit models. Our analyses are more focused and rigorous. We formulate a respondent-level model based on a mixture of quantal (0 vs. 1) and ratio-scaled (between 0 and 1) purchase intention measures. We account for scale differences and for response heterogeneity to provide posterior distributions for parameters that test whether matching website characteristics to cognitive styles affects purchase intentions. We compare models with and without "matches" and demonstrate the reasonableness of our models with posterior predictive tests.

We begin with a brief review of the managerial issues, website characteristics, and cognitive styles. We next detail the specific characteristics and styles, describe our response model, and present and interpret the results. We close with a discussion of future directions.

2. Managerial Context, Cognitive Styles, and Website Characteristics

Managerial Context

Today almost every firm uses websites as part of their marketing and selling efforts, and researchers have recognized the importance of understanding the visit-to-sale conversion process (Moe and Fader 2004). Good website designs communicate well, build brand images, and convert clicks to sales. Poor designs are confusing and difficult to use, alienate customers, and lose sales. In the last ten years website designs have evolved from portals that gave customers as much information and as many options as possible to websites with reduced complexity and improved visual appeal.

If all consumers had the same cognitive styles, a website designer could use experimentation and standard market-research methods to optimize a single website (Google's website optimizer or conjoint analysis). Alternatively, when consumers are heterogeneous in their tastes, websites can be personalized. Examples include self-selected branching , collaborative filtering, usage mining, clustering, and customized content (Ansari and Mela 2003; Anand, Kearney and Shapcott 2007; Eirinaki and Vazirgiannis 2003, 2007; Im and Hars 2007; Montgomery, Li, Srinivasan, and Liechty 2004; Perkowitz and Etzioni 2000). But established customization either focuses on product recommendations, extensive data from each consumer, or active participation by the consumer. We seek to go beyond product recommendations to the basic manner in which the website displays information. We examine whether a firm can base customization on basic consumer styles that can be inferred quickly and easily even if the visitor is relatively new to the website (less data and less incentive for the consumer to spend time actively configuring a website to their tastes).

Cognitive Styles

A cognitive style "reflects the way in which (an) individual thinks" (Riding and Rayner

1998, p. 7) and has been defined as "a person's preferred way of gathering, processing, and evaluating information" (Allinson and Hayes 1996; Hayes and Allinson 1998). Cognitive styles have proven valuable in distance learning, web-based learning, digital libraries, and hypermedia navigation with recent interest from the marketing community for management decision making, advertising, and branding (Childers, Houston, and Heckler, 1985; Deakin and Aitken 2004; Frias-Martinez, Chen and Liu 2007; Hutchinson and Huang, 2008; Monga and John 2007; Monga and Lau-Gesk 2007; Novak and Hoffman 2009; Thompson and Hamilton, 2006; White, 2003, Witkin, et al. 1977).

While there is no consensus on a set of mutually exclusive and collectively exhaustive cognitive-style dimensions, Riding and Rayner (1998) suggest departure points. For the context of web-based sales of broadband subscriptions, the BT Group focused on analytic vs. holistic and visual vs. verbal (Allinson and Hayes 1996; Harvey, Hunt and Schroder 1961; Kirton 1987; Paivio 1971; Riding and Cheema 1991). They included impulsive vs. deliberative to capture consumers' risk preferences and willingness to invest time on searching for information on their website (Elangovan and Karakowsky 2003; Frederick 2005; Kopfstein 1973). Finally, while not traditionally defined as a cognitive style, they included leader vs. follower as relevant to the adoption of high technology (Rogers 1962; Rogers and Stanfield 1968, von Hippel 1988). The specific measurement scales in our data are summarized in Table 1.

Website Characteristics

A website characteristic is a basic property of the way information is presented on webpages that make up a website. Characteristics are defined at a moderately high level and developed so that they link to cognitive styles. Website designers then select website elements (fonts, colors, number of rows in a table, the amount of graphs and pictures) to implement website characteristics. In our application, websites varied on three dimensions: graphical vs. verbal, focused vs. general content, and small vs. large load. In our data, described next, eight website variations were systematically and randomly varied based on this 2 x 2 x 2 design. Table 1 gives examples of the website elements that that the BT Group chose to implement the three ipsative website characteristics.

Table 1
Cognitive-Style Dimensions and Website Characteristics

Targeted Cognitive Style	**Measurement Scales (from the literature, references in text)**
Visual vs. verbal, Analytic vs. holistic	I prefer to read text rather than to listen to a lecture. I enjoy deciphering graphs, charts, and diagrams. I will read an explanation of a graphic/chart before I try to understand the graphic/chart on my own. I see what I read in mental pictures. I am detail oriented, and start with the details in order to build a complete picture. I tend to see problems in their entirety and start by integrating pieces from different areas.
Leader vs. follower	I find it is easy to make decisions for others and to command and direct others to take certain actions. In a group conversation, I usually speak to the most. I have held a great deal of leadership positions in my life. My confidence level is higher than most other people's.
Impulsive vs. deliberative	A bat and ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost? 10 cents = impulsive. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? 100 minutes = impulsive. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? 24 days = impulsive.
Website Characteristic	**Example Website Elements**
Graphical vs. verbal	Graphs and diagrams vs. verbal (text and audio) Tables vs. audio information
Focused vs. general content	Targeted (e.g., technologists) vs. untargeted Technical magazine editor persona vs. general consumer persona Detailed product specifications vs. general recommendations. Basic vs. advanced topics in the learning center Technical vs. general threads in online communities
Small vs. large load	Fewer vs. more product features Fewer vs. more brands Long form vs. short form in learning-center topics Extensive vs. abbreviated comments in online communities

3. Data and Context

The BT Group sells broadband service in Great Britain. The market is highly competitive with over 16 firms offering service. Web-based marketing is key to their sales strategy with consumers coming to the BT website to gather information, compare plans, and, hopefully, subscribe. In the data available to us, potential consumers were assigned randomly to one of eight prototype websites that varied on the three website characteristics in Table 1. After exploring the prototype website, respondents indicated which broadband providers they would consider and, from among considered providers, they indicated their relative purchase intentions (normalized to sum to 100% across all considered providers).[1] At the end of the questionnaire, respondents completed the cognitive-style scales in Table 1.[2] Respondents were recruited from a respected British online panel (Research Now), screened to be in the market for online service, and given £15 for their participation. In total, 835 respondents completed the experimental study.

Cognitive Style Segments

Our focus in this paper is on whether matching cognitive styles to website characteristics increases sales. To be consistent with BT's application and prior papers we adopt the cognitive dimensions used by BT. Specifically, Hauser et al. (2009) used exploratory, then confirmatory, factor analyses to identify four cognitive-style dimensions. Once the factors were identified, they averaged the scales to obtain indicators (e.g., Churchill 1979). Visual vs. verbal and analytic vs. holistic loaded together and were combined into a single factor. Leader vs. follower and impulsive vs. deliberative loaded cleanly and were retained as two separate factors. Reliabilities (Cronbach's α) were reasonable, but did indicate some noise in the data (0.56, 0.55, and 0.80, respectively). A fourth factor appeared to be driven by a single scale, reader vs. listener. Based on the literature, they retained it as a single-item factor (Bergkvist and Rossiter 2007, Drolet and Morrison 2001). An appendix provides the factor loadings.

The next step was driven by application. The primary use of cognitive-style-website-characteristics matching is to change websites dynamically to match cognitive styles as revealed by consumer behavior such as clicks. Computational issues and the practical challenge of creating multiple website variations limit such variations to a small finite number. Thus, consistent

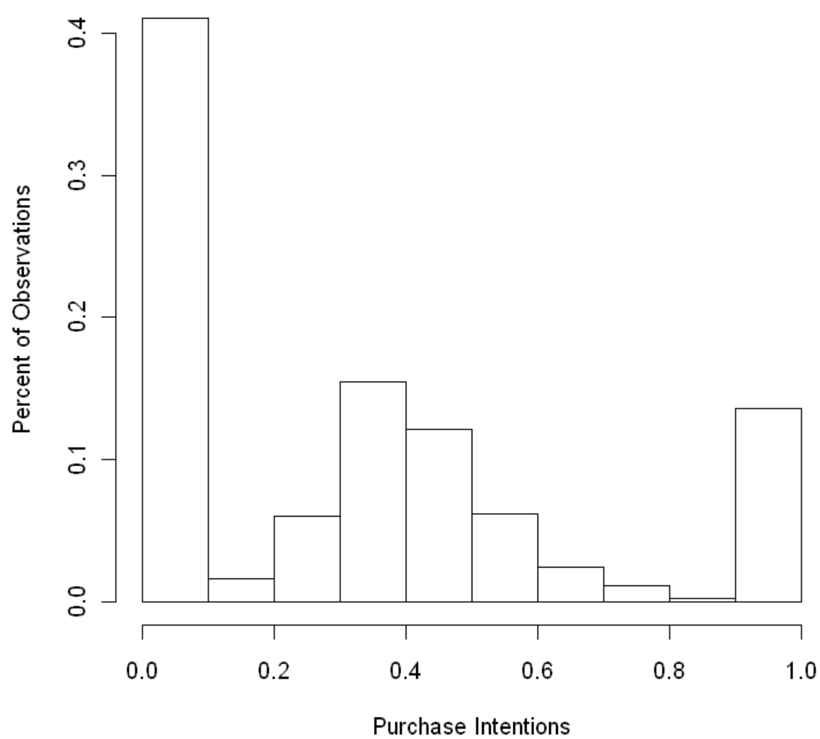
[1] Although the survey was pretested carefully to avoid demand artifacts, we normalize the intentions data as a further precaution. In this paper our focus is on the <u>differential</u> effect of cognitive styles on purchase probabilities. Thus, we require only that any residual demand effect is not correlated with cognitive styles.
[2] Additional data were collected that are tangential to the study in this paper. For details see Hauser et al. (2009).

with the definition of cognitive styles as ipsative dimensions and consistent with the practical use of cognitive-style segments in website design, we classify respondents into 16 cognitive style segments (2 x 2 x 2 x 2) based on median splits of the four cognitive-style factors. This transformation is conservative with respect to finding characteristic-to-style matches.

Dependent Measure

The dependent measure is purchase intentions for BT. We denote this dependent measure by y_h for each of h = 1 to H respondents. The histogram is shown in Figure 1. For respondents who consider more than one broadband provider y_h is the relative purchase-intention measure bounded between 0 and 1. For other respondents y_h is 1 if the respondent considers only BT and 0 if the respondent does not consider BT.

Figure 1
Histogram of Purchase Intentions for the BT Group's Broadband Service



4. Consumer Response Model

We seek to model respondent-level purchase probabilities as drawn from $f(y_h|\boldsymbol{\beta}_h, \boldsymbol{\phi}, \mathbf{x}_h)$, the posterior distribution of y_h conditioned on respondent-level (heterogeneous) parameters, $\boldsymbol{\beta}_h$, homogeneous parameters and hyperparameters, $\boldsymbol{\phi}$, and observed variables (cognitive styles, website characteristics, and their interactions), $\mathbf{x}_h$.

We take into account the two data regimes for y_h. Let q be the probability that the respondent answers with $y_i \in \{0, 1\}$, that is, the probability that the respondent either considers only BT ($y_i = 1$) or does not consider BT ($y_i = 0$). For these respondents we model purchase probabilities, p_h, drawn from the standard logit model.

$$p_h = \frac{e^{\boldsymbol{\beta}_h \mathbf{x}_h}}{1 + e^{\boldsymbol{\beta}_h \mathbf{x}_h}} \tag{1}$$

When we observe $y_i \in (0,1)$ we model the response as drawn from a beta distribution with shape parameters, a_h and b_h such that $E[y_h] = a_h/(a_h + b_h)$. We introduce a parameter, s, to control for the polarization of the beta distribution and to enable us to link the explanatory variables to $E[y_h]$. Finally, because two-regime measurement might have introduced a scale parameter we include γ to account for any induced variance between the two data regimes (e.g., Train 2003). Specifically,

$$\begin{gathered} \mu_h = E[y_h | \boldsymbol{\beta}_h, \mathbf{x}_h] = \frac{e^{\gamma \boldsymbol{\beta}_h \mathbf{x}_h}}{1 + e^{\gamma \boldsymbol{\beta}_h \mathbf{x}_h}} \\ a_h = s\mu_h \qquad b_s = s(1 - \mu_h) \end{gathered} \tag{2}$$

We now express the conditional likelihood as:

$$f(y_h | \boldsymbol{\beta}_h, \boldsymbol{\phi}, \mathbf{x}_h) = \left\{q p_h^{y_h} (1 - p_h)^{1 - y_h}\right\}^{\delta_h} \left\{\frac{1 - q}{B(a_h, b_h)} y_h^{a_h - 1} (1 - y_h)^{b_h - 1}\right\}^{1 - \delta_h} \tag{3}$$

where $\delta_h = 1$ if $y_h \in \{0, 1\}$ and $\delta_h = 0$ if $y_h \in (0, 1)$.

The prior distribution on the heterogeneous parameters is multivariate normal to allow correlated effects for the explanatory variables: $\boldsymbol{\beta}_h \sim MVN(\overline{\boldsymbol{\beta}}, \boldsymbol{\Sigma})$. We place weakly-informative, zero-mean multivariate normal hyperpriors on $\overline{\boldsymbol{\beta}}$, μ, and $\log(s)$. The hyperprior for $\boldsymbol{\Sigma}$ is an inverse Wishart distribution with k +2 degrees of freedom and a location parameter equal to a k-by-k identity matrix where k is the number of explanatory variables.

We drew the conditional posterior distributions of $\overline{\boldsymbol{\beta}}$, μ, s, $\boldsymbol{\Sigma}$, and the $\boldsymbol{\beta}_h$'s using Markov chain Monte Carlo simulation (MCMC). For all models, we generated 600,000 draws from three independent chains, checking convergence using the Brooks-Gelman-Rubin scale reduction factor and visual inspection of chain histories (Brooks and Gelman 1998). Initial iterations were burned and we retained every fifteenth draw from the last 30,000 draws. The procedure resulted in a total of 2,000 draws for each chain for each model.

5. Model Comparisons and Posterior Predictive Checks

The potential explanatory variables in the model of consumer response are the cognitive styles, the website characteristics, and their interactions. To evaluate whether or not sales increase when website characteristics are matched to cognitive styles we seek to examine whether the interactions are non-zero. For example, if there is an interaction between small-load website characteristics and holistic/verbal cognitive styles, then we would recommend that sparse website formats be used for holistic/verbal consumers.

We sample posterior distributions for three models. The first model includes main effects only (no interactions). We compare this model to two models that include potential interactions. The saturated model includes all potential interactions. The parsimonious model includes only those interactions that had the highest credible confidence intervals for the interactions in the saturated model.

We summarize the results in Table 2 by reporting the mean and the 90% highest posterior density credible interval for the posterior distribution of the $\boldsymbol{\beta}_h$'s. For ease of interpretation all interactions are framed in the (observed) positive directions. To assess relative model fit, we report log Bayes factors relative to the main-effects model (Kass and Raftery 1995), the deviance information criterion (DIC, Gelman, et al. 2004, p. 183-184), AIC-M (an MCMC-appropriate estimate of AIC presented in Raftery, et. al. 2007, p. 16), the mean-square error (MSE) between expected and observed results, and the percent of uncertainty explained by the model (U^2, Hauser 1978). All five fit measures support the proposition that interactions among cognitive styles and website characteristics influence stated purchase likelihoods. Four of the five fit measures support the saturated model relative to the parsimonious model.

Table 2.
Purchase Propensity Models (Posterior Means and 90% Highest Posterior Credible Interval)

	Explanatory Variables	Main Effects	Parsimonious Matches	Saturated Matches
Website Characteristics	**Intercept**	**-2.03** (-3.05, -0.34)	**-1.92** (-2.91,-0.05)	**-2.42** (-3.31,-0.96)
	Graphical vs. Verbal	**-1.02** (-1.71, -0.29)	**-1.32** (-2.29,-0.50)	**-1.72** (-2.57, -0.97)
	Focused vs. General Content	-0.39 (-1.07, 0.82)	-0.18 (-0.97,1.20)	-0.34 (-1.30, 0.63)
	Small Load vs. Large Load	**-1.13** (-1.88, -0.49)	**-1.40** (-2.24, -0.64)	**-1.52** (-2.22, -0.88)
Cognitive Styles	Leader vs. Follower	**0.91** (0.40, 1.57)	**1.15** (0.59, 2.20)	0.72 (-0.14, 2.05)
	Visual/Analytic vs. Holistic/Verbal	0.01 (-0.71, 1.46)	0.07 (-0.65, 1.34)	-0.05 (-0.97, 1.44)
	Impulsive vs. Deliberative	**-0.76** (-1.30, -0.19)	**-0.98** (-1.54,-0.40)	**-1.18** (-2.02, -0.28)
	Read vs. Listen	**-1.31** (-2.13, -0.46)	**-1.43** (-2.29, -0.62)	**-1.81** (-2.74, -0.96)
Website-Characteristics-to-Cognitive-Style Matches	Graphical to Visual/Analytic			0.73 (-0.05, 1.54)
	Graphical to Deliberative			0.25 (-0.77, 1.10)
	Graphical to Reader			0.22 (-0.49, 0.72)
	Focused to Follower		**0.49** (0.01, 0.98)	**0.57** (0.15, 1.22)
	Focused to Holistic/Verbal			0.36 (-0.45, 1.20)
	Focused to Impulsive			0.56 (-0.15, 1.19)
	Focused to Listener		0.23[1] (-0.29, 0.82)	**0.68** (0.16, 1.33)
	Small Load to Follower			0.17 (-0.95, 1.25)
	Small Load to Holistic/Verbal		**1.09** (0.38, 1.67)	**1.52** (0.74, 2.20)
	Small Load to Deliberative		**0.83** (0.38, 1.46)	**0.77** (0.12, 1.30)
	Small Load to Reader			0.11 (-0.82, 1.18)
Model Fit	Log Bayes Factor (higher is better)	—	44.2	**80.9***
	DIC (lower is better)	1044.0	743.9	**148.8***
	AIC-M (higher is better)	-3257	**-3029***	-3847
	MSE (lower is better)	0.035	0.032	**0.021***
	U^2 (higher is better)	0.36	0.37	**0.44***

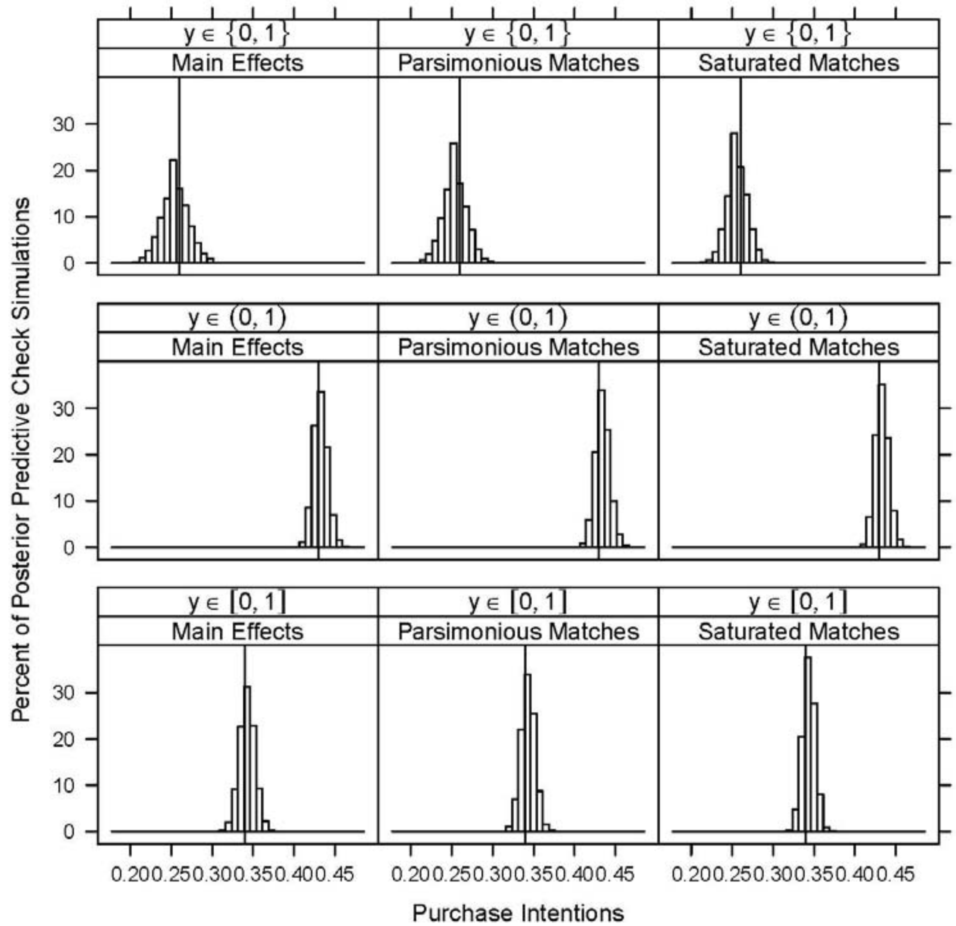
[1]The "Focused to Listener" 80% highest posterior density credible interval is entirely positive. *Best in row.

Finally, we evaluate the model in an absolute sense through posterior predictive checks (Rubin 1984; Gelman, Meng and Stern 1996). The idea behind posterior predictive checks (PPCs) is that a model is well-calibrated if simulations from the posterior predictive distribution, under the proposed model, look like the observed data. The phrase “looks like” can be interpreted in many different ways, so typically a researcher selects test statistics of interest and compares the posterior predictive distributions of those test statistics to the data. The “Bayesian *p*-value” is the proportion of simulated datasets with a test statistic below the test statistic for the observed data. Our test statistic is the mean of the stated probabilities, which we compute for the observed dataset and for 10,000 simulated datasets. Figure 2 summarizes the histograms for the simulated test statistics. The vertical line indicates the observed values. The Bayesian p-values are 45.5%, 42.6%, and 38.8% for the main effects, parsimonious, and saturated models, respectively. As we expect from a well-calibrated model, the observed values lie close to the centroid of the simulated distributions of the test statistic.

Figure 2 enables us to evaluate an assumption that the respondent-level parameters are drawn from the same distribution for both data regimes. We thus evaluate whether the scale parameter, γ, is a reasonable representation of the difference in response induced by the two data regimes.

The PPCs in Figure 2 suggest that all models replicate the observed data reasonably well, so we rely on the relative comparisons in Table 2 for model selection. We therefore conclude that the data support the hypothesis that matching website characteristics to cognitive styles enhances online sales. We are more confident in this claim because the data are conservative due to the facts that (1) the cognitive styles are measured with error (moderate reliabilities) and (2) we transformed the interval-scaled cognitive-style dimensions to cognitive-style segments to match the way in which characteristic-to-style matches are used in industry practice.

Figure 2
Posterior Predictive Checks for Population Mean of Purchase-Intention Probability



6. Interpretation of Website-Characteristic-to-Cognitive-Style Matching

The parameters in Table 2 indicate how website characteristics, cognitive styles, and their interactions affect sales as indicated by purchase intentions. The effect on sales may differ from what a respondent prefers. For example, a deliberative respondent might prefer to receive more information (large load) relative to an impulsive respondent, but if we present less, well-organized information the deliberative respondent might be more likely to make a positive purchase decision. This is indicated in our data by a positive coefficient for the small-load-to-deliberative interaction. (We use the classical term "significant" as shorthand for stating that the 90% highest posterior density credible interval does not contain zero.)

There are three other "significant" interactions in our data. To enhance sales it is better to give focused content to listeners and to followers. And it is better to give small loads to holistic/verbal respondents and to deliberative respondents. Other interactions are all suggested in the saturated model, but the parameter values for these interactions are not all in the 90% highest posterior density credible interval.

Besides addressing the scientific question of whether the interactions exist, Table 2 provides insight for BT's web designers. For example, the main effect of a small load is negative (−1.40 in the parsimonious model), but when BT targets verbal/holistic respondents (+1.09) who are deliberative (+0.83) the net effect is positive (−1.40 + 1.09 + 0.83 = +0.52). As another example, consider that focused content has an "insignificant" negative main effect (−0.18), but has a strong positive impact on followers (+0.49) and listeners (+0.23). In both of these examples targeted website characteristics reverse main effects. (We get similar reversals in the saturated model.)

7. Summary and Future Directions

This paper presents evidence that matching website characteristics to cognitive styles enhances purchase intentions (sales). This evidence is relevant because published methodologies enable firms to identify cognitive styles from online click streams and "morph" website characteristics based on these sales. Those methods are being extended by General Motors, FT Orange, and Google to customize banner advertising, customize mobile-phone alerts, and provide location-sensitive capabilities for GPS-enabled mobile devices (Urban, et al. 2009). The Bayesian methods applied in this paper are applicable to extensions now underway at Suruga Bank in which website characteristics are being customized to cultural as well as cognitive styles (Hofstede 2001; Nisbett, et al. 2001).

References

Allinson, Christopher W. and John Hayes (1996), “The Cognitive Style Index: A Measure of Intuition-Analysis for Organizational Research,” *Journal of Management Studies*, 33, 1, (Jan), 119-135.

Anand, Sarabjot Singh, Patricia Kearney and Mary Shapcott (2007), "Generating Semantically Enriched User Profiles for Web Personalization," *ACM Transactions on Internet Technology*, 22,1-26.

Ansari, Asim and Carl F. Mela (2003), “E-Customization,” *Journal of Marketing Research*, 40, (May), 131-145.

Bergkvist, Lars, and John R. Rossiter (2007), "The Predictive Validity of Multiple-Item Versus Single-Item Measures of the Same Constructs." *Journal of Marketing Research*, 2, 64 (May) 175-184.

Brooks, Stephen P., and Andrew Gelman (1998), "Alternative Methods For Monitoring Convergence Of Iterative Simulations," *Journal of Computational and Graphical Statistics*, 7, 434-755.

Childers, Terry L., Michael J. Houston and Susan E. Heckler (1985), "Measurement of Individual Differences in Visual Versus Verbal Information Processing," *Journal of Consumer Research,* 12, 2, (September) 125-134.

Churchill, Gilbert A., Jr. (1979), “A Paradigm for Developing Better Measures of Marketing Constructs,” *Journal of Marketing Research*, 16 (February), 64-73.

Deakin, Julia, Michael Aitken, Trevor Robbins and Barbara Sahakian (2004), "Risk Taking During Decision-Making In Normal Volunteers Changes With Age," *Journal of the International Neuropsychological Society*, 10, 4, 590-598.

Drolet, Aimee L. and Donald G. Morrison (2001), “Do we really need multiple-item measures in service research?” *Journal of Service Research*, 3, 3, (February), 196-204.

Eirinaki, Magdalini, and Michalis Vazirgiannis (2003), "Web Mining for Web Personalization." *ACM Transactions on Internet Technology*, 3, 1,1-27.

------ (2007), "Web Site Personalization Based on Link Analysis and Navigational Patterns," *ACM Transactions on Internet Technology*, 7, 1-27.

Elangovan, A.R. (Elango), and Leonard Karakowsky (2003), "Toward an Understanding of the Sources of Influence on Male and Female Executive Decision-Making under Risk and Uncertainty: Individual, Group and Organizational-level Factors," *Advances in Psychology Research*, 26, 101-119.

Frederick, Shane (2005), “Cognitive Reflection and Decision Making.” *Journal of Economic Perspectives*, 19(4). 25-42.

Frias-Martinez, Enrique, Sherry Y. Chen and Xiaohui Liu (2007), “Automatic Cognitive Style Identification of Digital Library Users for Personalization,” *Journal of the American Society for Information Science and Technology*, 58, 2, 237-251.

Gelman, Andrew, John B. Carlin, Hal S. Stern and Donald B. Rubin (2004), *Bayesian Data Analysis, 2E*, (New York, NY: Chapman & Hall/CRC).

------, Xiao-Li Meng and Hal S. Stern (1996), "Posterior Predictive Assessment of Model Fitness via Realized Discrepancies (with discussion)," *Statistica Sinica*, 6, 4, 733-807.

Harvey, O.J., David E. Hunt and Harold M. Schroder (1961), *Conceptual Systems and Personality Organization*, (New York, NY: Wiley and Company).

Hauser, John R. (1978), "Testing the Accuracy, Usefulness and Significance of Probabilistic Models: An Information Theoretic Approach," *Operations Research*, 26, 3, (May-June), 406-421.

Hauser, John R., Glen L. Urban, Guilherme Liberali and Michael Braun (2009), "Website Morphing," *Marketing Science*, 28, 2, (March-April), 202-224.

Hayes, John and Christopher W. Allinson (1998), "Cognitive Style and the Theory and Practice of Individual and Collective Learning in Organizations," *Human Relations*, 31, 7, 847-71.

Hofstede, Geert (2001), *Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations Across Nations, 2E* (Thousand Oaks, CA: Sage Publications, Inc.)

Hutchinson, J. Wesley, and Yanliu Huang (2008) "Counting Every Thought: Implicit Measures of Cognitive Responses to Advertising," *Journal of Consumer Research*, 35, 1, (June), 98-118.

Im, Il, and Alexander Hars (2007), "Does a One-Size Recommendation System Fit All? The Effectiveness of Collaborative Filtering Based Recommendation Systems Across Different Domains and Search Modes," *ACM Transactions on Information Systems,* 4, 1-30.

Kass, Robert, and Adrian Raftery (1995), "Bayes Factors," *Journal of the American Statistical Association*, 90, 773-795.

Kirton, M.J. (1987), *Adaption-Innovation Inventory KAI Manual*, (Hatfield, UK: Occupational Research Centre).

Kopfstein, Donald (1973), "Risk-Taking Behavior and Cognitive Style," *Child Development*, 44, 1, 190-192

Moe, Wendy W. and Peter S. Fader (2004), "Dynamic Conversion Behavior at E-Commerce Sites," *Management Science*, 50, 3 (March), 326-335.

Monga, Alokparna Basu, and Deborah Roedder John (2007), "Cultural Differences in Brand Extension Evaluation: The Influence of Analytic versus Holistic Thinking," *Journal of Consumer Research*, 33, 4, (March), 529-536.

------ and Loraine Lau-Gesk (2007) "Blending Cobrand Personalities," *Journal of Marketing Research*,44, 3, 389-400.

Montgomery, Alan L., Shibo Li, Kannan Srinivasan and John Liechty (2004), "Modeling Online Browsing and Path Analysis Using Clickstream Data," *Marketing Science*, 23, 4, (Fall), 579-585.

Nisbett, Richard E., Kaiping Peng, Incheol Choi and Ara Norenzayan (2001), "Culture and Systems of

Thought: Holistic Versus Analytic Cognition," *Psychological Review*, 108, 2, 291-310.

Novak, Thomas P., and Donna L. Hoffman (2009), "The Fit of Thinking Style and Situation: New Measures of Situation-Specific Experiential and Rational Cognition." *Journal of Consumer Research*, 36, 1, (June), 56-72.

Paivio, Allan (1971), *Imagery and Verbal Processes*, (New York, NY: Holt, Rinehart & Winston, Inc.).

Perkowitz, Mike, and Oren Etzioni (2000), "Towards Adaptive Web Sites: Conceptual Framework And Case Study," *Artificial Intelligence,* 118, 1-2, 245-275.

Raftery, Adrian, Michael A. Newton, Jaya M. Satagopan and Pavel N. Krivitsky (2007), "Estimating the Integrated Likelihood via Posterior Simulation Using the Harmonic Mean Identity." *Bayesian Statistics*, 8, 1-45.

Riding, Richard J. and Indra Cheema (1991), "Cognitive Style: An Overview and Integration," *Educational Psychology*, 11, 3&4, 193-215.

------ and Stephen Rayner (1998), *Cognitive Styles and Learning Strategies: Understanding Style Differences in Learning and Behavior*, (London, UK: David Fulton Publishers).

Rogers, Everett M. (1962), *The Diffusion of Innovations*, (New York, NY: The Free Press).

----- and J. David Stanfield, "Adoption and Diffusion of New Products: Emerging Generalizations and Hypotheses," *Applications of the Sciences in Marketing Management*, Frank Bass, et. al., eds. (New York, NY: John Wiley & Sons, Inc.), 227-250.

Rubin Donald B. (1984), "Bayesianly Justifiable and Relevant Frequency Calculations for the Applied Statistician," *Annals of Statistics*, 12, 4, 1151-1172.

Thompson, Debora Viana and Rebecca W. Hamilton (2006), "The Effects of Information Processing Mode on Consumers' Responses to Comparative Advertising," *Journal of Consumer Research*, 32, 4, (March), 530-540.

Train, Kenneth (2003), *Discrete Choice Methods with Simulation*, (New York, NY: Cambridge University Press).

Urban, Glen L., John R. Hauser, Guilherme Liberali, Michael Braun and Fareena Sultan (2009), "Morph the Web to Build Empathy, Trust, and Sales," *Sloan Management Review*, 50, 4, 53-61

von Hippel, Eric (1988), *Sources of Innovation*, (New York, NY: Oxford University Press).

White, J. Chris, P. Rajan Varadarajan and Peter A. Dacin. "Market Situation Interpretation and Response: The Role of Cognitive Style, Organizational Culture, and Information Use." *Journal of Marketing*, July 2003: 63-79.

Witkin, H. A., Moore, C., Goodenough, D. and Cox, P. (1977), "Field-dependent and Field-independent Cognitive Styles and their Educational Implications," *Review of Educational Research*, 47, 1-64.

Appendix (to be web-based)
Factor Loadings Used to Define Cognitive-Style Dimensions

The measures were purified based on pretests. Exploratory principal component analysis with varimax rotation and Kaiser normalization identified cognitive-style factors. The best solution was based on the scree rule, the EGO rule, and judgment and was tested with confirmatory factor analysis. The measures of each dimension were then created by averaging the individual elements (e.g., Churchill 1979). Reliabilities are given in the text. As an example, we reproduce the exploratory factor loadings here.

	Cognitive-Style Dimension			
Cognitive-Style Survey Measure	**Leader vs. Follower**	**Visual/Analytic vs. Holistic/Verbal**	**Impulsive vs. Deliberative**	**Reader vs. Listener**
I prefer to read text rather than listen to a lecture.	0.020	0.062	0.023	**0.950**
I enjoy deciphering graphs, charts, and diagrams.	0.116	**0.529**	-0.210	0.087
I will read an explanation of a graphic /chart before I try to understand the graphic/chart on my own.	-0.093	**0.569**	0.139	0.140
I see what I read in mental pictures.	0.118	**0.601**	0.146	-0.117
I am detail oriented, and start with the details in order to build a complete picture.	0.126	**0.714**	-0.039	0.063
I tend to see problems in their entirety and start by integrating pieces from different areas.	0.287	**0.534**	-0.154	-0.179
I find it easy to make decisions for others and to command and direct others to make certain actions.	**0.644**	0.247	-0.072	0.031
In a group conversations, I tend to speak the most.	**0.760**	0.040	0.085	-0.045
I have held a great deal of leadership positions in my life.	**0.849**	0.078	-0.034	-0.002
My confidence level is higher than most other people's.	**0.824**	0.081	-0.031	0.033
A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?	-0.022	-0.007	**0.651**	0.039
If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?	0.024	0.056	**0.716**	-0.015
If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half the lake?	-0.027	-0.069	**0.762**	0.001