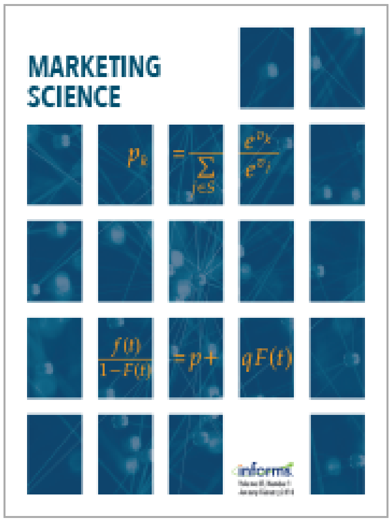

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Mapping the Bounds of Incoherence: How Far Can You Go and How Does It Affect Your Brand?

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Consumers often have to evaluate products comprising a combination of attributes that is not expected by them, given their beliefs about how attributes normally co-vary in the product category. Such an attribute combination implies that the claimed level of a product attribute is then different from what the consumer might infer, given the level of another attribute, resulting in what we call *product incoherence*. We develop a model to calibrate the effect of incoherence on perceptions, uncertainty, preference, and ultimately purchase. Our model can allow managers to determine consumers' acceptance for different positions in the multiattribute space, so they can optimize their product's positioning. Our model implies that a product that combines positively valued attributes might increase some elements of preference for the product, but if those attributes occur in unexpected combinations, incoherence will also increase uncertainty which in turn might lower other elements of preference. The net risk-adjusted preference for a product in our model accommodates both the benefit from the expected attribute levels and the uncertainty associated with incoherence. We derive implications from the model and provide an empirical test that supports those implications.

Key words: product positioning; product management; new products; brand management
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1. Introduction

We examine the situation in which a consumer receives information about two attributes whose levels are expected to be correlated, but where the claimed level of one attribute is far from what the consumer would expect given the claimed level of the other. Consider the 2005 Honda Accord hybrid, which claims to be a "*surprisingly* fuel efficient 255 horsepower" car (*Newsweek* 2004). A car with high fuel efficiency *and* power is called surprising because the commonly observed negative correlation between these attributes makes this new combination unexpected. Specifically, the consumer must reconcile the car's claim of high fuel efficiency with an inference of low fuel efficiency, based on the belief of negative correlation between fuel efficiency and power (and conversely). We call this phenomenon *product incoherence*, where unlikely attribute combinations provide the consumer with discrepant attribute information about product performance. Our goal in this paper is to develop a methodology to calibrate the effect of incoherence and its antecedents on preference, allowing managers to make better decisions about how to optimize product positioning in practice.

While incoherence has been studied in the behavioral science literature in various forms—concept incoherence (Murphy and Medin 1985), schema incongruity (Meyers-Levy and Tybout 1989), and category incoherence (Rehder and Hastie 2004)—that literature has not produced a quantitative model of the effect of product incoherence or its antecedents on consumer preference. In the absence of such a model, it is difficult to calibrate the effect of unexpected attribute combinations on preference. For example, if powerful cars are thought to be fuel guzzlers, safe cars are believed to be boring, and cola sodas are known to be brown, then to what extent will the market accept a "powerful *and* fuel efficient" car (2005 Honda Accord hybrid), a "safe *and* stylish" car (Volvo V70, see http://volvocars-pr.com), or "a blue-colored cola" (Pepsi Blue, see http://www.spudart.org/pepsiblue/)? Our model can provide a manager with information about the effects of different positions in multiattribute space on market acceptance. As a result, such a model can inform several important marketing problems, including (1) improving product design and selection of optimal attribute combinations, (2) choosing a credible position for a new product launch into an existing market structure, and (3) developing effective communication strategies that emphasize coherent attributes.

Our model integrates a utility-maximizing consumer's (i) beliefs of interattribute covariation, (ii) attribute perceptions, (iii) uncertainty about those perceptions, and (iv) risk aversion, leading to an expression for the risk-adjusted preference for the product. Our main result shows that while combining positively valued attributes may increase expected preference for the product even if those attributes occur in unexpected combinations, incoherence will increase uncertainty about the product's attributes because of the conflict with the consumer's interattribute covariation beliefs. If the utility loss due to increased uncertainty (adjusted by the consumer's risk aversion) is greater than the expected benefits offered, the consumer's net preference for a product suffers. Our model provides managers with the capability to understand the risks associated with unique and unexpected attribute combinations that might be offered in pursuit of differentiation.

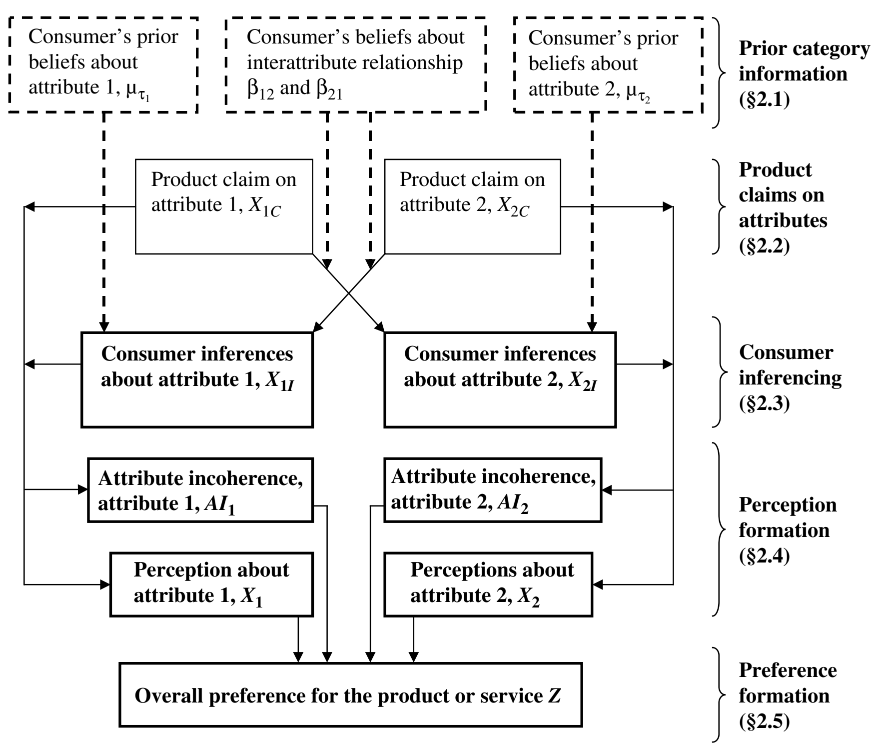
There are many cases that result in incoherence besides those involving unlikely attribute combinations (e.g., high fuel efficiency and power). These include unexpected brand-attribute combinations (e.g., caffeinated 7UP as discussed in McGill 1989), brand-category combinations (e.g., Aaker and Keller's 1990 Heineken popcorn example), marketing mix combinations (e.g., a cheap Porsche, a Rolex watch in Kmart, or American Express Centurion Black cards advertised in *USA Today*), and co-branding (e.g., Starbucks coffee in McDonald's as discussed in Crossan and Kachra 2002). In this paper, we model only the effect of the incoherence that arises from unlikely attribute combinations, and we address possible model extensions in the final section.

In the next section, we present our model and derive predictions of when and how incoherence affects preference. We then describe an empirical test of the model's predictions, which supports our model structure. We conclude with an assessment of the implications (and limitations) of our work, as well as an agenda for future research.

2. Model of the Effect of Incoherence on Preference

In Figure 1, we present our model's conceptual basis, which is drawn from the behavioral science literature. Our model assumes that consumers use their

Figure 1 **Conceptual Model of Perception and Preference Formation For a New Product in an Existing Category**



Note. Dotted lines indicate prior information that the consumer brings to the inferencing process. The boxes in bold indicate constructs to which we model the antecedents.

perceived interattribute correlations in a category to infer the level of one attribute given the performance level claimed by the firm on the other attributes. This inferencing presents the consumer with two pieces of information about the attribute performance level: the product's claim and their own inference. We propose that the consumer forms perceptions of the attributes by putting together these two pieces, ultimately integrating these uncertain perceptions into a risk-adjusted preference. In this section, we present the formal model along with a justification for our assumptions.

We discuss our model in terms of two attributes and symmetric effects of attributes on each other. While our model is individual and product specific, we suppress those subscripts for simplicity. We denote the consumer's (i) perceptions of products in the category on attributes 1 and 2, respectively, as x_1 and x_2, (ii) inferences of performance of the focal product as X_{1I} and X_{2I}, and (iii) perceptions of the focal product as X_1 and X_2. We denote the focal product's claims of performance by X_{1C} and X_{2C}. Uncertainty is denoted with the same subscripts.

2.1. Prior Information About the Product Category

We assume that the consumer has beliefs about (i) typical attribute levels in the category and (ii) interattribute covariation in the category. Our main interest here lies in covariation beliefs. These beliefs are formed by consumers on the basis of empirical observation and/or subjective conceptual theories and are known to be difficult to change (Pechmann and Ratneshwar 1992, Broniarzcyk and Alba 1994a, Fugelsang and Thompson 2003).

We represent the consumer's belief of how the level of attribute 1 in the product category is affected by the level of attribute 2, as follows:

$$x_{1|2} = \tau_1 + \beta_{12} \cdot x_2 + \varepsilon_{12}, \tag{1}$$

where $x_{1|2}$ is the perceived level of performance on attribute 1 given the level of attribute 2, τ_1 is the intercept, β_{12} is the partial regression coefficient, and ε_{12} is an error term indicating that the attributes are not perfectly correlated. The consumer's interattribute covariation belief is represented by β_{12}, the partial regression coefficient (Belsley et al. 1980). τ_1 represents information about attribute 1 that does not come from the level of attribute 2. We assume that the consumer knows β_{12}, that ε_{12} follows a normal distribution $N(0, \sigma^2_{\varepsilon_{12}})$, and that τ_1 is $\sim N(\mu_{\tau_1}, \sigma^2_{\tau_1})$. We assume an analogous model for $x_{2|1}$, the consumer's belief of the level of attribute 2, given the level of attribute 1.

2.2. Product Claims About Attribute Performance

We assume that a firm makes claims of product performance on the two attributes and that the consumer has some uncertainty about these claims, denoted by σ^2_{1C} and σ^2_{2C}. We further assume that the consumers' distribution of beliefs about the claim on each attribute is normal with mean $\bar{X}_{1C}$ and $\bar{X}_{2C}$, respectively.

2.3. Inference Formation

Consumers use their interattribute covariation beliefs to make inferences (see Dick et al. 1990, Broniarzcyk and Alba 1994b). We therefore assume that the consumer accesses beliefs about covariation, as described in §2.1, to *infer* the information that each attribute provides about the other. Using Equation (1) and the fact that $E(\varepsilon_{12}) = 0$, we assume that the consumer takes the maximum likelihood value of inferences about the mean level of X_1, embodied in the level of $\bar{X}_{2C}$. Thus, $\bar{X}_{1I}$, given $\bar{X}_{2C}$, is

$$\bar{X}_{1I} = \mu_{\tau_1} + \beta_{12} \cdot \bar{X}_{2C}. \tag{2}$$

Because τ_1 represents the consumer's information about attribute 1 that does not come from the level of attribute 2, we assume that $\beta_{12} \cdot X_{2C}$ and τ_1 are independent. The variance of X_{1I} is then

$$\sigma^2_{1I} = \sigma^2_{\tau_1} + \sigma^2_{\varepsilon_{12}} + \beta^2_{12} \cdot \sigma^2_{2C}. \tag{3}$$

We can derive analogous expressions for the mean and variance of the distribution of X_{2I}. The assumption of normality for the distributions of τ_1, τ_2, X_{1C} and X_{2C} implies that the distributions of X_{1I} and X_{2I} are also normal.

2.4. Perception Formation

To form a perception of attribute 1 (X_1), the consumer must reconcile information about the performance of the product on attribute 1 that comes from the distribution of the claim, denoted by $\phi_{1C}(x)$, and the distribution of the inference, denoted by $\phi_{1I}(x)$. We now assume that the consumer uses X_{1C} with probability p_1 and X_{1I} with probability $(1 - p_1)$. Given this assumption, the resulting distribution of perceptions $\phi_1(x)$ is a mixture of the distribution of claims and inferences (see Appendix A.1 for the proof), as follows:

$$\phi_1(x) = p_1 \cdot \phi_{1C}(x) + (1 - p_1) \cdot \phi_{1I}(x), \tag{4}$$

where $0 \le p_1 \le 1$. The expected value and variance of X_1 are

$$E[X_1] = \bar{X}_1 = p_1 \cdot \bar{X}_{1C} + (1 - p_1) \cdot \bar{X}_{1I}, \quad \text{and} \tag{5}$$

$$\operatorname{var}(X_1) = \sigma^2_1 = p_1 \cdot (1 - p_1) \cdot \{\bar{X}_{1C} - \bar{X}_{1I}\}^2 + p_1 \cdot \sigma^2_{1C} + (1 - p_1) \cdot \sigma^2_{1I}. \tag{6}$$

We now seek weights p_1 and $(1 - p_1)$ that make the expected value of X_1 tend toward "accept the claim" as the variance of the inference (σ_{1I}^2) becomes relatively large, and "accept the inference" as the variance of the claim (σ_{1C}^2) increases. Following Bell et al. (1975), we propose the following US/(US + THEM) weighting:

$$p_1 = (\sigma_{1I}^2)^\alpha / \{(\sigma_{1C}^2)^\alpha + (\sigma_{1I}^2)^\alpha\}, \tag{7}$$

where α is a parameter to be estimated, reflecting the consumer's uncertainty intolerance (i.e., the greater α is, the more weight the consumer places on a more certain estimate). This specification of p_1 is somewhat more general than that used in Bayesian updating. For simplicity and tractability, we specify p_1 as proportional to the square of precision (i.e., $\alpha = 2$). Analogous expressions to Equations (2)–(7) can be obtained for attribute 2 by symmetry.

Equations (5)–(7) have some appealing properties. In Equation (5), the consumer's mean perception is a weighted sum of the means of the distribution of the two components (the claim and the inference) with the weights dependent on the variances, consistent with Gatignon's (1984) advertising information model. The variance in the consumer's perception of attribute 1, σ_1^2, increases with the distance between the means of the distributions of the claim and the inference, consistent with behavioral findings that discrepant information increases uncertainty (Einhorn and Hogarth 1985). Because $\{\bar{X}_{1C} - \bar{X}_{1I}\}^2$ increases as the attribute combination deviates from what is expected, we formally define *attribute incoherence* (AI_1) as

$$\mathrm{AI}_1 = \{\bar{X}_{1C} - \bar{X}_{1I}\}^2. \tag{8}$$

Attribute incoherence for attribute 2 follows by analogy.

2.5. Preference Formation

We now model how the consumer translates uncertain perceptions (Equations 5 and 6) into preference. Following Keeney and Raiffa (1976), we assume a constantly risk-averse consumer whose utility function is negative exponential. While this specification has previously been used to derive expected utility for a single variable (see Roberts and Urban 1988, Chatterjee et al. 1988), the consumer has information on two *correlated* variables in our case. Assuming that the joint distribution of X_1 and X_2 can be approximated with a bivariate normal density function, the consumer's risk adjusted preference Z for the product is as follows (see Appendix A.2 for derivation):

$$\begin{aligned} Z &= \{w_1 \cdot \bar{X}_1 + w_2 \cdot \bar{X}_2\} \\ &\quad - \{(r/2) \cdot (w_1^2 \cdot \sigma_1^2 + w_2^2 \cdot \sigma_2^2 + 2w_1 w_2 \sigma_{12})\} \\ &= \mu_v - (r/2) \cdot \sigma_v^2, \end{aligned} \tag{9}$$

where Z is monotonically related to expected utility, w_1 and w_2 are relative importance weights of attributes 1 and 2, r is the risk-aversion parameter, and σ_{12} is the covariance between X_1 and X_2. For simplicity, we hereafter call μ_V "mean preference" and σ_V^2 "preference uncertainty."

The two terms in the first bracket of Equation (9) comprise the mean value for a product with two attributes, which can be expressed in terms of the claimed and inferred mean attribute levels using Equation (5) and its attribute 2 analog. The terms in the second bracket represent the effect of variance or uncertainty on expected utility. These terms are shown in expanded form in Equation (6), its attribute 2 analog, and Equation (20). Note that while this expression is a complex function of the variances, it is linear in the attribute incoherences. Furthermore, under suitable assumptions about measurement error, the risk-adjusted preference function can be converted into a model of choice using a logit formulation (Roberts and Urban 1988).

2.6. Implications of the Model

We first analyze the effect of incoherence on preference uncertainty (§2.6.1) and then study its effect on risk-adjusted preference (§2.6.2).

2.6.1. The Effect of Incoherence on Preference Uncertainty. To examine the impact of incoherence on preference uncertainty, we substitute the variance in attribute perceptions (Equation 6) into the preference uncertainty term in Equation (9) to obtain[1]

$$\begin{aligned} \sigma_v^2 &= \{w_1^2 p_1 \cdot (1-p_1) \cdot \{\bar{X}_{1C} - \bar{X}_{1I}\}^2 + w_2^2 p_2 \cdot (1-p_2) \\ &\qquad \cdot \{\bar{X}_{2C} - \bar{X}_{2I}\}^2 + g[\sigma_{1C}^2, \sigma_{2C}^2, \sigma_{1C,2C}]\} \\ &= \{w_1^2 p_1 \cdot (1-p_1) \cdot \mathrm{AI}_1 + w_2^2 p_2 \cdot (1-p_2) \cdot \mathrm{AI}_2 \\ &\qquad + g[\sigma_{1C}^2, \sigma_{2C}^2, \sigma_{1C,2C}]\}. \end{aligned} \tag{10}$$

In general, these results imply that incoherence directly increases preference uncertainty. However, this increase in uncertainty will be smaller under two circumstances. First, if the consumer believes that the interattribute correlation is very low, the inference would be more uncertain, resulting in the claim dominating the inference in determining the consumer's attribute perception. Mathematically, $\sigma_{\varepsilon_{12}}^2$ in Equation (1) will be large, leading to a higher σ_{1I}^2 so that $(1-p_1)$ will be very small. Because attribute incoherence $\{\bar{X}_{1C} - \bar{X}_{1I}\}^2$ is weighted by $\{p_1 \cdot (1-p_1)\}$ in

[1] We specify the total effect of uncertainty of claims and covariance between claims by a function "g" because these effects are not central to this paper. Because the mean levels of the attribute claims and incoherence are independent of the function g (which contains only variance and covariance terms), the effect of attribute incoherence on preference can be estimated independently of the effect of the terms in the function g.

Equation (10), the effect of incoherence on preference uncertainty will be reduced when $(1-p_1)$ is small. Second, if the attribute is unimportant (i.e., if w is small), then even high levels of incoherence would have a very small effect on preference uncertainty. This effect is also captured in Equation (10) because the terms $\{\bar{X}_{1C}-\bar{X}_{1I}\}^2$ and $\{\bar{X}_{2C}-\bar{X}_{2I}\}^2$ are weighted by w_1 and w_2, respectively.[2]

To provide a useful managerial diagnostic, we create an overall measure of product incoherence (PI) as follows:

$$\begin{aligned}\mathrm{PI} = \big[&w_1^2\cdot p_1\cdot(1-p_1)\cdot(\bar{X}_{1C}-\bar{X}_{1I})^2\\ &+w_2^2\cdot p_2\cdot(1-p_2)\cdot(\bar{X}_{2C}-\bar{X}_{2I})^2\big],\end{aligned}\tag{11}$$

which is a weighted sum of the incoherence of each attribute.

2.6.2. The Effect of Incoherence on Risk-Adjusted Preference. Given two positively valued and positively correlated attributes, attribute 2 incoherence (AI_2) increases as the claimed level of attribute 2 increases beyond that inferred from a fixed level of attribute 1. As per §2.6.1, an increase in attribute incoherence increases preference uncertainty, resulting in a negative effect on preference. However, as the claimed level of attribute 2 increases, the consumer's mean perception of attribute 2 also increases, resulting in a positive effect on preference. The net effect of the increasing attribute level on preference then depends on the relative magnitude of the positive and negative effects and the consumer's risk-aversion parameter (i.e., the net effect is a mean-variance trade-off).

We formally determine the net effect in Appendix T.A3. The main analytical finding is that for a fixed $\bar{X}_{1C}$, preference increases as $\bar{X}_{2C}$ increases but only up to a performance level $\bar{X}_{2C}^*$, after which preference decreases with further increases in $\bar{X}_{2C}$. Because an increase in $\bar{X}_{2C}$, holding $\bar{X}_{1C}$ constant, also implies an increase in incoherence, the net effect of increasing one attribute in isolation on preference generally follows this inverted U-shape curve. If the consumer is highly risk averse, the negative effect of incoherence will overshadow the positive effect quickly, resulting in a curve that is *close* to strictly downward sloping. In contrast, if the consumer approaches *risk neutrality*, the curve is strictly upward sloping in the limit.

For moderate levels of risk aversion, increasing the level of an attribute might increase preference despite increased incoherence, but too much incoherence always hurts preference. This appealing result is consistent with a main finding in the schema incongruity literature (Meyers-Levy and Tybout 1989), which shows that moderate incongruity is preferred over both congruity and extreme incongruity. Its explanation is based on the interaction of affect and cognitive ability in resolving incongruity, while ours emerges from a simpler mean-variance trade-off by a utility-maximizing consumer. Our result is also consistent with Keller and Aaker's (1992) findings on the risks of "overextending" a brand.

To summarize, our model predicts that the magnitude of interattribute correlation determines how strongly incoherence will affect preference uncertainty (see §2.6.1) and therefore risk-adjusted preference. If the interattribute correlation is high, we predict a strong negative effect of incoherence on preference. Thus, the negative incoherence effect of increasing the claimed level of attribute 1 (beyond that inferred from a fixed level of attribute 2) will overshadow its positive mean effect quickly, resulting in an inverted U-shaped relationship. This net effect will not be as pronounced, nor will it be observed as quickly, in the low interattribute correlation case. Our empirical study tests these predictions.

3. Empirical Assessment of Model Predictions

An empirical assessment of our model predictions requires a context where (i) there are multiple attributes that significantly determine preference, (ii) consumers have relatively homogenous category experiences so that covariation beliefs can be elicited, and (iii) realistic product concepts can be constructed, with attribute levels manipulated in such a way that incoherence can be varied and measured at the individual level. In addition, the task must be relevant to respondents. We now describe such a context.

3.1. Experimental Design

A context that meets these requirements is the selection of elective courses by second-year students in a major MBA program. In this MBA program, students are asked to respond to a battery of 24 Likert scale teaching effectiveness items (defined here as attributes) at the end of each course. Students use published past ratings of each course on each attribute to select future electives.

To obtain a measure of expected relationships between attributes in this population, we analyzed historical, individual-level teaching effectiveness data from five large classes. Based on the correlations between the 24 attributes, we selected the following two pairs of attributes to test our prediction that the

[2] If attribute 1 were not important in Equation (10), i.e., w_1 was small, attribute 1 incoherence would not affect preference uncertainty and thus preference. However, the claim on attribute 1, $\bar{X}_{1C}$, could still have a substantial effect on preference through attribute 2 incoherence $\{\bar{X}_{2C}-\bar{X}_{2I}\}^2$ because $\bar{X}_{2I}$ is a function of $\bar{X}_{1C}$. This is consistent with an extensive literature on the impact of irrelevant attributes on preference (Carpenter et al. 1994).

effect of incoherence on preference depends on interattribute correlation: (1) *high interattribute correlation:* "The importance of the course to MBA graduates" and "The extent to which the course was interesting," and (2) *low interattribute correlation:* "The preparedness of the lecturer" and "The extent to which the course was interesting."

The wording of each of the three Likert scale items was: "This course is important for MBA graduates to understand," "Overall, I think this course is interesting," and "This lecturer is always prepared for class." The average ecological correlation between "importance" and "interesting" was 0.79 ($p < 0.001$) in the historical teaching effectiveness data, while that between "preparedness" and "interesting" was 0.39 ($p < 0.001$). Each attribute was a statistically significant driver of overall course assessment.

We then constructed a hypothetical product (a course here), shown in Appendix T.A4, by describing a prospective second-year elective, providing only the attribute ratings given by students in the previous year. These ratings were declared to be hypothetical—no course or professor names were given to avoid confounding brand-name effects. We presented the ratings in the same summary format to which students were accustomed, with average ratings for the course on each attribute as well as the percentage of responses for each scale point of the five-point scale. In our framework, these two measures translate into the mean and variance of the distribution of the claim.

Next, we constructed several other hypothetical courses that varied in terms of mean performance on each attribute. By varying the mean attribute performance levels, we varied the level of incoherence that would be perceived by respondents. For example, if a respondent believed that "importance" and "interesting" were strongly correlated, then a course with both attributes as good or bad would be viewed as more coherent than a course with level of one attribute high and the other low. We varied the mean of both attributes at two levels (3.0 and 4.5). This 2 (attribute 1 mean) × 2 (attribute 2 mean) design implied that each respondent would rate only four courses. To obtain more data from each respondent, we constructed four additional courses by varying the distribution of past student responses for each scale point on attribute 1 without changing the mean attribute level. Each respondent was shown eight hypothetical courses in a 2 (attribute 1 mean) × 2 (attribute 2 mean) × 2 (attribute 1 variance) within-respondents full factorial design. The two pairs of attributes (high and low correlation) were separately administered as between-respondents conditions.

3.2. Measurement Procedures

We recruited 77 second-year MBA students for the experiment, all of whom had completed similar sets of first-year courses and, at the time of the experiment, were making choices of electives for the first term of the second year. We randomly assigned respondents to a between-respondents condition. Between-respondents groups were homogenous in terms of demographics (age, gender, and international student proportion).

In Part 1 of the study, respondents provided ratings of each of the 8–10 courses they took in the first year of the program on the relevant attribute pair, allowing us to estimate individual-level covariation beliefs. In Part 2 of the study, we showed respondents a hypothetical course and measured their perceptions of that course on each attribute and their overall preference for the course (measured on sliding scale that we converted to a 0–100 scale). We repeated these steps for each of the eight courses. We dropped data for four students because their responses had close to zero variance, leaving 73 respondents for analysis.

3.3. Analysis

We first used the data from Part 1 to obtain individual-level estimates of the expected interattribute relationship. We fit Equation (1) (and its attribute 2 analog), estimating μ_τ and β for each respondent (denoted by i). We then constructed individual-level estimates of attribute incoherence (AI_1) as follows:

$$\widehat{\mathrm{AI}}_{1,i} = \{X_{1C} - \hat{X}_{1I,i}\}^2, \tag{12}$$

where $\hat{X}_{1I,i}$ is the estimate of the individual's inference of attribute 1, given by

$$\hat{X}_{1I,i} = \hat{\mu}_{\tau_1} + \hat{\beta}_{12,i} \cdot X_{2C}. \tag{13}$$

Analogously, we estimated $\widehat{\mathrm{AI}}_{2,i}$, attribute 2 incoherence. Individual-level estimates of attribute incoherence provided sufficient dispersion to measure the effect of incoherence on preference.

We can rewrite Equation (9) in terms of perceptions of the two attributes and attribute incoherence as follows:

$$Z_i = \eta_0 + \eta_1 \cdot \bar{X}_{1,i} + \eta_2 \cdot \bar{X}_{2,i} + \eta_3 \cdot \mathrm{AI}_{1,i} + \eta_4 \cdot \mathrm{AI}_{2,i}, \tag{14}$$

where $\eta^0 = \eta^0(g(\sigma 2))\eta_1 = w_1$, $\eta_2 = w_2$, $\eta_3 = -(r/2) \cdot \{w_1^2 \cdot p_1 \cdot (1-p_1)\}$, $\eta_4 = -(r/2) \cdot \{w_2^2 \cdot p_2 \cdot (1-p_2)\}$, $0 \le p_1, p_2 \le 1$, and $r, w_1, w_2 > 0$.

We can now directly test the predictions of our model by fitting the preference model in Equation (14) to the data. The attributes in our study were positively valued, so we expect η_1 and η_2 to be positive and significant. The most direct test of the predictions of our model is the sign of the coefficients η_3 and η_4, which was expected to be negative as per Equation (14). As noted in §2.6.2, we expected these

Table 1 Empirical Model Estimates

	Coefficient	Variable	High correlation condition		Low correlation condition	
			Estimate	t-stat	Estimate	t-stat
Mean preference						
	η_0	Intercept	3.55	3.87[a]	3.11	4.30[a]
	η_1	$\overline{X}_1$	5.93	3.64[a]	2.11	2.24[b]
	η_2	$\overline{X}_2$	6.60	4.75[a]	11.55	12.56[a]
Preference uncertainty						
	η_3	AI_1	−3.49	−3.15[a]	−0.57	−0.64
	η_4	AI_2	−1.34	−1.98[b]	−1.04	−1.03

Note. In the high correlation condition, attributes 1 and 2 were "course is important" and "course is interesting," respectively. In the low correlation condition, attributes 1 and 2 were "lecturer is well-prepared" and "course is interesting," respectively.
[a]$p < 0.01$, [b]$p < 0.05$

coefficients to be more significant in the high correlation condition than the low one. In estimating Equation (14), we mean centered the variables and corrected for heteroscedasticity to obtain more efficient estimates (Greene 1997).

3.4. Results

The results of estimating Equation (14) are shown in Table 1.[3] The results for the high correlation condition show that both attributes are significant drivers of preference. The key finding relates to the sign and significance of the measures of attribute incoherence. As expected, η_3 and η_4 are negative and significant. These results show that students will discount their preference for a course that is very interesting but not important (and vice versa). Because the importance of a course and how interesting it is are believed to be highly positively correlated, any substantial departure from this relationship produces incoherence, uncertainty, and lower overall preference. These results are consistent with our model predictions.

Results for the low correlation condition also show that both attributes are significant drivers of preference. The interesting finding here is the lack of statistical significance of η_3 and η_4. This result suggests that in the range we tested, the correspondence between the level of interest of a course and lecturer preparation does not significantly influence overall preference. Given the weak correlation between the two variables, this result is not unexpected.

In addition to testing the model predictions, we compared the fit and out-of-sample predictive ability of our model to a null model (Equation (14) without the incoherence terms). The AIC (Akaike's Information Criterion) for our model was smaller than that for the null model (2488 versus 2503) in the high correlation condition but only slightly smaller than that for the null model (2067 versus 2075) in the low correlation condition, as expected. We tested the predictive ability of our model against the null model via a jackknife procedure.[4] In the high correlation condition, our model predicted better than the null model by 10.08% as measured by the median absolute error. In the low correlation condition, our model predicted better than the null model by 4.22%. Given this rather conservative test of our model—the experiment was designed to be within the range of the past experience of the respondents and, hence, not overtly incoherent—we find this level of predictive validation supportive of our model.

3.5. Optimizing Attribute Combinations

While the previously reported analyses were intended to validate our model's predictions, we can use the empirical estimates obtained for the models in Equations (12)–(14) to find the preference-maximizing level of an attribute, given a fixed level of performance on the other attribute. We provide details of this optimization methodology in Appendix A.3. For the average consumer in the high correlation condition of our empirical study, we find that given a claim of 3.00 on the "importance" attribute, the optimal claim on the "interesting" attribute is 4.44. For the low correlation condition, the lack of statistical significance of η_3 and η_4 does not indicate any constraints on the level of attribute 2 given a fixed level of attribute 1.

4. Discussion, Conclusions, and Future Research

Incoherence presents a risk that marketers often fail to recognize when launching new products, brand extensions, or product repositionings. To address this issue, we built a formal model of the effect of incoherence and its antecedents on preference. We found empirical support for our model prediction that incoherence will have a significant negative effect on preference in the high correlation condition in contrast to the low correlation condition.

This research offers two theoretical contributions. First, although incoherence has been studied in the behavioral literature, ours is the first mathematical model of the effect of incoherence and its antecedents on preference. We have calibrated the effect of incoherence and shown how it can be integrated into preference and choice models. Second, we have relaxed

[3] We also controlled for the variance in attribute 1 claim, which was one of the manipulated variables. The results are substantively the same with and without this variable in the model.

[4] We dropped one observation at a time, estimated both models, used the estimates to predict preference for the dropped observation, and repeated this procedure for all observations. We used two other methods of resampling—a jackknife method by dropping one respondent rather than one observation at a time, and a split-sample method by using 20% of the sample as holdout—with similar results.

the standard assumption of preference independence frequently made in the modeling literature, permitting the development of models with correlated attributes.

Our research has significant managerial implications. Most significantly, we provide a methodology that can be used to assess the market acceptance of different positions in the multiattribute space after taking into account incoherence. Also, our model calibrates the effect of the antecedents of incoherence on preference, thus allowing managers to understand how to manage the negative effects of incoherence. For example, a manufacturer may purposely accept a lower position on a less important attribute to gain a strong inference on a more important one. Consider the design of Eveready flashlights (*Australian Financial Review Magazine* 2004), purposely designed to look ugly because the company found that sturdy products in this category were usually ugly. A product that is not ugly might be inferred to be less sturdy and therefore less preferred by consumers. In contrast, Body Smarts, a healthy candy line launched by Pfizer with much fanfare, died a quick death perhaps because no attempt was made to deal with the effects of the incoherence of "healthy and candy" (Beirne 2002). Our model can also be used to address product repositioning, new product introduction, and brand extension issues by incorporating it into other models (such as discrete choice models in McFadden 1974 and the ASSESSOR model in Silk and Urban 1978).

While we have made a first step toward developing a model of incoherence, there are limitations, many of which provide opportunities for further research. Our model includes only two attributes and although the approach can be extended to more than two, the mathematics becomes more complex. The utility transformation for the multivariate case (see Appendix T.A2) can be used as a foundation for this extension. We note, however, that in practice two dimensions often can describe the principal components of a set of attributes (e.g., Hauser and Shugan's 1983 Defender model and the price-quality inferencing literature, Ordonez 1998); our model allows these factors to be oblique. Another extension could involve dynamic updating of covariation beliefs, perhaps in a Bayesian framework. We assume symmetric effects of attributes on each other. It would be useful to relax our model to allow for asymmetric effects (e.g., see Moreau et al. 2001, p. 18). It might also be interesting to examine the strategic behavior of firms that account for incoherence-induced uncertainty (Guo 2005, Syam et al. 2005). Finally, it would be useful to examine the model's validity in contexts involving other products and services.

In addition to the interattribute extensions described here, it would be valuable to generalize our model to situations where incoherence comes from the following combinations: brand-brand (cobranding), brand-category (product line extensions), brand-attribute (new product development), category-attributes (market development), and brand-marketing mix (positioning and brand support). While this paper is a first attempt to formally model the effect of incoherence and its antecedents on preference, we hope it can provide a platform for further analytical developments and practical applications.

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Appendix

A.1. Derivation of the Model of Perception Formation (Equations (4)–(6) and Covariance)

We propose that consumers form perceptions (X_1 and X_2) by using the information in the claim and inference distributions (§2.4). We assume that for each attribute k ($k = 1, 2$), the consumer uses X_{kC} with probability p_k and X_{kI} with probability $(1-p_k)$. Let Y_k be a dummy variable with $\Pr(Y_k = 1) = p_k = 1 - \Pr(Y_k = 0)$. We assume Y_1 and Y_2 to be independent. Then,

$$(X_k \mid Y_k = 1) = X_{kC} \quad \text{and} \quad (X_k \mid Y_k = 0) = X_{kI}, \quad k = 1, 2. \tag{15}$$

With this formulation, we find that

$$\Pr(X_k \le x) = p_k \cdot \Pr(X_{kC} \le x) + (1 - p_k) \cdot \Pr(X_{kI} \le x). \tag{16}$$

Let the densities of X_{kC} and X_{kI} be denoted as ϕ_{kC} and ϕ_{kI}, respectively. Because X_{kC} and X_{kI} are normally distributed, the density of X_k, ϕ_k, is a mixture of two normal densities as follows:

$$\phi_k(x) = p_k \cdot \phi_{kC}(x) + (1 - p_k) \cdot \phi_{kI}(x). \tag{17}$$

The mean and variance of X_k are

$$\begin{aligned} \overline{X}_k &= E(X_k) = E_{Y_k} E(X_k \mid Y_k) = p_k E(X_{kC}) + (1 - p_k) E(X_{kI}) \\ &= p_k \cdot \overline{X}_{kC} + (1 - p_k) \cdot \overline{X}_{kI} \end{aligned} \tag{18}$$

$$\begin{aligned} \sigma_k^2 &= E[(X_k - E(X_k))^2] = p_k \cdot E_{\phi_{kC}}[X_k^2 - 2X_k\overline{X}_k + \overline{X}_k^2] \\ &\quad + (1 - p_k) \cdot E_{\phi_{kI}}[X_k^2 - 2X_k\overline{X}_k + \overline{X}_k^2] \\ &= p_k \cdot (1 - p_k) \cdot \{\overline{X}_{kC} - \overline{X}_{kI}\}^2 + p_k \cdot \sigma_{kC}^2 + (1 - p_k) \cdot \sigma_{kI}^2. \end{aligned} \tag{19}$$

Given the model assumptions, the covariance of X_1 and X_2 is

$$\begin{aligned}\sigma_{12} &= E(X_1X_2) - \bar{X}_1\bar{X}_2 = E_{Y_1,Y_2}E(X_1X_2 \mid Y_1, Y_2) - \bar{X}_1\bar{X}_2 \\ &= \{p_1p_2\bar{X}_{1C}\bar{X}_{2C} + p_1(1-p_2)\bar{X}_{1C}\bar{X}_{2I} + p_2(1-p_1)\bar{X}_{1I}\bar{X}_{2C} \\ &\quad + (1-p_1)(1-p_2)\bar{X}_{1I}\bar{X}_{2I}\}. \qquad (20)\end{aligned}$$

A.2. Derivation of the Model of Preference Formation (Equation (9))

In §2.5, we specify the consumer's utility function as

$$\begin{aligned}U &= a - b\cdot\exp(-r(\mathbf{w}'\mathbf{X})) \\ &= a - b\cdot\exp(-r(w_1X_1 + w_2X_2)), \qquad (21)\end{aligned}$$

where a and b are scaling constants and r is the risk-aversion parameter.

We assume that the joint distribution of X_1 and X_2 can be approximated with a bivariate normal density function (the reasonableness of this assumption is discussed in Appendix T.A1). We take the expectation of U in Equation (21) and integrate over the bivariate normal distribution of X_1 and X_2 to obtain the expression for expected utility (see Appendix T.A2 for proof) as

$$\begin{aligned}E(U) &= -\exp-\{r\cdot\{(w_1\bar{X}_1 + w_2\bar{X}_2) - (r/2) \\ &\qquad \cdot(w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\sigma_{12})\}\} \\ &= -\exp(-rZ), \qquad (22)\end{aligned}$$

where the scaling constants have been dropped for simplicity and σ_{12} is given in Equation (20).

A.3. Optimization of Attribute Combinations Using the Empirical Estimates

In §2.6.2 and Appendix T.A3, we show how the analytical model in Equation (9) can be used to select the preference-maximizing level of an attribute given a fixed level of the other attribute. The empirical analysis uses a parsimonious version (Equation (14)) of the analytical model. We now show how the empirical model can be used to determine the preference-maximizing level of an attribute given a fixed level of the other attribute, thus providing managers with a methodology to make better product positioning decisions. We rewrite Equation (14) without individual-level subscripts as follows:

$$Z = \eta_0 + \eta_1\cdot\bar{X}_1 + \eta_2\cdot\bar{X}_2 + \eta_3\cdot\mathrm{AI}_1 + \eta_4\cdot\mathrm{AI}_2, \qquad (23)$$

where $\bar{X}_1 = \{p_1\cdot\bar{X}_{1C} + (1-p_1)\cdot\bar{X}_{1I}\}$, $\bar{X}_2 = \{p_2\cdot\bar{X}_{2C} + (1-p_2)\cdot\bar{X}_{2I}\}$, $\mathrm{AI}_1 = \{\bar{X}_{1C} - \bar{X}_{1I}\}^2$, and $\mathrm{AI}_2 = \{\bar{X}_{2C} - \bar{X}_{2I}\}^2$.

We note that Z can be expressed in terms of only $\bar{X}_{1C}$ and $\bar{X}_{2C}$ because the inferences $\bar{X}_{1I}$ and $\bar{X}_{2I}$ are functions of the claims $\bar{X}_{2C}$ and $\bar{X}_{1C}$, respectively (see Equation (13) and its attribute 2 analog). We then obtain the first derivative of Z with respect to $\bar{X}_{2C}$ and set it to zero to obtain $\bar{X}^*_{2C}$, the optimal level of attribute 2 given a fixed claimed level of attribute 1 as follows:

$$\bar{X}^*_{2C} = (1/\theta_1)\cdot\{\theta_2 + \theta_3\cdot\bar{X}_{1C}\}, \qquad (24)$$

where $\theta_1 = 2\cdot\{\eta_3\cdot\beta_{12}^2 + \eta_4\}$,

$$\theta_2 = \{2\mu_{\tau_2}\eta_4 - \eta_2p_2 - (1-p_1)\beta_{12}\eta_1 - 2\mu_{\tau_1}\beta_{12}\eta_3\}, \quad \text{and}$$

$$\theta_3 = \{2\beta_{12}\eta_3 + 2\beta_{21}\eta_4\}.$$

Estimates of η_1, η_2, η_3, and η_4 are obtained from estimating Equation (14). Estimates of $\mu_{\tau_1}, \mu_{\tau_2}, \beta_{12}$, and β_{21} are obtained from estimating Equation (1) and its attribute 2 analog on the data from Part 1 of the study. To obtain an estimate of p_1, we substitute the expression for $\bar{X}_{1I}$ from Equation (2) into Equation (5):

$$\begin{aligned}\bar{X}_1 &= p_1\cdot\bar{X}_{1C} + (1-p_1)\cdot(\mu_{\tau_1} + \beta_{12}\cdot\bar{X}_{2C}) \\ &= (1-p_1)\mu_{\tau_1} + p_1\cdot\bar{X}_{1C} + (1-p_1)\cdot(\beta_{12})\cdot\bar{X}_{2C}. \qquad (25)\end{aligned}$$

We regressed attribute 1 perceptions on $\bar{X}_{1C}$ and $\bar{X}_{2C}$ (all from Part 2 of the study), using the estimated coefficient for $\bar{X}_{1C}$ as an estimate of p_1. An estimate for p_2 is obtained analogously. For the high correlation condition in our empirical study, estimates for the average consumer were as follows:

$$\mu_{\tau_1} = 2.97; \quad \beta_{12} = 0.38; \quad \mu_{\tau_2} = 2.41; \quad \beta_{21} = 0.55;$$
$$p_1 = 0.77; \quad p_2 = 0.74.$$

We substituted these estimates into Equation (25) to obtain the optimal level of attribute 2 (interesting) as 4.44 given the claimed level of 3.00 on attribute 1 (importance).

Technical Appendix

Interested readers are directed to the *Marketing Science* website for the technical appendix including:

T.A1 Assessing the assumption of bivariate normality for the joint distribution of X_1 and X_2.

T.A2 Derivation of an expression for expected utility in the multivariate case.

T.A3 Derivation of the net effect of incoherence on preference.

T.A4 Measurement instrument used in the experiment.

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