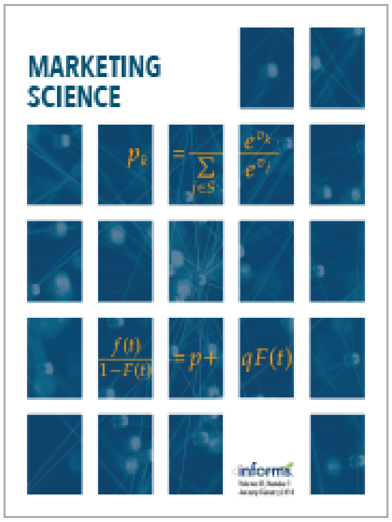

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The Variety of an Assortment: An Extension to the Attribute-Based Approach

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Research Note

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Abstract

In recent years, interest in category management has surged, and as a consequence, large retailers now systematically review their product assortments. Variety is a key property of assortments. Assortment variety can determine consumers' store choice and is only gaining in importance with today's increasing numbers of product offerings. To support retailers in managing their assortments, insight is needed into the influence of assortment composition on consumers' variety perceptions, and appropriate measures of assortment variety are required. This paper aims to extend the assortment variety model recently proposed by Hoch et al. (1999) in *Marketing Science.* It conceptualizes assortment variety from an attribute-based perspective and compares this with the product-based approach of Hoch, Bradlow, and Wansink (HBW). The attribute-based approach offers an alternative viewpoint for assortment variety. Attribute- and product-based approaches reflect basic conceptualizations of assortment variety that assume substantially different perception processes: a consumer comparing products one-by-one versus a consumer examining attributes across products in the assortment. While the product-based approach focuses on the dissimilarity between product pairs in an assortment, the attribute-based approach that we propose focuses on the marginal and joint distributions of the attributes. We conjecture and aim to show that an attribute-based approach suffices to predict consumers' perceptions of assortment variety.

In operationalizing the attribute-based approach, two measures of assortment variety are described and compared to product-based measures. These two measures relate to the dispersion of attribute levels, e.g., if all products have the same color or different colors, and the dissociation between attributes, e.g., if product color and size are unrelated. The ability of product-based and attributed-based measures to predict consumers' perceptions of assortment variety is assessed. The product-based measures (*Hamming*) tap the dissimilarity of products in an assortment across attributes. The attribute-based measures tap the dispersion of attribute levels across products (*Entropy*) and the dissociation between product attributes ($1-$*Lambda*) in an assortment. In two studies, we examine the correlations between these measures in a well-behaved environment (study 1) and the predictive validity of the measures for perceived variety in a consumer experiment (study 2).

Study 1, using synthetic data, shows that the attribute-based measures tap specific aspects of assortment variety and that the attribute-based measures are less sensitive to the size of assortments than product-based measures are. Whereas HBW focus on assortments of equal size, study 1 indicates that an extension to assortments of unequal size results in summed Hamming measures that correlate highly with assortment size. The latter is important when assortments of different size are compared. Next, we examine how well the measures capture consumers' perception of variety.

Study 2, a consumer experiment, shows that the attribute-based measures account best for consumers' perceptions of variety. Attribute-based measures significantly add to the prediction of consumers' perceptions of variety, over and above the product-based measures, while the reverse is not the case. Interestingly, this study also indicates that assortment size may not be a good proxy for perceived assortment variety.

The findings illustrate the value of an attribute-based conceptualization of assortment variety, since these measures (1) correlate only moderately with assortment size and (2) suffice to predict consumers' perceptions of assortment variety. In the final section we briefly discuss how attribute-based and product-based measures can be used in assortment management, and when product- and attribute-based approaches may predict consumers' variety perceptions. We discuss how an attribute-based approach can identify which attribute levels and attribute combinations influence consumers' perceptions of variety most, while a product-based approach can identify influential products. Both approaches have applications in specific situations. For instance, an attribute-based approach can identify influential attributes in an ordered, simultaneous presentation of products, while a product-based approach can assess the impact of sequential presentations of products better. In addition, we indicate how the random-intercept model estimated in study 2 can be further extended to capture the influence of, e.g., consumer characteristics.

(*Retailing; Product Assortment; Variety Perception; Variety Measurement*)

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1. Introduction

The variety of the assortments that retailers carry is an important determinant of store choice, satisfaction and sales (Kahn and Lehmann 1991, Kahn and McAlister 1997). An industry expert in the hardware category voiced this as: "Variety, assortment, and product quality are key concerns of the hardware consumer. Catering to those concerns can help a retailer maximize category sales and profits and develop hardware's potential as a destination category" (*Progressive Grocer,* August 2000). In response to these challenges, retailers, such as Kmart, have implemented systems of ongoing category review (*Discount Store News,* March 2000). Yet, it is not obvious how consumers perceive the variety of an assortment, how assortment variety can be measured, and hence how retailers can cater to the variety concerns of their consumers. For consumers, assortment variety may be more than a large number of products to choose from (Raftery 1993). Therefore, more insight is needed into the influence of assortment characteristics on consumers' perceptions of variety to support retailers in managing their assortments optimally.

Recently, Hoch, Bradlow and Wansink (1999; hereafter HBW) proposed a new model of assortment variety, based on the dissimilarity between products in an assortment. The model advances existing knowledge about the assortment variety construct and its measurement and provides important insights into the process of variety perception. At the heart of the model is a product-based conception of variety. The present paper aims to extend the HBW approach by advocating an attribute-based conception of assortment variety. It describes attribute-based measures of variety, examines the sensitivity of product- and attribute-based approaches to the size of an assortment, and explores the ability of both approaches to predict consumers' perceptions of assortment variety. The empirical results offer initial support that it matters which approach is used.

The next section introduces product- and attribute-based approaches to assortment variety, and specific measures to operationalize them. The pattern of correlations between these measures is examined in study 1, using synthetic data, while study 2 investigates their ability to predict consumers' variety perceptions. The final section offers suggestions for applications of the variety measures in assortment management and for future research.

2. Two Approaches to Assess Assortment Variety

Since products are bundles of attributes, the variety of an assortment of products can be conceptualized from a product-based and from an attribute-based perspective (Bettman et al. 1998). The HBW model follows a *product-based approach*, by examining the degree of dissimilarity between product pairs in the assortment. The more dissimilar the products are, the more variety there is in the assortment. A product-based approach converts information provided by the attributes into measures of product dissimilarity. An *attribute-based approach* focuses on the marginal and joint distributions of the attributes themselves.

2.1. Product-Based Approach to Assortment Variety

The general product-based model of assortment variety proposed by HBW is:

$$V_k(A) = \alpha_k + \sum_u \psi_k(u)n_u + \beta_k X_{kA}, \qquad (1)$$

where $V_k(A)$ is the perceived variety of assortment A to person k. Perceived assortment variety is based on a person-specific intercept (α_k), reflecting baseline variety perceptions, a generalized (psychological) distance function (ψ_k), the distinction pattern between two products (u), the number of product pairs (n_u) with a particular distinction pattern, a vector of covariate slopes (β_k), and a set of covariates for assortment A (X_{kA}). The covariates can account for aspects of the task and assortment, such as presentation format (e.g., organized versus random display), and will not be considered in the empirical illustrations that follow.

The model specifies perceived assortment variety as a function of the dissimilarity between product pairs. HBW operationalize product dissimilarity by the *Hamming measure*, a count of the number of attributes on which a product pair differs. For example, a product pair that differs on two attributes has a Hamming measure of 2. When the distance function ψ is unrestricted, a model with fitted regression weights can be estimated, based on the number of product pairs in the assortment with distinction patterns of 0 to U. Several a priori specifications for ψ can be considered as well. The best fitting a priori model for the majority of subjects in HBW's study has diminishing returns to multiple distinctions (by taking the square root of the *Hamming measure*), and equal importance of attributes and spatial positions. We will use this model in study 1 (synthetic data) and a model with fitted regression weights in study 2 (consumer experiment), as will be explained.

To illustrate the measures, consider the following assortment of four shirts that differ in color and fabric. The assortment has two blue cotton shirts and two green silk shirts. For such an assortment, $n_1 = 0$ and $n_2 = 4$, the summed Hamming measure equals 8 (*SumHM*: 4*2), and the measure from HBW's best a priori specification of ψ equals 5.66 (*SumSRHM* = sum of the square roots of the Hamming measures: $4^*\sqrt{2}$).

2.2. Attribute-Based Approach to Assortment Variety

An attribute-based approach to variety focuses on the patterns of attribute levels. It has been applied, among others, to predict preferences for subsets of products from an assortment (Farquhar and Rao 1976, Harlam and Lodish 1995, Bradlow and Rao 2000). We describe an attribute-based approach for the variety of an assortment as a whole. The basic model is:

$$V_k(A) = \alpha_k + \beta_1 \sum_{m=1}^{M} f(n_1, \ldots, n_{L_m}) + \beta_2 \sum_{m_1<m_2}^{M} f(n_{11}, \ldots, n_{L_{m_1}L_{m_2}}), \qquad (2)$$

where m is the number of attributes $(1,\ldots,M)$ with attribute levels l $(1,\ldots,L_m)$; $n_1,\ldots,n_{L_{m_1}}$ are marginal frequencies of attribute levels 1 to L_m for attribute m, $n_{11},\ldots,n_{L_{m_1}L_{m_2}}$ are joint frequencies of attribute levels for each pair of attributes (m_1, m_2), and other symbols are as in Equation (1).

The basic model describes perceived assortment variety as a function of a person-specific intercept, the dispersion of attribute levels (marginal frequencies), and the dissociation between all unique pairs of attributes (joint frequencies). To illustrate this, consider the cross tabulation of color and fabric from the previous example (assortment of four shirts):

Attribute m_1:	Attribute m_2: Fabric	
Color	Cotton $(n_1 = 2)$	Silk $(n_2 = 2)$
Blue $(n_1 = 2)$	$n_{11} = 2$	$n_{12} = 0$
Green $(n_2 = 2)$	$n_{21} = 0$	$n_{22} = 2$

An assortment is varied to the extent that the attribute levels are dispersed. In the example, two of the shirts are blue and two are green. This assortment is more varied than one that has, e.g., only blue shirts. An assortment is also more varied to the extent that the association between each pair of attributes is lower (i.e., the dissociation is higher). In the example, all cotton shirts are blue and all silk shirts are green. This assortment is less varied than one that contains all four possible combinations of the attribute levels.

To operationalize the attribute-based approach, specific measures of attribute dispersion and dissociation are needed. Following HBW, the empirical illustrations employ categorical product attributes. We choose *Entropy* as a straightforward measure of dispersion for categorical variables. It is derived from information theory (Kullback 1959) and has been applied in economics and marketing, for instance to measure variety seeking (Mitchell et al. 1995), dispersion of industrial activity (Jacquemin and Berry 1979), and budget and brand shares (Mazumbar and Papatla 2000, Theil and Finke 1983). For advantages of *Entropy* over alternative measures such as the

Herfindahl index, see e.g., Jacquemin and Berry (1979). The *Entropy* of attribute m is:

$$Entropy_m = -\sum_{l=1}^{L} p_l \ln p_l, \tag{3}$$

with p_l denoting the proportion of products in the assortment with attribute level l (i.e., n_l/N). *Entropy* is zero when only a single attribute level is present in the assortment (all shirts are green). It is largest when all attribute levels occur in equal proportions. Higher values of *Entropy* indicate higher levels of variety in the assortment. In the sample assortment, the dispersion of both color and material is 0.69.[1] As dispersion is based on the marginal frequency of single attributes only, it does not respond to changes in the joint distributions of attributes. This may miss important information about the variety of assortments, since attributes with widely different joint distributions (attribute associations) can have the same marginal frequencies, and vice versa. For this, a measure is required that focuses on the association between attributes.

To operationalize association between attributes, we use *Lambda*, a measure of association between categorical variables, with a simple probabilistic interpretation (Goodman and Kruskal 1954). It captures the extent to which information on one attribute reduces error in predicting another attribute. For advantages of *Lambda* over χ^2-based measures such as the contingency coefficient, see e.g., Leach (1979). The *Lambda* for attributes m_1 and m_2 is given in Equation (4). To facilitate interpretation, assume attribute levels $m_1 = 1, \ldots, L$ and $m_2 = 1, \ldots, C$.

$$Lambda_{m_1 m_2} = \frac{\sum_{l=1}^{L} \max_c(n_{lc}) + \sum_{c=1}^{C} \max_l(n_{lc}) - \max_c(n_{\cdot c}) - \max_l(n_{l\cdot})}{2N - \max_{\cdot c}(n_{\cdot c}) - \max_l(n_{l\cdot})}, \tag{4}$$

where n_{lc} is the number of products with attribute levels l and c for attributes m_1 and m_2, $n_{l\cdot}$ is the number of products with attribute level l for attribute m_1 (marginal count), $n_{\cdot c}$ is the number of products with attribute level c for attribute m_2 (marginal count), and N is the number of products in the assortment. *Lambda* lies between 0 (no association) and 1 (perfect association). In the sample assortment *Lambda* is 1.0. In the sequel, we use (1 − *Lambda*) as a measure of *dissociation*, which increases when variety increases.

Since they are based on the same information about the assortment, product- and attribute-based measures are likely to be correlated. To examine the extent to which they are correlated, and, more importantly, how well the measures predict consumers' perceptions of assortment variety, two studies are performed. Study 1 examines correlations between the variety measures in a well-behaved environment, using synthetic data. Study 2 examines the predictive validity of the measures for perceived variety in a consumer experiment.

3. Study 1: Correlation Between Variety Measures

Correlations between the product-based and attribute-based measures were examined across a large number of assortments (synthetic data). As product-based measures, we used the sum of the classic Hamming measures (*SumHM*) and the sum of the square roots of the Hamming measures (*SumSRHM*; based on $\psi(u) = \sqrt{u}$). The attribute-based measures were *Entropy* and (1 − *Lambda*), summed across attributes and attribute pairs, respectively. We also included the number of products in the assortment (*Size*), which has been used as a global indication of assortment variety in previous research (Chiang and Wilcox 1997, Hoch and Banerji 1993).

The constructed products had three attributes, and each attribute could have four levels. This led to 64 different products. Assortments with 8, 12, or 16 products were considered to allow sufficient size variation. A random sample of 3000 product assortments was drawn from the population of $64^8 + 64^{12} + 64^{16} = 7.9 * 10^{28}$ possible assortments, allowing for

[1]The normalized *Entropy* (*Entropy* divided by $Entropy_{max}$) is sometimes used (e.g., Mazumbar and Papatla 2000). In the two studies in this paper *Entropy* and normalized *Entropy* are identical. For ratio, interval, and binary attributes, variance-based measures of attribute dispersion (Bradlow and Rao 2000, McAlister and Pessemier 1982) and correlation-based measures of attribute association could be used.

duplicate products. Of the assortments, 1000 consisted of 8 products, 1000 of 12 products, and 1000 of 16 products.

If attribute- and product-based measures tap a similar underlying variety construct, dispersion and dissociation should be significantly correlated with the product-based measures. In addition, if dispersion and dissociation tap different components of variety, their intercorrelation should be low. To the extent that the product- and attribute-based measures of assortment variety capture more information than is contained in the size of the assortment, their correlation with the latter should be modest only.

Table 1 indicates clear differences in the size of the correlations between measures. As expected, attribute-based measures have low intercorrelation (0.06) and a moderately high correlation with product-based measures (between 0.45 and 0.59). Also, the attribute-based measures have a moderately high correlation with assortment size (0.55 for *Entropy* and 0.48 for (1−*Lambda*)). Table 1 shows a high correlation between the product-based measures and assortment size (0.99).[2] This high correlation is due to the fact that adding one additional product to an assortment of size N leads to the addition of N product pairs in the summed measure. This relationship between product-based measures and assortment size may complicate interpretations of assortment variety, when assortments of different size are compared. Using *averaged* Hamming measures instead is not a solution.[3] The results suggest that the attribute-based measures are distinct and not strongly correlated with assortment size. Whether this matters is examined in study 2.

Table 1 Correlations Between the Variety Measures in Study 1

	Product-Based		Attribute-Based	
	SumHM	*SumSRHM*	*Entropy*	(1 − *Lambda*)
SumSRHM	1.00			
Entropy	0.59	0.57		
(1 − *Lambda*)	0.45	0.47	0.06	
Assortment Size	0.99	0.99	0.55	0.48

Note: $n = 3{,}000$; correlations are significant at $p < 0.001$.

4. Study 2: Consumers' Perception of Assortment Variety

An experiment was conducted to assess the predictive validity of product-based and attribute-based measures for consumers' perceptions of assortment variety.

Participants and Design. Participants were 62 undergraduate students from a university in The Netherlands, each of whom evaluated 12 product assortments. The setup was a 2 (assortment size) × 2 (dispersion level) × 3 (dissociation level) within-subjects design, to ensure that assortments differed sufficiently.

Stimuli. HBW (1999) kindly made their stimuli available to us. These consist of 64 nonexisting products, characterized by three attributes: color (red, blue, yellow, green), shape (square, rectangle, circle, triangle), and name (CAM, NUX, ZOL, VIK).[4] Products were arrayed in rows of four products each. The specific attribute levels (e.g., whether the first product is red, blue, yellow, or green) were randomized. Products were presented in an organized man-

[2] The large correlation between the product-based measures and assortment size is not due to the relatively large steps in which assortment size was increased. Follow-up analyses with assortments differing less in size (8, 9, and 10) gave a correlation between *SumSRHM* and *Size* of 0.98.

[3] In our data set, averaged Hamming measures show small correlation (0.04) with *SumHM* and *SumSRHM,* no significant correlation with assortment size, and a negative correlation (−0.28 and −0.10) with (1 − *Lambda*). Especially the negative correlations are undesirable. In addition, averaged Hamming measures can decrease when products are added to an assortment, which is undesirable as well. For instance, consider an assortment with a blue cotton shirt and a green silk shirt, giving an average Hamming measure of 2. Adding a blue silk shirt would increase assortment variety, but decrease the average Hamming measure to 1.33.

[4] Two of the original product names were slightly changed, as in Dutch one is a meaningful object and the other a slang word.

Table 2 Product Assortments, Variety Measures, and Perception in Study 2

	Differences Between Product Assortments			Measures of Assortment Variety							
Assortment Number	No. of Different Products	Attribute Dispersion	Attribute Dissociation	*Size*	*Sum SRHM*	n_1	n_2	n_3	*Sum Entropy*	*Sum* (1 − *Lambda*)	Mean Variety Perception
1	4	1:1:1:1	All low	8	41.57	0	0	24	4.16	0.00	3.85
2	8	1:1:1:1	All high	8	44.68	0	12	16	4.16	1.33	7.18
3	4	1:1:3:3	All low	8	38.11	0	0	22	3.77	0.00	3.01
4	8	1:1:3:3	All high	8	42.78	0	18	10	3.77	1.60	6.51
5	4	1:1:1:1	All low	16	166.28	0	0	96	4.16	0.00	3.51
6	16	1:1:1:1	All high	16	184.96	0	72	48	4.16	2.00	8.90
7	4	1:1:3:3	All low	16	152.42	0	0	88	3.77	0.00	3.48
8	16	1:1:3:3	All high	16	176.18	12	72	36	3.77	2.00	7.46
9	8	1:1:1:1	2 high, 1 low	8	44.30	4	4	20	4.16	0.89	6.19
10	8	1:1:3:3	2 high, 1 low	8	42.20	6	6	16	3.77	1.07	5.37
11	16	1:1:1:1	2 high, 1 low	16	182.65	24	24	72	4.16	1.33	7.81
12	12	1:1:3:3	2 high, 1 low	16	171.52	28	28	60	3.77	1.33	6.06

Note: n_u is the number of products with u different attributes, as used in HBW and Equation (1).

ner, to simulate a regular store shelf. Products were grouped by color and within color by form. Since similar products and attributes were in close proximity, both product- and attribute-based processing strategies should be relatively easy to use.

Product Assortments. Table 2 summarizes the product assortments and variety measures. Assortments consisted of 8 or 16 products. Attributes were either equally dispersed (all levels occurred in equal proportions), or two of the levels dominated the other two (in proportion 3 to 1). Three levels of attribute dissociation were used: high, low, and partial (see Table 2). Assortments with low attribute dissociation contained replicas. In partial dissociation, color and form were associated, while brand name was dissociated from color and form.

Procedure. The study was administered on personal computers using the program Authorware (Macromedia 2002). Instructions were similar to HBW. Participants were told that the purpose of the study was to investigate variety perceptions. The instruction mentioned a visit to an unspecified number of different stores and asked participants to answer questions about assortments of an imaginary product called "jinko." The instruction explained that jinkos are comparable to other product categories, where products can differ on characteristics such as name, taste, size, color, and so on. Next, all possible types of jinkos (64) appeared sequentially on the computer screen for two seconds each, as in HBW. After training, participants were exposed to the assortments of jinkos in random order, and answered the following questions (each with a ten-point response scale, with endpoints labeled "not at all" and "very much"): "Does this assortment of jinkos offer variety?", "Does this store offer a dull assortment of jinkos?", and "Does this store offer a diverse assortment of jinkos?". Cronbach alphas, calculated across participants for each of the assortments, are between 0.70 and 0.89, with an average of 0.77. Scores across the three items were averaged after reverse coding the negatively worded item. Participants proceeded at a self-determined pace, and product assortments remained visible during the task. Participants took about 20 minutes to complete the total study, and received the equivalent of $5 for their participation.

4.1. Findings

The last column of Table 2 provides the mean variety perception of each assortment. We estimated multilevel linear regression models, using MLwiN (Rasbash et al. 2000) to account for the fact that each participant judged multiple assortments (Bryk and Raudenbush 1992). The models predict variety perceptions from the product- and attribute-based measures and assortment size while accounting for individual heterogeneity in mean perceived variety, through a random intercept. The following general regression model was estimated:

$$V_k(A) = \beta_0 + \beta_1 n_{1_A} + \beta_2 n_{2_A} + \beta_3 n_{3_A} + \beta_4 Size_A + \beta_5 Disp_A + \beta_6 Dissoc_A + u_{0k} + e_{0Ak} \quad (5)$$

where n_{1_A}, n_{2_A}, n_{3_A} are the number of product pairs in assortment A with respectively 1, 2, and 3 different attribute levels[5], $Size_A$ is the size of assortment A, $Disp_A$ is attribute dispersion of assortment A (i.e., *Entropy*), $Dissoc_A$ is attribute dissociation of assortment A (i.e., $1-Lambda$), β_o is the overall mean, β_q are regression weights, u_{0k} is the estimated participant-level residual, and e_{0Ak} is the estimated assortment-level residual.

Restricted versions of model (5) are compared, to determine the incremental contribution of attribute- and product-based measures, and assortment size. We use the general product-based model with fitted regression weights (HBW 1999) as the benchmark model (n_1, n_2, n_3), since this provides a stronger test than *SumSRHM*, which is based on a predefined distance function. Table 3 provides a summary of the estimations.

Assortment Size Model. Model 1 contains only *Size* as a predictor. By itself, *Size* accounts for only 3.4% of the variance in perceived variety. Hence, assortment size is not a good proxy for perceived assortment variety in this study.

Product-Based Model. Model 2 in Table 3 is the fitted regression weights model of HBW, and it accounts for 43.1% of the variance in perceived assortment variety. The negative coefficient for n_3 is unexpected, since it differs from the positive coefficients found by HBW. The explanation lies in the impact of assortment size in the current dataset. If only assortments of equal size are considered, the coefficients become 0.49, 0.73, and 0.76 (n_1, n_2, and n_3) for assortments with 8 products, and 0.13, 0.18, and 0.19 for assortments with 16 products, which matches the findings of HBW. The number of product pairs increases rapidly when assortment size rises, which affects the product-based measures. By including *Size* in model 3 we adjust for this inflation of the measures, hence the negative coefficient for *Size* of -1.99 in that model.[6]

Product-Based and Assortment Size Model. Model 3 contains the product-based measures and assortment size. Clearly, the empirically weighted product-based measures capture a significant portion of variance in variety perceptions over and above the variance accounted for by assortment size. This model outperforms model 1 (assortment size only) and model 2 (product-based only), as indicated by the model tests in Table 3.

Attribute-Based Model. Model 4 is the attribute-based model of assortment variety. As expected, both increases in attribute dispersion (coefficient = 8.44; *t*-ratio = 10.16) and increases in attribute dissociation (coefficient = 4.72; *t*-ratio = 32.58) promote higher perceived variety. Model 4 also performs best in predicting consumers' perceptions of assortment variety in this study. The model comparisons in the lower part of Table 3 show that the attribute-based variety model can not be significantly improved by adding the product-based measures and assortment size (model 4 versus 6: $L^2 = 4.1$, $df = 4$, $p = 0.393$). The reverse is not the case: the attribute-based measures improve the prediction of variety perceptions over and above the product-based measures and assortment size (model 3 versus 6: $L^2 = 189.7$, $df = 2$, $p < 0.001$).

[5] Following HBW, n_0 is not estimated due to collinearity problems.

[6] Dividing each of the measures, n_1 to n_3, by *Size* does not improve their predictive power. A model with $n_1/size$, $n_2/size$, and $n_3/size$ ($-2LL = 3006.2$; #par = 6) still has a negative coefficient for the latter variable, and adding *Size* significantly improves it (likelihood-ratio chi-square: $L^2 = 134.3$, $p < 0.005$). Other results are similar to Table 3 as well.

Table 3 Model Estimates and Model Comparisons in Study 2

Model	Coefficient	*t*-ratio	*p*-value	−2LL	#par.	Assortment Level Variance Accounted For
0. *constant*	5.777	53.365	<0.001	3,452.2	3	–
1. *constant*	4.499	15.900	<0.001	3,428.8	4	3.4
size	0.107	4.864	<0.001			
2. *constant*	5.171	33.247	<0.001	3,068.2	6	43.1
n_1	0.043	5.695	<0.001			
n_2	0.052	18.755	<0.001			
n_3	−0.016	6.667	<0.001			
3. *constant*	15.908	15.191	<0.001	2,968.5	7	50.8
n_1	0.139	11.952	<0.001			
n_2	0.205	13.686	<0.001			
n_3	0.210	9.567	<0.001			
size	−1.991	10.360	<0.001			
4. *constant*	−7.674	6.914	<0.001	2,782.9	5	62.5
entropy	2.816	10.155	<0.001			
(1 − *lambda*)	2.378	32.575	<0.001			
5. *constant*	−7.869	7.038	<0.001	2,781.0	6	62.6
size	0.019	1.387	0.171			
entropy	2.812	10.154	<0.001			
(1 − *lambda*)	2.357	31.749	<0.001			
6. *constant*	−8.683	2.314	0.024	2,778.8	9	62.7
n_1	0.004	0.221	0.826			
n_2	−0.008	0.316	0.753			
n_3	−0.006	0.159	0.874			
size	0.074	0.230	0.819			
entropy	2.922	5.418	<0.001			
(1 − *lambda*)	2.446	14.262	<0.001			

Model Comparisons		L^2	*Df*	*p*-value
1–3	adding product-based measures to size	460.3	3	<0.001
2–3	adding size to product-based measures	99.7	1	<0.001
1–5	adding attribute-based measures to size	647.8	1	<0.001
4–5	adding size to attribute-based measures	1.9	1	0.168
3–6	adding attribute-based measures to product-based measures and size	189.7	2	<0.001
4–6	adding product-based measures and size to attribute-based measures	4.1	4	0.393

5. Conclusion

The findings illustrate the value of an attribute-based conceptualization of assortment variety. Attribute-based measures correlated less with assortment size than product-based measures did, and they were sufficient to predict consumers' perceptions of assortment variety. Retailers express a keen interest in knowing the effects of changes in assortment size and composition on consumers' variety perceptions, such as when new products are introduced and others are eliminated. They also seek comparisons of assortment variety across competing stores or across different stores of a single chain. In such instances, assortment sizes may be larger than in the current applications and more unequal in size. If the current findings generalize to such situations and consumers' perceptions of variety are the criteria, an attribute-based approach to variety measurement appears preferable.

Since the perception process itself was not examined, we cannot be sure that consumers formed their variety perceptions through the attributes, but the predictive performance is encouraging. An attribute-based approach is also consistent with evidence that for large assortments, consumers emphasize attribute information (Bettman et al. 1998), find information on attribute levels more helpful than information on individual products (Huffman and Kahn 1998), and are influenced by the availability of attribute levels (Boatwright and Nunes 2001).

In view of the controlled conditions of the current research and the limited work comparing attribute- and product-based variety measures, we are somewhat reluctant to formulate specific guidelines for retailers based on our findings. Rather, the following section discusses the limitations of the current research and offers directions for future research based on that. It also identifies circumstances in which product- and attribute-based approaches may be more or less predictive of consumers' variety perceptions.

5.1. Limitations and Future Research

There are several limitations of the current attribute-based model and its operationalization, which constitute opportunities for future research. A first limitation concerns the inclusion of only attribute dispersion and the *bivariate dissociation* between attributes. Using an ANOVA analogy, the current model captures the main effects and two-way interactions of variation in attributes. But consumers' perceptions may be sensitive to *m*-variate dissociation between attributes. To account for this, the current model would need to be extended, for instance along the lines proposed by Goodman and Kruskal (1954), to assess *m*-variate dissociation. Processing these higher-order dissociations may become progressively taxing to consumers, and only future research can establish if and when they significantly improve the prediction of consumers' variety perceptions. If such higher-order dissociations are influential, taking them into account should enhance the predictive performance of the attribute-based approach, and retailers' insight into the composition of their assortment and the opportunities to adapt it.

A second limitation concerns the way in which *heterogeneity* was modeled. The basic attribute-based model in Equation (2) and the regression model in study 2 captured heterogeneity through a random-intercept formulation, which allows consumers to differ in their mean perceived variety. To examine heterogeneity in further detail, the regression coefficients for the variety components could be allowed to vary randomly and systematically across consumers and tasks as well, in a slopes-as-outcomes model (Bryk and Raudenbusch 1992, Boatwright and Nunes 2001). With such a formulation it can be tested whether the effect of attribute dispersion and dissociation on variety perceptions is heterogeneous and which consumer and task characteristics systematically account for this. We did not explore such a model here because of the current focus on overall differences between the variety approaches, but the availability of multilevel software (e.g., Bryk and Raudenbusch 1992, Rasbash et al. 2000) facilitates such extensions in future work.

A third limitation concerns the use of *categorical attributes*, and the related measures of dispersion and dissociation. Product attributes such as price are continuous, and future work may examine categorical and continuous attributes jointly. Such work may apply alternative operationalizations of dispersion and dissociation for continuous attributes, such as variance or correlation-based measures. It may also examine to what extent consumers' perceptions of variety are sensitive to variations in continuous variables, and test the appropriateness of recoding continuous attributes into brackets (e.g., price brackets).

More opportunities for future work exist. Both approaches to assortment variety can support decisions about *changes in the composition* of an assortment.

Boatwright and Nunes (2001) found that, across a range of food categories, in particular the number of available brands and flavors influenced sales significantly. Modest reductions in these "meaningful attributes" increased the sales volume, as returning customers bought more, but reduced the purchase likelihood, as the preferred attribute levels of some consumers were deleted. In the same way, an attribute-based approach to assortment variety may examine which attributes and attribute combinations are most meaningful in terms of their influence on consumers' perceptions of variety and perhaps on purchase decisions. Likewise, a product-based approach may examine which specific products have the largest effect on consumers' perceptions of assortment variety. Perhaps, all other things being equal, consumers' preferred products have larger effects on perceived assortment variety than alternative products have. In view of this, a combination of product- and attribute-based measures may be most useful when retailers are managing assortment variety.

More attention to the effects of *assortment presentation* appears fruitful as well. Consumers in the current study evaluated an organized display of the assortment, as is common in retailing. Stores often organize their assortment on attributes such as brand (soups), product form (liquid detergents), size (television sets), or occasion (greeting cards). To the extent that the assortment presentation is hierarchical (brands, flavors within brands, sizes within flavors), some attributes may affect perceptions of variety more than others, and attribute dispersion may dominate attribute dissociation (as the former may be more readily assessable), a conjecture that future work may test.

In the current study, assortment sizes were small enough to present the complete assortment simultaneously. In practice, assortments may become so large that they are offered *sequentially* (as in web-based applications) or that consumers move through them sequentially (as in a store aisle). Will consumers use the first products in such sequential presentations to form an initial impression of assortment variety, which is updated by the subsequent products presented? If so, product-based measures more so than attribute-based measures would be predictive of perceived assortment variety.

The influence of *task and consumer characteristics* in assortment variety also deserves further consideration. Task characteristics such as time pressure and consumer characteristics such as involvement and expertise influence the motivation and ability to process information, and as such may influence the consumer's approach to assortment variety. Processing-by-product tends to take more time and is more taxing than processing-by-attribute (Russo and Dosher 1983), which suggests, if it generalizes to perceptions of assortment variety, that an attribute-based approach is emphasized under time pressure and a product-based approach when there is sufficient time. Likewise, high levels of consumer involvement and expertise may be more conducive to a product-based approach, or to the joint use of a product-based and attribute-based approach. Establishing the influence that these and other presentation, task, and consumer characteristics have on the predictive ability of attribute- and product-based approaches is a challenge for future research on perceived assortment variety.

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