Identifying Constellations of Website Features:
Documentation of a Proposed Methodology

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His early career... academically, rising from Assistant Professor to tenured Professor at Purdue University, his extensive published research spanned the realms of psychology (especially consumer, social, and cross-cultural), marketing, regional science, sociology, community development, applied economics, and even forestry. Professionally, he was a consultant to the U.S. State Department and to the USDA, as well as to private firms.

Later on...on the professional front, he co-founded a marketing research firm, Tactical Decisions Group, and turned it into a million dollar organization. After merging it with another firm to form Triad Research Group, it was one of the largest market research organizations based in Ohio. His clients ranged from large national firms (e.g., Merck and Co., Dupont, Land o’ Lakes) to locally based organizations (e.g., MetroHealth System, American Greetings, Progressive Insurance, Liggett Stashower Advertising). On the academic side, he moved to Cleveland State University and co-founded the Consumer-Industrial Research Program (CIRP). Some of Cleveland’s best and brightest young marketing research professionals are CIRP graduates.

In the last few years...academically, he is actively focusing upon establishing CIRP as a center for cutting edge consumer research. Professionally, he resigned his position as Chairman of Triad and is now Senior Consultant to Action Based Research and consultants with a variety of clients.

Currently enrolled in the Consumer-Industrial Research Program at Cleveland State University, Nick graduated with honors from Virginia Wesleyan College with degrees in Psychology and Business. While an undergraduate, he received “Outstanding Senior in Psychology” honors and was an officer in Virginia Wesleyan’s Phi Chi chapter. Prior to graduation, Nick completed independent research on memory of commercials and the mitigating factors involved in recognition of commercial brand names, which resulted in his study on Advertisement Recognition Based on Commercial Sequence and Program Content. His interests include, but are not limited to, the role of advertising in decision making and consumer behavior, product positioning, and research techniques to acquire this information.

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Abstract

A “feature preference constellation” is a set of commercial website features similar in appeal to shoppers. That is, the features in a constellation: covary in attractiveness (i.e., correlate), are similar in elevation (mean attractiveness), are treated as intact entities rather than being redefined as the partial reflections of underlying factors or dimensions, and can represent more than a single function or meaning. Identification of constellations is useful to practitioners as a guide for developing new websites and to scientists as a predictor/explanation for adoption and diffusion of sites throughout a market. A constellation is a different construct from a “dimension” and cannot be gauged via the factor analytic procedures popularly used to assess dimensions. A 10-step procedure was developed to identify constellations. Dependent upon sample representativeness and research objectives, feature preferences may first be adjusted for sample (here, demographic) characteristics by the use of “rescaled residual scores.” Feature similarity indices, Lin coefficients sensitive to both elevation and covariance, are subjected to multidimensional scaling. Features, as points in multidimensional space, are grouped by a two phase hierarchical/partition clustering procedure. Comparison with the most popular factor analytic approach showed that the proposed procedure yielded meaningful feature groupings more homogeneous in elevation while comparable in within group covariation and in separation among groups. It was concluded that the procedure can operationalize the constellation construct, and do so more effectively than can the popular factor analytic approach. It was suggested that the constellation concept, because of its unique suitability for particular applications, be considered by both scientists and practitioners.

A condensed version of this study appears in the RRCB paper, “Website feature preference constellations: Conceptualization and measurement” by the present authors.
Identifying Constellations of Website Features: Documentation of a Proposed Methodology

Which website features attract consumers to an online shopping site? The answer is important to behavioral, information, and marketing scientists’ attempts to understand the dynamics of this new and innovative form of commerce. The answer also is pivotal to practitioner efforts to enhance the effectiveness of shopping sites. To date, these studies have used one of three approaches: a feature by feature basis, joint effects of separate features, or underlying dimensions or functions played by sets of features. Unexplored in past studies has been the missing piece in the puzzle; let us refer to this as the “website feature preference constellation.” This study defines the constellation, documents a procedure to identify them, and compares the approach with the popular dimensional prospective.

Current Approaches

Numerous studies have suggested particular single features that can enhance the appeal of a shopping site. The hallmark of this perspective is to consider a feature’s drawing power as independent of other features, i.e., to view the appeal as constant no matter what other features a website provides. Illustrative of this perspective are the studies of interactivity (e.g., Amichai-Hamburger, Fine, and Goldstein, 2004; Chen and Yen, 2004). Still, other studies have devised models assessing the simultaneous impacts of multiple (but separate) variables (e.g., Chakraborty, Lala, and Warren, 2002; Ghose and Dou, 1998; Jarvenpaa, Tractinsky, Saarinen, Vitale, 1999; Liu and Arnett, 2000; Swaminathan, Lepkowska-White, and Rao, 1999).
The third approach is to assess sets of attributes that have a common function such as ensuring security, enhancing convenience, increasing the fun of usage, etc. Overwhelmingly, the dominant procedure is to identify the functions via factor analysis. These functions can then be interpreted as evaluative dimensions consumers use to judge a website and, so, are proposed as yardsticks a professional can use to evaluate the quality of a website. Examples are Aladwani and Palvia, 2001; Chang, Torkzadeh and Dhillon, 2004; Chen and Wells, 1999; Kim and Stoel, 2004; Liu and Arnett, 2000; Panganathan and Ganapathy, 2002; Torkzadeh and Dhillon, 2002; van Iwaarden, van der Wiele, Ball and Millen, 2004).

Website Feature Preference Constellations: Concept

Based on the concept of the “innovation attribute preference net” proposed by Blake, Dostal, and Neuendorf (2005), let us define a “constellation” as a set of site features similar in appeal. First, the features in a constellation covary in attractiveness to shoppers. The appeal of a given feature correlates positively with the appeal of other features in that constellation more highly than with the appeal of features not in that constellation. The more do shoppers want one, the more do they want the other features in that constellation. Second, the features in a constellation are similar in elevation, i.e., in overall appeal as seen in their means on the attractiveness index. Third, the features are treated as intact entities; they are not redefined and seen as simply the sum of two or more other entities. Hence, a feature can be in only one constellation; it is not possible for a certain portion of that feature’s preference to be in one constellation and another portion of it to be in another constellation. The fourth aspect of a constellation is that the features can represent more than a single function or evaluative dimension. Consumers
can appreciate feature X in a constellation for one reason (e.g., convenience) and feature Y in that same constellation for another reason (e.g., fun).

Why should we care about the constellation concept? All four aspects enhance the utility of the constellation concept to practitioners developing new sites or evaluating extant ones. That features covary tells the practitioner that if shoppers are known to prefer one feature they can be predicted to desire other features in that constellation also. That some shoppers prefer a constellation’s features more than do other shoppers makes it easier to identify and target the shopper segments most likely attracted to a website which provides the features in that constellation. Next, that features are comparable in elevation suggests which alternative features may be substitutable for difficult to deliver features and still maintain the overall appeal of a website.

Treating a feature as a whole entity is what practitioners must do if they are to make a decision whether or not to incorporate a feature in a site. That is, viewing a feature as a composite of other “things” can complicate rather than simplify the decision as to which specific features to include in a specific site. Next, the absence of a single function constraint may have little relevance to website developers once they have already considered covariance and elevation. To a researcher investigating constellations on behalf of practitioners, however, the elimination of a unifunctional constraint permits the researcher to assess a wider range of features for inclusion in a particular constellation.

For scientists, the constellation construct offers possibilities beyond those provided by a purely dimensional (factor analytic) approach. Thanks to the covaration and elevation similarity facets, a constellation may well provide a simpler, and perhaps
more efficient, predictor/explanation for certain phenomena than would a dimensional perspective. For example, consider a website whose features spring from a constellation of features with a high elevation (i.e., are homogeneously high in appeal). Such a website would be predicted to diffuse more quickly through a population, especially in comparison to a website whose features are drawn mainly from a constellation homogeneous in their low elevation. In contrast, diffusion rate predictions are more complicated when using a factor analytically derived feature grouping. In such a grouping, first, some features can have a high elevation while others can be lower in elevation. Second, since a feature may have a substantial loading on more than one factor, predictions have to take into account a feature’s multiple group membership.

From a different perspective, while the whole entity facet may have more of a payoff for practitioners than for theoreticians, the elimination of the single function constraint does encourage scientists’ attention to higher order composites of features, each composite representing multiple evaluative dimensions or functions.

**Constellations: Measurement**

As noted above, investigations of groupings of feature preferences overwhelmingly have relied upon a dimensional approach. Feature ratings are factor analyzed (almost always by principal components with orthogonal rotation); then each factor defines a group of features. A factor score then serves as the index for that group, and/or features are assigned to the groups on which they have the highest loading. But, as typically conducted, factor analysis is not suited to reveal constellations, due to the comparable elevation and the intact entity requirements of the constellation. That is, the $r$ and the covariance are insensitive to elevation, thereby permitting high $r$’s or substantial
covariation among variables with radically disparate elevations.\(^1\) Further, the use of factor scores is incompatible with the intact entity requirement since factoring redefines the constellation, going from a set of individual features to a composite in which the individual features are no longer distinguishable. A factor, by definition, is composed of a certain proportion of each of the multiple features. A given feature can contribute a particular proportion of its variability to more than one factor score (although that feature may be loaded highly on only one factor). Similarly, assignment of a feature to a group (factor) based on its highest loading considers only some of that item’s variability (that variability shared with the one factor).\(^2\)

We propose a 10 step “similarity” approach as an alternative to the popular dimensional approach; attractiveness ratings of a theoretically justifiable set of features are obtained. Scores are adjusted for respondent sample characteristics if appropriate. A correlation sensitive to both covariance and elevation, the concordance coefficient devised by Lin (1989), measures similarity among feature ratings. Then multidimensional scaling generates a similarity space; cluster analysis groups the items in this space. The extent to which a set of proposed constellations embody the construct’s facets is assessed by using the criteria recommended by Blake, Dostal, and Neuendorf

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1 The insensitivity can be seen clearly is the formula \( r = \frac{\sum z_x z_y}{N} \). The correlation is the mean of the cross products of the standard (\( z \)) scores. A standard score is the number of standard deviations a given score is above or below the mean. Hence, the means of the \( x \) and \( y \) scores are irrelevant to the calculation of the correlation. Further, covariance is calculated as: \( \text{cov} = \frac{\sum x_i y_i}{N} \), where \( x_i \) and \( y_i \) are the algebraic deviations of \( x_i \) and \( y_i \) from the means of the \( x \) and \( y \) variables, respectively. Again, the mean does not enter the calculation.

2 This limitation of factor scores and of assignment based on highest loading may be acceptable, though, when the factor analysis produces a very good fit with simple structure achieved on orthogonal factors, i.e., when the factors account for a high proportion of the variance, the communalities of the features are high, a feature is loaded highly on one and only one factor, and all features have a high loading on some factor. Due perhaps to halo effects and/or to noise in the measurement, however, past factor analytic studies of website feature preferences have not achieved these criteria.
Although the approach has limitations, it does address all four facets of a constellation and does overcome the fatal flaws inherent in applying the popular correlational approach currently used to identify underlying dimensions to the identification of constellations.  

Methodology

Questionnaire

Along with items irrelevant to this study, the questionnaire contained demographic questions (described later): age, income, education, employment, gender, marital status, and state of residence. Respondents, filtered on ever having shopped (visited or purchased) any online commercial website, were asked to rate each of 23 features (discussed later) on a 7-point scale anchored by “strongly discourages me” (1), neither encourages nor discourages me” (4), and “strongly encourages me” (7) to shop at one shopping site rather than others (see appendix). Additional questions concerned the length of time one has used the Internet, the number of hours spent per week on the Internet, and how often, if at all, one shops online.

Data Collection

The questionnaire was posted on the University’s website. Adults (18+) known by the seven member research team were individually emailed and, when possible, phoned with an invitation to visit the University site. The invitation included the site password, the description of the study, assurances of anonymity, as well as other details specified by the University’s Institutional Review Board for all research with human subjects. The online survey was conducted November 2003 – April 2004.

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3 This observation does not imply that alternate correlational – factor analytic techniques might overcome these limitations.
Respondents

Only persons residing in the USA were included. A total of 294 responded; 218 provided complete responses. While all regions of the country were represented, 66.1% resided in the Midwest (see Table 1).

(INSERT TABLE 1 HERE)

The respondents tended to be experienced with the Internet (see Table 2). Over half reported using the Internet for seven years or more; similarly, slightly over half the sample stated they are online over 10 hours per week. Almost three quarters indicated that they shop (visit or purchase) at least sometimes, but only 49.1% indicated once a month or more frequently. It appears, then, that the sample was composed principally of Internet users who shop periodically, with about a quarter (25.9%) shopping once a week or more.

(INSERT TABLE 2 HERE)

As seen in Table 3, the sample tended to be more often female, married, early middle aged, well educated, employed full time, with an above average income.

(INSERT TABLE 3 HERE)

Procedure and Results

**Step 1:** *Select a broad range of features tapping theoretically relevant feature domains.*

Eventhough an investigator may be interested in only a subset of features, identification of constellations requires a broad listing of features. A 23 feature list was based on Blake
Neuendorf’s (2004) analytic framework for assessing cross-national differences in website feature preferences. That framework has been used successfully by Blake, Neuendorf, and Valdiserri (in press) to discern how a site can be structured so as to appeal to those most likely to be initial shoppers. Their 20 feature list was devised to operationalize for shopping sites the Rogers (1995) conceptualization of the five innovation properties that facilitate adoption. These features were then merged with the dimensions of site evaluation identified by Torkzadeh and Dhillon (2002). An additional three features were added for the current study to yield the 23 displayed in Table 4.

We should note here that the terms “features” and “attributes” are used interchangeably in this report.

Step 2: Obtain individual level indicators of the relative attractiveness of site features.

Ratings on a 7-point appeal index were averaged to yield the mean scores shown in Table 4. Means ranged from a low of 4.55 (“site is new and different”) to 5.404 (“reputation and credibility of the company”), a rather narrow range.

A preliminary factor analysis of these “raw” scores, with principal component and Varimax rotation (not shown), revealed a large first factor accounting for 36.84% of the variance. The high and fairly similar means, coupled with the substantial intercorrelation of the ratings, suggested that this demonstration of the approach is conservative; such homogeneity of preferences would make it different to unearth separate constellations.

Step 3: Determine whether preference scores should be adjusted to remove the influence of sample characteristics (here, demographics), considering not only representativeness...
**but also research objectives.** The decision must be based upon, first, the mission of the study, and second, the sample’s representativeness of the population of interest. The classic article by Calder, Phillips, and Tybout (1981) distinguished three objectives of a study. A “theory falsification” objective is to test a theoretical hypothesis; for this goal a sample’s being nonrepresentative does not necessarily damage the study’s internal validity (i.e., its success in testing an hypothesis within the setting investigated), although it does harm the study’s external validity (i.e., the ability to generalize the results to the population of interest). Thus, even with unrepresentative respondents we can validly assess the accuracy of the hypothesis, albeit only in the subpopulation represented, and albeit when the theory being tested does not specify an interaction between the variables analyzed and those respondent characteristics on which the sample is unrepresentative.

“Intervention falsification,” the second objective, pertains to the evaluation of the impact/effectiveness of a program or policy. For this goal, insights can be obtained even from samples unrepresentative of the entire population, e.g., a best case respondent sample (“If the program doesn’t work with these people, it won’t work anywhere!”). Finally, the “effects application” objective pertains to research undertaken to generalize specific numerical results from the sample to the population of interest. Here, sample representativeness is essential.

Adjustment involves removing the effects of differences among respondents in given characteristics from the feature preference ratings and, so, eliminating from the obtained constellations their dependence upon those characteristics (demographics, Internet usage behaviors, etc.). We propose that for a theory falsification study (e.g., assessing hypotheses about the impact of given site features) adjustments should not be
made unless the theory specifies interactions of the study variables with those particular respondent characteristics in which the sample is unrepresentative. In such a case, the study could not test the interaction, but the analysis of other theoretical propositions would not be confounded by the unmeasured impacts on the interaction. For an intervention falsification study (e.g., assessing the relative effectiveness of alternative sites, each with a different constellation of features), we propose that an adjustment be made when the internal validity of the comparisons between program/policy conditions would be compromised by respondent characteristics. For an effects application study (e.g., a survey to find the relative appeal of various site features in a given national market), faced with a clearly unrepresentative respondent sample, we propose that something can be saved by adjusting, e.g., by suggesting the nature of the phenomenon in that context when person characteristics are controlled.

Here, adjusted scores were used for demonstration purposes.

**Step 4:** If necessary, adjust preference scores for respondent characteristics via "rescaled residual scores," so as to maintain between feature differences in elevation while eliminating effects of sample characteristics. Here, adjustment was made for the direct effects of selected demographic characteristics upon feature preferences.

Table 5 describes the six demographics used, the levels of each variable, and the category deleted in the regression analysis. The income variable (see Table 6) was a special case. For each of the eight response categories, the scale midpoints were converted to standard (z) scores. A person who selected a given income category was
assigned that respective z-score. The income variable was then treated as a continuous interval measure in the subsequent regression analysis.

The fourteen demographics were then entered as a single block into a multiple linear regression predicting a feature’s preference scores. This was done separately for each feature to obtain each person’s predicted preference score. Table 7 presents the multicollinearity checks for the predictor set. Tolerance and VIF scores were quite satisfactory, indicating no apparent multicollinearity problems with this predictor set.

Tables 8 to 30 present the results of the regression for each of the 23 features. Site feature preferences were only slightly related to respondent demographics; $R^2$s ranged from .036 to .123 and the adjusted $R^2$s ran from .000 to .063.

Adjustments were made by what can be termed “rescaled residual scores.” For each respondent on each attribute the residual score was calculated by subtracting from the “raw” attractiveness score the attractiveness score predicted from the multiple regression. These unstandardized residuals in themselves would be inappropriate for our use because they would mask the differences in elevation among features (the mean of the residuals would be equivalent for all attributes). Hence, the intercept (regression constant) calculated in each regression was added to each feature residual score. These
“rescaled residuals,” then, restored differences among features in elevation while retaining the residual’s independence of the demographic effects (at least as the linear additive effects of the demographics). Tables 31-53 describe the raw, unstandardized residuals, and the rescaled residual scores of each attribute. Mean rescaled scores ranged from -.111 to 8.103 with a grand mean of 5.128.

Step 5: For each pair of features, calculate a similarity index responsive to both covariance and to elevation differences. The Lin concordance coefficient (Lin, 1989) is a correlation analogous to the Pearson $r$ except that it corrects for differences between the two variables in elevation (i.e., the regression line runs through the origin); its strength decreases (i.e., approaches .00) as the differences between the means of the two variables increases. Figure 1 displays the formula for the Lin coefficient ($r_l$); Figure 2 provides an example of the (Pearson) $r$ versus the $r_l$; and Figure 3 charts the hypothetical example.

The Lin coefficient was calculated for each of the 253 pairs of features. Each correlation, then, described the linear relationship between the two features; the magnitude of the index is sensitive to both the covariance and the elevation difference.

The distribution of the 253 Lin coefficients appears in Table 54. For comparison, the Pearson or coefficient was also calculated, and the algebraic difference between the
two coefficients ($r-r_l$) is also shown. The Lin coefficients were all positive, ranging from .011 to .708, with a median of .288. Pearson $r$’s varied between .033 and .762 with a median of .320. The difference scores ranged from .000 to .239. In other words, the Lin coefficients were equal to or less than the Pearson $r$’s with a typical (median) difference of .042. These differences are expectable in that adjustment for elevation differences reduces the size of the correlation. Differences were fairly small reflecting the narrow range of raw score means in this fairly homogeneous data set.

**Step 6:** Conduct a multidimensional scaling (MDS) to establish dimensions of differences among features and a multidimensional space in which points (features) can be grouped. Although a variety of similarity based MDS algorithms are suitable (e.g., Young and Hamer, 1994; Borg and Groenen, 1997), the classic Multidimensional Analysis procedure in the alternating least squares approach of Young, Takane, and Lewyckyj (1978), as incorporated in the widely available SPSS/ALSCAL program, was employed. A dissimilarity score was obtained for each feature pair by subtracting each Lin coefficient from 1.00. The single matrix Classical Multidimensional Scaling (CMDS) then was performed on the 23 X 23 matrix of dissimilarity scores, yielding a Euclidian space in which features are located as points on a specified number of dimensions. A solution was obtained for dimensionality 1 through 6. The two measures of fit, Kruskal’s stress and $R^2$ (see Table 55 and Figure 3) show that the three dimensional solution had a workable stress and variance explained; it was not necessary to go to a higher dimensionality.

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(INsert Table 55 and Figure 4 here)
Figure 5 displays the location of the 23 features in three dimensional space.

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**Step 7:** *Assessing the suitability of alternative solutions, use hierarchical cluster analysis to determine both the number of constellations and the starting points in space for the next analytic stage (identify features within a constellation).* Each feature’s position on each of the three dimensions was entered into a hierarchical cluster analysis (average group linkage). The goal of the clustering was to find “seeds” or starting points for the subsequent K-means clustering, seeds that were adequately spread throughout the three dimensional space. The focus was to find a smallest number of clusters, with the shortest interpoint distances (as seen in the number of agglomeration steps) among features within a cluster, that would include most, if not all features, and not assign an overly large number of items to a single cluster.

Alternative solutions (A-F) were generated, as shown in Figures 6-11. Comparison of the solutions suggests a good deal of comparability among the cluster solutions. The best solution appeared to be the five cluster solution F.

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For comparison sake, Steps 8 and 9 were performed for each of the alternative cluster solutions (A-E) to determine if radically different results would have been obtained if an alternative hierarchical cluster solution was accepted. These analyses (Appendix 2) showed fair (although not complete) similarity of results for the alternatives. This comparability increases our confidence in the stability of the results.
**Step 8:** Treating features as intact entities, assign features to constellations by using the features’ locations on dimensions as the clustering variable and the mean of the features composing the hierarchical derived cluster as the starting point in a partition clustering of the features. A 5 (cluster) X 3 (dimension) matrix of scores was calculated, each score being the mean location of a constellation’s features on a given dimension. The means were the starting points for a K means clustering analysis (nearest centroid with floating centroids), which sorted the 23 features into the nearest five categories.

The floating centroid procedure replaces the initial location of the cluster’s centroid with the location of the new centroid as successive iterations sort the features into the nearest centroid. The procedure terminates when the centroids are no longer appreciatively shifting in space.

Figure 12 shows the locations in space and the cluster (constellation) membership of the 23 features. Figure 13 shows more clearly the features that the K means clustering assigned to each constellation.

A composite picture including feature identification numbers, cluster membership, and cluster centroids is displayed in Figure 14.
As shown in Table 56, the number of features in each constellation is:

<table>
<thead>
<tr>
<th>Constellation</th>
<th>Number of Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

Also shown in the table is the distance between the location of the feature in the three dimensional space and the centroid of the constellation’s items. The distance is expressed as the Euclidian distance and as the rank order (1 = smallest) of the distances. We may assume that the items nearer the centroid are more representative of that constellation.

Step 9: Assess the viability of the cluster solution based upon (1) within cluster homogeneity in feature elevation and in covariance, and (2) between cluster separation in elevation and in covariance. Based upon the criteria proposed by Blake, Dostal, and Neuendorf (2005) for identifying innovation attribute preference nets, the assessment was conducted in several different ways. First, considering as data points the locations of each feature on each dimension, an ANOVA compared means of the features in one cluster with the means of the features in other clusters on each dimension. The results
(Table 57) showed that the items differed between clusters on each dimension. The weakest difference was on the third dimension. Hence, all three (but particularly the first two) dimensions contributed to constellation differences.

Next, based on features’ rescaled residual scores, the cluster homogeneity, as assessed by Cronbach’s alpha, was computed (see Table 58). Recall that alpha is insensitive to elevation differences among features and so is a rough guide to cluster homogeneity. The homogeneities were all acceptable.

Also in Table 58 are the Lin coefficients between constellations. For each respondent the mean of the rescaled residual scores of the features composing a constellation was calculated; this yielded a score for each person on each constellation. The Lin coefficients in the table are the correlation between respondents’ scores on one constellation and their scores on another constellation. There were weak to moderate relationships (.038 to .626) among constellations.

In Table 59 are the relationships via the more familiar Pearson $r$. The conclusions are the same. The partial overlap (i.e., moderate separation) of constellations is quite expectable given the previously noted homogeneity of the raw preference scores for these features in the data set.

Perhaps a more meaningful assessment of compactness and separation given the insensitivity of alpha to elevation differences can be obtained by the use of median Lin
coefficients (see Table 60). That is, for each feature, the median of its Lin correlations with the other features within its own constellation reveals how similar that item is to the other items in the cluster. This “within cluster median” can be compared to the median of its Lin correlations with the features not in that constellation. The latter “without cluster median” should be lower than the former within cluster median, indicating that that feature is more similar to its own constellation items than to the other features. This relative (within to without) similarity can be seen in the ratio of the within divided by the without medians. For comparison purposes, Table 60 includes for each item its median correlation with the other 22 items in the full feature set and the (previously reported) distance of that item to the cluster centroid.

It can be seen that the ratios were above 1.00 (and some considerably above 1.00, most notably feature 3’s ratio of 5.8636) for 21 of the 23 features. One, the .9788 of easy ordering process, was close to 1.00; another, the .8391 of fast customer response time, was considerably less than 1.00. For almost all the items, then, there was more similarity within a cluster than outside a cluster. This was no small accomplishment given the homogeneity (intercorrelation and limited range in means) of the raw attractiveness ratings.

For comparison sake, the median correlations were computed using the popular Pearson $r$ (see Table 61). The Pearson $rs$ yielded comparable conclusions although with modest
differences; 21 of 23 ratios were above 1.00. But, one of the items below 1.00 with Lin coefficients was above 1.00 using Pearson rs, while the converse held for a second item.

In Appendix 3 are the median correlation analyses obtained using cluster solutions A through E.

A final view of the compactness-separation can be seen in Figures 15 to 17. Figure 15 is based upon the mean preference rating of each feature (i.e., the mean rescaled residuals). The mean and the standard deviation of the features in a constellation are displayed in the table. Not surprisingly in light of the limited differences among means of the raw attractiveness scores, differences among constellation means were modest; the biggest differences involved constellations 1 and 5.

Would different results have been obtained if we gave more emphasis to features that were more representative of that cluster? We previously suggested that the distance between a feature and the centroid of the features in its cluster is an index of the feature’s representativeness of the cluster. Thus, we can weight a feature based on its distance from the constellation centroid; the closer to the centroid, the greater the weight. Figure 16 shows the weighting formula used and Table 62 gives a hypothetical example of the computation. Figure 17 shows the ranges using the weighted data. For all intents and purposes, the weighted and the unweighted data yielded equivalent results.
Step 10: Interpret each constellation, using as a guide the degree to which a specific feature is typical of the constellation. As a comparison point, let us first consider a factor analytic approach. Since a factor is assumedly a dimension underlying a set of variables, we typically interpret a factor by use of the variable loadings, focusing more upon the higher loaded items. Interpretation is in terms of what the variables have in common (usually in the case of website feature studies, the thrust is upon functions played by the features or a meaning common to the features).

Features in a constellation, however, may not have a single meaning or function in common. But, if the features in a cluster do not share the same meaning or function, then why do they group together? Recall, in fact, that the clustering is based upon proximity in a space defined by multiple dimensions of similarity. It might be proposed, then, that a constellation is comprised of items selected on the basis of multiple (here, three) bases of similarity. We suggest three major reasons why features group together in a constellation. First, as in a dimensional perspective, features may group together in a constellation because they have a common function or meaning. Second, they may be precursors to or consequences of those common functions. Third, they have common delivery systems. That is, perhaps, individuals not only judge the appeal of a particular website by looking at the attractiveness of the features offered by that site, but they may also evaluate the attractiveness of certain features in terms of whether favorite sites have that feature. In this case, Internet users may prefer particular features and the comparable elevations because those features are offered by their favorite sites. The high intercorrelation between the features in a constellation, then, could be due not only to
common functions, precursors or consequences of those functions, but also to the co-
occurrence of those features in a variety of sites.

When interpreting constellations we should pay more attention to those features
more typical of a constellation (i.e., are closer to the cluster centroid in three dimensional
space); this is like in a factor analysis basing interpretation of a factor more heavily upon
the highest weighted items in a factor.
The first constellation seems to pertain to financial arrangements that are non-threatening and even encouraging. They are not threatening in regard to being overly
expensive (items a, c, and d); they are not threatening in respect to the medium of payment (item f). If respondents shop online because they hope to find better prices on products they desire, then the products they are looking for are the less expensive ones (item e). Finally, if one is to find non-threatening and appealing costs, then in the USA one may restrict one’s shopping to those in American English. These are the sites whose prices are in U.S. dollars, whose prices may not involve “hidden” or unexpected challenges (fluctuating exchange rates, unanticipated taxes or surcharges etc.), and, overall, may be seen to involve a more familiar form of purchasing.

The composition of this constellation is a good example of the distinction between a constellation and a “function” or a “dimension.” The latter features are similar in what they are perceived to do for a shopper or in their inherent meaning. In contrast, features in a constellation may have a similar function (here, provide low prices) or have overlapping meaning (items a, c, d). The constellation can also include features that co-occur due to: (a) the structure of the website familiar to those shoppers, or (b) their role as causes or consequences of the functions performed by the other features in the constellation.

The second constellation may involve the positive assessments of the company/site by other customers. Friends and family are important “others” (item i). If one wants to see positive feedback from other customers, then he or she will want to see sites which provide customer feedback (item j). Reputation and credibility of the company (item g) are what people mean by a company enjoying positive evaluations by others. Finally, if one wants fast customer service (item h), then one will want a site
enjoying good customer service satisfaction. Poor customer service is a sure way for a site to lose its reputation and credibility.

The third constellation contains features that facilitate the speed of a transaction. Short delivery time (item k) and download speed (item m), by definition, decrease the time to completion. The easier it is to order (item l), the quicker one can place the order. The result of quick and easy completions? A website that is enjoyable to use.

The features in the fourth constellation provide flexibility in one’s choices. Diverse product lines (item r) give a wider range of product choices. An easy return policy (item p) allows one to change one’s mind about product choice. The site’s provision of product information (item o) gives the shopper the means to sort through the products and services offered. Finally, the availability of diverse price incentives (item q) allows one to “mix and match” one’s resources to exercise these options.

The final constellation pertains to the “buzz,” the word of mouth/media attention a site receives. Hearing about it via the mass media (item t) and attention to it in one’s immediate social milieu (item v) define “buzz.” And what leads to this buzz? New and unique sites (item u), typically interactive in nature (item w) with entertaining graphics (item s), are the types of sites that receive the buzz.

SUPPLEMENTARY ANALYSES

Let us compare the present results to those that would have been obtained if the typical dimensional approach were used and features were factor analyzed by principal components with orthogonal (Varimax) rotation, followed by assignment of the 23 items to the group (dimension) on which it was most heavily loaded.4

4 Note that we are not proposing that this technique is a suitable procedure to find constellations. We employ the factor approach most popularly used in this realm as a point of comparison. Other forms of
A scree plot (see Figure 18) showed that after the first three factors little is gained by a higher dimensionality. The eigenvalue criterion (see Table 63), though, identifies five dimensions with values greater than 1.00. Since the MDS-clustering procedures yielded five groups, the five dimensional factor solution was used.

Table 64 presents the rotated loadings of items on the five factors. For comparison, the cluster membership and the Euclidian distance to cluster centroids are also presented. It appears that the five groupings (items based on highest loading) would be as follows:

<table>
<thead>
<tr>
<th>Factor</th>
<th>Number of Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
</tr>
</tbody>
</table>

The factor analytically devised groupings were more “lopsided,” with two groupings having few features, than were the more comparably sized groups yielded by the MDS-clustering approach.

Second, loadings indicated the absence of simple structure. Eight features (numbers 13, 4, 16, 9, 11, 8, 23, and 12) had substantial (above +/- .40) loadings on a factor analysis (e.g., oblique rotations, weighted covariances, etc.) may be superior to the popular approach in identifying constellations.
second factor. With about one-third of the features having secondary loadings, the factors were not “clean.”

Third, the items in a factor based group did not completely correspond to the item groupings produced by the MDS-clustering approach, as anticipated.

Table 65 - Group membership of features in factor based and MDS-cluster based groupings

<table>
<thead>
<tr>
<th>Factor Based Groupings</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>17, 13, 10</td>
<td>18</td>
<td>20</td>
<td>21, 22, 15</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>2, 4, 16</td>
<td>1, 9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>8</td>
<td>14, 3, 19, 11, 23</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>5, 7</td>
<td>12</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Factor group 3 and MDS-cluster group 5 are quite similar. MDS-cluster based groups 1 and 4 are combined in factor based group 1. Conversely, factor groups 1 and 2 are combined in MDS-cluster group 1.

(INSERT TABLES 66 and 67 HERE)

Next, let us consider the compactness and separation of the factor based groupings. Table 65 shows the Lin coefficients (computed in the manner previously described) and alpha coefficients for the factor based groupings. Table 66 shows the
Pearson \( r \) correlation among groupings. Alphas were acceptable and generally comparable numerically to those achieved by the MDS-clustering approach (Table 58). Lin coefficients for the factor based groupings (Table 66) show moderate separation among groups, with coefficients numerically slightly better (i.e., lower) than those in the MDS-clustering groupings. On the other hand, the Pearson \( r \)s showed numerically better results for the MDS-clustering than for the factors.

It appears, then, that looking at the correlations among features in a cluster, the factor analysis and the MDS-clustering procedures yielded different solutions. But, the homogeneity (alphas) and the separation (group intercorrelations) indices were fairly comparable. They both yielded clusters that were homogeneous and somewhat separate.

Let us now compare the two approaches in regard to elevation similarity. Table 68 displays, first, in Column 3 the mean rescaled residual preference score for each feature in a cluster. Column 4 contains the mean of the means shown in Column 3. Thus, Column 4’s mean of the means represents the residual preference for the cluster as a whole. Column 5 is the absolute deviation of each feature’s mean residual preference score from the cluster’s residual preference score (the mean of the means in Column 4). Column 6 is the mean of the absolute deviation scores and represents the deviation from the cluster mean of the typical feature in that cluster. The smaller the mean absolute deviation in Column 6, the more compact and the more equivalent in elevation are the features in that cluster. Column 7 presents the standard deviation of the absolute deviation scores in a cluster. Again, the lower the standard deviation, the more
comparable are the items in a cluster. Table 68 presents the same information for the factor based groupings.

Which approach has more groupings with more comparable item elevations? Visual inspection suggests that, as seen in columns 6 and 7, there appears to be less deviation of elevations around the group means in the MDS-cluster groups than the factor groups. Table 70 shows this more clearly. Column 2 is the mean of the 23 absolute deviation scores in column 5 of Tables 68-69. The mean absolute deviation score for the MDS-cluster solution (.24897) is significantly less than that for the factor based groups (.36784). Column 3 shows the variance of the 23 absolute deviation scores in each solution. The variance in the factor groupings is significantly greater ($F = 2.18, df = 22/22, p < .05$) than that found in the MDS-cluster groupings. The ratio of variance is 2.18 or 218%, in fact.

In summary, the MDS-cluster results were better than the factor based approach. First, the present procedure yielded clusters with better distribution of items within groups (i.e., fewer very large and very small groupings). Second, the two approaches had comparable homogeneity within the groupings and appeared comparable in group separation. Third, the MDS-cluster approach was superior in generating groups composed of features with similar elevation. It is our belief that in a data set with greater
differences among features in elevation the superiority of the MDS cluster procedure would be even greater.

Discussion and Implications

First, this is the first study, at least as known to the authors, that considers an issue of importance both to theoreticians and practitioners, the website feature preference constellation. As defined by high feature covariance, comparable elevations, consideration of features as intact entities, and by the lack of a constraint that a grouping’s features represent a single function or meaning, the constellation construct merits further analysis. It is a concept quite distinct from a “dimension” as analyzed previously. A dimensional perspective is useful to practitioners, e.g., constructing measurable criteria for evaluating website effectiveness (e.g., Chang, Torkzadeh, and Dhillon, 2004). As noted earlier, the constellation perspective can have different applications for practitioners (e.g., indicating how to devise a new website) and for basic researchers (e.g., explaining user preferences for websites, accounting for the adoption and diffusion of particular websites) different from those provided by a dimensional perspective.

Second, the technique proposed to study constellations was found to yield statistically viable feature groupings. It achieved acceptable levels of homogeneity, group separation and within group equivalence of feature elevation. Features were assigned to groups as intact units, and features in groups were similar along multiple (three) dimensions of similarity. The success of the procedure was clear in its comparison to the currently popular way of studying feature groupings – principal component factor analysis with orthogonal rotation. Both the factor analysis and the
similarity approach yielded groupings with good within group homogeneity and acceptable between group correlations. The proposed approach, though, generated a better (i.e., flatter) distribution of cluster sizes and was decidedly superior in producing groupings of features with similar elevation. 5

A key component of the approach is to use as input to the MDS a correlation coefficient sensitive to both covariance and elevation differences between the features. The Lin coefficient overcomes well known limitations of using correlation coefficients as indices of similarity in MDS (e.g., Hair, Anderson, Tatham, and Black, 1998). Further, the two stage clustering procedure (hierarchical followed by partition) helps to overcome the instability often encountered when clustering variables (e.g., Hair, et al., 1998). There can still be some arbitrariness, though, in the solution (cf. Everitt, 2001). Fortunately, a variety of practical well established procedures (e.g., Myers, 1996) are available to help ensure the replicability of a cluster solution. Third, the five constellations revealed here merit further investigation with larger representative samples of respondents. Do these constellations emerge throughout the USA? Are the constellations found in national markets with extensive online shopping experience the same as those that occur in environments with a limited history of online shopping, e.g., in Eastern Europe?

Finally, the present procedure may well be applicable to other issue areas, e.g., the identification of personal value domains as studied by Schwartz (1994) and others.

5 We do not propose that a constellation perspective is superior to a dimensional perspective in all applications. We do suggest that the constellation concept has particular value in addition to that offered by a dimensional approach in determining groupings of feature preferences. Similarly, we do not propose that the approach proposed here is better than factor analysis for studying the drawing power of site features. We do suggest that for the identification of constellations the current procedure is better than the form of factor analysis that is popularly used in detecting dimensions underlying consumer reactions to website features.
Analyses of value structures have relied upon correlational/covariance analyses with their inherent limitation of insensitivity to elevation. The similarity approach, then, might be useful. Do we obtain the same domains using the present procedure as did Schwartz with smallest space analysis? Or are the value domains at the heart of Schwartz’s theory dependent upon using the analytic technique employed?
References


