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Modeling Distance Structures in Consumer Research: Scale Versus Order in Validity Assessment

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Confirmatory multidimensional scaling (CMDS) is presented as a spatial technique for structural modeling based on ordinal assumptions, and as an alternative to metric techniques such as LISREL. The article links both techniques to the multitrait-multimethod matrix and presents a system for deriving measures of symmetric construct relationships, measurement error, and goodness of fit. Examples show that CMDS and LISREL often give comparable results, but that LISREL is sensitive to the magnitude of correlations whereas CMDS is sensitive only to their order. The trade-offs involved in assumptions, results, and interpretations with these methods are highlighted in the conclusion.

For the assessment of convergent and discriminant validity in consumer research, one of the dominant approaches for the past 25 years has been Campbell and Fiske's (1959) multitrait-multimethod matrix (MTMM).[1] Since its inception, many methods have been suggested for its analysis (Levin, Montag, and Comrey 1983; Schmitt and Stults 1986). However, because of the ambiguous rules for assessing the various validity criteria, researchers have often turned to techniques such as analysis of variance (Stanley 1961), factor analysis (Jackson 1975), principal component analysis (Golding and Seidman 1974) and various types of causal modeling (Werts and Linn 1970), including covariance structure analysis via LISREL (Bagozzi 1980).

Using these more powerful methods of data analysis has overshadowed a critical property of the original MTMM approach—the *ordinal* nature of the analysis. For example, the basic MTMM criteria for discriminant validity are expressed in ordinal terms; each indicator of a given trait must be *more highly correlated* with other indicators of that trait than with the indicators of another trait (particularly if the indicators share a common method). In contrast, metric methods such as factor analysis or covariance structure analysis move well beyond ordinal criteria and specify MTMM criteria in parametric terms.

This article discusses confirmatory multidimensional scaling (CMDS) as a structural modeling technique based on ordinal assumptions about the level of measurement, rather than the metric assumptions of covariance structure analysis. We add to earlier work on confirmatory multidimensional scaling (Denison 1982; Fornell and Denison 1981, 1982) by presenting (1) a new system for placing measurement and theory constraints on multidimensional scaling (MDS) solutions, (2) a new method for estimating constructs, symmetric construct relationships, and measurement error, and (3) a new approach to assess goodness of fit.

It is suggested that CMDS can be both an alternative and a complement to covariance structure analysis. Both methods deal with multiple measures, multiple constructs, and the incorporation of a priori theory- and measurement-based constraints in a solution. We also suggest that nonmetric methods are, in many ways, closer to the original MTMM formulation than is covariance structure analysis.

After a presentation of the CMDS approach to structural modeling, our approach is illustrated with two examples. These results are compared to parallel analyses using LISREL VI (Jöreskog and Sörbom 1984). The subsequent discussion compares the assumptions, parameter estimations, and interpre-

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[1]See the review by Peter (1981).

tations of the two methods, and highlights the inherent trade-offs presented by structural modeling with CMDS.

CMDS AND THE MULTITRAIT-MULTIMETHOD MATRIX

The interpretation of a CMDS solution follows the MTMM logic very closely. Measures of proximity (such as correlations) are represented as distances such that variables with the highest proximity appear closest together in the solution. The clusters of variables closest together are treated as multiple measures of the same construct. Adjacent clusters of variables are interpreted as related constructs. Thus, the basic MTMM logic necessary to distinguish convergent and discriminant validity can easily be translated into a multidimensional scaling model.

Imposing theoretical constraints on an MDS solution via CMDS makes the MTMM logic more explicit by providing an additional set of theoretically derived distance constraints, defined in MTMM terms, that must be satisfied by the solution. Thus, the final confirmatory solution must represent not only the original correlations or proximity measures, but also the constraints implied by convergent, discriminant, and nomological validity.

One fundamental difference between factor analysis and multidimensional scaling must be acknowledged at the outset: in multidimensional scaling, constructs are primarily represented by clusters of variables, rather than by underlying dimensions as in factor analysis. Although the underlying dimensions themselves may have meaning in MDS, they also serve to translate the proximity data into distances. Once dimensionality has been established, assessment of validity is based upon an analysis of the distances between points, rather than the dimensions in which distances are displayed. Clusters of variables, as well as dimensions, represent constructs.

There are several computer algorithms now available for CMDS. The analyses presented here use CMDA (Borg and Lingoes 1980), although similar results can be obtained with other techniques such as MDSCAL-5 and KYST (Kruskal and Wish 1978). Other techniques permit linear constraints (Bentler and Weeks 1978; Carroll, Pruzansky, and Kruskal 1980), non-linear constraints (Lee and Bentler 1980) and equality constraints (Bloxom 1978) to be imposed on MDS solutions.

IMPOSING VALIDITY CONSTRAINTS

This section defines a system for placing theory- and measurement-based constraints, derived using the MTMM framework, on a CMDS solution. Convergent validity requires that multiple measures of the same construct converge on that construct, and discriminant validity implies that constructs can be distinguished from one another through their measures.

Convergent and Discriminant Validity

To define a set of constraints that assess convergent and discriminant validity, we propose a system that provides sets of constraints that *vary* in the stringency of the convergent-discriminant validity requirements (cf. Borg 1977; Guttman 1959).

To illustrate, suppose that two constructs under consideration are represented by two geometric regions R_a and R_b, with n_a and n_b points, respectively. In this case, a definitional mapping system for clustering points according to convergent-discriminant requirements can be expressed as follows: each point of R_a must be closer to (n_a, $n_a - 1, \ldots, 1$) points of R_a than it is to (n_b, $n_b - 1, \ldots, 1$) points of R_b.

Constraint condition $n_a n_b$, for example, requires that each point within R_a (or each indicator of construct 1) be closer to all other points in that region (all other indicators of the same construct) than to any point in region b. Constraint condition n_a, $n_b - 1$ implies that each point within R_a be closer to all other points within the region than to all but one point in region b. The $n_a n_b$ set of constraints represents the most stringent form of convergent-discriminant validity, while the other possible constraint conditions represent progressively weaker operationalizations of convergent-discriminant validity.[2]

Nomological Validity

A similar approach can also be used to define a system for imposing a set of theory-based constraints. This form of validity requires that the solution reflect links between constructs as suggested by a substantive theory. As an illustration, consider a three-construct model where the theory specifies that construct B mediates the relationship between construct A and construct C. In this case, a definitional mapping system that operationalizes a set of nomological validity constraints would specify that each point of R_a must be closer to (n_b, $n_b - 1, \ldots, 1$) points of R_b than to (n_c, $n_c - 1, \ldots, 1$) points of R_c, where R_b is a region adjacent to R_a; R_c is a region distant from R_a; and n_a, n_b, and n_c are the number of points in each of the respective regions.

So, for example, constraint condition n_b^*, n_c^* requires that each point of region A be closer to all points within region b than to any point within region c. (An asterisk is added to distinguish nomological from convergent-discriminant constraints.) This represents testing criteria that operationalize the theoret-

[2]This approach represents an extension of Lingoes' (1981, p. 290) system for defining regionality and contiguity.

ical assertion that construct A should be more closely related to construct B than to construct C. As in the convergent-discriminant example presented previously, the other possible conditions specified by the mapping schema (n_b^*, $n_c^* - 1$ and $n_b^* - 1$, n_c^*, and so on) provide operationalizations of weaker forms of nomological validity.

Since structural modeling requires that both measurement- and theory-based constraints be placed on a solution simultaneously, the analyst's task is to pick a combination of more or less stringent operationalizations of these two types of validity. The combination $n_a n_b n_b^* n_c^*$ represents the most stringent set of constraints. Less stringent interpretations of measurement- and theory-based validity may also be defined. One of the features of the system is flexibility. Any combination of constraints can be imposed, and the system can easily be extended to more complex models with a greater number of latent constructs and variables.

EVALUATIVE STATISTICS: ASSESSING FIT

Before estimating the relationships between specific variables, it is necessary to assess the congruence between the model and the data. Some measure of fit is needed for any procedure that attempts to compare the congruence of a theoretical model and empirical data. Much like the literature on evaluating the fit of covariance structure models, the choice of fit index in distance models is not without controversy.

This article follows the approach taken by Lingoes and Borg (1983a, 1985), who suggest using an "efficacy coefficient" as an overall measure of fit. This coefficient is based on the partial correlation between the order of the distances in the theoretically constrained and unconstrained configurations, partialing out the order of the original proximity data. This partial correlation, $\rho(X, Z \cdot Y)$—where X represents the order of the distances in an unconstrained MDS configuration; Z, the order of the distances in a corresponding MDS configuration with theoretical constraints; and Y, the order of the original proximity data—thus represents the association between the constrained and unconstrained configurations that cannot be attributed to the original proximity data. When the ratio of the partial correlation ρ to the coefficient of alientation (K),

$$\frac{\rho(X, Z \cdot Y)}{\sqrt{1 - \rho(XZ)^2}}, \tag{1}$$

exceeds 3, there is evidence for an acceptable fit, but if the ratio is less than 1, there is a lack of fit. These cutoffs are obviously somewhat arbitrary, although not totally void of a statistical argument. In this sense, they are similar to the fit indices for covariance structure analysis developed by Bentler and Bonett (1980), Sörbom and Jöreskog (1982), and Fornell and Larcker (1981). The statistical argument is analogous to the rule of thumb that measures of association two to three times greater than their standard error are interpreted as "significant." For intermediate cases with a ratio between 1 and 3, Lingoes and Borg (1983b) describe an alternative decision rule that takes into account the sample size, the number of variables, the number of dimensions, and the percentage of distances that has been constrained.

MODEL PARAMETERS

If a model demonstrates an acceptable fit according to the criteria discussed in the previous section, the estimation of constructs, the indicator-construct relationships, and the construct-construct relationships become of interest. The scaling procedure presented here allows numerical values to be assigned to each of these parameters.

Construct Measurement

For any set of multiple measures of a single construct in covariance structure analysis, it is assumed that at least some of the variation is due to a "true" value. If measurement errors are random, classical measurement theory implies that the true value of the unobserved variable is approximated by the expected value of the observed indicators. Thus, the true value for an MDS cluster of indicators representing an unobserved construct may be calculated by using the mean value on each dimension for the points in the region. That is,

$$C_{ik} = \frac{1}{n_i} \sum_{j=1}^{n} x_{ijk}, \tag{2}$$

where C_{ik} is the projection of the ith centroid on the kth dimension, x_{ijk} is the projection of the jth indicator of the ith construct in the kth dimension, and n_i is the number of indicators in the ith construct.

Indicator-Construct Measurement

Once the centroid is determined, the Euclidian distance between an indicator and its associated construct serves as a measure of association that provides a basis for addressing measurement error.[3] Similar to true score theory, measurement error is thus considered to be equal to the difference between observed and true values. Summing over dimensions, we represent errors in measurement as:

[3]It should be recognized that this estimate of measurement error is relative and dependent on other variables in the model, rather than an absolute measure of reliability that could be compared across analyses, such as an alpha coefficient.

TABLE 1

CORRELATION MATRIX FOR OBSERVED INDICATORS

Indicator	x_1	x_2	x_3	y_1	y_2	y_3	z_1	z_2	z_3
x_1	1.00								
x_2	.523	1.00							
x_3	.611	.522	1.00						
y_1	.571	.781	.481	1.00					
y_2	.696	.707	.659	.826	1.00				
y_3	.692	.585	.659	.533	.613	1.00			
z_1	.656	.801	.508	.875	.819	.599	1.00		
z_2	.537	.668	.417	.815	.770	.493	.825	1.00	
z_3	.523	.775	.537	.755	.740	.578	.808	.719	1.00

NOTE: N = 100; simulated data is from Jagpal and Hui (1980, p. 359), and is reprinted with permission from the American Marketing Association.

$$e_{ij} = [\sum_{k=1}^{m} (C_{ik} - x_{ijk})^2]^{1/2}, \qquad (3)$$

where e_{ij} is the distance between the ith construct and its jth indicator.

Construct-Construct Measurement

Euclidian distances between the centroids that represent the constructs in a structural model are the basis for computing construct-construct links. That is,

$$d_{pq} = [\sum_{k=1}^{m} (C_{pk} - C_{qk})^2]^{1/2}, \qquad (4)$$

where d_{pq} is the distance between the pth and qth constructs, m is the number of dimensions, C_{pk} is the projection of the pth centroid in the kth dimension, and C_{qk} is the projection of the qth centroid in the kth dimension.

AN ANALYSIS STRATEGY

The previous sections outlined methods for imposing validity constraints, assessing fit, and obtaining model parameters. This section describes an approach that combines these elements into an analysis strategy and an integrated system for modeling distance structures. A brief overview of the general strategy precedes an illustration of the procedure with two empirical examples.

Modeling distance structures via CMDS begins with a matrix of proximity measures representing the relationships between the observed variables to be modeled. Proximity measures may be correlations, similarity judgments, or other measures of proximity, as long as at least ordinal-level assumptions are met. This matrix is then scaled to determine the number of dimensions needed to adequately represent the proximity measures as distances in multidimensional space.

Once dimensionality is established, confirmatory testing can begin by imposing the most rigorous set of measurement and theory constraints, such as the strong cluster/strong theory condition ($n_a n_b n_b^* n_c^*$) discussed earlier. This allows for the strongest possible test of a theory and clearly reveals those indicators not in keeping with the constraints implied by the combined set of convergent-discriminant and nomological validity constraints. If the strongest set of constraints is satisfied, the model and data are assumed congruent, and the model parameters can be computed. The analysis, in this instance, is straightforward.

The more typical result is a less than perfect fit. Convergent-discriminant or nomological constraints may be violated by particular indicators, and clusters may overlap to varying degrees. Again, this is similar to the analysis of fit in covariance structure analysis. Rarely, if ever, does the fitting function reach its minimum of zero. Even when a likelihood ratio statistic is used, a decision still must be made regarding the acceptability of the resulting fit.

When an acceptable fit is not obtained, one may either reject the model or pose an alternative set of constraints that is less rigorous, yet still theoretically defensible. If the less rigorous set of constraints can be satisfied, one may then conclude that the model fits well enough to justify computing parameters.

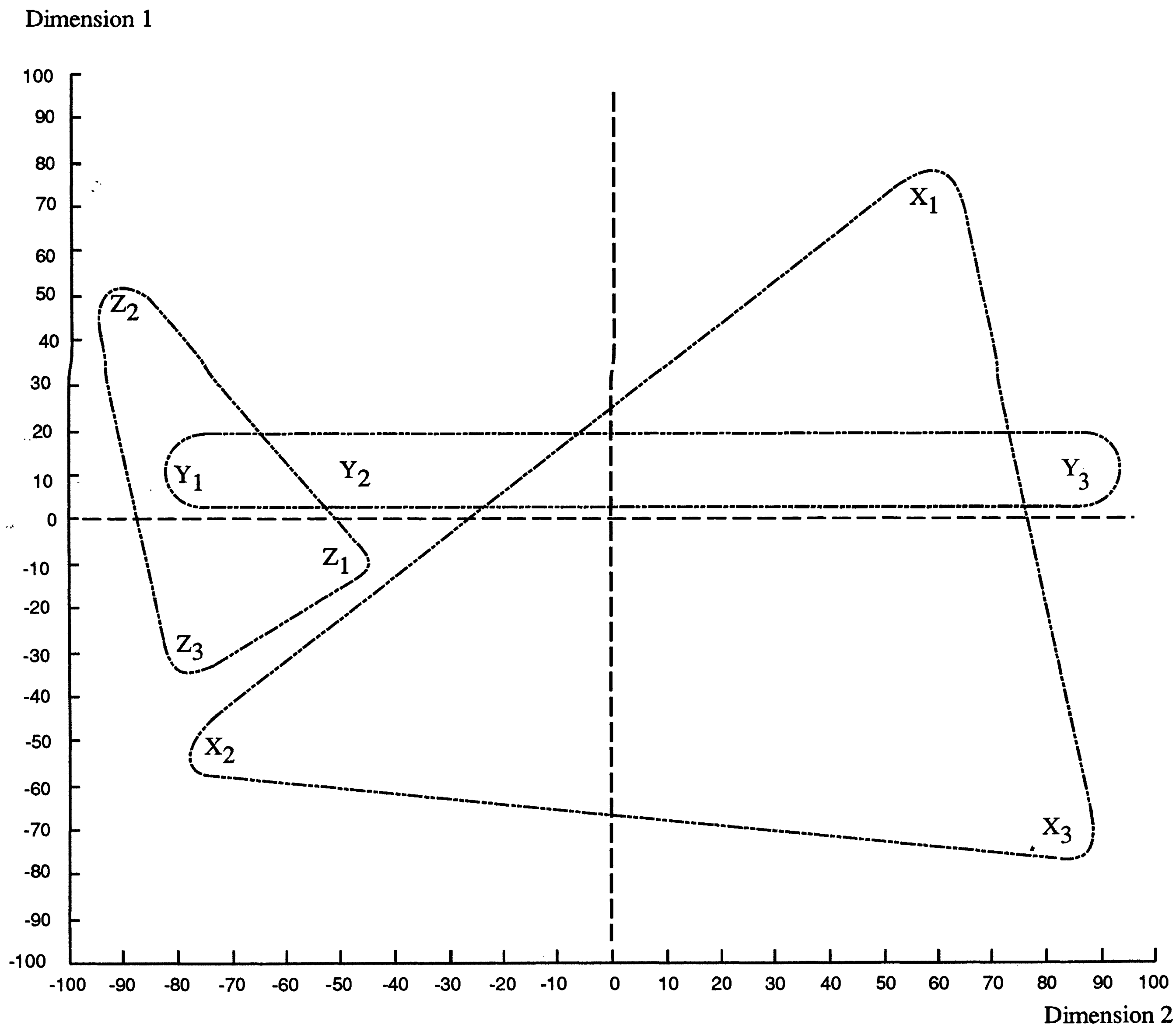
The goal is to obtain a parsimonious representation of the proximities, the distances, and the theoretical constraints. The data must first be represented in the smallest geometric space, so that little or no new information can be added by moving to a higher dimensionality. Then, theoretical constraints are added to make the alternative interpretations of the distances between points and clusters explicit, and to provide a test of the degree of fit between the data and the theory. Until a solution can satisfy both data and theory constraints, a truly parsimonious expression of the model has not been obtained.

ILLUSTRATIONS

Two step-by-step applications of the suggested analysis strategy are presented, and the results are

FIGURE A

MINISSA SOLUTION IN TWO DIMENSIONS



NOTE: X_i = awareness measures; Y_i = preference measures; Z_i = intention measures.

compared to a covariance structure analysis using LISREL to highlight some of the relative advantages and disadvantages of modeling distance and covariance structures.

Example of a Poor Fit

The data used for this illustration are drawn from a traditional hierarchy of effects model of awareness, preference, and intention. The correlation matrix (adapted from Jagpal and Hui 1980, p. 359) is presented in Table 1.[4] A path analysis of these data was interpreted as providing support for the hierarchy of effects model by the original authors.

[4]The reason we are using a correlation matrix in our illustration is to demonstrate the differences and similarities between distance structures and covariance structures modeling. Correlational data generally represent metric input, necessary for covariance structure analysis but not for distance structure analysis. In some cases, it is possible to use covariance structure analysis on ordinal data (Muthen 1983), but then the assumption is that the variables are generated by underlying continuous variables.

TABLE 2

CONSTRAINT MATRIX FOR STRONG CLUSTER/STRONG THEORY ($n_a n_b n_b^* n_c^*$) CMDA TESTS

Variable								
x_1								
x_2	3							
x_3	3	3						
y_1	2	2	2					
y_2	2	2	2	3				
y_3	2	2	2	3	3			
z_1	1	1	1	2	2	2		
z_2	1	1	1	2	2	2	3	
z_3	1	1	1	2	2	2	3	3

NOTE: The values in the matrix represent ordered distance constraints: 3s represent the strongest associations and smallest distances, while 1s represent the greatest distances. There are no constraints on the order of distances within a given category (e.g., all 2s need not be equal, but can assume any order as long as each 2 distance is smaller than each 1, yet larger than each 3).

Using this model and data as a point of departure for a CMDS analysis, we begin by asking a fundamental question: Are the latent variables (awareness, preference, and intention) as measured in this study, in fact "different"? The first suggestion of limited convergent-discriminant validity comes from visual inspection of the initial unconstrained MDS configuration presented in Figure A (Guttman 1968). This two-dimensional configuration fits the data reasonably well (Guttman/Lingoes coefficient of alienation (K) = 0.13, stress = 0.07). However, the latent variables seem to exhibit very little convergent-discriminant validity. The clusters are not distinct, and the awareness and preference constructs each have elements that are far more closely related to the intention construct than to their own shared elements.

Imposing a set of strong validity constraints on this solution provides a test of both convergent-discriminant and nomological validity. These constraints are presented in Table 2.

The Lingoes-Borg efficacy coefficient for this test shows that the congruence hypothesis is not supported. The criterion $\rho(X, Z \cdot Y) = 0.130$ with the coefficient of alienation $K = 0.881$ does not even approach the minimum level of fit, $\rho(X, Z \cdot Y) > K$. Thus, the lack of congruence between this form of the model and the proximity data is quite clear.[5]

Several weaker forms of the model were also tested. Convergent-discriminant and nomological constraints were relaxed both jointly and alternatively for those data points in the model that did not fit the required order. Even with these weaker interpretations of the constraints implied by the model and operationalization of the theory, the fit remained poor. When constraints on variables X_2, X_3, Y_1, and Y_3 were removed, the partial correlation coefficient $\rho(X, Z \cdot Y) = (0.23)$ was still much smaller than the coefficient of alienation ($K = 0.80$). This makes it apparent that even the most minimal test of the congruence hypothesis cannot be met.

As a point of comparison, the data matrix in Table 1 was analyzed using LISREL VI to examine the differences between CMDS and covariance structure analyses of these data. These analyses provided similar results to the CMDS analyses. The fit was poor, and there were substantial problems with discriminant validity. As some of the constraints were relaxed, the fit improved somewhat, but not appreciably. This also parallels the CMDS results as the constraints were gradually relaxed.

Example of a Good Fit

A second example illustrates the application of CMDS and the estimation of model parameters in a case where the data fit the model quite well. This example is drawn from research on the S-O-R model of consumer involvement (Arora 1982; Slama and Tashchian 1987). This model distinguishes three types of consumer involvement: situational involvement (S), which stems from certain purchase situations; enduring involvement (O), which stems from values important to the individual consumer; and response involvement (R), which is derived from the mental and behavioral responses during purchase decisions.

Slama and Tashchian (1987) present a series of analyses of the MTMM matrix (see Table 3). This 9 $\times$ 9 matrix compares three measures (Likert scale, semantic differential, and Stapel scale) of each of the three types of consumer involvement. Slama and Tashchian demonstrate, through covariance structure analyses of the data, that the S-O-R form of the model fits the data reasonably well, but that enduring involvement is a much weaker predictor of response involvement than is situational involvement. Furthermore, the impact that enduring involvement has on response involvement can be accounted for through the indirect path from enduring involvement to situational involvement to response involvement. Eliminating the direct effect from enduring involvement to response involvement does not diminish the fit. Their results for their revised model are presented in Table 4.

Figure B presents the CMDS analyses of the Slama-Tashchian matrix. The unconstrained data scaled

[5]A second fitting criterion, the maximum likelihood ratio used by MacKay and Zinnes (1984), also shows a much poorer fit when the theoretical constraints are added to the solution. Without theoretical constraints, the likelihood of the solution in Figure A is 58.02. When theoretical constraints are added, this likelihood drops to 13.47. For probabilistic approaches to multidimensional scaling, see DeSarbo, DeSoete, and Eliashburg 1987; DeSarbo, Oliver, and DeSoete 1986; DeSarbo and Rao 1986; MacKay and Zinnes 1986; and Zinnes and Mac Kay 1983.

TABLE 3

SLAMA-TASHCHIAN MULTITRAIT-MULTIMETHOD MATRIX

Variable	x_1	x_2	x_3	y_1	y_2	y_3	z_1	z_2	z_3
x_1	1.000								
x_2	0.624	1.000							
x_3	0.610	0.628	1.000						
y_1	0.524	0.514	0.524	1.000					
y_2	0.386	0.489	0.484	0.697	1.000				
y_3	0.384	0.488	0.484	0.735	0.725	1.000			
z_1	0.444	0.409	0.349	0.313	0.275	0.310	1.000		
z_2	0.294	0.317	0.303	0.269	0.170	0.251	0.673	1.000	
z_3	0.301	0.337	0.300	0.262	0.246	0.221	0.772	0.664	1.000

NOTE: x_1, y_1, z_1 = Likert scale items; x_2, y_2, z_2 = semantic differential items; x_3, y_3, z_3 = Stapel scale items. This material is reprinted with permission from the Academy of Marketing Science.

TABLE 4

MAXIMUM LIKELIHOOD PARAMETER ESTIMATES AND T-VALUES FOR THE REVISED S-O-R MODEL[a]

	Shampoo	
Model parameter	Parameter value	T-value
λ_1	1.000[b]	–
λ_2	1.056	7.628
λ_3	1.026	7.450
λ_4	1.000[b]	–
λ_5	0.958	9.625
λ_6	0.995	10.079
λ_7	1.000[b]	–
λ_8	0.837	8.697
λ_9	0.947	10.101
β_1	0.803	6.008
β_2	0.615	4.514
β_3	0.000[b]	–
ζ_1	0.588	4.181
ζ_2	0.362	4.137
ζ_3	0.594	4.934
ϵ_1	0.412	5.260
ϵ_2	0.258	4.432
ϵ_3	0.183	3.023
ϵ_4	0.345	4.682
ϵ_5	0.319	5.104
ϵ_6	0.429	5.812
ϵ_7	0.381	5.012
ϵ_8	0.265	4.525
ϵ_9	0.268	4.278

[a] $\chi^2 = 19.12$, $df = 25$, $p = 0.791$ (from Slama and Taschian 1987).
[b] Constrained parameters.

nicely in two dimensions, ($K = 0.07$). The strongest set of validity constraints, identical to those presented in Table 2, produced a partial correlation ratio of 0.966 to 0.065. This ratio of 14.9 is well in excess of the 3.0 criterion recommended by Lingoes and Borg (1983b, 1985).

The model parameters shown in Figure C lead to the same interpretation as the LISREL analyses originally presented by Slama and Tashchian. The indicator/construct links are high in all cases, and situational involvement is much more closely related to response involvement than is enduring involvement. The placement of the situational involvement cluster on a direct axis (the underlying dimension of cause-effect) from the enduring cluster to the response cluster also implies, like the LISREL analysis, that there is little about the association between the enduring and response clusters that cannot be attributed to the situational cluster.

CMDS does not, of course, make inferential statements of theory-data fit, but the fit does remain constant as sample size and magnitude of the input correlations vary. As several authors (Babakus, Ferguson, and Jöreskog 1987; Fornell and Larcker 1981) have noted, this is not the case with a covariance structure analysis.

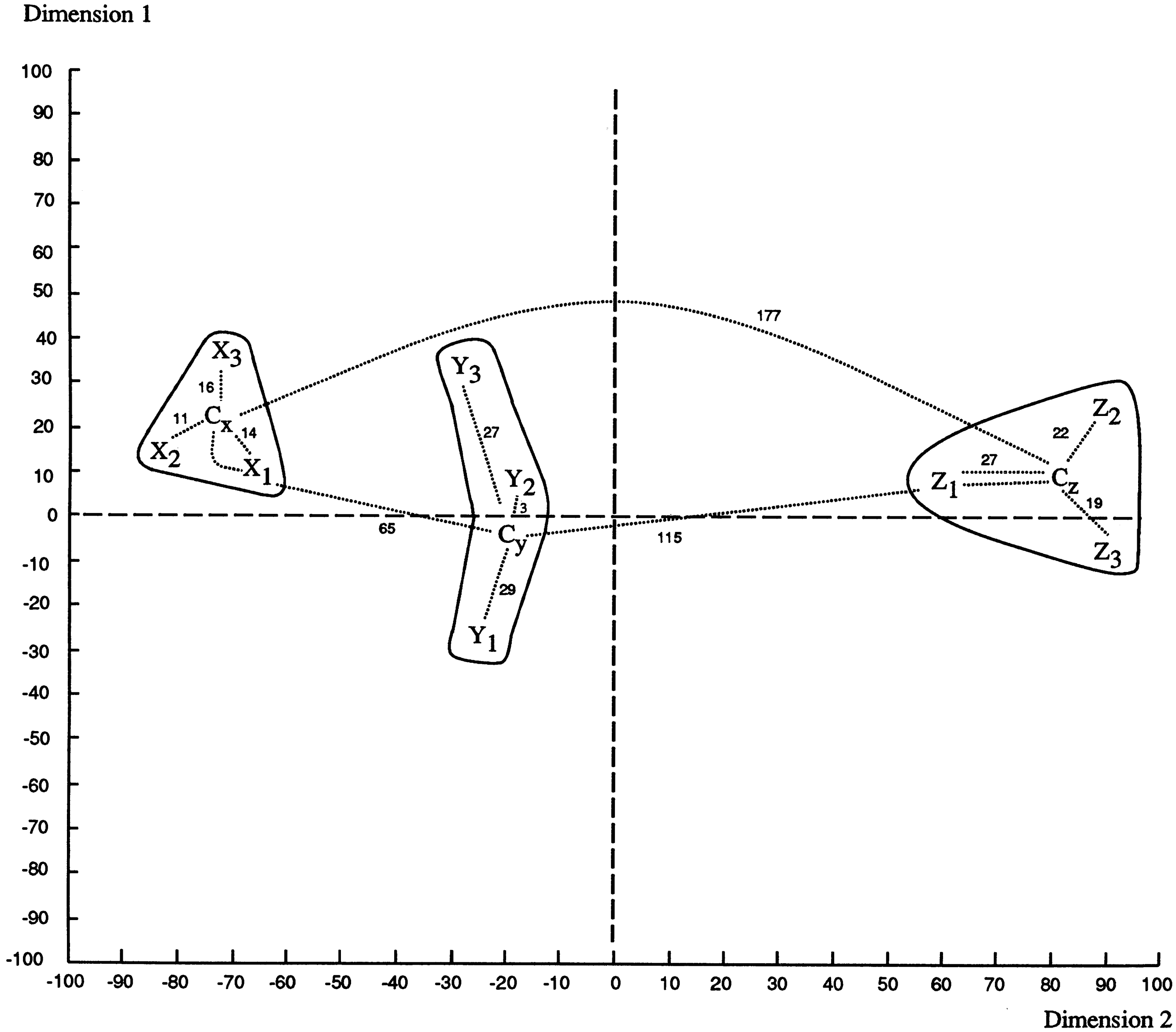
To illustrate this, a separate series of LISREL analyses was conducted, systematically varying the magnitude of the input correlations (r) from 0.8 to 1.2 times those in the original input matrix. The effects of this on the probability of fit, the Bentler-Bonett index, and the χ^2/df ratio are presented in Figure C.

Figure C shows that the two most commonly used measures of fit, the chi square ratio and its associated probability, both change from a nearly perfect fit when correlations are reduced in the $0.8r$ solution to a highly unacceptable fit in the $1.1r$ and $1.2r$ solutions. A third measure of fit, the Bentler-Bonett index, which was specifically developed to address the problems associated with the first two measures, also shows slightly worse (but still highly acceptable) fit as the strength of correlations is increased. Model parameters in the LISREL model also increase as the magnitude of the underlying correlations increases. The fit and parameters of a CMDS model, of course, would remain constant across each of these cases.

This illustration suggests that covariance structure analysis can be highly sensitive to the magnitude of the correlations between observed variables and relatively insensitive to order relations. This is because

FIGURE B

CMDA ANALYSIS OF CONSUMER INVOLVEMENT MODEL



NOTE: X_i = enduring involvement measures; Y_i = situational involvement measures; Z_i = response involvement measures.

weak correlations result in weak cross-products and small resulting fractions in the loss function. CMDS, in contrast, is invariant with respect to changes in magnitude as long as order relations are maintained. The correlations may be large or small (or even positive or negative) as long as the order does not vary.

SUMMARY AND DISCUSSION

This article has presented a new approach to structural modeling and validity testing—distance structure analysis using nonmetric confirmatory multidimensional scaling. There are many similarities with covariance structure analysis: both methods are fundamentally concerned with evaluating the degree of congruence between a hypothesized model and empirical data where the model specifies a system of related constructs, each with one or more measures. The relationship of the techniques to the MTMM logic is virtually identical.

The MTMM approach as formulated by Campbell and Fiske (1959) is specified in ordinal terms, but a

FIGURE C

THE EFFECTS OF MAGNITUDE OF CORRELATION ON COVARIANCE STRUCTURE ANALYSIS

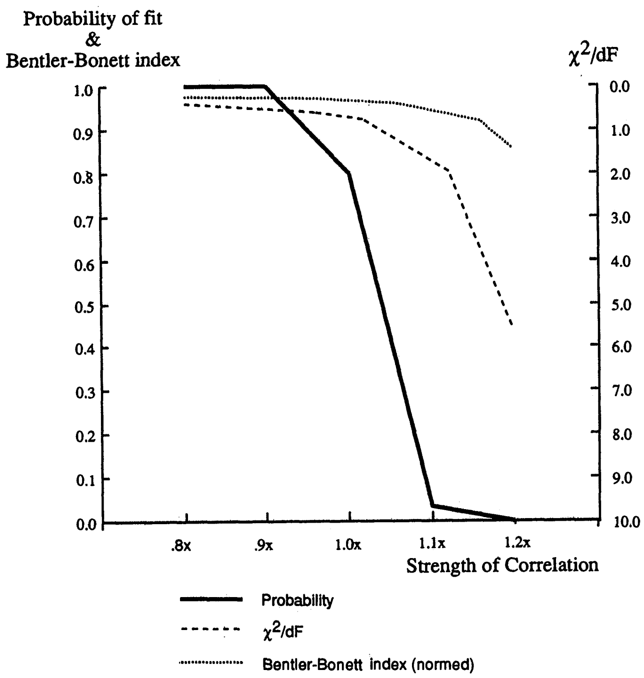


TABLE 5

SUMMARY COMPARISON OF DISTANCE STRUCTURE AND COVARIANCE STRUCTURE ANALYSIS

Dimension	Distance structure analysis	Covariance structure analysis
Level of measurement	Ordinal non-parametric	Interval parametric
Criterion of validity	Order	Metric
Nature of constructs	Regions in geometric space (indirectly observable)	Factors or dimensions (unobservable)
Measurement error	Distance between geometric centroid and indicator position in space	Unique variance for each indicator
Inferential properties	Rudimentary	Strong (if assumptions are satisfied)
Functional form of relationships	No specific functional form	Linear functional form
Impact of sample size, role of null hypothesis	Conventional: lower power leads to higher probability of rejecting a true model	Non-conventional: lower power leads to higher probability of failing to reject a false model
Impact of magnitude of observed correlations	No impact	Lower correlations make models easier to fit
Assumptions on data	Weak	Strong

metric scale is assumed whenever covariance structure analysis is applied. As this article illustrates, it can make a great difference which assumption is made. Which is more important—scale or order? By default, the CMDS user favors ordinal measurement (which seems appropriate in the MTMM context), whereas the covariance structure analyst favors a metric scale. However, in many circumstances both properties would seem important for validity assessment and can be used in a complementary fashion.

Table 5 summarizes the key differences between CMDS and covariance structure analysis and can serve as a guide for joint application of these techniques: The differences are presented in terms of the implications of the scale versus order assumption, the differences in measurement, validity criteria, inferential powers, functional forms, and the impact of sample size and magnitude of input correlations.

Basically, this table shows that CMDS provides a descriptive modeling technique based on a weaker set of assumptions and a more conventional application of the null hypothesis. The trade-off is that a statistical theory for inferential power has yet to be developed for individual parameters as well as model fit.

In conclusion, there are several situations in which distance structure analysis may be a useful complement or even an alternative to covariance structure analysis. First, it seems that when correlations are low to begin with (as in the case of large measurement errors), covariance structure analysis should be used with caution. Not only is the fitting criterion insensitive under these circumstances, but the additional problems of the possibility of low power of the chi-square test and the reversal of the role of null and alternative hypotheses suggest a high risk of finding support for a faulty model. Second, when discriminant validity between latent variables is an issue, distance structure analysis often helps to clarify the distinction between lack of discriminant validity on the one hand and a strong predictive relationship on the other. Third, if the analyst is unwilling to assume multinormality, independence of observations, and linear functional form, or if the sample size is small, the distance structure analysis approach developed in this article would appear to be a viable alternative to covariance structure analysis.

Distance structure analysis may also be a useful technique for specific analytic tasks. For example, one common approach to the problem of correlated measurement error is to remove one common factor on the grounds that it represents a response tendency, person mean, or method effect. Since CMDS is responsive only to ordinal properties of the data, such a procedure is unnecessary; removing true "halo" would not change the order of the data, only the magnitude. Another interesting application of CMDA is in the case of a theory that implies a non-linear structure such as a circumplex or radex (e.g., Quinn, Denison, and Hooijberg 1989). Such theories are well suited to analysis via CMDS but difficult to test using covariance structure analysis.

The limitations of distance structure analysis are also quite clear. The statistical model underlying the method is basically descriptive and makes limited claim to inferential power. Interpreting distance models with both positive and negative measures of association represented as distances also requires special attention. Nevertheless, the approach developed here should be of value to most traditional MDS-type of applications in marketing (e.g., positioning analysis, perceptual mapping) or whenever the analyst wants to incorporate prior notions (theory) into the analysis within a multitrait-multimethod framework.

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