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Compositional methods for generating product spaces from attribute data differ in their capacity to recover objective dimensions that discriminate between brands These differences, which have important implications for the usefulness of various scaling techniques to managers, are illustrated by an example from consumer esthetics involving the evaluation of recordings by jazz saxophonists The emphasis is on contrasts among the compositional approaches that result in different kinds of dimensions being prominent in reduced space solutions

Using Attribute Ratings for Product Positioning: Some Distinctions Among Compositional Approaches

In an age when product-positioning decisions have become central to the firm's competitive strategy, the choice of an appropriate method for defining the desired image of a brand with respect to its competition has become increasingly problematic Well-established *decompositional* methods based on the multidimensional scaling of pairwise brand similarities data (e g , see Green and Rao 1972) may generate product spaces whose dimensions are difficult to interpret In some circumstances, the derivation of product spaces from attitude data promises to help overcome this problem, but a brief review of the literature on such *compositional* approaches reveals conflicting opinions and contradictory advice as to the preferred approach For example, Howard and Sheth (1969) propose a type of principal components analysis, whereas Urban (1975) and Hauser and Koppelman (1977) advocate the general factor model, and Pessemier (1977) recommends discriminant analysis More general treatments of the product-positioning problem, such as those by Shocker and Srinivasan (1974) or Aaker and Myers (1975), discuss various *alternative* representations, but offer little guidance as to which is better suited to a given managerial situation Working with attribute (as well as similarities) data, Green and Rao (1972) compare a variety of product spaces that can be derived Their simulation studies indicate, however, that most of the available techniques may be interchangeable in terms of recovering a known configuration Accordingly, even if attention is confined to compositional approaches, it appears that the market analyst wishing to produce a useful set of perceptual dimensions based on brand attribute ratings can select from a variety of available techniques, reasonably choosing whichever method best fits the nature of the data, the available software, or his momentary whim

Despite the prevailing confusion, there are important, if little understood, distinctions among various compositional approaches to building product spaces from attribute data In particular, methods differ in their treatments of affect It is well known, for example, that a principal components solution derived from semantic differential judgments generally contains an evaluative dimension (Osgood, Suci, and Tannenbaum 1957) The evaluative component orders brands by the respondents' average degree of liking and thus may serve as an important indicant of brand health But because this factor is, by definition, uncorrelated with the other perceptual factors and is therefore not predictable as a linear combination of

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these other factors, it remains essentially sterile in terms of being explained by them Consequently, a principal components solution including such an affective dimension may warn the analyst that a brand is unpopular *without* isolating dimensions that explain *why* it is disliked

Whether a product space should include the affective dimension depends on its intended use In some contexts, it is advantageous to produce a relatively affect-free set of perceptual dimensions as a basis for product-positioning decisions Confining attention to compositional methods, the authors examine several alternative approaches to purging the affective component from perceptual dimensions based on brand attribute judgments The first is merely to ignore or delete the orthogonal evaluative dimension The second involves creating a more precise index of affect and partialing out its effect prior to analysis The third submits the principal components solution to multiple discriminant analysis to derive dimensions that, for reasons shown hereafter, are often affect-free

The purpose of this article is to show that there are important differences among the compositional approaches that have hitherto been considered largely equivalent These differences arise from the dimensions that are revealed rather than the positioning of a brand on a particular dimension and thus can be understood better by comparing the loadings on the dimensions rather than the resultant spaces

The basic finding is that the use of partials and/or discriminant analysis (as opposed to straightforward principal components analysis) produces dimensions that are more objective in reflecting homogeneous perceptions across consumers In addition, these solutions are more likely to be "actionable" as defined by Shocker and Srinivasan (1974)—that is, they are more likely to "indicate specific actions the manufacturer must take to build such a product" (p 292) Conversely, straight principal components analysis often provides solutions that are more sensitive to the meaning of attributes Such analyses might be more appropriate in, say, an advertising study where managerial attention is focused on semantic labeling instead of objective brand differences Thus rather than advocating the use of one compositional approach over another, the authors attempt to differentiate among methods and to define where their uses are appropriate

These points are illustrated by a study based on attribute ratings of recordings by jazz saxophonists using data previously described by Holbrook and Huber (1979) Though such an "esthetic" data set may be somewhat novel to marketing researchers more familiar with branded products, artistic offerings are certainly marketable commodities of great managerial interest to concert promoters, radio stations, and record manufacturers The data have an additional advantage in that the recordings were selected to represent certain objectively defined characteristics The degree to which the competing solutions match these predefined dimensions provides a measure of relative objective content

PERCEPTIONS OF JAZZ RECORDINGS AN ILLUSTRATIVE STUDY OF CONSUMER ESTHETICS

The stimuli for the study consisted of 14 recordings by jazz saxophonists of conventional 12-bar blues Each selection contained three choruses (36 measures of music) from the saxophonist's solo These recordings were similar in musical form and accompaniment, but differed with respect to whether the saxophone was alto or tenor and whether the artist was influenced primarily by Lester Young ("West Coast School") or Charlie Parker ("East Coast School") These two factors were crossed so that there were altos and tenors in each of the schools The selections also differed in two uncontrolled factors key and tempo Thus, as summarized in Table 1 and described more fully elsewhere (Holbrook and Huber 1979), the stimuli spanned a number of explicit dimensions

The 14 selections, each recorded on a separate tape cassette, were played by respondents in randomized orders and evaluated on 93 semantic differential scales The bipolar adjectives defining these 6-position scales were derived from informal interviews with jazz listeners, popular jazz periodicals, and introspection on the part of the authors and were intended to encompass most ways such selections might be discriminated

Sixteen subjects were recruited by advertisements on university bulletin boards Each was paid $5 for participating in the task which took from 1 1/2 to 2 1/2 hours to complete Because of the small number in the sample and its restriction to students or near-students (spouses, friends, secretaries), perceptual judgments of the selections cannot be assumed to represent those of society at large However, for the purposes of this study, the sample provides a very credible illustration of the solutions derived by different analytic techniques Furthermore, the strong interest in jazz expressed by the respondents coupled with the large number of ratings from each participant led to perceptual dimensions that were both consistent and stable The solutions therefore represent coherent perceptions of the recordings even if those percepetions are not completely representative of the overall jazz market

As suggested by Bass and Wilkie (1973) each semantic differential rating (coded 1 to 6) was divided by the sum of ratings across objects for a given subject and attribute This normalization of the data causes a respondent's ratings on an attribute to sum to 1 0 across stimuli, thus limiting both scale-unit and yea-saying effects

The input to the analysis thus consisted of a three-

Table 1

DESCRIPTION OF JAZZ SAXOPHONE RECORDINGS USED AS STIMULUS OBJECTS[a]

Style	*Type of saxophone*	*Performer*	*Key*	*Beats per minute*	*Title of tune*	*Record label and number*
West Coast	Tenor	Lester Young	D-flat	222	"Ad Lib Blues"	Verve VE-2-2502
		Stan Getz	B-flat	238	"Down Beat"	Verve MG V-8321
		Zoot Sims	G	262	"Zoot Swings the Blues"	Prestige P-24061
		Al Cohn	B-flat	203	"John's Bunch"	Famous Door HL-107
	Alto	Paul Desmond	E-flat	210	"St Louis Blues"	Columbia C2S-826
		Lee Konitz	B-flat	108	"Cork 'N' Bib"	Atlantic 1258
		Art Pepper	B-flat	200	"Marty's Blues"	Archives of Jazz AJ510
East Coast	Alto	Charlie Parker	F	218	"Jam Blues"	Verve VE-2-2508
		Sonny Stitt	F	259	"Au Privave"	Verve MG VS-6108
		Sonny Criss	F	262	"California Screamin'"	Prestige 7628
		Phil Woods	E-flat	145	"The Stanley Stomper"	Prestige P-24065
	Tenor	Sonny Rollins	B-flat	154	"Bluesnote"	Blue Note BN-LA401-H2
		Dexter Gordon	B-flat	232	"Wee-Dot"	Steeplechase SCS-1025
		John Coltrane	F	196	"Some Other Blues"	Atlantic 1354

[a]This table is taken from Holbrook and Huber (1979)

dimensional matrix of normalized scores from 16 subjects (consumers) rating 14 recordings (brands) on 93 scales (attributes) As this kind of data is typical of that often collected by marketing researchers using compositional approaches, it is important to compare various aggregate perceptual dimensions that can be derived from such a data cube First, the effect of modifying a principal components solution by replacing simple correlations with partial correlations is described Then the effect of chaining discriminant analysis to the principal components solution is considered

A Comparison of Solutions Based on Raw Versus Partial Correlations

Interattribute correlations were derived by stacking the object-by-attribute matrices for all 16 respondents into one long matrix with columns representing each attribute and rows representing each respondent's rating of each object The 93 × 93 interattribute correlation matrix based on these data then served as input to principal components analysis The resulting factors with eigenvalues greater than 1 0 were rotated to a more interpretable varimax structure, and the dimensions of the aggregate product space were formed by taking an average across the 16 respondents' scores for each jazz selection on each factor

Two aspects of this compositional approach to deriving perceptual dimensions bear comment The first concerns the computation of correlations with data that are pooled across both stimuli and respondents The second involves the choice of principal components over the general factor model

The pooling issue has long been recognized as a problem beclouding the meaning of factor spaces Consider first the pooling across subjects To the extent that subjects have different views about the way adjectives are related to each other, an aggregate solution may obscure or distort important individual differences This effect can be called *respondent-by-scale interaction* in that the resultant dimensions are a function of the particular respondents chosen Pooling across objects may produce a corresponding *object-by-scale interaction* to the extent that different objects evoke different relations between attributes In marketing, the first problem relates to perceptual heterogeneity across consumers whereas the second relates to perceptual heterogeneity across brands A test for both kinds of interaction is available (Cleavenger, Lazier, and Clark 1965), or one might account for certain kinds of interaction with three-mode factor analysis (Belk 1974, Levin 1965)

Strong interaction would dictate grouping either the subjects or the brands into smaller, more homogeneous subsets and running the analyses within these subgroups In the present case, however, the stimuli were selected to be very similar so as to minimize the first kinds of interaction Furthermore, the main objective of this type of analysis is to identify those dimensions that are *common* among consumers and across brands Too many subgroups, just like too many dimensions, might result in a more accurate model that would be less useful managerially

The second methodological issue is related to the use of principal components instead of the more elegant and complex factoring methods that do not place 1 0's in the diagonals of the correlation matrix Without reviewing the details of this complicated issue, one can state that the principal components solution is a data-reduction technique that preserves, as far as possible, distances between objects in the original data matrix What it lacks as a conceptual and statistical model by not accounting for unique variance it compensates for by avoiding the factor-score indeterminancy that plagues other methods of factor analysis (Green 1976, Nunnally 1978, Ch. 11).

In the analysis of the jazz data, principal components solutions were derived by two contrasting approaches. One was simply to use the raw data as input and then control for affect by ignoring the evaluative factor that emerged as the initial principal component.

The second approach followed a method proposed by Myers (1965) in using data from which an index of affect had been removed statistically. This index of affect was formed by summing the values of the nine semantic differential scales that had correlations of greater than 0.70 with the good/bad scale: tasty/distasteful, talented/untalented, tasteful/tasteless, creative/unimaginative, exciting/dull, pleasant/unpleasant, memorable/forgettable, interesting/boring, and good/bad. The good/bad scale was chosen as an anchor because it has reasonable face validity as a measure of affect for recordings and because it had the highest loading (0.88) on the affective factor that emerged from the principal components analysis of the raw data. This summative index of affect was then partialed out of the remaining scales so that a matrix of partial correlations (rather than the original raw correlations) served as input to the principal components analysis. This second approach may be equivalently viewed as replacing the original ratings by new variables uncorrelated with the index of affect, where the new variables are formed by regressing attribute ratings on the affective index.

Table 2

SELECTED FACTORS WHERE PRINCIPAL COMPONENTS ON RAW ATTRIBUTE RATINGS WERE *SIMILAR* TO COMPONENTS ON RATINGS WITH THE AFFECTIVE INDEX PARTIALED OUT

On raw data				*On partials*		
Factor number	*Item*	*Loading*[a]	*Factor name*	*Factor number*	*Item*	*Loading*[a]
			Activity			
2	Busy/lazy	83		1	Busy/lazy	81
	Fast/slow	81			Fast/slow	80
	Energetic/listless	75			Energetic/listless	78
			Coolness			
4	Cool/warm	78		2	Cool/warm	73
	Intellectual/emotional	66			Intellectual/emotional	66
	Pristine/funky	55			Pristine/funky	60
			Structure			
3	Structured/random	55		4	Structured/free	74
	Composed/improvised	66				
			Contemporaneity			
5	Contemporary/traditional	81		5	Contemporary/traditional	80
	New/old	77			New/old	75
	Progressive/regressive	70			Progressive/regressive	74
			Labor			
6	Labored/effortless	50		18	Labored/effortless	56
			Flatness/heaviness			
7	Flat/sharp	56		7	Flat/sharp	65
	Heavy/light	59			Heavy/light	60
			Solo			
8	Solo/ensemble	78		11	Solo/ensemble	55
			Fidelity			
9	Well-/poorly recorded	78		9	Well-/poorly recorded	80
	High-/low fidelity	69			High-/low fidelity	84
			Masculinity			
10	Masculine/feminine	81		15	Masculine/feminine	77

[a] Direction of the scales was randomized, but here items with negative loadings are reversed to facilitate interpretation. Only those attributes with loadings greater than 0.50 are included.

and then replacing the original variables with the residuals

The justification of using partials instead of the raw data is that it removes the affective component of the ratings—leaving, presumably, a denotative core It must be acknowledged, however, that there is some arbitrariness in this index of affect itself Indeed, in certain instances attributes may be strongly correlated with affect but logically distinct from it, safety in airplanes being an obvious example In such cases, adjusting for affect could cause some important dimensions to be overcorrected However, as support for this type of analysis, Myers (1965) found that partialing out an index of job level from ratings of various job descriptions produced a factor structure that was both more useful and more readily interpretable than principal components By extension to the context of a perceptual space for jazz saxophonists, this partialing procedure may produce perceptual dimensions less distorted by affective overtones

Clearly, however, the raw components solution provides a more straightforward way to remove affect If a major evaluative factor emerges, the easiest expedient is to disregard this orthogonal factor Thus, the critical question is whether better results are obtained by simply removing the entire evaluative component or by more laboriously partialing out a selective index of affect

Tables 2 and 3 show that, at least with respect to the jazz data, Myers' more cumbersome method appears to be preferable Table 2 lists factors where the two solutions are similar whereas Table 3 accounts for those that differ and indicates that, as expected, the solution based on partial correlations lacks an affective dimension Moreover, it has gained two new components depth and lyricism These components had been part of the affective factor in the analysis of the raw data

Thus, the preliminary partialing out of the index of affect produces a solution that is largely similar to that derived from the raw data but (1) avoids the evaluative factor and (2) reveals dimensions that might otherwise be lost in that evaluative component The latter property is important because dimensions like depth or lyricism, that are correlated with but not equivalent to affect, may be of substantial use to managers Partialing out an index of affect is a more precise tool that can be likened to the surgical removal of that part of an organ that is cancerous, whereas disregarding the whole component is more like excising the entire organ one is more certain that the cancer is expunged with the second technique, but there may not be much left of the patient

Discriminant Versus Principal Components Analysis

In addition to the use of partial correlations, a second compositional method for treating affect is to derive perceptual dimensions by using discriminant analysis in the manner proposed by Johnson (1971) In this use of discriminant analysis, the brands define the groups, and the analysis determines linear combinations of the original attributes that best discriminate between these dependent category variables If this application of the technique has been relatively rare in marketing (Ginter and Pessemier 1973, Lehmann and Pessemier 1973), it is perhaps because neither the intuitive nor the managerial meaning of the discriminant dimensions has been well understood, particularly in contrast with factor analysis (Shocker and Srinivasan 1974, p 294) Briefly, discriminant analysis tends to extract dimensions based on those attributes about which respondents agree in their perceptual

Table 3

SELECTED FACTORS WHERE PRINCIPAL COMPONENTS ON RAW ATTRIBUTE RATINGS WERE *DIFFERENT* FROM COMPONENTS ON RATINGS WITH THE AFFECTIVE INDEX PARTIALED OUT

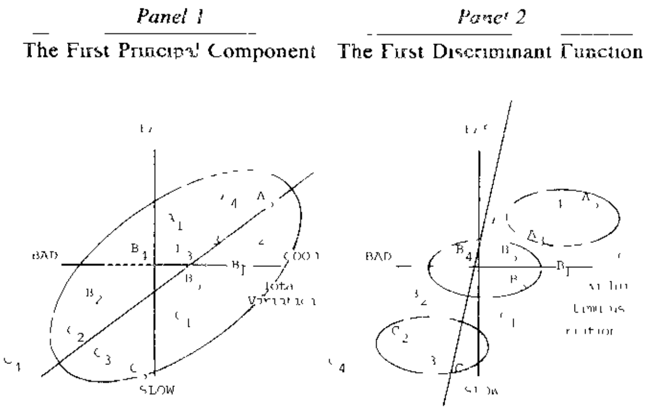
On raw data				*On partials*		
Factor number	*Item*	*Loading*[a]	*Factor name*	*Factor number*	*Item*	*Loading*[a]
			Affect			
1	Good/bad	88				
	Creative/ unimaginative	85		Not represented		
	Talented/ untalented	84				
			Depth			
	Not represented			3	Full/empty	83
					Deep/shallow	82
			Lyricism			
	Not represented			13	Wistful/sardonic	65
					Lyrical/epic	45

[a] Direction of the scales was randomized, but here items with negative loadings are reversed to facilitate interpretation With the exception of "lyrical/epic," only those attributes with loadings greater than 0 45 are included

positioning of the brands, whereas principal components analysis produces factors tending to emphasize those attributes that prompt agreement about the *meaning of the adjectives*.

The mathematical details of this distinction, derived from an excellent discussion by Green and Carroll (1976), are presented in the Appendix. To understand its conceptual basis and its relation to affect, it is useful to consider a space in two dimensions where the attributes are fast/slow (as an example of a relatively objective attribute) and good/bad (a more subjective attribute). A discriminant function based on such data can be expected to have a greater orientation to the more objective attribute whereas the principal component will be more oriented toward the affective dimension. For example, both panels in Figure 1 contain the same hypothetical scatter of responses. The first principal component, as represented by the 45-degree line in Panel 1, is that projection which accounts for the most variance in responses measured across both subjects and objects. In contrast, as shown in Panel 2, multiple discriminant analysis begins by partitioning the total variation into within-object and between-object variance. For each object, the within variation is represented by the small ellipse, where each ellipse can be thought of as a probability contour defining equal density of finding a rating on an object. In the example shown, the within variation on the good/bad dimension is much greater than that on the fast/slow dimension, indicating simply that there is much more heterogeneity of ratings for objects on the former attribute than on the latter. By minimizing Wilks' lambda criterion, the first discriminant function is that linear combination which best discriminates among all objects on the basis of their

Figure 1
ILLUSTRATION OF THE DIFFERENT ORIENTATIONS OF THE FIRST PRINCIPAL COMPONENT AND THE FIRST DISCRIMINANT FUNCTION
(evaluation of stimuli A, B, and C for 5 respondents)



attributes. Given this criterion, the orientation pictured in Panel 2 is more in the direction of the objective, fast/slow dimension and away from the more subjective good/bad dimension. Thus, given attributes with equivalent between-object variation, discriminant analysis orients the reduced space toward those attributes that have *smaller* within-object variation whereas principal components analysis orients the space more toward those attributes with *larger* within-object variation.

In other words, all else being equal, principal components analysis tends to put greater weight on those attributes about which people disagree in their ratings, and discriminant analysis puts greater weight on those attributes about which people agree. A component solution thus tends to emphasize attributes that

1. Are heavily affect-laden so that ratings vary because of different preferences, or
2. Are ambiguous or vague so that people disagree on ratings, or
3. Differ across subjects but are not necessarily affect-laden. Examples of such attributes are "good to dance to" or "unpredictable" where differences in individuals' experience or ability lead to high within-object variation.

Thus, if one defines "objective" attributes as those about which people agree in their ratings and "subjective" attributes as those about which they disagree, one can expect the former to be more prominent in a discriminant analysis and the latter to emerge in a principal components solution.

These expectations were confirmed in the analysis of the jazz recordings data. In this case the discriminant analysis was performed on the reduced principal components solution rather than on the original 93 scales because analysis on such a large number of attributes produced unstable and largely uninterpretable results. Furthermore, chaining discriminant analysis to a principal components solution provides a clear contrast between the methods. Table 4 shows the four dimensions that were significant at the $p < 0.10$ level. The discriminant analyses on both the raw and partial principal components solutions were remarkably similar except for a divergence at the fourth discriminant function. As expected, neither solution had an affective dimension. This fact implies that the affective dimension is one on which respondents were semantically homogeneous, but perceptually heterogeneous. That is, they agreed on the *meanings* of words so that a brand viewed as "good" was also likely to be called "creative," "talented," "tasteful," and so on, and this agreement resulted in the prominence of the affective dimension in the principal components analysis. However, respondents disagreed on the affective positioning of brands—whether a particular brand was "good" or "bad"—and this judgmental heterogeneity accounts for the lack of an affective dimension

Table 4
DISCRIMINANT DIMENSIONS FROM RAW AND PARTIAL COMPONENTS

On raw data				*On partials*		
Discriminant dimension	*Factor*	*Standardized coefficient*	*Name*	*Discriminant dimension*	*Factor*	*Standardized coefficient*
1	Activity	90	*Tempo*	1	Activity	89
2	Flat/Heavy	48	*Heaviness-masculinity*	2	Flat/Heavy	42
	Masculinity	43			Masculinity	34
3	Fidelity	53	*Recency*	3	Fidelity	43
	Contemporary	52			Contemporary	51
	Group-feminine				*Lyrical*	
4	Masculinity	− 51		4	Lyrical	45
	Solo	− 49				

in the discriminant solution Similarly, both "coolness" and "structure" appear to be applied too inconsistently to emerge as discriminant dimensions [1] Thus, the prominence of some attributes in the principal components analysis but not in the discriminant solution reflects the fact that some attributes were cognitively fixed across subjects whereas others showed substantial variability

In sum, compared with principal components, discriminant analysis provides dimensions that are more objective in the sense of representing homogeneity of perceptions across subjects Such dimensions may be closer to those that are "objective" in a scientific sense—namely, representing brand characteristics about which consumers agree The next section describes a test of the extent to which the various compositional approaches do in fact produce external, verifiable representations of the data on jazz recordings

The Objective Content of the Perceptual Dimensions

In total, four four-dimensional solutions were derived from the data on recordings of jazz saxophonists two principal components analyses (one on the raw data with the evaluative factor dropped and one on data with an affective index partialed out), and two discriminant analyses (each based on one of the principal components solutions) The analyses are not strictly comparable because the principal components solutions contain many more significant dimensions than the discriminant solutions However, because the purpose of a reduced space is to achieve a manageable dimensionality, it is reasonable to compare the solutions on the basis of the first four dimensions Table 5 shows the correspondence between these solutions and three external, objective characteristics (1) tempo (measured as the number of beats per minute), (2) school of jazz with which the saxophonist is most associated (East or West Coast), and (3) type of saxophone (alto or tenor) The measures of correspondence are based on the canonical correlations between the various four-dimensional solutions and this set of three objective attributes If the solutions perfectly reflected the objective characteristics, the three canonical roots would each have an R^2 of 1 0 Therefore the average of the three R^2's measures the proportion of possible objective variance explained by each competing analysis (Whether maximal representation of the objective characteristics *should* be the researcher's goal is considered in the discussion section)

In all cases, tempo emerged as the first root, and the second and third roots represented combinations of the East/West and alto/tenor distinctions But, as expected, both discriminant solutions surpassed the principal components solutions in their degree of correspondence to the objective dimensions ($\bar{R}^2$ = 67 and 74 versus 49 and 61) Furthermore, partialing the affective index seemed to be more effective than merely dropping the affective dimension ($\bar{R}^2$ = 61 and 74 versus 49 and 67) This finding suggests that, if one's goal is to derive perceptual dimensions that are as objective as possible, affect should be removed by partial correlation, principal components should be derived, and then discriminant analysis should be used to create a final reduced space

DISCUSSION

Two major conclusions can be drawn from the preceding analysis

[1]This interpretation is supported by analyses of variance showing the *absence* of significant differences among saxophonists in the index of affect (F = 1 00, n s) or in coolness (F = 1 19, n s) or structure (F = 1 55, n s) but the *presence* of significant intersaxophonist differences in perceived activity (F = 15 33, $p <$ 001), heaviness (F = 2 67, $p <$ 01), masculinity (F = 3 18, $p <$ 001), fidelity (F = 3 80, $p <$ 001), contemporaneity (F = 3 63, $p <$ 001) and solo (F = 2 12, $p <$ 05) (all d f = 13, 206 due to four missing observations)

Table 5

CORRESPONDENCE OF PERCEPTUAL DIMENSIONS TO PRIOR OBJECTIVE CHARACTERISTICS

Solution 1
Components on raw attributes

Canonical root	*Objective label*	R^2
1	Tempo	86
2	East Coast-tenor	52
3	East Coast-alto	08
Proportion of possible variance explained		$\bar{R}^2$ = 49

Solution 2
Components on partials

Canonical root	*Objective label*	R^2
1	Tempo	93
2	East Coast-alto	64
3	East Coast-tenor	24
		$\bar{R}^2$ = 61

Solution 3
Discriminant on raw components

Canonical root	*Objective label*	R^2
1	Tempo	95
2	East Coast-tenor	79
3	East Coast-alto	26
Proportion of possible variance explained		$\bar{R}^2$ = 67

Solution 4
Discriminant on components on partials

Canonical root	*Objective label*	R^2
1	Tempo	94
2	East Coast-tenor	80
3	East Coast-alto	47
		$\bar{R}^2$ = 74

1 Partialing out an index of affect may lead to a more clearly interpretable solution that better represents objective dimensions

2 Discriminant analysis provides dimensions on which respondents agree about the positioning of objects Where preferences are relatively heterogeneous, it therefore tends to remove the affective factor In the present study, it also produced more objective dimensions than did principal components analysis

An important remaining issue is the extent to which compositional approaches *should* reflect objective dimensions Clearly the decision depends on the managerial task To the extent that management is attempting to design a new brand or redesign an old one, the more objective dimensions arising from discriminant analysis are likely to be of greater use in an engineering sense However, though it must be acknowledged that more subjective dimensions will typically perform better in predicting brand preference or choice (Hauser and Koppelman 1975, Holbrook and Huber 1979), it is no great feat to predict brand preference with an affective dimension The real trick is to predict preference or choice from dimensions that management can control Indeed, if marketing managers could alter affect directly there would be no need for studying product spaces in the first place

In contrast to such problems of product design the development of promotional or communications strategy may involve less need for discriminant analysis and more use for principal components solutions In a promotional campaign one is concerned with the *meaning* that words communicate about a product In such a context, where the analyst focuses, for example on the associations evoked by labeling a beer as having "gusto," the homogeneity of linguistic connotations revealed in factor analysis is much more important than whether consumers are objective or even consistent in judging various brands on that attribute Moreover agreement among respondents on the ratings of brands might actually impede movement of a particular brand along an attribute if established social beliefs thwart attempts at repositioning Thus, in sharp contrast to the product design problem, the promotion-design problem might lead the analyst to disregard the more objective dimensions of the discriminant solution and concentrate instead on the more subjective principal components

Furthermore, for certain product categories the "objective" dimensions that emerge from discriminant analysis may be affect-laden This happened in the soft drink study by Lehmann and Pessemier (1973) where "popularity with others" was a major discriminating dimension This result makes sense because in the soft drink market popularity with others *is* a relatively objective characteristic (witness the frustrated attempts at repositioning by minor brands) Similarly, in Ginter and Pessemier's (1974) study of automobiles the two strongest discriminant dimensions were "pleasing style" and "popularity with friends " The fact that a third, essentially affective attribute, "good value for your money," was less strongly represented indicated that, although respondents agreed about which cars had higher quality and popularity, they disagreed on which was a better deal

The foregoing suggests that although discriminant analysis tends to remove affective overtones from some data sets, it will not do so in cases where preferences are homogeneous In particular, for a mature product class, overall liking may be a good discriminator between brands In such cases, it may be better to remove the offending dimension by creating an index of general affect or market share and running the analysis with that index partialed out The results of the present study suggest that the latter strategy is likely to be more fruitful than ignoring the entire dimension

The important point is not that one compositional method is better or worse than another for forming product spaces, but rather that the key differences among methods may render one more or less appropriate for a specific task In particular

1 *Principal components* analysis tends to orient a space to dimensions that have high variance both within and between objects Hence the semantic meaning of the adjectives with high loadings is very stable This kind of analysis is particularly relevant to formulating a communication strategy in which the linguistic relations between attributes are critical
2 *Discriminant analysis* orients a space to those dimensions that have high variance across objects but low variance for subjects rating a given object This method is especially appropriate where one is concerned with product design attributes that can be clearly and unequivocally perceived by consumers
3 *Partialing* out an index of an offending variable may result in a more interpretable and useful product space Dropping the entire factor is less preferable because more than just the unwanted variable is likely to be lost

Thus there are no foolproof compositional methods for generating product spaces from attribute data, only judicious choices Understanding some of the important distinctions underlying these choices makes the search for an appropriate approach less bewildering and arbitrary Consequently, the results are likely to be more useful to marketing managers

APPENDIX
PRINCIPAL COMPONENTS ANALYSIS AND DISCRIMINANT SPACES

The purpose of this appendix is to show that discriminant and principal components analyses both involve the eigen-decomposition of data matrices but that the former operates on the total variance-covariance matrix whereas the latter operates on the ratio of the between-object to within-object covariance matrices. The results are given in more detail by Green and Carroll (1976)

Assume one has a data cube with elements X_{ijk} for the rating of the i^{th} subject with respect to the j^{th} object on attribute k The within-object cross-products matrix then has elements for attributes k and l,

$$\mathbf{W}_{kl} = \sum_i \sum_j (X_{ijk} - \bar{X}_{jk})(X_{ijl} - \bar{X}_{jl}) \tag{1}$$

whereas the between-objects matrix, $\mathbf{B}$, has elements

$$\mathbf{B}_{kl} = \sum_i \sum_j (\bar{X}_{jk} - \bar{\bar{X}}_{k})(\bar{X}_{jl} - \bar{\bar{X}}_{l}) \tag{2}$$

These sum to the total matrix

$$\mathbf{A}_{kl} = \sum_i \sum_j (X_{ijk} - \bar{\bar{X}}_{k})(X_{ijl} - \bar{\bar{X}}_{l}) \tag{3}$$

so that

$$\mathbf{A} = \mathbf{W} + \mathbf{B} \tag{4}$$

Principal components analysis operates on the $\mathbf{A}$ matrix to find a linear combination, $\mathbf{At}$, of the original values such that their variance is a maximum subject to the constraint that

$$\mathbf{t}'\mathbf{t} = 1 \tag{5}$$

This reduces to solving

$$(\mathbf{A} - \boldsymbol{\lambda}\mathbf{I})\mathbf{t} = 0 \tag{6}$$

where the $\boldsymbol{\lambda}$, are the principal roots

By contrast, multiple discriminant analysis seeks the linear combination of the original attribute scores that maximizes the ratio

$$\boldsymbol{\lambda} = \frac{\mathbf{V}'\mathbf{B}\mathbf{V}}{\mathbf{V}'\mathbf{W}\mathbf{V}} \tag{7}$$

It can be shown that $\boldsymbol{\lambda}$ is maximized when

$$(\mathbf{W}^{-1}\mathbf{B} - \boldsymbol{\lambda}\mathbf{I})\,\mathbf{V} = 0 \tag{8}$$

But, because $\mathbf{W}^{-1}\mathbf{B}$ is not symmetric, the eigenvectors $\mathbf{V}$ will not be orthogonal even though the discriminant scores in reduced space will be uncorrelated Further, as $\mathbf{V}$ is not an orthonormal transformation, it does not preserve the distances in the original data In practice, however, it is fairly close to orthonormal so that the distortion is not very great

Thus, the two techniques are mathematically very similar except that discriminant analysis substitutes the *ratio* of the between-to-within for the *total* of between-plus-within variance Practically, of course, there is a big difference between adding the within variance and dividing by it Both methods focus on dimensions whose between variance is large, but, other things being equal, principal components concentrates on attributes over which people disagree whereas multiple discriminant analysis stresses those attributes about which they agree

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