# METHODOLOGY FOR INVESTIGATING HETEROGENEOUS PERCEPTUAL STRUCTURES

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## Abstract

Groups of consumers differ in the way they perceive and think about products. This paper presents methodology to assess and test these differences. Our emphasis is on the perceptual structure, that is, the number and nature of the criteria consumers use to evaluate products in a given class. We demonstrate how these differences can help us understand the formation of product preferences.

The methodology is applied to a purchasing problem for industrial cooling systems, where natural groups of individuals can be found according to job responsibility and background. The application of the methodology leads to a deepened understanding of buying behavior and provides a meaningful basis for targeting differentiated communication programs.

## 1. Introduction

The demise of general audience periodicals like the Saturday Evening Post and the dedication of a recent (August 1978) issue of the Journal of Marketing Research to market segmentation both signal the same trend: more targeted messages for segmented audiences. Yet we often deal with consumer responses to marketing actions as if the consumers were a homogeneous population.

There is a good reason for this: aggregation is simple and methods for testing for heterogeneity are not well understood.

The purpose of this paper is to develop a sound procedure for testing whether groups of individuals are perceptually homogeneous: do women "think about" cars in the same way as men do? Do frequent users of wine use the same dimensions to evaluate the beverage as do occasional users? Do engineers and purchasing agents in a company evaluate cooling systems for a new plant in the same way?

What do we know about the risks of aggregation? Davis (1976) points out problems associated with oversimplifying the role of the participants in family purchase decisions. Shuptrine and Samuelson (1976) note that product attribute saliency may vary substantially with purchasing roles in family decisions. In industrial markets, empirical studies (Lehman and O'Shaughnessy (1974); Scott and Wright (1976)) have suggested differences in product-attribute importance among decision participants. The lack of methodology to assess these differences has limited the managerial usefulness of these results, however.

This paper develops methodology to address the following:

- Do groups of individuals differ in (a) the number and (b) the composition of criteria used to assess products in a particular class?
- Do these differences help understand how individuals form preferences?

Application of the procedure to a purchasing problem for industrial cooling systems is reviewed and managerial implications are discussed.

## 2. The Measurement of Heterogeneous Perceptual Structures

The concept of cognitive or perceptual structure used here is consistent with that of an n-dimensional perceptual hyper-space used in psychology (Osgood, Suci and Tannenbaum (1957); Kelly (1955); Zajonc (1960). Product perceptions can be viewed as points in that space, the basic dimensions of which are referred to in the literature as product performance dimensions (Hauser and Urban (1977)) or evaluation criteria (Howard and Sheth (1969)). An individual's perception of a brand is, then, a vector of coordinates in the space.

The procedures used in marketing research to develop that space as well as to assess consumer product perceptions have been the subject of considerable controversy (see for instance Allaire (1973)). Two basic approaches to the problem can be followed. We refer to them as composition and decomposition analysis.

Composition Analysis. Here subjects are asked to react to specific product attributes. Responses are organized into a perceptual structure, usually through a factor analytic procedure. Subjects are also asked independently to indicate their relative preferences for the products. Various methods are then used to specify the analytical relationship between preferences and product perceptions. Urban (1976) and Silk and Urban (1978) illustrate this approach to modeling consumer response to new products.

Decomposition Analysis. Here, only similarity judgements or paired preferences for brands are collected. Then nonmetric multi-dimensional scaling procedures (Green and Rao (1970)) provide the coordinates of each brand in a multidimensional perceptual space. A review of these methods as applied in marketing appears in Green (1975).

With either approach, three levels of aggregation can be assumed in assessing consumers' perceptual structures:

- homogeneous structures: Here all individuals are assumed to perceive brands on a common set of evaluation criteria. This assumption is most often made in marketing research (see Hauser (1975) for a review).
- heterogeneous structures: Here the analyst assumes there are differences in the evaluation criteria used by sub-groups of individuals. The problem, then, is to find both a meaningful basis of aggregation and a test for the significance of the differences observed between groups.
- idiosyncratic structures: In this extreme situation, each individual is considered as unique so that no aggregation is possible. Each subject's perceptual structure has to be derived separately.

We focus here on heterogeneous perceptual structures. Basically we want to gain leverage in the study of consumer buying behavior by grouping individuals together who think about products in a similar way and separating those who do not. Two approaches can be followed to carry out this segmentation:

- Cluster-based Grouping: With this approach, the analyst first measures idiosyncratic perceptual structures for each individual. Cluster analytic methods are then used to find groups of individuals homogeneous in that respect. Allaire (1973), Green and Rao (1970), and Green and Wind (1973) provide illustrations of this approach.
- A Priori Grouping: Here, a meaningful basis for grouping is exogeneously determined. The problem is to test its relevance. This approach is conceptually similar to an analysis of variance design.

From a market segmentation standpoint, cluster-based grouping has both analytical and managerial weaknesses. First, although many procedures can identify individuals with similar perceptual structures, the groups are very sensitive to both the specific algorithm and the similarity measure chosen (Anderberg (1973), Choffray (1977)). Next, cluster analysis does not solve the problem of determining the number of evaluation criteria (the dimensionality of the perceptual structure) for a group. Neither does it provide tests for the significance of the differences across groups. And, finally, as the groupings formed may not correspond to accessible market segments, they may have limited managerial significance.

A priori grouping, on the other hand, is particularly attractive where participants form natural groups such as men, women and children in family decision making or decision participant classes such as engineers and managers in industrial purchasing situations. In such cases, differentiated communication strategies can be developed that consider the different nature of the evaluation criteria for each group.

## 3. Methodology to Assess Differences in Perceptual Structure Between Groups of Individuals

The methodology proposed here to investigate heterogeneity of perceptual structures in consumer buying assumes a priori grouping of individuals on the basis of managerially relevant variables. It follows the composition analysis approach. Product perceptions are measured independently from preferences on a set of unidimensional attribute scales. Common factor analysis investigates how consumers in different groups organize product attributes into higher order evaluation criteria. As pointed out by Hauser (1975) factor analytic procedures present substantial advantages over various decomposition methods in terms of uniqueness, invariance, and interpretability of the resulting evaluation criteria.

Factor analytic procedures, however, do not provide satisfactory tests for investigating similarity of factor space across groups of individuals. As Harman writes, the "empirical approach, employing indices of proportionality of factors ... seems not inappropriate at this time for the identification of factors across different studies ... [involving the same set of variables in different samples]." (Harman 1976, p. 346).

The methodology proposed here provides a series of sequential steps (and a new test) to investigate the similarity of factor spaces in the common factor analysis model. It therefore provides a sound basis for investigating whether different groups of consumers share the same perceptual structure:

- Do they use the same number of evaluation criteria in their assessment of product alternatives?
- Are these evaluation criteria essentially similar?

Figure 1 outlines the methodology. The input are the attribute ratings obtained for each of several product alternatives from each group studied. Variance-covariance matrices of the ratings obtained on all attribute scales are computed for each group. These covariance matrices are computed across product alternatives for each group of decision participants as suggested by Urban (1975). This way, we increase the number of degrees of freedom for estimation of the evaluation criteria for each group.

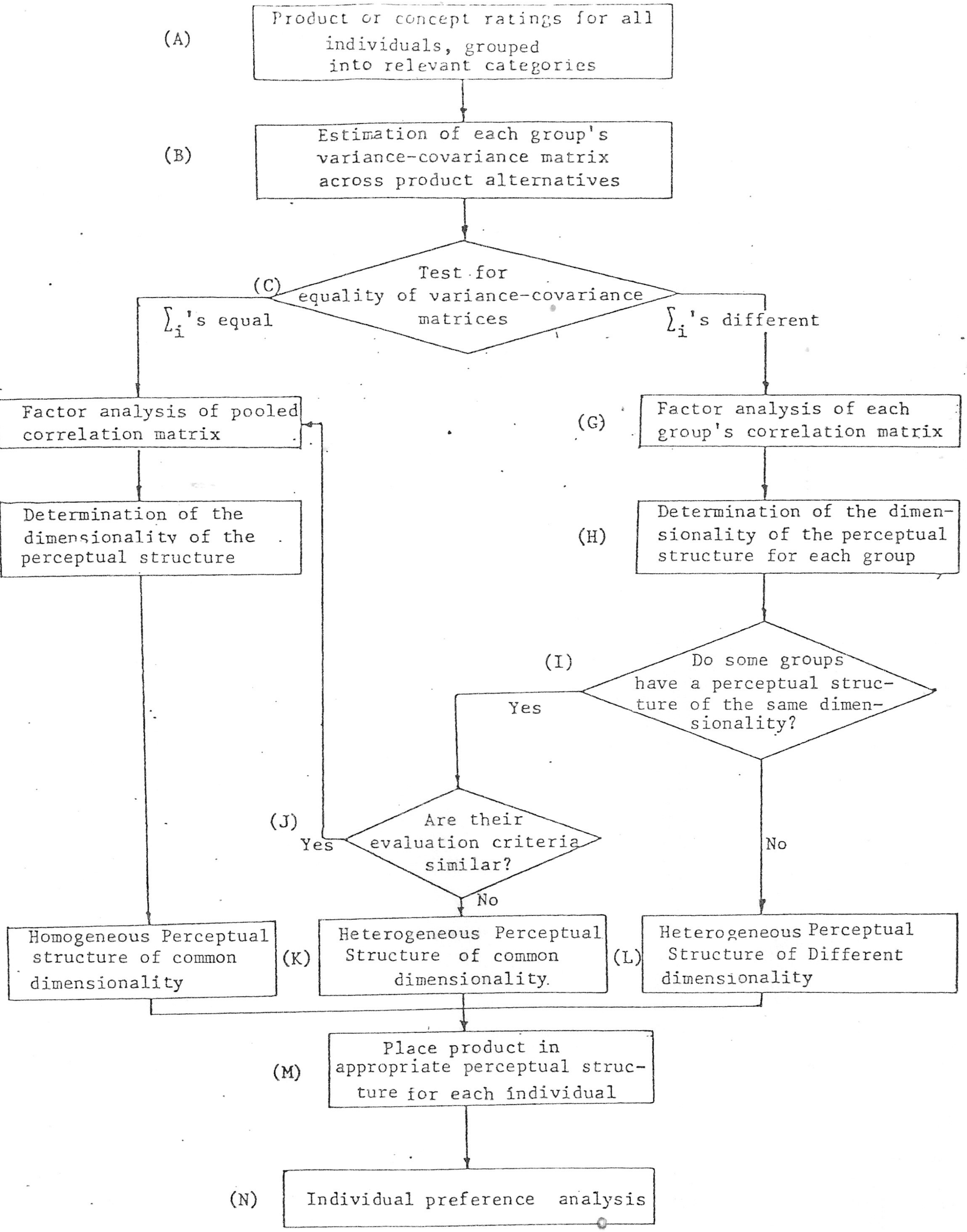


FIGURE 1: OUTLINE OF PERCEPTUAL STRUCTURE METHODOLOGY

The methodology then proceeds as follows. First the Box (1949) criterion tests for equality of all groups' covariance matrices. Let $\Sigma_i$ denote the population covariance matrix for group i and $S_i$ be the unbiased estimate of $\Sigma_i$ based on N degrees of freedom. Then, the hypothesis

$$H_0 : \Sigma_i = \ldots\ldots = \Sigma_k$$

of equality of covariance matrices across all k groups can be tested by a modified generalized likelihood-ratio statistic.

When $H_0$ is true, the test statistic is

$$M = \left( \sum_{i=1}^{k} N_i \right) \cdot \ln|S| - \sum_{i=i}^{k} N_i \ln|S_i|$$

where S is the pooled estimate of the covariance matrix:

$$S = \frac{1}{\sum_{i=1}^{k} N_i} \sum_{i=1}^{k} N_i S_i .$$

Under the assumption of multinormality of the perceptual ratings, the quantity M, when multiplied by appropropriate scale factors, is approximately distributed as an F-variate whose degrees of freedom are functions of the parameters k, n, and $N_i$. (See Cooley and Lohnes (1971), and Morrison (1976), for a discussion).

If the hypothesis of equal covariance matrices is accepted, the correlation matrix between perceptual ratings is computed across all individuals and factor analyzed (D). The dimensionality of the perceptual structure is determined (E), and the composition of the evaluation criteria common to all groups is appraised (F). Here, the analysis concludes with no substantial differences across natural groups of participants in evaluation criteria.

Box's test is very powerful, however. A recent Monte Carlo study found that the power of the test increases not only as the inequality of the covariance matrices increases, but also as the sample size or the number of variates increases (Greenstreet and Connor (1974).

Thus, rejection of the hypothesis of equality of groups' variance-covariance matrices should be used only as an indicator of possible differences in perceptual structure. Indeed, as common factor analysis does not make use of all information present in these matrices, it is possible that the evaluation criteria are similar even though the hypotheses of equality of covariance matrices is rejected.

If the hypothesis of equal variance-covariance matrices is rejected, separate factor analyses are performed for each group (G). The parallel analysis technique (Humphreys and Ilgen (1969)) determines the dimensionality of the perceptual structure for each group (H). The method factors a second correlation matrix identical in the number of variables and observations to the original data matrix, but obtained from randomly generated normal deviates. Montanelli and Humphreys (1976) show how to estimate the expected values of the latent roots of random data correlation matrices with squared multiple correlations on the diagonal. The following equation predicts the size of these eigenvalues very accurately ($R^2 \approx .99$):

$$\log \lambda_i = a_i + b_i \log (N-1) + c_i \log \left\{ \frac{n(n-1)}{2} - (i-1)n \right\}.$$

Here, i is the ordinal position of the eigenvalue, $a_i$, $b_i$ and $c_i$ are regression coefficients, N is the number of observations and n is the number of original variables.

Inequality of dimensionality (I) indicates substantial differences in Perceptual Structure (L).

On the other hand, when some groups have a perceptual structure of the same dimensionality, an additional test for the equality of evaluation criteria is necessary (J). This test is based on certain properties of the regression procedures used to assess factor scores in common factor analysis. As it is a new test, it is described in detail in appendix 1.

If all evaluation criteria are identical, the groups have a common perceptual structure and factor analysis of their pooled correlation matrix is now required (D). If at least one evaluation criterion is different, the analysis concludes, finding heterogeneous perceptual structure across groups with a given dimensionality.

The final step investigates the behavioral relevance of differences in evaluation criteria across participants. Products are placed on the appropriate evaluation criteria for each group and individual preferences are linked to products' evaluations through statistical estimation (Hauser and Urban (1977)).

This approach provides better estimates of the relative importance of evaluation criteria than do direct methods which involve estimation of importance weights by subjects (Allaire (1973)).

## 4. Application: Heterogeneous Perceptual Structures in an Industrial Purchasing Situation

Several conceptual models have been developed to describe and explain industrial buying behavior (Robinson and Faris (1967), Webster and Wind (1972), Sheth (1973), Choffray and Lilien (1978)). These models emphasize the multi-person nature of the industrial buying process and suggest that differences exist in the way members of the buying center, those individuals involved in the purchase decision, perceive and evaluate product alternatives. Thus, industrial purchasing provides a good opportunity to demonstrate and apply the procedure.

### 4.1 Data Collection

The data used were collected as part of an EDA funded project to explore the U.S. market potential for a new type of industrial air conditioning system (see Lilien et al (1977) for details). A sample of firms was selected by size, SIC code and geographic area and a senior management member was identified using Standard and Poor's Register of Corporations. He was sent a personal letter asking for the names of member(s) of his organization most likely to be involved in purchasing air conditioning equipment. A carefully pre-tested questionnaire (see Cheston and Doucet (1976) was then sent to the individuals mentioned. This two-step sampling procedure was used to increase the likelihood of reaching key people in the purchasing decision for this product class.

About 29% of the 706 companies selected returned the postcard, some with several names. Then, 57% of the decision participants identified returned 144 questionaires of which 130 were sufficiently complete to be included in this analysis.

The questionnaire requested information about the company, its requirements for products in this class, its decision process and personal information. Each respondent was also sent product concept statements, describing three industrial air conditioning systems.

Ratings were obtained for each of these concepts on a set of attribute scales. Seven-point Agree-Disagree scales were used for this purpose, and appear in Figure 2. Conditional preferences for the alternatives (see Wildt and Bruno (1974)) were also obtained, using both rank and constant sum paired comparison methods.

Purchase decision participants were grouped on the basis of the description of their background and major responsibilities in the company. This a priori grouping is consistent with Sheth's (1973) contention that product perception and evaluation criteria tend to differ among decision participants as a result of differences in role-positions in the organization.

Four groups of respondents were then distinguished:

- Production Engineers (N=35). These individuals have a common background (engineering) and all have operating responsibilities in their respective company, usually at a decentralized unit, or plant level.
- Corporate Engineers (N=23). These individuals act as internal engineering and design staff, serving several decentralized units.
- Plant Managers (N=21). They are usually the senior operating officer at a decentralized or plant location. Their responsibilities blend finance, purchasing, and accounting, with general management.

FIGURE 2: ATTRIBUTE SCALES : Industrial Cooling Study

| | | Strongly Disagree | | | | | | Strongly Agree |
|---|---|---|---|---|---|---|---|---|
| 1. | The system provides reliable air conditioning | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 2. | Adoption of the system protects against power failures. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 3. | The effective life of the system is sensitive to climate conditions. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 4. | The system is made up of field proven components. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 5. | The system conveys the image of a modern, innovative company. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 6. | The system cost is acceptably low. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 7. | The system protects against fuel rationing. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 8. | The system allows us to do our part in reducing pollution. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 9. | System components produced by several manufactures can be substituted for one another. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 10. | The system is vulnerable to weather damage. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 11. | The system uses too many concepts that have not been fully tested. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 12. | The system leads to considerable energy savings. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 13. | The system makes use of currently unproductive areas of industrial buildings. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 14. | The system is too complex. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 15. | The system provides low cost a/c. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 16. | The system offers a state of the art solution to a/c/ needs. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 17. | The system increases the noise level in the plant. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

- Top Managers (N=41). They have similar backgrounds to Plant Managers but a higher percentage have formal managerial education (MBA). They are usually responsible for the overall management of several decentralized operations.

The final sample contains 120 individuals grouped into these four categories. Ten individuals were discounted from our original sample of 130 due to ambiguous position or education descriptions.

## 4.2 Results of the Analysis

Following the methodology outlined in Section 3, individual covariance matrices were estimated for each of the four decision groups using the ratings obtained for the three product alternatives on the 17 attribute scales. The Box Criterion was used to test the equlaity of these covariance matrices, giving an F-ratio of 1.72 for 452 and 218,201 degrees of freedom. The hypothesis of equal covariance matrices was then rejected and a separate Principal Factor Analysis was performed for each decision group. (Squared multiple correlations were used as estimates of the communalities of the original perceptual scales, and were computed within each group.)

The number of evaluation criteria for each group was obtained by the parallel analysis method. Figure 3 presents the trace of observed eigenvalues and the trace of eigenvalues expected from randomly generated correlation matrices for Production Engineers. The point at which the two traces intersect indicates the maximum number of factors that should be retained; we are not interested in a factor that does not account for more variance than the corresponding factor obtained from a random correlation matrix. The number of evaluation criteria retained for each decision group is given in Table 1.

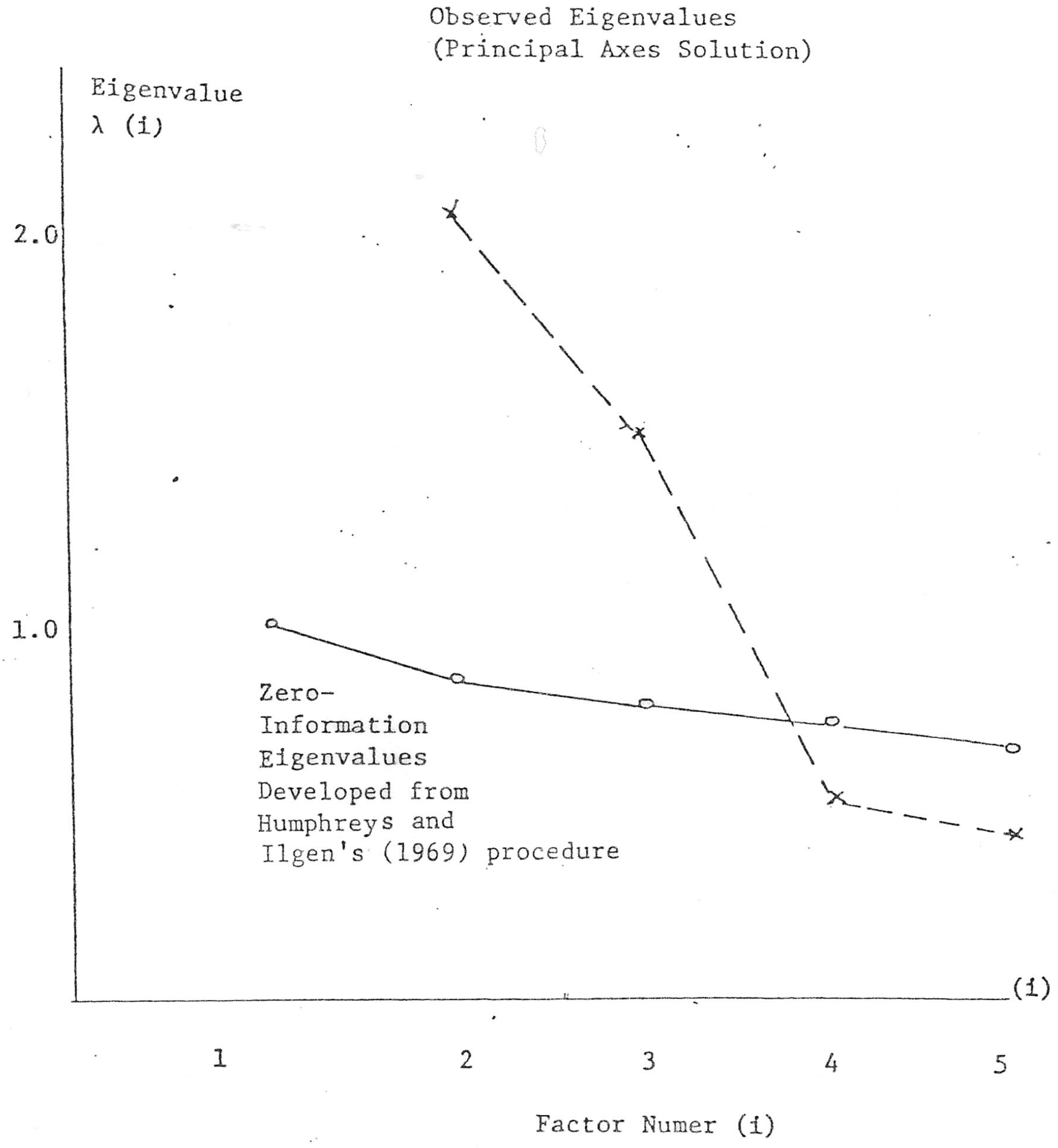


FIGURE 3: DETERMINATION OF DIMENSIONALITY OF EVALUATION SPACE FOR PRODUCTION ENGINEERS

TABLE 1: PERCEPTUAL STRUCTURE DIMENSIONALITY FOR DECISION PARTICIPANT GROUPS

| Decision Participant Group | Dimensionality of Evaluation Space |
|---|---|
| Production Engineers | 3 |
| Corporate Engineers | 2 |
| Plant Managers | 2 |
| Top Managers | 3 |

Production Engineers and Top Managers have a three dimensional Perceptual Structure. The other two groups have perceptual space of dimensionality two. These results suggest that Production Engineers and Top Managers, who exert more influence in the purchase of industrial air conditioning systems (Cheston and Doucet (1976)), use more evaluation criteria to assess product alternatives.

Separate Principal Factor Analyses were run for Corporate Engineers and Plant Managers, and for the pooled example. A varimax rotation was performed in each case, and the coefficient of determination associated with each factor was computed. Table 5 in Appendix 2 reproduces these factor structures. Most similar factors were identified and their equivalence tested one at a time. Table 6 in appendix 2 gives the result of this analysis.

Factor B is significantly different for the two groups and Factor A is nearly so. Hence the hypothesis of equality of the evaluation criteria used by Corporate Engineers and Plant Managers is rejected.

Similarly, a Principal Factor Analysis, followed by a varimax rotation, was run for Production Engineers, Top Managers and both groups together. (The complete analysis for Production Engineers and Top Managers is found in Choffray (1977)). It also showed significantly different factor-compositions between the two groups. Thus, we reject the hypothesis of equality of the evaluation spaces of Production Engineers and Top Managers. Table 2 interprets the product evaluation criteria for Corporate Engineers and Plant Managers.

In sum, our analysis shows that these groups based on similarity of background and role position differ not only in the number of evaluation criteria that they use to assess product alternatives but, also in the composition of these criteria.

## TABLE 2: COMPARISON OF FACTOR SOLUTIONS FOR PLANT MANAGERS AND CORPORATE ENGINEERS

| | Factor 1 | Factor 2 |
|---|---|---|
| Plant Managers (PM) | (+) Energy Savings<br>(+) <u>Low Cost a/c</u><br>(+) Fuel Rationing Protection<br>(+) <u>Use Unproductive Areas</u><br>(+) Reduce Pollution<br>(+) <u>State of the Art Solution</u><br>(+) Modern Image<br>(+) <u>Power Failure Protection</u> | (-) Field Proven<br>(-) Reliability<br>(+) Not Fully Tested<br>(-) <u>Substituability of Components</u><br>(=) Climate Sensitivity |
| Corporate Engineers (CE) | (+) Not Fully Tested<br>(-) <u>System's Cost</u><br>(-) Field Proven<br>(-) Reliability<br>(+) <u>Vulnerability to Weather</u><br>(+) <u>Complexity</u> | (+) Reduce Pollution<br>(+) Fuel Rationing Protection<br>(+) Energy Savings<br>(+) Modern Image |

Notes:

- Based on factor loadings greater than .50 presented in decreasing order of importance.
- Underlined items appear in the corresponding group of decision participants and <u>not</u> in the other.
- The sign appearing on the left hand side is the loading's sign.

A key question is: does the consideration of these different evaluation criteria lead to a better understanding of preference formation?

To answer this question, we study the relationship between preferences for the three alternatives and the evaluation of these alternatives as measured by the corresponding factor scores. We use a regression model, the coefficients of which are referred to as the preference parameters. Following a suggestion by Urban (1975), for each category of decision participants we perform a regression across choice alternatives and individuals. We use three different sets of assumptions:

A1: <u>Homogeneous Perceptual Structure; Homogeneous Preference Parameters</u>:
Evaluation criteria are the same across all decision groups as are preference parameters.

A2: <u>Homogeneous Perceptual Structure, Heterogeneous Preference Parameters</u>:
The evaluation criteria are the same across all decision groups, but preference parameters are allowed to differ for each of these groups.

A3: <u>Heterogeneous Perceptual Structures, Heterogeneous Preference Parameters</u>:
Both the evaluation criteria and the preference parameters differ across groups.

Prior to modeling, the two measures of individual preferences requested in the survey -- ranks and constant-sum paired comparisons -- were used to eliminate individuals inconsistent in their preference judgements. Then, two sets of regressions were run, using actual rank-ordered preference and ratio-scaled preference, (obtained from the paired comparison data via Torgenson's (1958) method), as a dependent variable. In all cases, estimated factor scores were computed for each individual and each product and were used as predictor variables.

Preference recovery (for both first preference and the actual rank order of each individual's preferences) are sensible goodness of fit measures for preference regressions (Hauser and Urban (1977), Wildt and Bruno (1974)). With three alternatives, a random model would recover first preference 1/3 of the time and full rank order preference 1/6 of the time.

Table 3 summarizes the preference recovery results under all three sets of assumptions. It appears that preference recovery is best when heterogeneity of evaluation criteria and preference parameters is considered (Assumption A3). First preference recovery can be compared with the percent correct first choice prediction for a model which equally weights all evaluation criteria: 31% under assumption A1 and A2 and 35% under Assumption A3.

The preference regressions are a bit difficult to interpret by eye, as each factor is made up of a combination of all the original items. The results under A3 are given in Table 4; a complete discussion including these and other results are found in Choffray and Lilien (1978). We discuss those results below.

Comparison of the results under Assumptions A1 and A2 require tests for equality of preference parameters. Although separate regressions showed that some shifts seemed to occur in the preference parameters, the Chow Test (1960) for equality of regression coefficients in the four decision groups leads to an F-Ratio of 2.27 with 3 and 297 deg[illegible] null hypothesis

TABLE 3: PREFERENCE RECOVERY ANALYSIS

| | Homogeneous Evaluation Criteria<br>Homogeneous Preference Parameters | | Homogeneous Evaluation Criteria<br>Heterogeneous Preference Parameters | | Heterogeneous Evaluation Criteria<br>Heterogeneous Preference Parameters | |
|---|---|---|---|---|---|---|
| | Rank Order Preferences | Cst. Sum Preferences | Rank Order Preferences | Cst. Sum Preferences | Rank Order Preferences | Cst. Sum Preferences |
| 1st. Preference Recovery | .65 | .63 | .61 | .60 | .69 | .66 |
| Full Rank Order Preferences Recovery | .42 | .44 | .41 | .39 | .49 | .47 |

TABLE 4: RANK-ORDER REGRESSION UNDER ASSUMPTION A3: HETEROGENEOUS EVALUATION CRITERIA & HETEROGENEOUS PREFERENCE PARAMETERS

| | Constant | Coefficient for 1st. Factor | Coefficient for 2nd. Factor | Coefficient for 3rd Factor | $R^2$ | F-Statistic (degrees of freedom in ( )) |
|---|---|---|---|---|---|---|
| Production Engineers | 1.99 | -.39 (4.83) | -.15 (1.69) | .23 (2.57) | .29 | 10.9 (3;82) |
| Corporate Engineers | 2.02 | .44 (4.66) | -.18 (1.79) | - | .29 | 11.0 (2;59) |
| Plant Engineers | 2.00 | -.26 (2.29) | .18 (1.69) | - | .23 | 5.78 (2;51) |
| Top Mangers | 1.99 | -.35 (4.40) | -.27 (3.22) | .14 (1.45) | .25 | 9.73 (3;90) |

t-statistics in (·)

of equal preferences parameters in the four groups when we assume a homogeneous perceptual structure cannot be rejected at the .05 level.

The comparison of the results under A2 and A3 homogenous vs. heterogeneous perceptual structures is interesting. Production Engineers weight reliability and complexity issues heavily. This is not seen under Assumption A2. The same observation holds for the issues of protection against power failure and use of unproductive areas that are of significant importance to Plant Managers and Top Managers. An important divergence from the results obtained under assumption A2 appears for Top Managers. Indeed, heterogeneous evaluation criteria reveal that Top Managers are willing to make trade-offs between the reliability of industrial cooling systems and the better efficiency in energy use plus the added protection they offer against irregularities of traditional sources of energy supply.

Hence, the preference regression run under assumption A2 -- common evaluation space and heterogeneous preference parameters -- lead to a poorer recovery of individual preferences. It also overlooks the issues of system complexity and substitutability of components, important to Production Engineers, and the issues of protection against power failures and use of impordductive areas that affect Plant Managers and Top Managers' preferences. In addition, the regression results under Assumption A2 did not isolate the important trade-offs that Top Managers seem willing to make.

The explicit consideration of heterogeneous evaluation criteria across decision groups therefore revealed some important aspects of perceptual and preference structure that did not emerge when all decision participants were pooled and analyzed as a whole.

## 5. Conclusion

This paper develops and demonstrates the use of a sequential factor analytic procedure to investigate heterogeneous perceptual structures in consumer buying. The procedure is deisgned for use when one wishes to test for perceptual differences in a priori groupings of individuals. It provides objective tests for the appropriateness of either separate or combined preference analysis. The selection of the correct path here will often lead to insight into the structure of consumer preferences that are hidden in other analyses.

The methodology is applied to groups of purchasing participants considering industrial air conditioning systems. That application showed that aggregate analysis was unable to reveal key differences between groups (an inferred liking for more complex, challenging systems by production engineers, for example) that were hidden in more aggregate analyses.

The procedure should be considered for use whenever an analyst is tempted into grouping individuals to boost his sample size. This grouping (when inappropriately applied) can threaten the validity of the statistical results and lead to incorrect conclusions and recommendations.

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## APPENDIX 1

## USE OF THE CHOW TEST IN ESTABLISHING EQUALITY OF SEVERAL FACTORS OBTAINED FROM THE SAME SET OF VARIABLES IN DIFFERENT SAMPLES

A1. The Chow Test: Consider two regression models:

(1) $Y_1 = X_1\beta_1 + \varepsilon_1$

(2) $Y_2 = X_2\beta_2 + \varepsilon_2$

where $Y_i$ is $(n_i \times 1)$, $X_i$ is $(n_i \times m)$, $\beta_1$ and $\beta_2$ are vectors of coefficients and $\varepsilon_1$, $\varepsilon_2$ are vectors of disturbances. The null hypothesis, $\beta_1 = \beta_2$ gives rise to the reduced model:

(3) $$Y = \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} \beta + \varepsilon$$

If we let $e_1$, $e_2$ and $e$ be residual vectors associated with least squares estimation of (1), (2) and (3), respectively, then Chow (1960) shows that, under the null hypothesis,

(4) $$C = \left\{ \frac{e'e}{e_1'e_1 + e_2'e_2} - 1 \right\} \frac{N-2m}{m}$$

is distributed as F with m, (N-2m) d.f. (where $N = n_1 + n_2$).

A2. Application to the Comparison of Factors Obtained in Different Samples

The common factor analysis model expresses each observed variable $\{z_j, j=1,\ldots q\}$ as a linear combination of a small number of common factors

$\{F_p, p=1,...m\}$ with $m \leq q$ plus a unique factor $U_j$.

$$(5) \quad z_{ji} = \sum_{p=1}^{m} s_{jp} F_{pi} + k_j U_{ji} \quad ,$$

where $a_{jp}$ and $k_j$ are the factor pattern coefficients, and subscript i refers to a particular individual in the sample $(i=1,...n)$.

The factors $F_p$, $p=1,...m$, however, are hypothetical unobserved constructs. In the case of most common factor analysis techniques, the factor scores have to be estimated indirectly. Linear regression on the original variables $\{a_j, j=1,...q\}$ is often used for this purpose (Harman (1976). The model may be expressed as follows:

$$(4) \quad F_{pi} = \sum_{j=1}^{q} \beta_{pj} \cdot z_{ji} + \varepsilon_{pi}$$

where $\beta_{pj}$ is the regression coefficient — or factor score coefficient -- of factor $F_p$ on variable $z_j$.

When the common factors are orthogonal, Harman (1976) shows that $R_p$, the coefficient of multiple correlation associated with the estimation of factor $F_p$, can be calculated as

$$(5) \quad R^2_p = \sum_{j=1}^{q} b_{pj} s_{jp}$$

where the $b_{pj}$'s are least squares estimates of the $\beta_{pj}$'s and $\{s_{jp}, j=1,...q; p=1...m\}$, are the correlations between the variable $z_j$'s and the factor $F_p$'s.

Under the usual assumptions of the common factor analysis model, it can be shown that:

$$(6) \quad \sum_{i=1}^{n} (F_{pi} - \hat{F}_{pi})^2 = n(1-R_p^2)$$

We can then use (6) in (4), as $\sum_{i=1}^{n} (F_{pi} - \hat{F}_{pi})^2$ is the sum of the squared residuals $e'_p e_p$ associated with the estimation of the factor scores $F_p$.

Hence, the statistic

$$(7) \quad C_p = \left\{\frac{N(1-R_p^2)}{n_1 \cdot (1-R_{p1}^2) + n_2(1-R_{p2}^2)} - 1\right\} \frac{N-2q}{q}$$

can be used to test the equality of a specific factor obtained from the same set of variables in two different samples, where

$R_{p1}^2$, $R_{p2}^2$ are the squared multiple correlations associated with the estimation of factor p in sample 1 and 2 respectively,

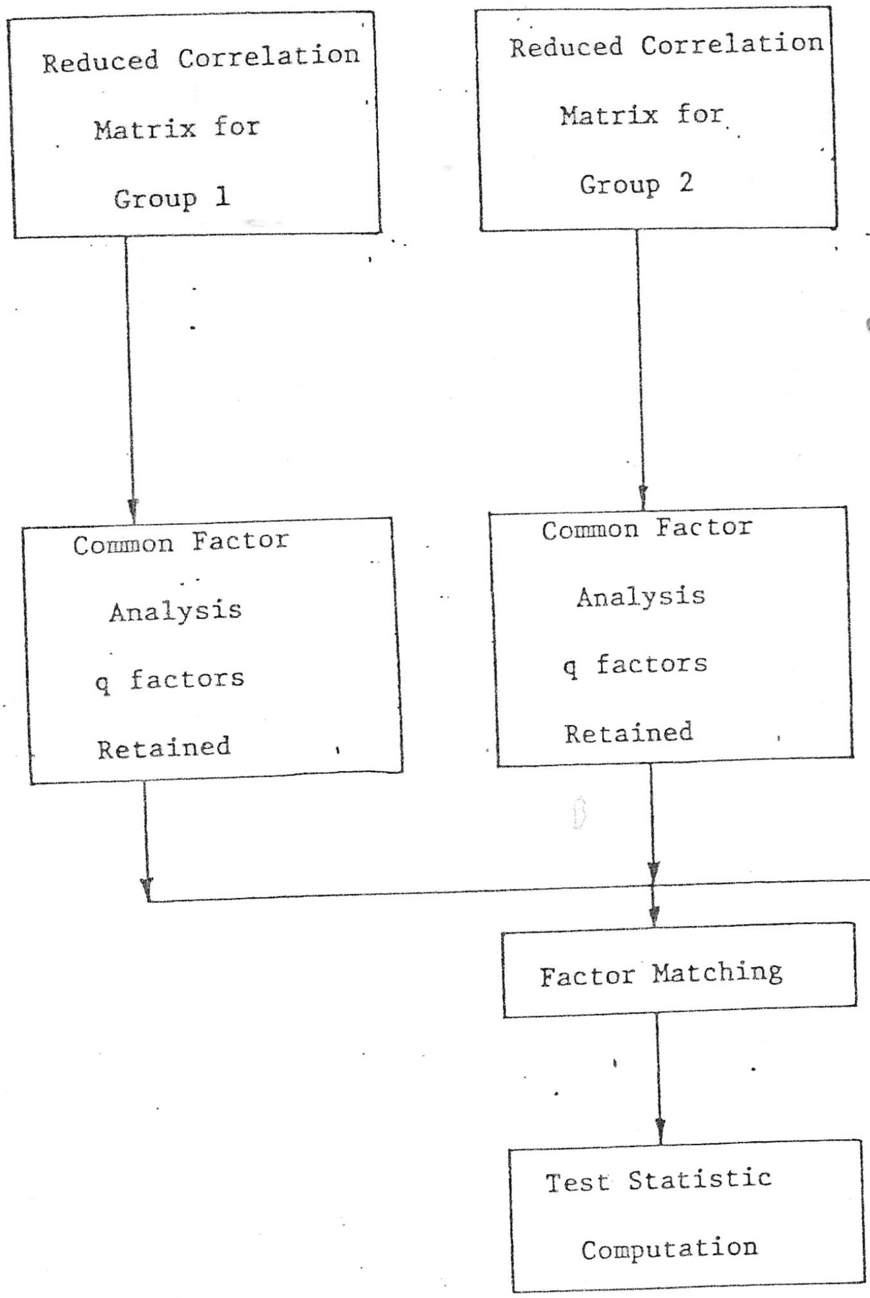
$R_p^2$ is the squared multiple correlation associated with factor p in the pooled sample, and

$N$ $= n_1 + n_2$

A3. Computation

In terms of the methodology discussed in this article, Figure 4 outlines the steps involved in the computation of the test statistic $C_p$ for assessing the similarity between individual evaluation criteria obtained from different groups of consumers that present an evaluation space of same dimensionality. The description involves only two groups, but the method is general and can be readily extended to any number of groups.

FIGURE 4: OUTLINE OF THE PROCEDURE FOR ASSESSING INTER-DECISION GROUP DIFFERENCES IN EVALUATION CRITERIA



Assume that step (I) in the product evaluation space methodology led to the identification of three factors for group 1 and 2. After rotation by the VARIMAX criterion these factors provide the respective evaluation criteria. Call these evaluation criteria $f^1_1$, $f^1_2$, $f^1_3$ and $f^2_1$, $f^2_2$, $f^2_3$, for group 1 and group 2 respectively and let $\rho^2_{11}$, $\rho^2_{12}$, $\rho^2_{13}$ and $\rho^2_{21}$, $\rho^2_{22}$, $\rho^2_{23}$, denote the coefficients of determination associated with the estimation of these factors.

In order to assess the similarity between pairs of potentially similar factors, we first compute the reduced correlation matrix between the n perceptual items in the pooled sample. The same number of common factors -- 3 in this case -- are extracted and a VARIMAX rotation is performed to ensure both uniqueness and maximum interpretability. Let $f_1$, $f_2$, $f_3$ and $R^2_1$, $R^2_2$, $R^2_3$ denote the resulting evaluation criteria and their associated coefficient of determination in the pooled sample

Next, similar evaluation criteria are matched. Several methods can be used for this purpose. Usually, simple visual inspection of the three VARIMAX rotated factor structures and/or the use of simple matching coefficients will suffice to isolate potentially similar factors. Let $f^1_i$, $f^2_h$ and $f_k$ denote such a set of potentially similar factors.

We can then compute the statistic $C_p$ by equation 7.

When the value for $C_p$ exceeds F (m, N-2m; α) where α denotes the level of significance of the test, the null hypothesis of equality of factor score coefficients $H_0 : \beta^1_i = \beta^2_h$ is rejected, leading to the conclusion that the two factors $f^1_i$ and $f^2_h$ are different.

TABLE 5: VARIMAX ROTATED FACTOR MATRICES

| | Corporate Engineer | | Plant Engineer | | Pooled Sample | |
|---|---|---|---|---|---|---|
| Item # | FACTOR 1 | FACTOR 2 | FACTOR 1 | FACTOR 2 | FACTOR 1 | FACTOR 2 |
| 1 | -0.726 | -0.169 | -0.037 | -0.798 | -0.783 | -0.102 |
| 2 | 0.338 | 0.135 | 0.521 | 0.366 | 0.336 | 0.355 |
| 3 | 0.439 | 0.208 | 0.165 | 0.595 | 0.476 | 0.221 |
| 4 | -0.776 | -0.307 | -0.287 | -0.877 | -0.810 | -0.305 |
| 5 | 0.166 | 0.612 | 0.589 | -0.026 | 0.087 | 0.616 |
| 6 | -0.781 | 0.027 | -0.208 | -0.352 | -0.603 | -0.081 |
| 7 | 0.011 | 0.750 | 0.750 | 0.327 | 0.130 | 0.734 |
| 8 | 0.237 | 0.779 | 0.633 | 0.321 | 0.250 | 0.738 |
| 9 | -0.388 | 0.202 | 0.127 | -0.620 | -0.483 | 0.148 |
| 10 | 0.571 | 0.408 | 0.420 | 0.407 | 0.496 | 0.418 |
| 11 | 0.830 | 0.407 | 0.227 | 0.727 | 0.780 | 0.344 |
| 12 | 0.320 | 0.692 | 0.788 | 0.284 | 0.293 | 0.729 |
| 13 | 0.253 | 0.350 | 0.703 | -0.062 | 0.216 | 0.512 |
| 14 | 0.537 | 0.134 | -0.227 | 0.445 | 0.490 | 0.011 |
| 15 | 0.082 | 0.471 | 0.772 | -0.047 | 0.031 | 0.584 |
| 16 | -0.180 | 0.458 | 0.604 | 0.057 | -0.093 | 0.533 |
| 17 | -0.486 | 0.079 | -0.312 | -0.487 | -0.476 | -0.090 |
| Percentage of common Variance* | .59 | .23 | .57 | .26 | .59 | .24 |
| Coefficient of determination | .902 | .845 | .897 | .915 | .879 | .841 |

* The percentage of common variance is defined in terms of the principal axes solution.

TABLE 6: TEST FOR FACTOR EQUALITY FOR PLANT MANAGERS AND CORPORATE ENGINEERS

| | F-RATIO | Degrees of Freedom |
|---|---|---|
| A. Matched Perceptual Dimensions: Plant Managers F1 / Corporate Engineers F2 | 1.46 | (17,119) |
| B. Matched Perceptual Dimensions: Plant Managers F2 / Corporate Engineers F1 | 2.14*** | (17,119) |

*** Significant at .01 level.

Note: Fi represents the $i^{th}$ factor in the original varimax solution for the corresponding decision group.