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Methodology for Investigating Differences in Evaluation Criteria Among Industrial Buying Influences

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ABSTRACT

Industrial purchasing frequently involves several individuals with different backgrounds and job responsibilities. This paper develops methodology based on objective tests to assess differences in product evaluation criteria between categories of purchasing decision participants. It then determines the importance of these differences in the formation of individual preferences.

Implementation of this methodology for purchase of an industrial air conditioning system is reviewed. The analysis leads to new insights in the development of marketing strategies for industrial products.

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Organizational buying behavior differs from consumer buying behavior in several respects. First, organizational buying decisions frequently involve several people with different backgrounds and responsibilities. Second, industrial purchasing tends to deal with more technical product complexities. Third, the organizational decision process can be separated into phases more easily than the consumer decision process, and different individuals are usually associated with different phases. Finally, these decisions typically take longer to make, leading to lags between the application of marketing strategy and buying response (Webster and Wind [31]).

The purpose of this paper is to develop and apply methodology to address an important problem associated with organizational buying behavior -- the heterogeneity of purchasing decision-participants and the implications of that heterogeneity for marketing decision-making. Specifically, the methodology:

- measures differences in evaluation criteria (the perceptual dimensions or criteria individuals use to evaluate products) between groups of individuals with similar backgrounds or job responsibilities, and
- uses those differences to more adequately explain the formation of individual preferences.

Use of this methodology allows more careful development of marketing programs, tailored to the product-characteristics most important to each group.

1. The Role of the Individual in Industrial Purchasing

Several conceptual models have been developed to describe and explain industrial buying behavior. (Robinson and Faris [24], Webster and Wind [31], Sheth [27]) These models emphasize the multi-person nature of the industrial buying process and suggest differences exist in the way members of the buying center, those individuals involved in the purchase decision, evaluate product alternatives. Choffray and Lilien [6] develop an operational model to assess industrial market response which treats this source of heterogeneity in organizational buying behavior.

Several empirical studies have concentrated on industrial buyers' product evaluation strategy and choice behavior.

Lehman and O'Shaughnessy [18] find significant differences in the relative importance of several evaluation criteria, both among industrial buyers and across categories of product purchased. Parket [22], [23] investigates the effect of the perceived similarity between available alternatives on industrial buyers' behavior. Wind [35], on the other hand, investigates source loyalty and assesses its importance in the purchasing decision for industrial components. Cardozo and Cagley [3] analyze procurement managers' preference for specific bids and bidders that involve different levels of risks. Hakansson and Wootz [11] investigate a similar problem, but in an international environment. Both studies note the importance of perceived risk in individual buying behavior.

Wilson [34] finds evidence of the existence of individual decision-making styles which are related to buyers' personality traits such as need for certainty, need for achievement and level of self-confidence.

Different patterns of industrial buyers' risk reducing behavior are also reported by Sweeney et al [28].

Several studies have used attitude models to explain the way decision participants form preferences. Scott and Bennett [25] report a study of linear attitude models to account for engineers' preferences for different brands of widely used resistors. Wildt and Bruno [32] use a linear compensatory model to predict rank-ordered preference for capital equipment. Lavin [17] investigates the power of both compensatory and lexicographic models to explain the adoption of data processing equipment.

Scott and Wright [26] analyze decision participants' product evaluation strategy for component parts. Their results suggest that engineers might consider more evaluation criteria than purchasing agents when forming preference for products in this class.

These studies have important limitations. First, many rely upon a small sample of purchasing agents whose role in the decision process is often limited (Werground [32], Choffray and Lilien [7]). Second, several of these studies have been performed in structured experimental settings whose external validity has not been verified.

Our objective here is to develop and present methodology not dependent on a single class of decision-makers and which can be applied in a non-experimental setting.

2. Measurement of Produce Evaluation Criteria

Most studies of how individuals perceive and evaluate products have been done in the consumer goods area. Several methodologies have been proposed that systematically investigate consumers' product evaluation dimensions and the way perceptiosn relate to individual preferences along these dimensions.

Allaire [1], proposes a methodology to measure heterogeneous semantic, perceptual and preference structures. Hauser and Urban [14] develop methodology to assess response to consumer innovations, linking product perceptions to individual probabilities of choice. A similar approach is also used in Urban's [30] PERCEPTOR model.

These methodologies share the same theoretical foundations. They assume a multidimensional product attribute space. In order to model the formation of individual preferences they suggest reducing the attribute space to a subspace of lower dimensionality whose coordinate axes represent the performance evaluation dimensions (Hauser and Urban [14]) or evaluation criteria (Howard and Sheth [15]) used to assess products in the class. An evaluation criterion, then, is a combination of product attributes over which individuals' product evaluations are defined.

Given the importance of personal evaluation criteria for decision participants in indistrial purchasing situations, several authors have suggested that the methodologies developed in the consumer area be extended to industrial markets (Sheth [27], Hauser [13]).

Straightforward transfer of these procedures to industrial markets, is not possible, however: they do not treat the problems associated with the multi-person nature and differences in role-responsibility in industrial purchasing.

The approach adopted here follows the recommendation by Howard and Sheth [15] to assess the set of relevant evaluation criteria common to a group of individuals. Three steps are usually involved in the associated measurement process:

- First, relevant attributes of the product class are identified. Several methods have been used successfully for this purpose. They include, focus group interivews, word association and projective techniques. A scale is then developed and tested for each attribute.
- Second, product ratings are obtained from a sample of individuals from each relevant category of decision participants. The product-stimuli are either physically presented or described in a concept statement and individuals' attribute ratings and references are recorded.
- Third, a set of relevant evaluation criteria for each group of potential decision participants are derived.

Methods to systematically perform the third step above are developed next.

3. <u>Methodology to Assess Differences in Evaluation Criteria Between Groups of Decision Participants</u>

The methodology proposed here assumes that individuals who belong to a given group, -- say design engineers, purchasing officers, etc. - share the same set of evaluation criteria. The methodology then addresses two questions:

- first, is the dimensionality of the evaluation space the same for different categories of decision participants? That is, do different groups of decision participants use the same <u>number</u> of evaluation criteria in their assessment of product alternatives?
- second, assuming that the dimensionality of the evaluation space is the same for different groups of participants, are their <u>evaluation criteria</u> essentially similar?

Figure 1 outlines the methodology. The input to the analysis are the attribute ratings obtained for each of several product alternative from each decision participant surveyed. Variance-covariance matrices of the ratings obtained on all attribute scales are computed for each group. These covariance matrices are computed across product alternatives assuming that the evaluation criteria derived for each group of decision participants are the same for all products in the class. This approach has been suggested and implemented by Urban [30] in the consumer goods area; it increases the number of degrees of freedom for estimation of the evaluation criteria for each group.

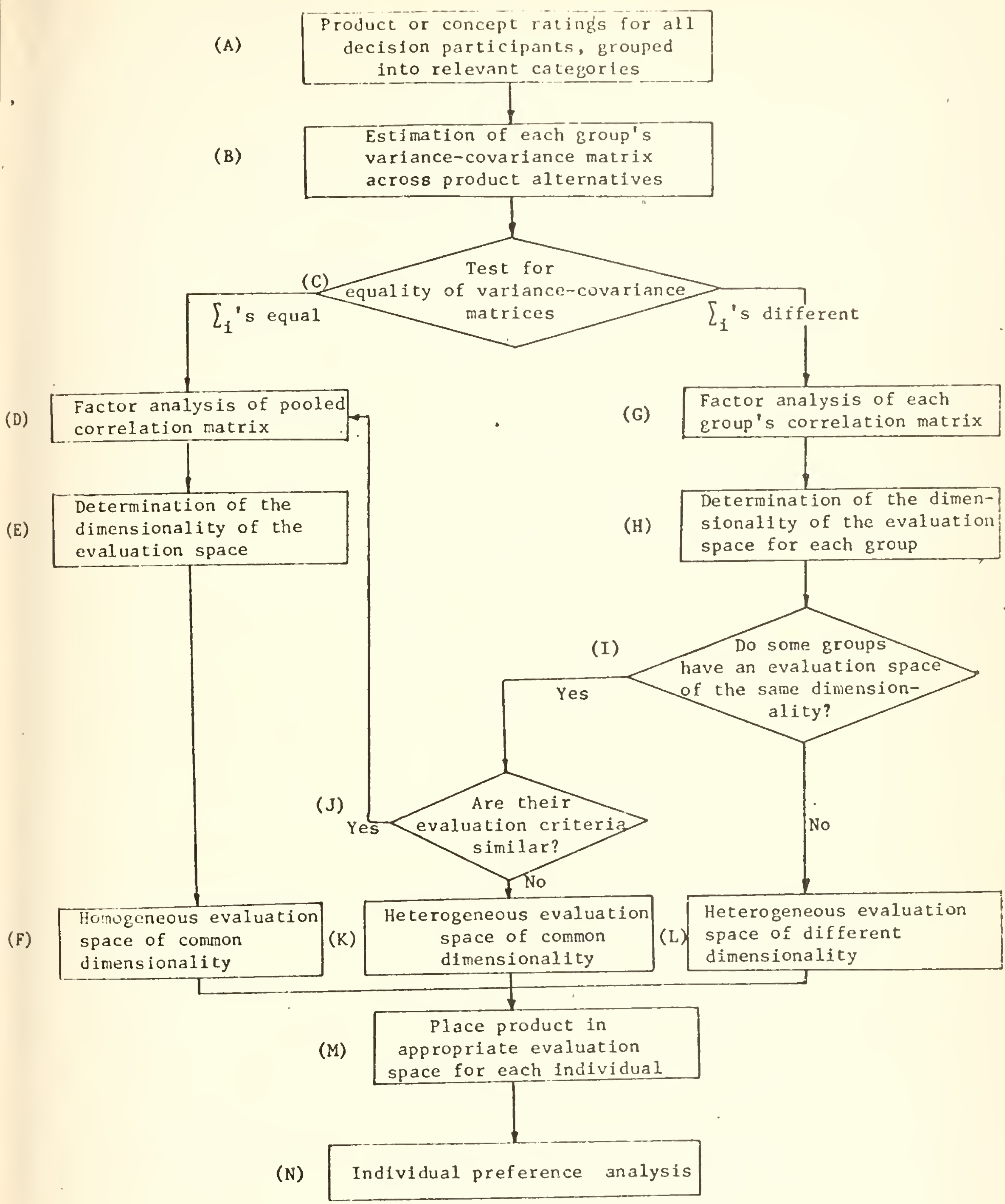

FIGURE 1: OUTLINE OF EVALUATION SPACE METHODOLOGY

The methodology proceeds as follows. First, the Box [2] criterion is used to test for equality of all decision groups' covariance matrices. Let Σ_i denote the population covariance matrix for decision group i and S_i be the unbiased estimate of Σ_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:

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

Under the assumption of multinormality of the perceptual ratings, the quantity M, when multiplied by appropriate scale factors is approximately distributed as an F-variate whose degrees of freedom are function of the parameters k, n, and N_i. (See Cooley and Lohnes [9], and Morrison [21], for a discussion of this test).

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 evaluation space is determined (E), and the composition of the evaluation criteria common to all categories of decision participants is appraised (F). In this case, the analysis concludes with no substantial differences across categories of decision participants in evaluation criteria.

Box's test is very powerful, however. A recent Monte Carol 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 [10]).

Thus, rejection of the hypothesis of equality of groups' variance-covariance matrices by the Box criterion should be used only as an indicator of possible differences in evaluation spaces. Indeed, as common factor analysis does not make use of all information present in these matrices, it is possible that the evaluation spaces 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 [16] is then used to determine the dimensionality of the evaluation space of each group of decision participants (H). The method involves factoring a second correlation matrix identical in the number of variables and observations as the original data matrix, but obtained from randomly generated normal deviates. Montanelli and Humphreys [20] provide a method of estimating the expected values of the latent roots of random data correlation matrices with squared multiple correlations on the diagonal. The following general

equation was found to predict 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 substantital differences in evaluation spaces (L).

On the other hand, when some groups have an evaluation space of the same dimensionality, an additional test for the equality of evaluation criteria is necessary (J). A description of this test is included as an appendix.

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

The final step investigates the behavioral relevance of the differences in the evaluation criteria: products are positioned in the appropriate evaluation space for each category of decision participants, and individual preferences are linked to products' evaluation via preference regression (Hauser and Urban [14]).

Allaire [1] reviews evidence which indicates that this approach provides better estimates of the importance of evaluation criteria than direct methods which involve estimation of importance weights by subjects.

4. Application of the Methodology: Heterogeneity of Decision Participants in the Industrial Air Conditioning Market

4.1 The Data

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 [18] for details). A sample of firms was selected by size, SIC code and geographic area and a senior management member was identified. He was sent a personal letter asking for the names of two or three members of his organization most likely to be involved in purchasing air conditioning equipment. A detailed questionnaire 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.

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 indistrial air conditioning systems. This approach is particularly suitable in industrial marketing as the technical complexity of product alternatives and the technical orientation of decision participants make accurate product descriptions a meaningful basis for judgement.

Ratings were obtained for each of these concepts on a set of attribute scales. Seven-point Likert scales were used for this purpose, and appear in Figure 2. Conditional preferences for the alternatives (see Wildt and Bruno [33])were also obtained, using both rank and constant sum paired comparison methods.

FIGURE 2: ATTRIBUTE SCALES

		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

Likely purchase decision participants were grouped on the basis of job responsibility. This decision is consistent with Sheth's [27] contention that product perceptions and evaluation criteria tend to differ among decision participants as a result of differences in educational background, experience, sources of information, and reference groups.

As some variation must be expected across companies in the responsibility corresponding to different job titles, the respondent was asked to describe his main job responsibility. Four groups of respondents were then distinguished:

	Sample Size
• Production engineers	35
• Corporate engineers	23
• Plant Managers	21
• Top Managers	41

4.2 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 equality of these covariance matrices, giving an F-ration 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, or dimensionality of the evaluation space 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 indictates 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.

Production Engineers and Top Managers have a three dimensional evaluation space. The other two groups have an evaluation space of dimensionality two. This suggests that Production Engineers and Top Managers, who are reported to exert considerably more influence in the purchase of industrial air conditioning systems (see Cheston and Doucet [1]), use more evaluation criteria to assess these 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 2 reproduces these factor structures. Most similar factors were identified and their equivalence tested one at a time using the test described in the Appendix. Table 3 gives the result of this analysis.

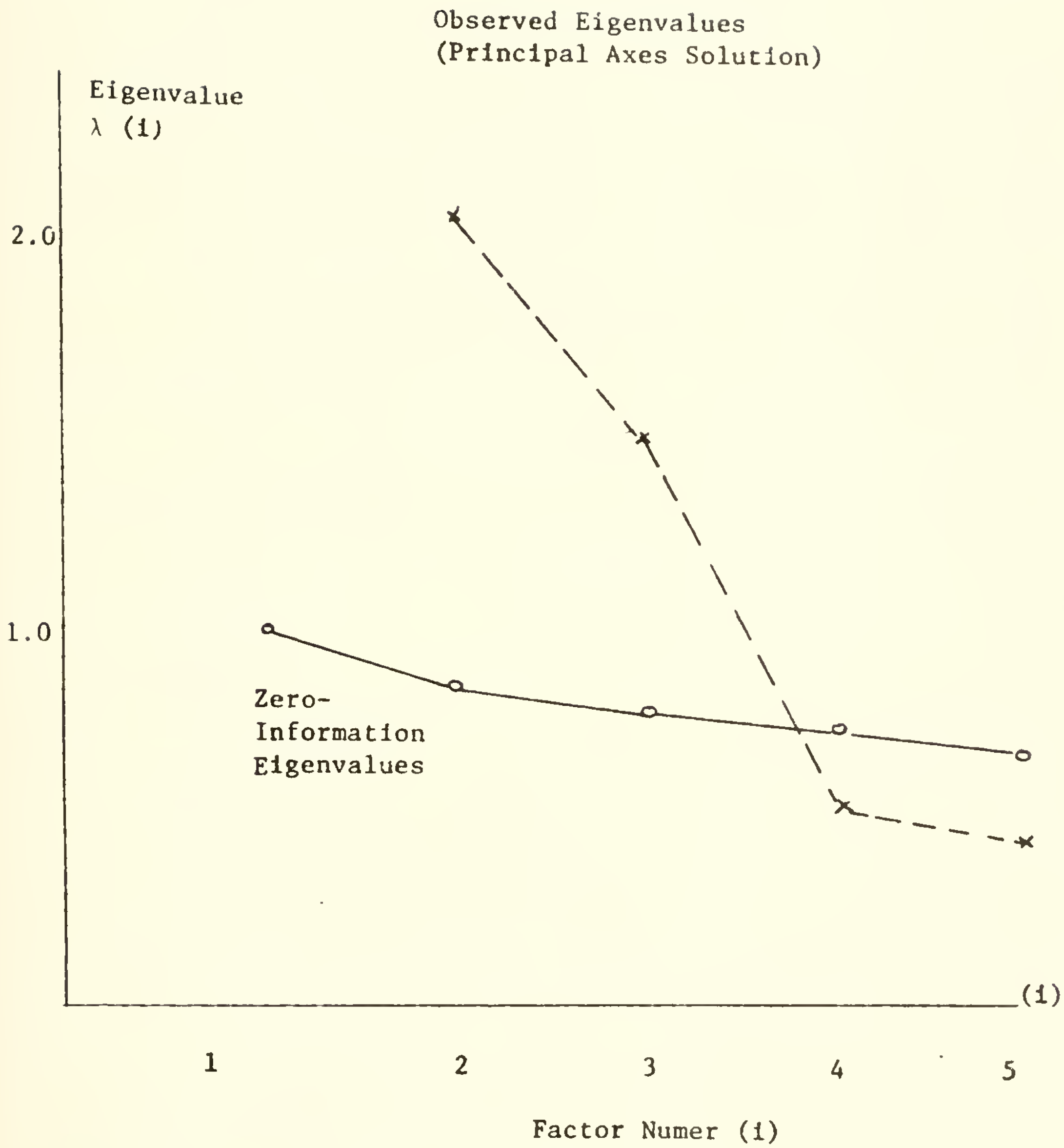

FIGURE 3: DETERMINATION OF DIMENSIONALITY OF EVALUATION SPACE FOR PRODUCTION ENGINEERS

TABLE 1: EVALUATION SPACE DIMENSIONALITY FOR DECISION PARTICIPANT GROUPS

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

TABLE 2: 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 3: TEST FOR FACTOR EQUALITY FOR PLANT MANAGERS AND CORPORATE ENGINEERS

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

*** Significant at .01 level.

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

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 CE and PM is rejected.

Similarly, a Principal Factor Analysis, followed by a varimax rotation, was run for Production Engineers, Top Managers and both groups together and 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.

As both pairs of decision groups show significantly different evaluation criteria we next examine these differences. Table 4 interprets the product evaluation criteria for Corporate Engineers and Plant Managers.

Substantial differences are evident here. Managers appear concerned about the the system's operating costs, its use of currently unproductive areas, and the protection it offers against irregularities of supplies of traditional energy sources. Corporate Engineers, on the other hand, are more concerned about the system's first-cost, its vulnerability to weather damage and its complexity.

Similarly, Table 5 interprets factor solutions for Top Managers and Production Engineers. Here too, substantial differences in the composition of the respective evaluation criteria of the two decision groups are apparent. Top Managers are especially concerned about the system's protection against power failures, its use of currently available unproductive areas, its vulnerability to weather damage and its impact on the noise level in the plant. Production Engineers, on the other hand, show more concern

<u>TABLE 4:</u> <u>COMPARISON OF FACTOR SOLUTIONS FOR PLANT MANAGERS AND CORPORATE ENGINEERS</u>

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

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 not in the other.
- The sign appearing on the left hand side is the loading's sign.

TABLE 5: COMPARISON OF FACTOR SOLUTIONS FOR TOP MANAGERS AND PRODUCTION ENGINEERS

	Factor 1	Factor 2	Factor 3
Top Managers (TM)	(+) Fuel Rationing Protection	(+) Vulnerability to Weather	(+) Noise Level
	(+) Reduce Pollution	(-) Reliability	(+) System's Cost
	(+) Energy Savings	(+) Climate Sensitivity	(+) (Field Proven)
	(+) Low Cost a/c	(+) (Not Fully Tested)	(-) (Not Fully Tested)
	(+) Modern Image	(-) (Field Proven)	
	(+) Power Failures Protection		
	(+) State of the Art Solution		
	(+) Use Unproductive Areas		
Production Engineers (PE)	(+) Low Cost a/c	(+) Field Proven	(+) Not Fully Tested
	(+) Energy Savings	(+) Substituability of Components	(-) Reliability
	(+) Reduce Pollution	(+) System's Cost	(+) Climate Sensitivity
	(+) Fuel Rationing Protection		(+) Complexity
	(+) Modern Image		
	(+) State of the Art Solution		

about the system's complexity and the substituability of its major components.

In sum, this analysis shows that these groups not only differ in the number of evaluation criteria that they use to assess product alternatives but, also in the composition of these criteria.

A last question addressed by the methodology concerns whether this analysis is behaviorally meaningful: does the consideration of these different evaluation criteria lead to a better understanding of the way decision participants form preferences?

In order to answer that question, we link individuals' preferences for the three alternatives to their evaluation of these alternatives as measured by the appropriate factor scores.

We use a linear regression model, the coefficients of which are refered to as the preference parameters. Following the approach suggested by Urban [30], for each category of decision participants a regression is performed across choice alternatives and individuals. This analysis is carried out under three different sets of assumptions:

A1: Evaluation criteria are the same across all decision groups as are preference parameters.

A2: The evaluation criteria are the same across all decision groups, but preference parameters are allowed to differ for each of these groups

A3: Both the evaluation criteria and the preference parameters differ across groups.

Assumptions A1 and A2 need an evaluation space common to all participant categories. Hence, a Principal Factor Analysis was performed for the total sample. Three factors were retained using the parallel method criterion and were rotated to simple structure.

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 judgments.

Two sets of regressions were run. First, actual rank-order preferences was used as a dependent variable. Although this dependent variable is only ordinal, evidence suggests that least squares regression closely approximates monotone regression for integer rank order preference variables (Hauser and Urban [14]). Second, the constant-sum paried comparison preference data were transformed to a ratio-scale via Torgerson's [29] method, and used as dependent variable. In both cases, estimated factor scores were computed for each individual and each product alternative. These factor scores represent each individual's evaluation of the three alternatives and were used as independent 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 [15], Wildt and Bruno [33]). With three alternatives, a random model would recover first preference 1/3 of the time and full rank order preferences 1/6 of the time.

Table 6 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). Although reassuring, this result is not in itself surprising, as more parameters were used to explain the same data. An unexpected result, however, is that preference recovery is somewhat superior under assumption A1 (that is homogeneous evaluation criteria and homogeneous preference parameters) than under assumption A2 (homogeneous evaluation criteria and heterogeneous preference parameters). This finding indicates that although A2 is a reasonable assumption in consumer marketing research (Allaire [1], Hauser [13]) it might not be reasonable in industrial markets, where different groups of decision participants exhibit substantial divergence in their assessment of product alternatives and in their evaluation criteria. 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.

Results of the rank-order preference regressions appear in Tables 7 to 9; the results in Table 9 should be matched against Tables 3 and 4 for interpretation.

From Table 7 it appears that under assumption A1 Factor 1 is most important. Although separate regressions indicate that some shifts may occur in the preference parameters (see Table 8), the Chow Test for equality of regression coefficients in the four decision groups leads to an F-Ratio of 2.27 with 3 and 297 degrees of freedom. Hence, the null hypothesis of

TABLE 6: PREFERENCE RECOVERY ANALYSIS

	Homogeneous Evaluation Criteria Homogeneous Preference Parameters		Homogeneous Evaluation Criteria Heterogeneous Preference Parameters		Heterogeneous Evaluation Criteria 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 7: RANK-ORDER PREFERENCE REGRESSION UNDER ASSUMPTION A1: HOMOGENEOUS EVALUATION CRITERIA & HOMOGENEOUS PREFERENCE PARAMETERS

	Constant	Coefficient for 1st. Factor	Coefficient for 2nd. Factor	Coefficient for 3rd. Factor	R^2	F-Statistic
Estimates	1.99	-.33	-.27	.12	.25	31.4
t-Statistic		(7.27)	(5.89)	(2.42)		(3;292)

equal preferences parameters in the four groups cannot be rejected at the .05 level.

A comparison of the results under A2 and A3 is interesting. These results are reproduced in Table 8 and 9 respectively. It appears that Production Engineers weight reliability and complexity issues heavily. This was not seen under assumption A2, as the issues of system complexity and substitutability of components did not even emerge in the common evaluation space. 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, when heterogeneous evaluation criteria are introduced in the analysis, it appears 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 paratmeters -- not only lead to a poorer recovery of individuals preferences but, it also overlooked the issues of system complexity and substituability of components, important to Production Engineers, and the issues of protection against power failures and use of improductive 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

TABLE 8: RANK-ORDER PREFERENCE REGRESSION UNDER ASSUMPTION A2:

HOMOGENEOUS EVALUATION CRITERIA & HETEROGENEOUS

PREFERENCE PARAMETERS

	Constant	Coefficient for 1st. Factor	Coefficient for 2nd. Factor	Coefficient for 3rd. Factor	R^2	F-Statistic
Production Engineers	1.98	-.39 (4.85)	-.25 (3.08)	.15 (1.67)	.29	10.9 (3;82)
Corporate Engineers	2.03	-.16 (1.51)	-.40 (4.07)	.23 (2.52)	.36	10.7 (3;58)
Plant Managers	2.09	-.34 (2.80)	-.36 (2.59)	-.11 (.71)	.22	4.6 (3;50)
Top Managers	1.96	-.36 (4.60)	-.22 (2.76)	.05 (.58)	.24	9.4 (3;90)

TABLE 9: 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
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)

evaluation criteria across decision groups therefore leads to a better understanding of how individual decision participants form preferences for industrial product alternatives.

5. Discussion

The methodology developed here provides new ways to assess the nature of differences in evaluation criteria across groups of industrial purchasing decision participants. It also allows careful investigation of the importance of these evaluation criteria in the formation of individual preferences.

This analysis allows the industrial marketer to:

- identify weaknesses in a product's design by assessing its position relative to competition on the evaluation criteria for each category of decision participant.
- develop salesmen's presentation-strategies that address the requirements of each category of decision participant.
- simulate the impact of changes in product design or positioning on the preferences of each category of individuals.

In the case of industrial air conditioning systems, substantital differences in evaluation criteria were registered across categories of decision participants. These differences justified separate preference regressions for each category of participants which elicited the relative importance of their respective evaluation criteria.

A salesman could use these results to adapt his sales presentation to his customer. Knowledge of the evaluation criteria usually used by this

category of participant might be quite helpful. Moreover, consideration of different evaluation criteria allows analysis of the input trade-offs in the design and positioning of an industrial product on different decision-participant categories.

The results of this methodology are most powerful when considered with an industrial market segmentation procedure suggested by Choffray and Lilien [7]. This segmentation strategy combines microsegments of organizations homogeneous in the composition of their buying center, making it feasible to target industrial marketing programs at key decision participant-categories within each segment.

category of participant would be quite helpful. The serial administration of different evaluation criteria allows analysis of the impact of changes in the design and positioning of an innovation/product on different decision-participant categories.

The results of this methodology are most powerful when associated with an industrial market segmentation procedure suggested by Choffray and Lilien (9). This segmentation strategy combines all respondents of organizations homogeneous in the composition of their buying centers, making it possible to target individual marketing programs at homogeneous decision-participant-categories within each segment.

6. Conclusion

This article develops methodology to assess differences in evaluation criteria across industrial buying decision participants. New tests are proposed which provide sound criteria on which to base such an analysis.

Implementation of the methodology for the purchase of an industrial air conditioning system shows differences among decision groups in the way their members combine basic product attributes into higher role evaluation criteria. The consideration of such differences in the modeling of individual preferences unveils new marketing opportunities for industrial products.

Choffray and Lilien [6] provide an overview of an operational model of industrial market response to marketing strategy which incorporates such sources of heterogenerity. The methodology presented here, however stands on its own in value, and can provide industrial marketers with useful information on which to base sound product development and communication strategies.

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APPENDIX

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 $(n_i \times m)$, β_1 and β_2 are vectors of coefficients and ε_1, ε_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 [8] shows that, under the null hypotheses,

(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

$\{F_p,\ p=1,\ldots m\}$ 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 $(i=1,\ldots n)$.

The factors F_p, $p=1,\ldots m$, however, are hypothetical <u>unobserved</u> constructs. In the case of most common factor analysis techniques, the factor scores have to be estimated indirectly. Linear regression on the original variables $[a_j,\ j=1,\ldots q]$ is often used for this purpose (Harman [12]). The model may be expressed as follows:

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

where β_{pj} is the regression coefficient -- or factor score coefficient -- of factor F_p on variable z_j.

When the common factors are orthogonal, Harman [12] 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 β_{pj}'s and $\{s_{jp},\ j=1,\ldots q;\ p=1\ldots m\}$, 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

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

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 decision participants 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.

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_2^1, f_3^1 and f_1^2, f_2^2, f_3^2, for group 1 and group 2 respectively and let ρ_{11}^2, ρ_{12}^2, ρ_{13}^2 and ρ_{21}^2, ρ_{22}^2, ρ_{23}^2, denote the coefficients of determination associated with the estimation of these factors.

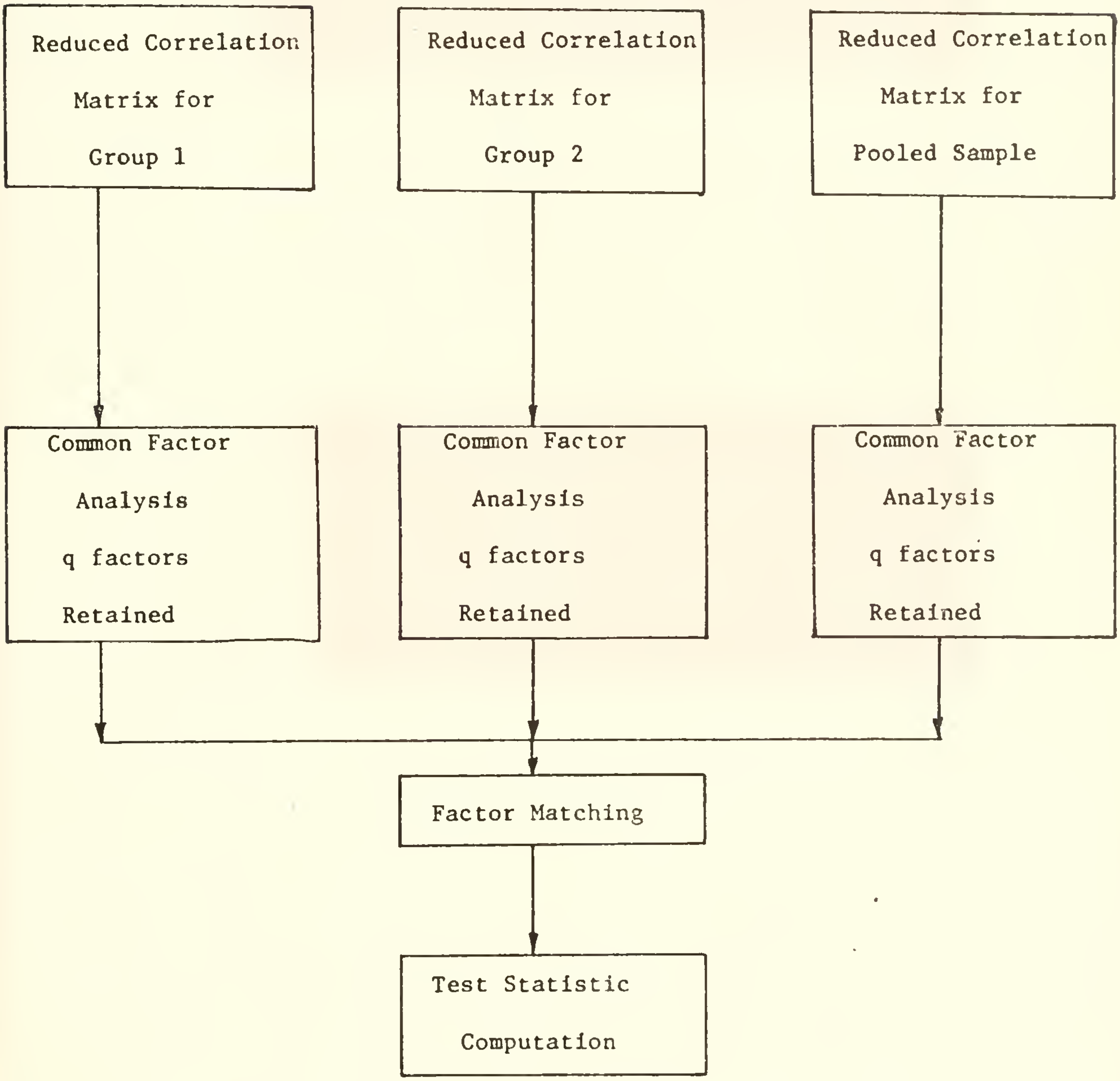
In order to assess the similarity between pairs of potentially similar factors, we first compute the reduced correlation matrix between the n perceptual items in the pooled sample. The same number of common factors -- 3 in this case -- are extracted and a VARIMAX rotation is performed to ensure both uniqueness and maximum interpretability. Let f_1, f_2, f_3 and R_1^2, R_2^2, R_3^2 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_i^1, f_h^2 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 $H_0 : \beta_i^1 = \beta_h^2$ is rejected, leading to the conclusion that the two factors f_i^1 and f_h^2 are different.

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



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