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WORKING PAPER
ALFRED P. SLOAN SCHOOL OF MANAGEMENT

METHODOLOGY FOR SEGMENTING INDUSTRIAL MARKETS ON THE BASIS OF BUYING CENTER COMPOSITION*

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W.P. No. 1038-79 January 1979

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ABSTRACT

This paper presents methodology for segmenting industrial markets on the basis of the pattern of functional involvement in the phases of the purchasing decision process. A decision matrix is developed as a structured measurement instrument to collect information about the composition of decision making units within target firms. The convergent and discriminant validity of the measurement obtained with this method is assessed. Parallel clustering methods are used to identify segments of organizations that exhibit similar patterns of involvement in their adoption process. Discriminant analysis is used to assess the differences between segments in terms of external company characteristics. The implications of this segmentation approach for industrial marketing strategy formulation are discussed.

1. Introduction

Markets, whether industrial or consumer, are heterogeneous. Customers have different needs, constraints, and incentives to satisfy them. As a theory, market segmentation is concerned with grouping potential customers into sets that are homogeneous in response to some elements of the marketing mix. This homogeneity of response allows refinement in the development of marketing strategy.

A segmentation basis is a criterion according to which potential customers are grouped. The choice of this criterion is critical. The "optimum" segmentation basis is that which minimizes the ratio of within segment variance to across segment variance for the response or behavioral variable of interest.

Historically, due to the difficulty and cost of transportation, marketers addressed geographically concentrated groups of customers (geographic segmentation basis). Demographic differences (e.g., age, education, family size) among customers are often associated with different consumption patterns and are used for segmentation as well (demographic segmentation basis). Recent developments in the theory of buyer behavior and in the measurement of customer attitudes have permitted even finer analysis (psychographic segmentation basis). Frank et al. *(14)* provide a comprehensive review of these developments.

A segment descriptor is a variable or characteristic that is (a) linked to segment membership and (b) relevant for marketing strategy formulation. In most segmentation studies, descriptors are used for prediction only. First, a segmentation is performed on a representative sample of the potential market. Second, statistical methods are used to relate segment membership to descriptors. The model can then be used predictively to assess the likelihood that a potential customer will belong to a specific segment.

Segmentation has become a fundamental concept of modern marketing (See Wind *(39)*). It provides a way of operationalizing the marketing concept and can be of considerable help in developing a firm's marketing strategy and allocating resources across markets and products.

For this strategy to be viable, however, market segments should meet three conditions. The first one is *homogeneity*, a measure of the degree to which potential customers in a segment are similar in terms of the response variable of interest. Unfortunately, there is no perfect segmentation. Very often, there is considerable segment overlap in terms of response to certain marketing variables. Young et al *(40)* examine this probleme in detail, discussing situations in which market segmentation should not be performed.

The second condition is *parsimony*, the degree to which the segments are large enough to be worth considering. An extreme segmentation would have every potential customer as a unique target. To be managerially meaningful (a requirement not met by most segmentation studies, according to Guiltinan and Sawyer*(16)*) a small set of substantial groupings of potential customers should be identified.

The third condition is *accessibility*, the degree to which one is able to characterize segments by observable descriptor variables in order to develop differentiated marketing strategies.

2. Segmentation Analysis and Industrial Buying Behavior

Segmentation methods have developed mainly in the field of consumer marketing. A recent review of the literature on organizational buying behavior indicates that market segmentation theory is not applied at anywhere near the level it has been used in consumer marketing. (Sheth *(32)*).

Industrial markets raise special segmentation issues. Companies have complex purchasing decision processes involving several individuals with different backgrounds and job responsibilities who interact within the framework of a formal organization (Webster and Wind *(36)*, Sheth *(31)*).

Few industrial market segmentation schemes are available in the literature. Cardozo *(7)* identifies only a handful of studies that suggest that industrial markets might be usefully segmented on the basis of (1) industrial buyers' purchasing strategies, (2) buyers' risk tolerance and cognitive styles, (3) differences among purchase requisitions and (4) differences in the environmental forces affecting different buyers. More recently, Wilson et al. *(37)* segmented industrial markets on the basis of the decision making styles of individual buyers. These studies, however, are of little direct use as they do not address implementation problems.

Existing classification schemes proposed in organization theory are of little help. They lack comprehensiveness and mostly rely on variables that have little managerial relevance. As McKelvey *(24)*, notes, "the study of organizational classification is at such a primitive stage that there is not even agreement about terms, let alone agreement about a theory of classification".

What is needed, then, is new methodology that recognizes the complexity of the organizational purchasing decision process, incorporates it in its measurement procedure, and provides sound criteria for classification of potential customer organizations. The rest of this paper develops such methodology.

3. A Strategy for Industrial Market Segmentation

Wind and Cardozo *(38)* review how segmentation analysis is carried out in industrial markets. Their survey reveals that segmentation strategies are used primarily after the fact, to assess products' past performance rather than to develop effective marketing programs. They stress that relevant segmentation methodology is lacking for industrial markets. Segmentation bases most useful for marketing strategy formulation --such as some of the characteristics of the Decision-Making Units (DMU's) or buying centers-- do not lend themselves easily to analysis. So, "second choice" bases, such as geographic location of potential customers and size purchase are used instead.

The segmentation strategy proposed here attempts to operationalize the two step approach suggested by (Wind and Cardozo *(38)*). First, a "macro-segmentation" is performed which groups firms in the target market that are likely to react to a product offering differently because of their industry (SIC code), geographic location, or other observable characteristics. Most data needed for this screening can be drawn from secondary sources. Second, macrosegments are further divided on the basis of similarities between decision-making units. This step of the analysis, "microsegmentation", requires development of new methodology. It is treated in detail here.

3.1. Measuring Decision-Making Unit (DMU) Composition

Which characteristic of the decision-making unit should we take as a basis for segmentation? A case could be made for using the average age of decision participants or the number of people in the buying center.

The procedure we suggest, however, uses the pattern of involvement in the buying decision process. This segmentation basis is both practically and theoretically sound. By "pattern of involvement", we mean the identification of those categories of individuals (managers, engineers, purchasing officers) who are involved in various phases of the decision-making process.

Available research about how to measure the role played by different decision participants in industrial buying decisions indicates that work on this subject should

- be limited to a single product at a time. This maximizes the chance of identifying inter-organizational variation in the purchasing process without the risk of contamination from differences in product characteristics (Kelly *(20)*).
- break the decision process into managerially meaningful areas of influence. This improves the reliability of self-reported data (Patchen *(27)*, Corey *(9)*). In this respect, Kelly concludes in his empirical study that there is surprisingly little disagreement between decision participants as to who in the organization had performed any of the five major functions involved in an industrial purchase.

. recognize that the measurement of the involvement or non-involvement of participants in the purchasing process leads to more reliable results than the measurement of their relative influence (Grashof and Thomas *(15)*).

Here, we propose a "decision matrix" as a measurement instrument to assess purchasing process involvement. A decision matrix is a double-entry table whose rows list categories of individuals likely to become involved in the decision process in customers' organizations and whose columns list relevant stages in the decision process. The respondent indicates what percentage of the task-responsibilities for each stage in the process belongs to each category of decision participant in his organization. Exhibit 1 gives an outline of a decision matrix. The request for constant-sum information forces respondents to specify only these decision participant categories that play a substantial role in each phase of the decision process or whose involvement in a specific phase is certain. A less constrained version of this method that did not request constant sum information was used in several other studies. (See for instance Buckner *(5)*, Scientific American *(30)*).

A decision matrix is then entirely product-market dependent. The purchase of an industrial product may involve different categories of individuals and/or a different disaggregation of the decision process than another product. Appendix 1 analyzes the convergent and discriminant validity of the measurements provided by this instrument.

EXHIBIT 1:

Outline of a Decision Matrix

Decision Participant Categories \ Phases Purchasing Decision Process	Description of Phase 1	. . .	Description of Phase n
Decision Participant Category 1	%	%	%
. . .	%	%	%
Decision Participant Category m	%	%	%
	100 %	100 %	100 %

3.2. Microsegment Formation

Our microsegmentation methodology uses agglomerative clustering methods for grouping target companies. These methods use as input a proximity matrix in which each cell describes the degree of similarity or dissimilarity between any two firms in the macrosegment.

3.2.1. Choice of a Proximity Measure

Let x_{ijh} denote the entry in row j and column h of the decision matrix answered by company i. This value represents the percentage of the task-responsibilities associated with decision phase h,

$h = 1 \ldots H$, associated with participant j,

$j = 1 \ldots J$, in the adoption process for company i: $(i=1\ldots I)$.

We have:

$$x_{ijh} \geq 0 \text{ for all } i, j, h$$

$$\sum_{j=1}^{J} x_{ijh} = 1 \text{ for all } i, h$$

A participant category, say j, is said to be involved in phase h of the purchasing process for company i whenever:

$$x_{ijh} > \varepsilon$$

where one might possibly set

- $\varepsilon = 0$. This would be reasonable in view of the request in the decision matrix for constant sum estimates of involvement in each phase of the decision process. Respondents are actually forced to mention only those categories of participants whose involvement they are sure of.

. $\varepsilon = \theta$, where θ is a function of the reliability of the measurements obtained with the decision matrix. For example, θ could be set at the 95 percentile of the empirical distribution of observed discrepancies between decision process involvement estimates obtained from different individuals in the same firm. In this case $x_{ijh} \geq \varepsilon$ is equivalent to being 95 % certain of individual j's involvement in phase h in firm i.

We assume above that the decision matrix measurements $\{x_{ijh}\}$ are reported without bias, even if reported with error. Appendix 2 develops a method of modification of these measurements to account for possible respondent bias.

Let

$$\delta_{ijh} = \begin{cases} 1 \text{ if } x_{ijh} \geq \varepsilon \\ 0 \text{ if } x_{ijh} < \varepsilon \end{cases}$$

The pattern of involvement in the decision process for firm i can then be viewed as a (JxH)- vector Δ_i containing 0's and 1's:

$$\Delta_i = \{\delta_{i11}, \ldots, \delta_{iJ1}, \delta_{i12}, \ldots \delta_{iJ2}, \ldots, \delta_{i1H}, \ldots, \delta_{iJH}\}$$

One such vector characterizes each firm in the sample.

The choice of a proximity measure is now limited to indices of association between vectors of binary variables. Hence, we can use matching coefficients, many of which have been used widely in numerical taxonomy (Sokal and Sneath (33), Bijnen (3)).

Our analysis makes it preferable from the standpoint of interpretation to use dissimilarity measures rather than similarity measures. We therefore suggest the following dissimilarity coefficient between two firms, r and s, using the decision matrix data:

$$D^2_{rs} = \sum_{j,h} (\delta_{rjh} - \delta_{sjh})^2$$

This coefficient may be viewed as a member of a more general class of distance functions involving the relationships between sets of (0,1) entities (Curry *(10)*). As such, D^2_{rs} satisfies the properties of non-negativity, symetry and the triangle inequality required of distances (Restle *(28)*). It may therefore be used as metric input in any subsequent analyses.

3.2.2. Hierarchical Clustering for Microsegment Formation

The general problem addressed by cluster analysis is how to partition a heterogeneous set of entities --in our case, industrial firms-- into mutually exclusive homogeneous subsets. To solve this problem, many cluster analytic models portray the entities as points in a metric space and search for regions in this space characterized by a high density of points. Clusters are formed from entities that are close to one another, while distant points become members of different clusters. An excellent review of cluster analysis is provided by Hartigan *(17)*.

The microsegmentation procedure developed here uses agglomerative hierarchical clustering methods. These methods form clusters by grouping most similar entities in the same clusters. They generate solutions that can be graphically presented as hierarchical trees or dendograms.

Agglomerative hierarchical clustering methods have two advantages over other clustering methods. First, they do not require any prior information about the number or composition of clusters. Second, they provide a visual representation of intra-cluster formation that can help interpret the clusters.

At each stage in the clustering process agglomerative methods form new clusters that minimize some function of inter-cluster distances. The proximity matrix is then re-computed to express the relationship between the new clusters and the remaining entities. The main difference among agglomerative clustering algorithms is found here: some define inter-cluster distances that asumme only ordinal dissimilarity measures (see for instance Johnson (19)); others assume an underlying metric and algebraically manipulate inter-cluster distances. (See for example Ward (35)). Both classes of methods are used here.

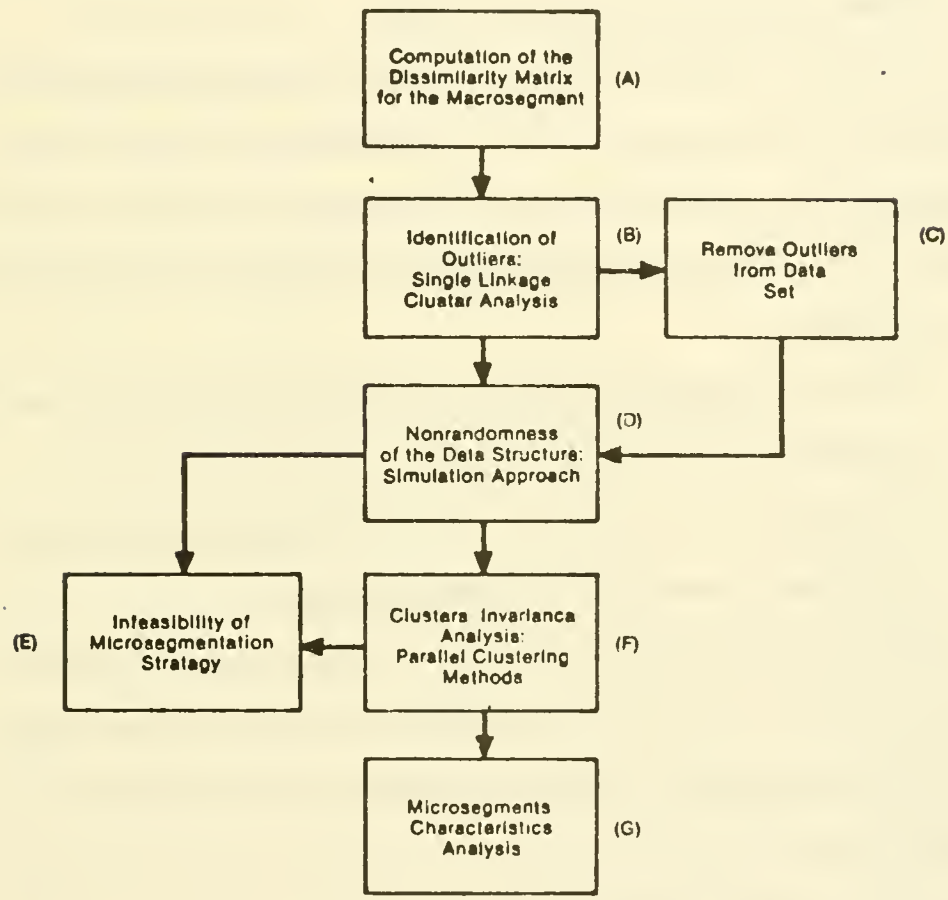
The use of cluster analysis for industrial market microsegmentation requires that several problems be solved (Choffray (8)). These include:

1. Tests on the sensitivity of cluster analysis results to extreme observations or outliers.
2. Tests on the non-randomness of the structure observed in a dissimilarity matrix, and the determination of the number of clusters to be retained.
3. Tests on the invariance of the clustering solution retained.

Exhibit 2 outlines the major steps of the microsegmentation procedure.

EXHIBIT 2:

Outline of Microsegmentation Methodology



Step 1: Computation of the Dissimilarity Matrix for the Macrosegment

This step involves the computation of the dissimilarity matrix using the measure D^2_{rs} defined earlier. Each entry in this matrix expresses the difference between firm r and firm s in the composition of their buying centers.

Step 2: Identification of Outliers

This step involves identification of outliers, organizations whose decision process bears little resemblance to that of other organizations. Inclusion of such organizations in any of the microsegments retained would indeed reduce intra-segment homogeneity and make it harder :

- to get a good description of the overall pattern of involvement within the microsegment, and
- to determine the link between microsegment membership and other observable organizational characteristics.

Following Blashfield *(4)*, single linkage cluster analysis is used to identify outliers. This method defines the distance d_{tw} between a new cluster t --made up of firm n and v-- and some other culster w as

$$d_{tw} = \min\ (d_{nw},\ d_{vw})$$

Hence, the quantity d_{tw} is the distance between the two closest members of cluster t and w.

A cluster identified by single linkage analysis is a group of entities such that every member of the cluster is more similar to at least one member of the same cluster than it is to any member of any other cluster. As a result, single linkage analysis has the tendency to form long clusters that are weakly connected. This property, called "chaining," provides a very powerful tool to identify firms that share little similarity with the rest of the sample. After examination of the decision process of these firms, they are removed from the analysis (C) and their purchasing decision process is the object of a separate analysis.

For example, in a study of the decision process for an industrial cooling system, ten companies were identified as outliers. They appear at the lower end of the hierarchical classification in Exhibit 3. Careful analysis of the decision process within these ten companies led to their elimination from further analysis.

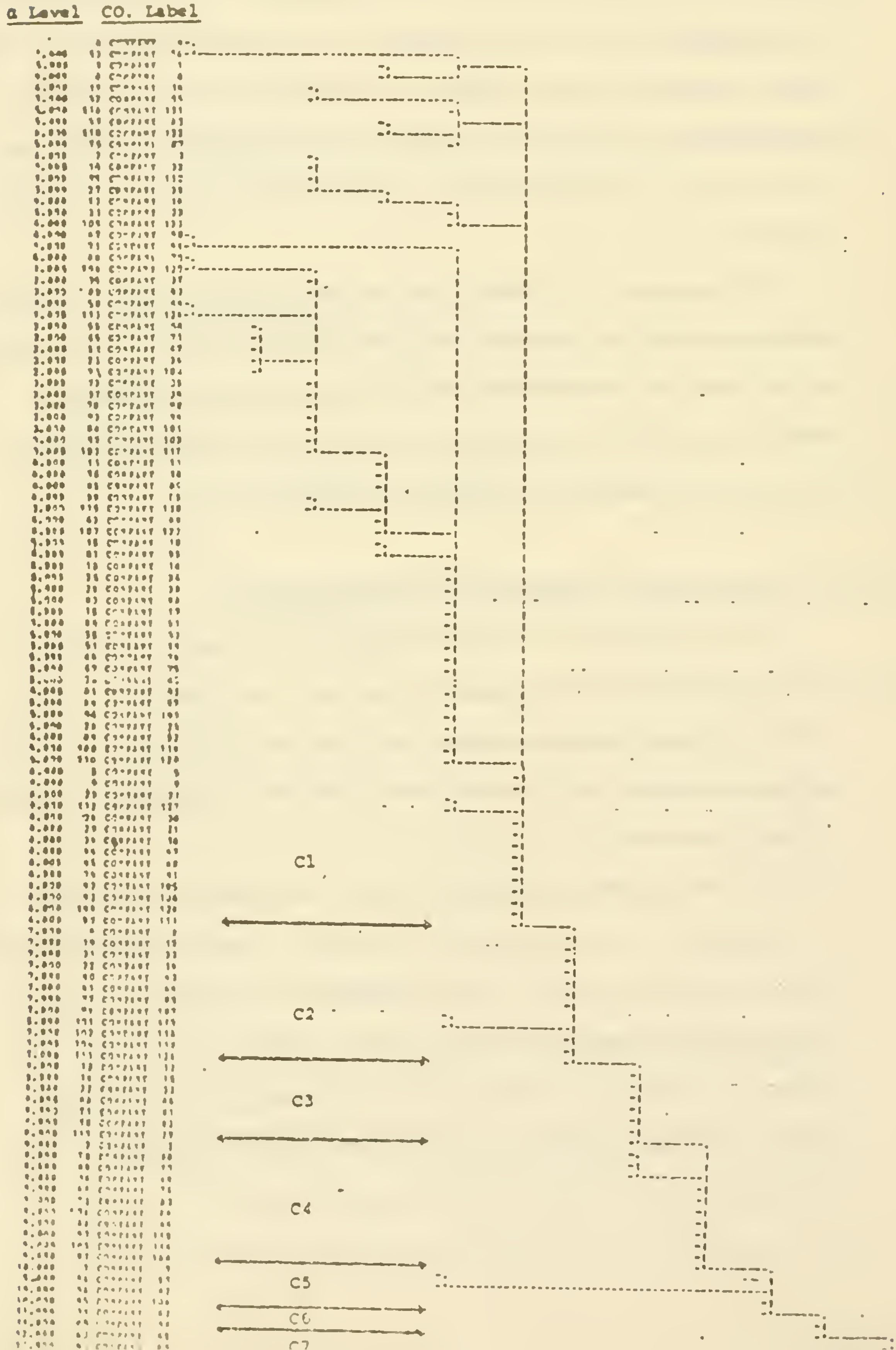
Step 3: Non Randomness of the Data Structure

This step concerns the non-randomness of the data structure and the determination of the number of clusters. The question is non-trivial. Cluster analysis methods, designed to form groups of similar entities in a data set, are very successful even when proximities are randomly generated.

As noted by Fleiss and Zubin *(13)*, a key defect in most clustering procedures is the absence of a statistical model. Some theoretical work has recently appeared in the literature and involves the application of graph theory to cluster analysis (Hubert *(18)*). Ling *(23)* proposes a probability theory of cluster analysis. He recognizes, however, that no compelling argument justifies his particular choice

EXHIBIT 3:

Single Linkage Cluster Analysis for the Industrial Cooling Study



of a model; and that in most real situations the conditions required by his model are not entirely satisfied.

In the absence of a satisfactory satistical model, simulation is recommended here to investiage the non-randomness of the structure observed in a dissimilarity matrix, and to determine a statistically significant range of clustering solutions.

The idea behind the simulation approach is that a researcher is not interested in a pattern of cluster formation that does not substantially differ from that which would be obtained if the dissimilarities had been generated independently.

Fast cluster analysis programs (Dalziel *(11)*) are generally available and relatively cheap to use. Moreover, it is our experience that cluster analytic solutions obtained from randomly generated dissimilarities are quite stable, so that a small number of simulations (5-10) is usually sufficient to get an estimate of the expected number of clusters and an estimate of the standard deviation of that number at various clustering levels.

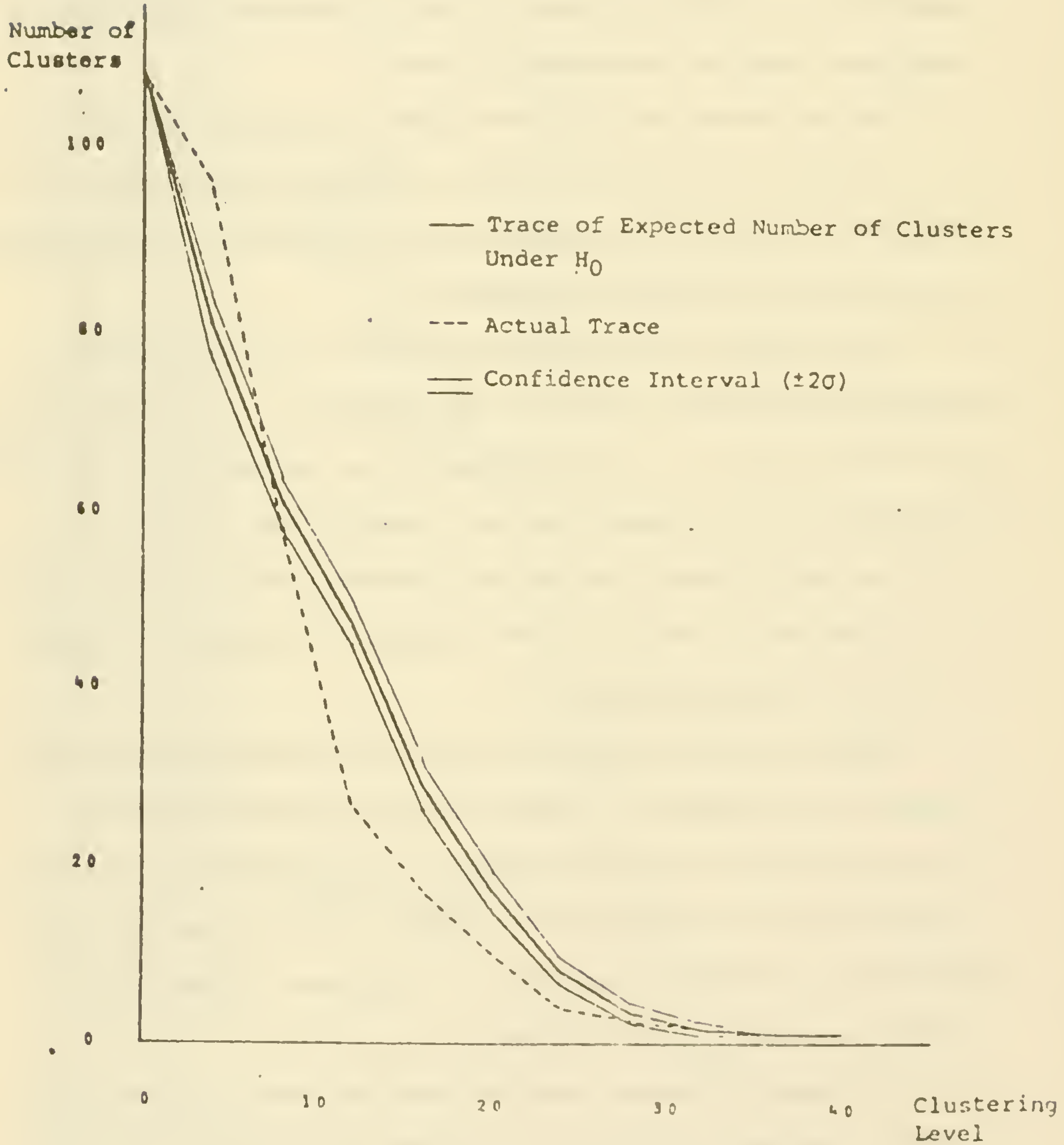
Exhibit 4 reproduces the results of the simulation analysis performed for the industrial cooling system microsegmentation. This simulation involved cluster analyzing 10 dissimilarity matrices whose individual entries were generated randomly from the same, empirical distibution of observed dissimilarities. Complete linkage cluster analysis was used for this purpose.

The number of clusters obtained from the observed dissimilarity matrix at various clustering levels departs significantly from the

EXHIBIT 4:

Results of the Simulation Study of the

Number of Clusters: Industrial Cooling Study



number that would be observed at these levels under the null hypothesis. Interestingly enough, the zero-information trace intersects the observed trace, indicating that:

- the actual data are characterized by a larger number of small, closely connected clusters, and that
- as the clustering proceeds, the dissimilarity matrix for the 108 companies contains significantly fewer clusters than would be observed under the random model hypothesis.

Therefore, meaningful structure exists here. Decision process similarities between industrial organizations in the target macrosegment for an industrial cooling system typically leads to a smaller number of microsegments than would be observed under a random model. Interpreted in another way, the simulation results indicate that within the range ($50 < n_\alpha < 4$) the data contain substantially more connected clusters --as evidenced by the smaller clustering level-- than under the null hypothesis.

When we consider these results --which indicate that a four cluster solution represents the fewest clusters that significantly depart from the random model-- together with the parsimony objective of the microsegmentation methodology, it appears that a four cluster solution is a reasonable choice in this case.

In case no clustering level is found that significantly departs from the random model, the analysis should conclude at the infeasibility of the microsegmentation.

Step 4: Cluster Invariance Analysis

This step involves the study of cluster membership invariance. There are two main reasons why cluster analytic solutions are not unique even when the researcher has decided upon the final number of clusters to be retained in his analysis. The first one has to do with the way a clustering method handles tied dissimilarities (see Choffray (8)).

The second reason for the indeterminacy of cluster analytic solutions is that clustering algorithms assume different scaling properties of the dissimilarity measures and compute distances between cluster entities differently. As a result, different methods lead to different cluster composition except for extremely stable clusters. Which of the many algorithms available should you use, then?

To date, no answer has been provided. Each clustering technique has its advocates and its critics (see the discussion by Anderberg (1)). Very few empirical studies compare relative performances. A recent analysis by Blashfield (4), however, suggests that some of these methods might be more accurate than others in recovering clusters generated under a mixture model involving several different populations.

For our purpose, the question of indeterminacy of cluster solutions is of considerable importance. The nature of dissimilarity measures defined over a finite set of binary variables (typically JxH variables in the decision matrix) suggests that ties will occur in any data set of reasonable size. In addition, the microsegments must be very stable if the remaining analysis is to make sense.

We suggest here using several clustering algorithms in parallel and analyzing the composition of the resulting clusters. If the set of clusters retained are indeed "real", their composition will vary little across clustering methods. This criterion of cluster composition invariance across clustering models has also been proposed by Everitt *(12)*.

For this purpose, we suggest three common agglomerative clustering models:

-- Complete linkage cluster analysis where a cluster is formed as a group of entities in which each member is more similar to all members of the same cluster than it is to members of any other cluster,

-- Average linkage cluster analysis, in which a cluster is formed as a group of entities in which each member has a greater mean similarity with members of the same group than with members of any other cluster, and

-- Minimum variance cluster analysis, which finds, at each stage of the process, the two clusters that (a) minimize within cluster variance or (b) minimize the increase in within cluster sum of squares.

Exhibit 5 gives a comparative analysis of the degree of convergence between these four clustering methods in the industrial cooling study. A conservative analysis would now only consider those organizations that were classified consistently across clustering methods.

EXHIBIT 5:

Comparative Analysis of the Degree of Convergence between Four Clustering Methods

	Complete Linkage	Average Linkage	Minimum Within Variance	Minimum Increase in Within Sum of Squares
Complete Linkage	—	—	—	—
Average Linkage	62 % (93.89)	—	—	—
Minimum Within Variance	61 % (99.18)	87 % (232.05)	—	—
Minimum Increase in Within Sum of Squares	64 % (127.99)	84 % (213.60)	86 % (213.60)	—

Upper Number : Percentage of Consistent Classification

Lower Number : Chi-Square Estimate with 9 d.f.

Step 5: Microsegment Characteristic Analysis

The final step of the microsegmentation methodology concerns the identification of differences across microsegements in terms of:

. the general pattern of decision participants involvement and

. the external characteristics of the firms they each comprise.

The pattern of involvement can be analyzed through the use of either univariate (Scheffé *(29)*) or multivariate (Morrison *(25)*) analysis of variance methods.

Of more interest is the use of the external characteristics of firms for prediction, to assess the likelihood that a given firm belongs to a microsegment. For this purpose, we suggest the use of multivariate discriminant analysis (Lachenbruch *(21)*).

4. Implementation of the Industrial Segmentation Methodology

We now review the microsegmentation procedure as applied in the industrial cooling study. (See Lilien *(22)* for a complete description of this research).

After careful definition of the target macrosegment for the product, a series of open-ended interviews were conducted within potential customer firms. These interviews allowed identification of five major phases in the purchasing decision process for industrial cooling systems.

1. Evaluation of needs and specifications of requirements,
2. Preliminary budget approval,
3. Search for alternatives and preparation of a bid list,
4. Equipment and manufacturer evaluation, and
5. Equipment and manufacturer selection.

We also found that the decision involved individuals whose major responsibilities could be grouped as follows:

Company Personnel - Production and maintenance engineers

Plant of factory managers

Financial controller or accountant

Procurement or purchasing department personnel

Top management

External Personnel - HVAC/Engineering firm

Architects and building contractors

A/C equipment manufacturers

Exhibit 6 outlines the resulting decision matrix.

Data was collected from 118 companies in the target macrosegment. Decision matrix measurements were then used as input to the microsegmentation methodology.

First, ten companies were identified by single linkage cluster analysis as potential outliers. They were eliminated from further analysis due to

- Over-emphasis on the role played in the purchasing process by participants external to the organization (5 companies).
- Over-emphasis on the role played by members of the purchasing department relative to other categories of decision participants (2 companies).
- Lack of discrimination in answering the decision matrix. Typically all categories of participants were mentioned as being involved in all phases of the decision process (3 companies).

EXHIBIT 6:

Decision Matrix for the Industrial Cooling Study

	DECISION PHASES / DECISION PARTICIPANTS	1 Evaluation of A/C Needs, Specification of System Requirements	2 Preliminary A/C Budget Approval	3 Search for Alternatives, Preparation of a Bid List	4 Equipment and Manufacturer Evaluation*	5 Equipment and Manufacturer Selection
COMPANY PERSONNEL	Production and Maintenance Engineers	%	%	%	%	%
	Plant or Factory Managers	%	%	%	%	%
	Financial Controller or Accountant	%	%	%	%	%
	Procurement or Purchasing Department Personnel	%	%	%	%	%
	Top Management	%	%	%	%	%
EXTERNAL PERSONNEL	HVAC/Engineering Firm	%	%	%	%	%
	Architects and Building Contractors	%	%	%	%	%
	A/C Equipment Manufacturers	%	%	%	%	%
	COLUMN TOTAL	100%	100%	100%	100%	100%

*Decision phase 4 generally involves evaluation of all alternative A/C systems that meet company needs, while decision phase 5 involves only the alternatives (generally 2-3) retained for final selection.

Next, four microsegments were identified. Their membership was quite stable when different clustering methods were used, as we discussed earlier in section 3.2.2. They represent 12 %, 31 %, 32 % and 25 % of the total potential of that macrosegment.

Two key questions remain to be addressed if one is to make managerial use of these results:

- How do the microsegments differ in the pattern of involvement in the purchasing process?
- How does membership in a particular microsegment relate to other characteristics of organizations?

We can look at the first question in two ways:

(1) How many phases is each decision participant involved in?

(2) How many participants are involved in each phase?

Exhibit 7 summarizes the results of the analysis of the number of decision phases each category of participant is involved in. Important differences are registrered among the four microsegments.

In microsegment 1, plant managers and top managers are involved in most decision phases, while production engineers and other categories of participants tend to be involved in a substantially smaller number of phases.

Microsegment 2 requires the almost continuous involvement of top management. In this segment, decision participants outside the organization, including mainly HVAC consultants and architects, tend to be involved in several phases.

In segment 3, production engineers are involved in pratically all phases of the decision process. HVAC consultants are also deeply

EXHIBIT 7:

Average Number of Decision Phases in which Each Category of Participants is Involved

	Micro-segment 1	Micro-segment 2	Micro-segment 3	Micro-segment 4	Level of Significance (ANOVA)
Production Engineers	1.91	1.54	<u>4.39</u>	<u>4.67</u>	α<.01
Plant Managers	<u>4.39</u>	.57	1.57	<u>2.83</u>	α<.01
Financial Controller	1.13	.50	.69	.50	α<.05
Purchasing department personnel	1.43	.71	1.79	.79	α<.01
Top Management	<u>2.91</u>	<u>3.68</u>	1.45	1.29	α<.01
HVAC/ Engineer Firm	1.48	<u>2.89</u>	<u>3.30</u>	.62	α<.01
Architects and Building Contractors	1.35	2.25	1.64	.70	α<.05
A/C Equipment Manufacturer	.35	.68	.36	.29	n.s.

Note: For ease of interpretation, the two largest entries in each segment are underlined.

involved, suggesting that companies in segment 3 rely heavily on engineers for guidance in the adoption of such products.

In segment 4, people at the plant level, including production engineers and plant managers tend to exert influence in the largest number of decision phases.

Thus, substantial differences exist across microsegments in the number of phases in which each category of participant is involved. This does not directly relate to actual category impact, as some participants who are involved in a small number of phases may place constraints on the decision taken in subsequent stages. It is logical to suppose, however, that those participants involved in the most decision phases also have the most chance to influence the final decision. They therefore deserve special consideration in the design of industrial marketing programs.

Consider now the number of decision participants categories involved in each phase. This analysis considers the amount of interaction evident in each phase of the process. Exhibit 8 summarizes the results; important differences are registered across microsegments.

For most decision phases, the number of categories of participants involved is consistently larger in segments 1 and 3 than in segments 2 and 4. The number of categories of participants involved does not lessen as the process moves closer to its final phase (a contention often made in the industrial marketing literature); rather, substantial differences exist in this respect across microsegments. Phase 1, however, the identification of needs, consistently involves the largest number of decision-participant categories.

EXHIBIT 8:

Average Number of Participants Categories Involved

in Each Phase of the Adoption Process

	Microsegment 1	Microsegment 2	Microsegment 3	Microsegment 4	Level of Significance (ANOVA)
Evaluation of Needs	<u>3.56</u>	<u>3.04</u>	<u>3.42</u>	<u>2.75</u>	n.a.
Preliminary Budget Approval	2.52	2.11	<u>3.45</u>	<u>2.71</u>	$\alpha < .01$
Search for Alternatives	2.69	2.46	2.69	2.08	n.a.
Evaluation	3.04	<u>2.75</u>	2.91	2.12	$\alpha < .10$
Selection	<u>3.13</u>	2.46	2.72	2.04	$\alpha < .01$

Note: For ease of interpretation, the two largest entries in each segment are underlined.

Thus, the microsegmentation procedure developed here identifies a number of meaningful microsegments. Differences exist between these microsegments in the pattern of involvement in the decision process, providing new insights into the industrial purchasing process.

Use of these results for industrial marketing strategy depends on our ability to characterize the microsegments retained on the basis of external variables.

Exhibit 9 gives a qualitative comparison of some characteristics of the organizations found in each microsegment. In order to assess formally the relationship between microsegment membership and these characteristics, a four group linear discriminant analysis was run, involving the following variables as predictors:

--X_1 : Company size, measured by sales

--X_2 : Number of separate plants

--X_3 : Percentage of plant area requiring industrial cooling

--X_4 : Company satisfaction with the current cooling system

--X_5 : Perceived organizational consequences if a new cooling system proved less economical than projected

--X_6 : Perceived organizational consequences if a new cooling system proved less reliable than projected.

Two discriminant functions were retained in this analysis. Exhibit 10 gives the standardized discriminant coefficients for each of these functions. No satistical inference can be made concerning these functions, however, as the assumptions of multinormality of the predictor variables and of equality of within group covariance structures are not satisfied by our data.

EXHIBIT 9:

Characteristics of Organizations in Each Microsegment

	Micro-Segment 1	Micro-Segment 2	Micro-Segment 3	Micro-Segment 4
Satisfaction with Current A/C System	medium high	low	medium low	high
Consequence If A/C System Is Less Economical Than Projected	medium high	low	medium low	high
Consequence If A/C System Is Less Reliable Than Projected	medium high	low	high	medium low
Company Size	medium	large	large	small
Percentage of Plant Area Requiring A/C	medium large	small	large	medium
Number of Separate Plants	medium large	small	large	medium small

EXHIBIT 10:

Standardized Discriminant Function Coefficients

Variable	Function 1	Function 2
X_1	-.43	-.05
X_2	.01	.23
X_3	-.01	.37
X_4	.39	.04
X_5	.27	.01
X_6	.04	.76
Wilks Λ	.625	.811
χ^2 (d.f)	53* (41)	26** (21)

* prob-value .10
** prob-value .25

This analysis led to 47 % correct classification. This percentage is higher than the percentage that would be obtained by randomly assigning the companies to four segments of equal sizes as those retained in this analysis (C_{pro} = 27 %). But it is likely that the percentage is biased due to the use of the total sample to estimate the discriminant functions (Morrison (26)).

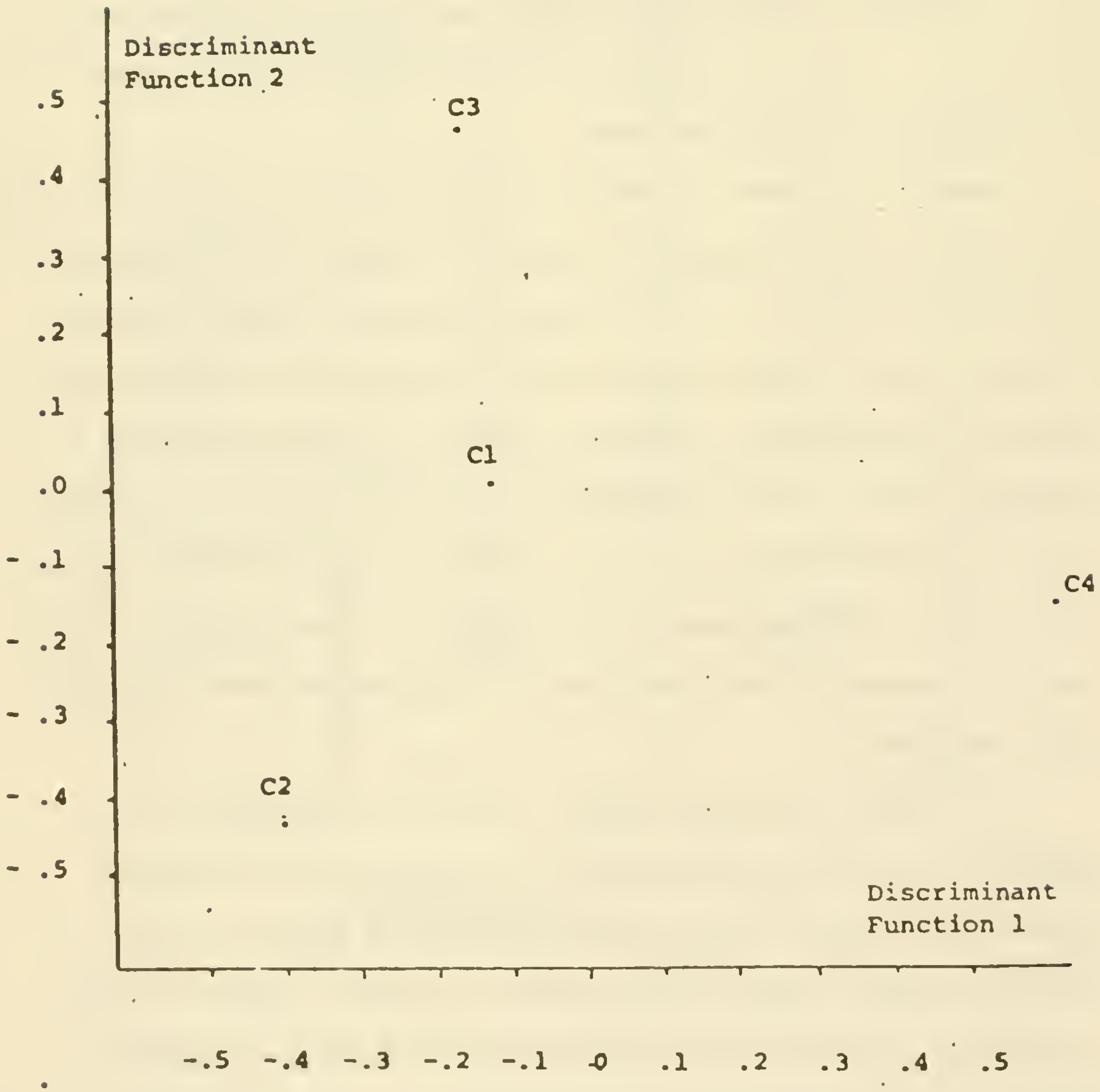
Although the results are exploratory, they point to some interesting relationships between microsegment membership and company characteristics. To illustrate, Exhibit 11 gives the microsegments centroids in the reduced discriminant space.

Companies in segment 4 tend to be smaller, more satisfied with their current air-conditioning system, and more concerned with the economic aspects of industrial air-conditioning. In terms of their purchasing processes, these companies are characterized by a more frequent involvement of Top Management. Moreover, they rely on external sources of expertise, such as HVAC consultants, to assist them in the assessment of air-conditioning needs, the search for alternatives, and the selection of particular equipment. On the contrary, larger companies represented in segments 2 and 3 use their own engineering capabilities for these same tasks.

The comparison between segments 1 and 3 is interesting as the segments do not substantially differ in terms of size of company. However, our analysis suggests that companies in segment 3 tend to have more plants, larger cooling needs, and greater concern for the reliability of industrial air-conditioning systems than companies in segment 1. It is therefore not surprising to note that companies in

EXHIBIT 11:

Microsegments' Centroids in Reduced Discriminant Space



segment 3 rely mainly on engineering functions in the process of purchasing an industrial cooling system, while companies in segment 1 involve mainly managerial functions.

Microsegment 2 groups large companies with a small number of plants. These companies view little risk in the purchase of an industrial air-conditioning system. As a result, they generally let these decisions be made at the plant level.

5. Strategy Implications

The procedure developed here isolates homogeneous sets of organizations and describes the decision process in each. This information helps develop strategies aimed directly at those categories of individuals most influential in the various microsegments.

Typically, the decision matrix is included as part of a personally administered or mailed survey instrument. Respondents are identified as those individuals within an organization most likely to influence the purchasing decision for a product in the class investigated. More than one individual per organization is studied when appropriate.

The procedure can be used when the potential market for an industrial product contains a small number of customers. Then, the decision matrix would be administered to each customer individually, providing information to develop specific account strategies. For larger industrial markets, the decision matrix would be administered on a sample of industrial organizations. As the industrial cooling study illustrates, implementation of the procedure yields the relative size of the microsegments and describes the structure of the purchase decision process within each.

This information can be used to:

- Concentrate communication efforts on those categories of individuals most often involved in the purchasing process in the largest microsegments. For an industrial cooling system, this might lead to a concentration of communication effort on production engineers and HVAC consultants who are most influential in microsegment 3.
- Predict the structure of the adoption process for a specific firm on the basis of its external characteristics. Promotional material or salesmen calls could then be directed at those categories of individuals most influential in the microsegment.
- Select communication vehicles. The categories of individuals involved in the purchasing process differ in their sources of information and communication consumption. In the industrial air-conditioning study, in microsegment 3, production engineers and HVAC consultants were most influential. Due to their common educational background, there is a substantial overlap in their sources of information and communication consumption patterns, suggesting the use of the same communication channels for both groups.

Hence, the microsegmentation procedure provides a better understanding of the industrial purchasing decision process and the variations that exist in it across firms. This information, as outlined above, is of considerable help in the design of relevant market strategies.

6. Summary

Market segmentation is a key aspect of industrial marketing strategy. Methodology is developed here to identify segments of organizations homogeneous in the structure of their purchasing decision process. The methodology relies on the information collected with a decision matrix from companies in the potential market for an industrial product. It uses parallel clustering methods to identify homogeneous groups of firms.

Implementation of the methodology in an application involving industrial cooling systems led to the identification of four segments of organizations. Analysis of the relationship between micro-segment membership and external characteristics of organizations suggests interesting relationships between the structure of the industrial purchasing process and some generic characteristics of firms, including company size, urgency of the need for the new product, satisfaction with past purchase and the nature of the risks associated with such purchases. This information provides marketers with a better understanding of the purchasing process. It is of immediate use in the development of differentiated communications strategies targeted at key individuals in different market segments.

The procedure developed here is still in its experimental phase. The external validity of the decision matrix measurements needs to be assessed, through studies over time in organizations actually facing decision-situations. At the same time, the ability of the decision matrix to assess the relative importance of individuals -- in relationship to the decisions being made-- could be studied. As Webster and Wind *(36)* note, "There are rich research opportunities in defining the influence of different members of the buying center at various stages of the process".

APPENDIX 1

Convergent and Discriminant Validity of Decision Matrix Measurements

A common denominator of most validity concepts is that of agreement or convergence between independent approaches. (Ayer (2), Campbell and Fiske (6)). Suppose that several decision participants in the same organization filled out the decision matrix separately. The extent of the agreement between these individuals about the categories of individuals involved in the phases of purchasing process is a measure of the convergent validity of the measurement procedure.

In order to investigate measurement validity, decision process involvement was measured twice, with different individuals, in several firms. Two products were studied in this analysis: an industrial cooling system (12 firms) and an "intelligent" computer terminal (13 firms).

We used two approaches to assess the convergent validity of the decision matrix measurements: the first, a simulation approach, considers if separate measurements in the same firm agree more than separate measurements in different organizations. The second method investigates the ability of respondents to discriminate between decision phases.

We use the following notation below:

$V = (v_i, v_i') : i = 1,\ldots N_1$ denotes the subsample of N_1 companies for which two measurements (v_i, v_i') were obtained with the decision matrix. We call this sample the validation sample.

$C = c_j : j = 1,\ldots N_2$ denotes the subsample of N_2 companies for which only one measurement was obtained with the decision matrix. We call it the main sample.

A. Simulation Approach to Validation

Here we use both the validation sample and the main sample. Our objective is to see if agreement between separate measurements of involvement in the same firm is significantly higher than measurements in different firms.

Exhibit A1 outlines the analysis. First, we compute the similarity s_i between each pair (v_i, v_i') of measurements in the validation sample. The quantities v_i and v_i' are vectors of binary variables reflecting the involvement or non-involvement of categories of participants in phases of decision process in company i. Then, we compute an average similarity index:

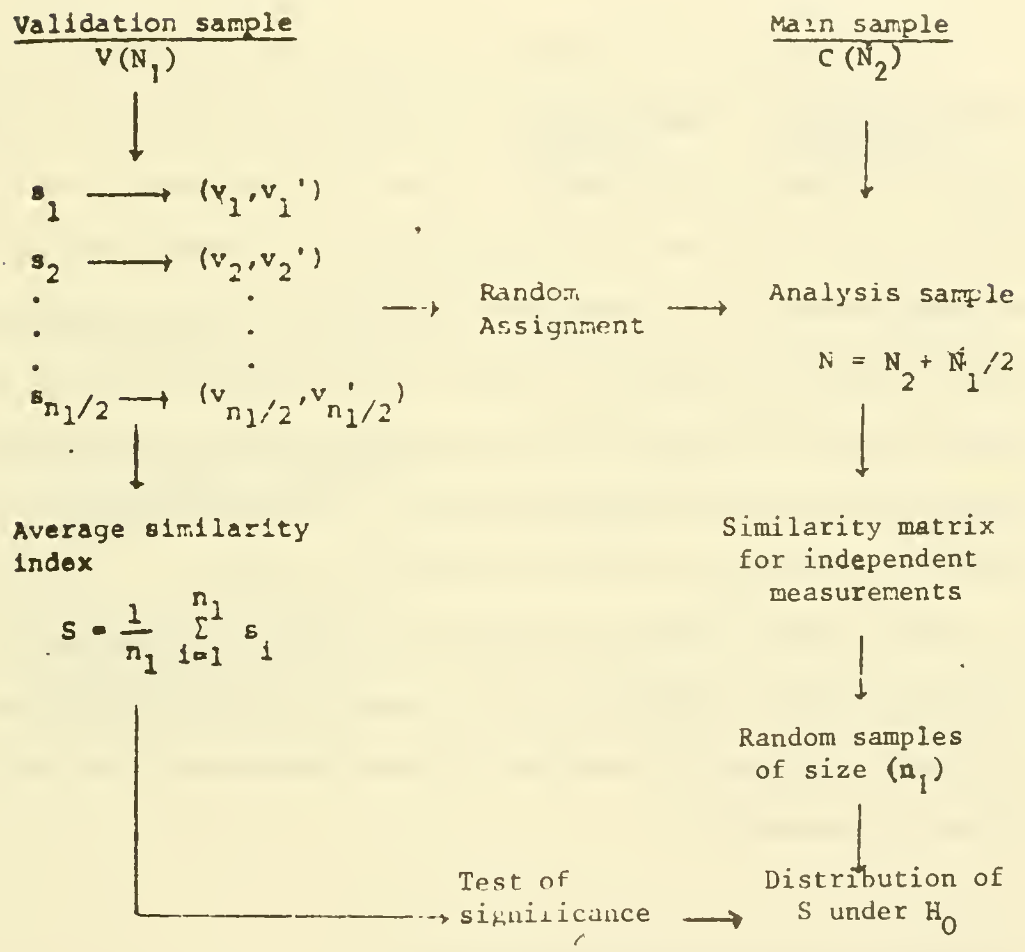
$$S = \frac{1}{n_1} \sum_{i=1}^{n_1} s_i$$

where s_i is the Sokal and Michener *(34)* matching coefficient.

Next, we generate the distribution of the statistic S under the hypothesis of mutually independent measurements. For this purpose, the main sample is augmented by adding one observation chosen randomly from each pair (v_i, v_i') in the validation sample. This augmented

EXHIBIT A1:

Outline of the Simulation Approach to the Validation of The Measurements obtained with the Decision Matrix



sample --called the Analysis Sample-- includes $N = (N_2+N_1/2)$ observations and represents independent measurements because each is from a different firm. The similarity coefficient between all different pairs of observations in the analysis sample is computed. There are $N(N-1)/2$ such similarities from which samples of size N_1 are drawn randomly, with replacement. Each of these samples leads to an estimate of S.

The results of the simulation analysis for the industrial cooling system and the intilligent terminal are reported in Exhibit A2. These results are based on 5000 samples of size N_1 drawn randomly under H_0. They indicate a substantially higher degree of agreement vetween separate measurements in the validation sample than in random samples of the same size generated under H_0. In view of the standard deviation of the distribution of the average similarity index under H_0, and the fact that none of the 5000 samples generated in both studies had an average similarity higher than that in the validation sample, H_0 is rejected at $\alpha < .001$. Hence, separate measurements obtained with the decision matrix in the same organization show a substantially higher degree of convergence than would be expected if these measurements had been obtained independently.

B. Convergent and Discriminant Validation

An important question is whether respondents can discriminate between decision phases in terms of decision-participant involvement. The method used here is a variant of the convergent and discriminant, validation approach proposed by Campbell and Fiske (6).

EXHIBIT A2:

Results of the Simulation Approach to the Validation of the Measurements obtained with the Decision Matrix

	Industrial Cooling System	Intelligent Terminal
Average similarity index in the validation sample	S = .825 (n_1 = 12)	S = .783 (n_1 = 13)
Mean of the distribution of the average index of similarity under H_0	E(S) = .641	E(S) = .652
Standard deviation of the distribution of the average index of similarity under H_0	σ(S) = .035	σ(S) = .037

Exhibit A3 outlines the main steps involved in this approach. First consider each pair of measurements of the type (v_i, v_i') in the validation sample and allocate each of them randomly to two "method" groups. Within each of these groups, we then estimate the average similarity between each pair of different decision phases (monomethod blocks). The Sokal and Michener's coefficient is used for this purpose. Similarly, we compute the average similarity between each pair of decision phases across groups (Heteromethod block). Exhibits A4 and A5 present the results of these computations for the industrial cooling system and the intelligent terminal respectively.

Following the conditions proposed by Campbell and Fiske, it appears that in both studies the values on the validity diagonals (underlined) are consistently higher than the values lying in the corresponding column and row of the heteromethod triangles. For instance, in Exhibit A4, .750 is superior to .533, .541, .646 and .562 as well as to .500, .541, .646, and .583. Hence a higher degree of agreement is observed between separate measurements of the involvement in the same decision phase than between separate measurements of the involvement in two different decision phases.

Moreover, for each decision phase, the value on the validity diagonal is higher than the corresponding values in the monomethod triangles, indicating that there is a higher degree of agreement between separate attempts to measure involvement in a given decision phase than between the estimates of involvement in any two decision phases provided by the same respondent.

EXHIBIT A3:

Convergent and Discriminant Validation of the Measurements obtained with the Decision Matrix

Validation sample

$V = \{(v_i, v_i'): i=1,\ldots n_1\}$

Random assignment

1^{st} "method" group

$\{v_i,\ i=1,\ldots n_1\}$

Within group
average similarities
(Heterodecisionphase-
monomethod block)

2^{d} "method" group

$\{v_i',\ i=1,\ldots n_1\}$

Within group
average similarities
(Heterodecisionphase-
monomethod block)

Across group
average similarities
(Heterodecisionphase-
heteromethod block)

EXHIBIT A4:

Convergent and Discriminant Validation Matrix

(Industrial Cooling System)

		Method Group 1					Method Group 2				
		Ph_1	Ph_2	Ph_3	Ph_4	Ph_5	Ph_1	Ph_2	Ph_3	Ph_4	Ph_5
Method Group 1	Ph_1	—									
	Ph_2	.541	—								
	Ph_3	.604	.541	—							
	Ph_4	.646	.646	.791	—						
	Ph_5	.625	.604	.770	.733	—					
Method Group 2	Ph_1	<u>.750</u>	.583	.541	.646	.562	—				
	Ph_2	.500	<u>.854</u>	.521	.583	.562	.562	—			
	Ph_3	.541	.521	<u>.833</u>	.771	.729	.562	.500	—		
	Ph_4	.646	.562	.729	<u>.812</u>	.729	.708	.583	.791	—	
	Ph_5	.583	.625	.729	.792	<u>.875</u>	.604	.625	.770	.770	—

Ph_j = j^{th} phase in the decision process as distinguished in the decision matrix.

EXHIBIT A5:

Convergent and Discriminant Validation Matrix

(Intelligent Terminal)

		Method Group 1				Method Group 2			
		Ph_1	Ph_2	Ph_3	Ph_4	Ph_1	Ph_2	Ph_3	Ph_4
	Ph_1	—							
	Ph_2	.732	—						
Method	Ph_3	.758	.765	—					
Group 1	Ph_4	.725	.711	.757	—				
	Ph_1	.835	.624	.593	.637	—			
	Ph_2	.677	.774	.690	.756	.688	—		
Method	Ph_3	.659	.765	.769	.759	.714	.719	—	
Group 2	Ph_4	.626	.745	.758	.780	.692	.771	.757	—

ph = jth phase in the decision process as distinguished in the decision matrix.

Note that the relatively high average similarities between decision phases in the monomethod and heteromethod blocks should not be taken as a potential source of invalidation. Rather, they suggest that decision participants who are involved in one phase of the decision process tend to be involved in other phases as well.

In sum, the results of our validation analysis indicate that:

- there is substantial agreement between separate measurements of purchasing involvement obtained with a decision matrix from different individuals in the same company, and that
- the measurements obtained show evidence of discriminant validity across decision phases. This suggests that the matrix allows respondents to discriminate between decision phases in terms of participants' involvement.

APPENDIX 2:

Modification of Decision Matrix Measurements to Account for Reporting Bias

We assume in section 3.2.1. that the decision matrix measurements, $\{x_{ijh}\}$, are reported without bias, even if reported with error. If such is not the case, bias has to be removed prior to selecting a critical value for parameter ε. This is also true if we wish to use the matrix measurements in their original, metric form.

The main source of respondent bias is overstatement of the respondent's own role with the (consequent) understatement of the role of other decision-participants. We need to use the following two assumptions to arrive at a simple solution to the problem :

Assumption 1: (Respondent Independence) On average, the importance of an individual (i.e., x_{ijh}) in the process, given that $x_{ijh} > 0$, should be the same independent of the category of the responding individual.

Assumption 2: (Job-Bias Independence) The degree of personal bias associated with the reporting of importance is, on average, independent of job title.

Following these assumptions we proceed as follows. First, fix h, the column of the decision matrix. The procedure is applied to each column independently and sequentially. Then let x_{ij} be job category j's involvement as specified by a respondent from company i.

Define the following:

$$y_{kj} = \frac{\sum\limits_{i\varepsilon\{k\}} x_{ij}}{\sum\limits_{i\varepsilon\{k\}} \delta_{ij}} , \quad j,k = 1,\ldots J$$

where

$\{k\}$ is the set of all respondents, $i=1\ldots I$, whose participant category is k, $k=1\ldots J$

and $$\delta_{ij} = \begin{cases} 1 & \text{if } x_{ij} > 0 \\ 0 & \text{otherwise} \end{cases}$$

y_{kj} can be interpreted as the average involvement of decision participant category j as seen by members of decision participant category k. We now look for a transformation of $\{y_{kj}\}$, call it $\{a_{kj}\}$, to $\{y_{kj}*\}$. Our ideal, transformed $y_{kj}*$ has, by assumption, the following properties:

(2) $$y^*_{kj} = y^*_{wj} \ \forall\ k,w,j$$

and

$$\sum_j y^*_{kj} = 1 \quad \forall\ k$$

Let:

$$y^*_{kj} = a_{kj}\ y_{kj}$$

Then (2) yields:

(3a) $$a_{kj} y_{kj} = a_{wj} y_{wj} \ \forall\ k,w,j$$

(3b) $$\sum_j a_{kj}\ y_{kj} = 1 \quad \forall\ k$$

Equation 3a represents J^2-J independent equations while equation 3b adds 1 independent equation. (The J-1 other equations are reduced to an equivalent equation by the application of (3a)). Thus we have J^2-J+1 independent equations in J^2 unknowns. Assumption 2 adds the following J-1 conditions:

$$a_{11} = a_{22} = \dots = a_{JJ} \tag{3c}$$

Now, this system will have an interpretable solution for realistic $\{y_{kj}\}$ as long as all $y_{kj} > 0$. Eliminating rows and columns with zero entries (usually job categories of negligible importance in the decision process) will eliminate this problem.

Going back to our original matrix, we can now modify the x_{ij} as follows:

$$x_{ij} = \frac{x_{ij}a_{k(i),j}}{\sum_j x_{ij}a_{k(i),j}} \tag{4}$$

where k(i) refers to the job category that respondent i belongs to. The results of equation 4 is a set of involvements, uncontaminated by respondent bias.

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