Industrial Market Segmentation by the Structure of the Purchasing Process

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This article presents a methodology for segmenting industrial markets on the basis of functional involvement in 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 implications of this segmentation approach for industrial marketing strategy formulation are discussed.

OVERVIEW OF SEGMENTATION

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.

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 concepts of modern marketing (see Wind [39]). It provides a way of making operational 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 problem 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 Guiltiman and Sawyer [16]) a small set of substantial groupings of

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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.

INDUSTRIAL BUYING SEGMENTS

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 markets [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 [31, 36]. 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 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" [24]. What is needed, then, is a methodology that recognizes the complexity of the organizational purchasing decision process, incorporates it in its measurement procedure, and provides criteria for classification of buying organizations.

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 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 (DMUs) or buying centers—do not lend themselves easily to analysis. Therefore, "second choice" bases, such as geographic location of potential customers and size of purchase are used instead.

Wind and Cardozo suggest a two-step approach to segmentation. First, a "macrosegmentation" is performed in order to group firms in the target market that are likely to react differently to a product offering 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 article suggests an approach to the microsegmentation step of the analysis.

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 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

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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 interorganizational variation in the purchasing process without the risk of contamination from differences in product characteristics [20].
- break the decision process into managerially meaningful areas of influence. This improves the reliability of self-reported data [9, 27]. 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 noninvolvement of participants in the purchasing process leads to more reliable results than the measurement of their relative influence [15].

A "decision matrix" is proposed 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. Table 1 gives an outline of a decision matrix. The request for constant-sum information forces respondents to specify only those 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 [5, 30]. A decision matrix is 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 provides a detailed analysis of the convergent and discriminant validity of the measurements provided by this instrument.

TABLE 1
Outline of a decision matrix

Phase Purchasing Decision Process / Decision Participant Categories	Description of Phase 1	. . .	Description of Phase n
Decision Participant Category 1	%	%	%
· · ·	%	%	%
Decision Participant Category m	%	%	%
	100%	100%	100%

Microsegment Formation

The procedure for microsegment formation involves three main steps: First, we define an index of interorganizational similarity in participant involvement. This index can be a correlation coefficient or any of a number of more general similarity measures (see Everitt [12] and Choffray and Lilien [8]). Second, we identify groups of organizations homogenous in the structure of their purchasing decision process. Cluster analytic procedures are used for this purpose. We suggest the use of agglomerative clustering methods. At each stage in the clustering process agglomerative methods form new clusters that minimize some function of intercluster distances. The proximity matrix is then recomputed to express the relationship between the new clusters and the remaining entities. The main difference among agglomerative clustering algorithms is found here: some define intercluster distances that assume only ordinal dissimilarity measures (see for instance Johnson [19]); others assume an underlying metric and algebraically manipulate intercluster distances (see for example Ward [35]. For details on the choice of appropriate cluster algorithms see Choffray and Lilien [8]. Third, each microsegment should be described in terms of the pattern of involvement in the purchasing process categories of individuals most likely to be participants in various decision stages are identified; differences in each group of organizations on the basis of factors external to the firm are also explored.

IMPLEMENTING THE INDUSTRIAL MARKET SEGMENTATION METHODOLOGY

We now review the microsegmentation procedure as applied in the industrial cooling study [22]. After careful definition of the target macrosegment for the product, a series of open-ended interviews are 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 specification of requirements.
2. Preliminary budget approval.
3. Search for alternatives and preparation of a bid list.
4. Equipment and manufacturer evaluation.
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 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

Table 2 outlines the resulting decision matrix. Data were 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

- Overemphasis on the role played in the purchasing process by participants external to the organization (five companies).
- Overemphasis on the rôle played by members of the purchasing department relative to other categories of decision participants (two 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 (three companies).

Then four microsegments were identified. 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?

One 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?

TABLE 2
Decision matrix for the industrial cooling study

	Decision Participants \ Decision Phases	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[a]	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%

[a]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.

Table 3 summarizes the results of the analysis of the number of decision phases each category of participant is involved in. Important differences are registered 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 microsegment 3, production engineers are involved in practically all phases of the decision process. HVAC consultants are also deeply involved suggesting that companies in segment 3 rely heavily on engineers for guidance in the adoption of such products. In microsegment 4, people at the plant level, including production engineers and plant managers tend to exert influence in the largest number of decision phases. 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. Table 4 summarizes the results; important differences are registered across microsegments.

For most decision phases, the number of categories of participants involved is consistently larger in microsegments 1 and 3 than in 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.

TABLE 3
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>	$\alpha < 0.01$
Plant Managers	<u>4.39</u>	0.57	1.57	<u>2.83</u>	$\alpha < 0.01$
Financial Controller	1.13	0.50	0.69	0.50	$\alpha < 0.05$
Purchasing Department Personnel	1.43	0.71	1.79	0.79	$\alpha < 0.01$
Top Management	<u>2.91</u>	<u>3.68</u>	1.45	1.29	$\alpha < 0.01$
HVAC/ Engineering Firm	1.48	<u>2.89</u>	<u>3.30</u>	0.62	$\alpha < 0.01$
Architects and Building Contractors	1.35	2.25	1.64	0.70	$\alpha < 0.05$
A/C Equipment Manufacturer	0.35	0.68	0.36	0.29	n.s.

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

TABLE 4
Average number of participants categories involved in each phase of the adoption process

	Micro-segment 1	Micro-segment 2	Micro-segment 3	Micro-segment 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.s.
Preliminary Budget Approval	2.52	2.11	<u>3.45</u>	<u>2.71</u>	$\alpha < 0.01$
Search for Alternatives	2.69	2.46	2.69	2.08	n.s.
Evaluation	3.04	<u>2.75</u>	2.91	2.12	$\alpha < 0.10$
Selection	<u>3.13</u>	2.46	2.72	2.04	$\alpha < 0.01$

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.

Table 5 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.

TABLE 5
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

Two discriminant functions were retained in this analysis. Table 6 gives the standardized discriminant coefficients for each of these functions. No statistical 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.

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 ($C_{pro} = 27\%$). However, it is likely that the percentage is biased due to the use of the total sample to estimate the discriminant functions [26]. Although the results are exploratory, they point to some interesting relationships between microsegment membership and company characteristics. To illustrate, Fig. 1 gives the microsegments' centroids in the reduced discriminant space.

TABLE 6
Standardized discriminant function coefficients

Variable	Function 1	Function 2
x_1	−0.43	−0.05
x_2	0.01	0.23
x_3	−0.01	0.37
x_4	0.39	0.04
x_5	0.27	0.01
x_6	0.04	0.76
Wilks Λ	0.625	0.811
χ^2	53[a]	26[a]
(d.f.)	(41)	(21)

[a]Prob value 0.10
[b]Prob value 0.25

Companies in microsegment 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 microsegments 2 and 3 use their own engineering capabilities for these same tasks.

The comparison between microsegments 1 and 3 is interesting as they do not substantially differ in terms of size of company. However, our analysis suggests that companies in microsegment 3 tend to have more plants, larger cooling needs, and greater concern for the reliability of industrial air-conditioning systems than those in 1. It is therefore not surprising to note that companies in microsegment 3 rely mainly on engineering functions in the process of purchasing an industrial cooling system, while companies in microsegment 1 involve mainly managerial functions. Microsegment 2 groups large companies with a small number of plants. These companies

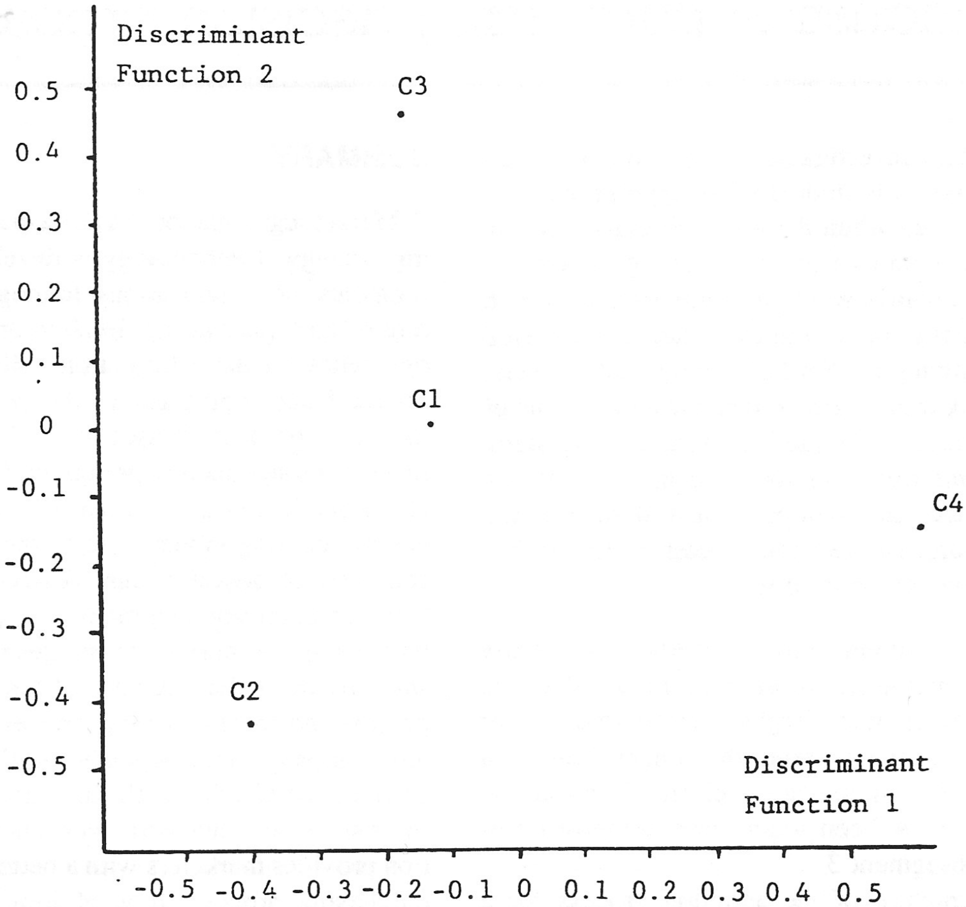


FIGURE 1. **Microsegments' centroids in reduced discriminant space.**

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.

STRATEGY IMPLICATIONS

The procedure developed here isolates homogeneous sets of organizations and describes the decision-making 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 in the 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.

The microsegmentation procedure provides an 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.

procedure provides an understanding of the industrial purchasing decision process

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 a real-life situation involving industrial cooling systems led to the identification of four segments of organizations. Analysis of the relationship between microsegment 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 relation to the decisions being made—could be studied. As Webster and Wind note, "There are rich research opportunities in defining the influence of different members of the buying center at various stages of the process" [36].

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 [2, 6]. Suppose that several decision participants in the same organization filled out the decision matrix separately. The extent of 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 whether 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:

$V = (v_i, v_i'), i = 1, \ldots N_1$, denotes the subsample of N_1 companies for which two measurement's (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.

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.

Table 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 noninvolvement 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 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

TABLE A1
Outline of the simulation approach to the validation of the measurements obtained with the decision matrix

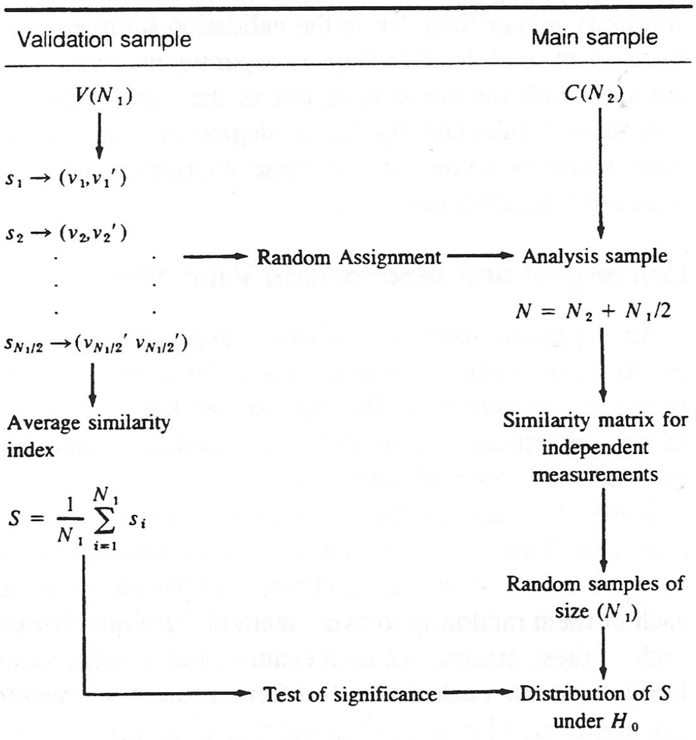
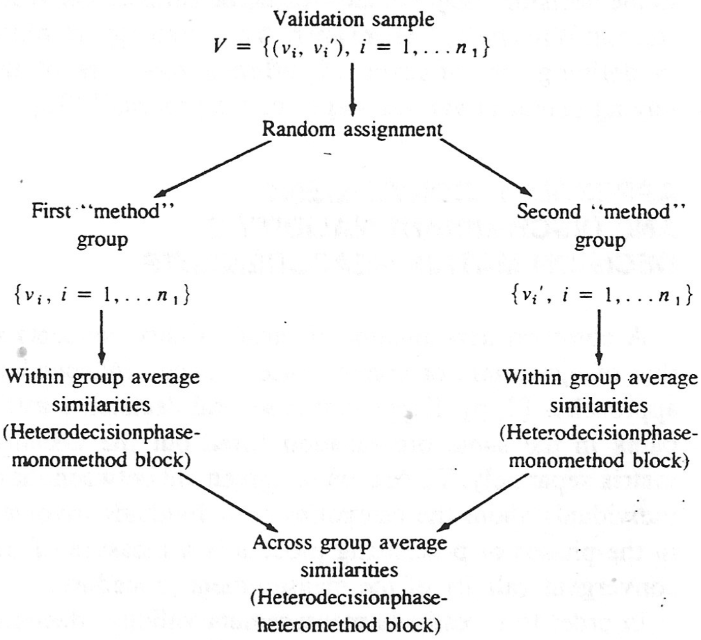


TABLE A2
Results of the simulation approach to the validation of the measurements obtained with the decision matrix

	Industrial Cooling System	Intelligent Terminal
Average similarity index in the validation sample	$S = 0.825$ ($N_1 = 12$)	$S = 0.783$ ($N_1 = 13$)
Mean of the distribution of the average index of similarity under H_0	$E(S) = 0.641$	$E(S) = 0.652$
Standard deviation of the distribution of the average index of similarity under H_0	$\sigma(S) = 0.035$	$\sigma(S) = 0.037$

TABLE A3
Convergent and discriminant validation of the measurements obtained with the decision matrix



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 intelligent terminal are reported in Table 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 between 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 $\alpha < 0.001$. Hence, separate measurements obtained with the decision matrix in the same organization show a substantially higher degree of convergence than would be expected had these measurements been obtained independently.

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].

Table 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). Tables 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 trianges. For instance, in Table A4, 0.750 is superior to 0.583, 0.541, 0.646, and 0.562, as well as to 0.500, 0.541, 0.646, and 0.583. 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.

Note that the relatively high average similarities be- 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.

TABLE 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	0.541	—								
	Ph_3	0.604	0.541	—							
	Ph_4	0.646	0.646	0.791	—						
	Ph_5	0.625	0.604	0.770	0.733	—					
Method Group 2	Ph_1	0.750	0.583	0.541	0.646	0.562	—				
	Ph_2	0.500	0.854	0.521	0.583	0.562	0.562	—			
	Ph_3	0.541	0.521	0.833	0.771	0.729	0.562	0.500	—		
	Ph_4	0.646	0.562	0.729	0.812	0.729	0.708	0.583	0.791	—	
	Ph_5	0.583	0.625	0.729	0.792	0.875	0.604	0.625	0.770	0.770	—

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

TABLE 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
Method Group 1	Ph_1	—							
	Ph_2	0.732	—						
	Ph_3	0.758	0.765	—					
	Ph_4	0.725	0.711	0.757	—				
Method Group 2	Ph_1	0.835	0.624	0.593	0.637	—			
	Ph_2	0.677	0.774	0.690	0.756	0.688	—		
	Ph_3	0.659	0.765	0.769	0.759	0.714	0.719	—	
	Ph_4	0.626	0.745	0.758	0.780	0.692	0.771	0.757	—

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

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

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.

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