A METHODOLOGY FOR INVESTIGATING THE NATURE OF THE INDUSTRIAL ADOPTION PROCESS AND THE DIFFERENCES IN PERCEPTIONS AND EVALUATION CRITERIA AMONG DECISION PARTICIPANTS

BY

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ABSTRACT

The objective of this research is to propose, test and illustrate methodology to investigate more systematically some important dimensions of the industrial adoption process.

First, methods are proposed to investigate the extent and nature of perceptual differences, as well as differences in evaluation criteria between several categories of decision participants (e.g., production engineers, plant managers, etc.) likely to become involved in the adoption of an industrial product. The methodology builds upon the latest approaches used in marketing research. It logically links several methods of multivariate data analysis and provides objective criteria to investigate the process of perception and evaluation of industrial product alternatives. A new, formal test to assess the similarity between factor analytic solutions obtained with the same set of perceptual scales from different groups of individuals is developed. This test is used to assess whether decision participants differ in the way they combine attributes of industrial products into higher-order evaluation criteria.

Implementation of the methodology for a new industrial cooling system powered by solar energy indicates that:

- there are definite perceptual differences across categories of decision participants likely to become involved in the adoption of an industrial cooling system,

- substantial differences also exist between these same groups in the way they structure industrial cooling systems attributes into higher-order evaluation criteria,

- consideration of these differences is necessary for understanding how individual decision participants form preferences for industrial cooling alternatives.

Second, methods are proposed to segment the potential market for an industrial product into subsets of firms homogeneous in the structure of their adoption process, that is, in the pattern of involvement of different categories of decision participants in the major phases of this process. A more constraining version of the decision matrix commonly used in industrial marketing research is proposed to collect information about each firm's adoption process. The convergent validity of the measurements obtained by this method from different individuals in the same firm is formally assessed. Methodology is then proposed to identify segments of potential customer firms homogeneous in the structure of their adoption process. The methodology logically combines several methods of cluster analysis and provides solutions to the problems of a) determination of the number of segments to be retained, b) non-randomness of these segments, and c) stability of their composition.

Implementation of this new method of industrial market segmentation for the solar cooling system leads to the identification of four segments of organizations which exhibit substantial similarity in the structure of their adoption process. The analysis of the characteristics of these segments indicates that:

- important differences in the structure of the adoption process exist between these segments, which were not initially observable from an analysis of the aggregate frequencies of involvement of the different categories of decision participants in the various phases of the adoption process, and that

- traditional bases of industrial market segmentation inadequately describe the new segments.

Finally, the results of our research are put into perspective and their managerial relevance is assessed. The general structure of a model to assess industrial market response to marketing strategy which incorporates the results of this research is described and promising areas for future work are discussed.

Thesis Supervisor: Gary L. Lilien
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et

Jean-Christophe

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CHAPTER 1: UNDERSTANDING THE ADOPTION PROCESS FOR NEW INDUSTRIAL PRODUCTS: PROBLEMS AND PROSPECTS.

1.1. Purpose of the Dissertation

The aim of this research is to develop, test and illustrate methodology for systematically investigating the industrial adoption process. As pointed out in the literature this area of research needs better measurement tools and methods of analysis which address the multiperson nature of industrial adoption decisions. (Webster [134], Choffray and Lilien [21]).

Two problems are addressed in this research:

- the development of methodology based on sound, objective criteria to assess perceptual differences as well as differences in product evaluation criteria between several categories of decision participants likely to become involved in the adoption of a new industrial product, and the investigation of the relevance of these differences in the formation of individual preferences ;

- the development of better measurement tools for assessing the structure of the industrial adoption process -- that is, the identification of those categories of individuals in potential customers' organizations that are likely to become involved in the adoption of a new industrial product -- and the development of methodology to segment industrial markets on that basis.

From a marketing research and managerial viewpoint, these two questions are closely interrelated. Indeed, the existence of differences among decision participants in the way they perceive and evaluate a new product alternative would be of limited use in the formulation of an industrial marketing strategy if no reasonably accurate method existed a) to identify what individuals are most likely to become involved in the decision process in potential customers' organizations and b) to group these organizations into segments of firms homogeneous in the structure of their adoption process. On the other hand, the usefulness of any measurement tool for assessing involvement in the industrial adoption process depends on the existence of managerially meaningful differences among decision participants.

The next sections will show why these two questions are critical to new industrial products' managers. First, we discuss the main problems associated with the introduction of new products in industrial markets and identify the reasons why many of them are commercially unsuccessful. Next, we review and critically appraise the existing literature about the adoption of new industrial products. An attempt is made to systematize this body of knowledge into a conceptual model of the industrial adoption process that elicits areas where additional research is most needed. Finally, an outline of the main chapters of the dissertation is presented.

1.2. New Products in Industrial Markets.

The future of an industrial company is closely linked to its ability to develop and successfully market new products. Few industrial firms can risk standing by a current product line for many years without contemplating product changes in response to a rapidly developing technological environment. Highly sophisticated industrial products are most prone to technological obsolescence. The only way for an industrial company to stay competitive is through its active participation in the development of the latest technologies, and through their implementation in a continuous process of improvement and renewal of its product line, leading to increased satisfaction of customer needs.

Industrial markets represent an important part of the economic activity in the United States. Rippe et al [104] estimated the total volume of goods sold for further processing in 1963 at $ 552 billion, compared to $ 375 billion for final sales at producers' prices to consumers. It is also projected that by 1980 the total value of transactions among business firms will equal the Gross National Product of the United States (Scientific American [110]).

Despite the importance of industrial markets, few researchers have systematically analyzed industrial buying behavior. This situation is specially alarming in view of the prohibitive costs

and high rate of failure associated with the development and commercialization of new industrial products.

1.2.1. New Products as a Source of Industrial Growth.

New products account for a significant part of the sales volume of industrial companies. A study by the National Industrial Conference Board [78] indicates that for the majority of industrial companies, more than one fourth of current sales is attributable to products introduced within the past five years. In that same study, it was also found that for many industrial companies, new products generate more than fifty percent of the current sales level.

New industrial products are also an important source of company growth. For instance, companies that relied heavily on new products during the period 1945 - 1965 experienced an average growth rate substantially higher than the Gross National Product of the United States (De Simone [33]). The importance of new products as a determinant of sales and company growth is also evidenced in a well known study by Booz, Allen and Hamilton [9]. We have reproduced in figure 1.1. their estimates of the expected contribution of new products to the sales volume in different industrial sectors.

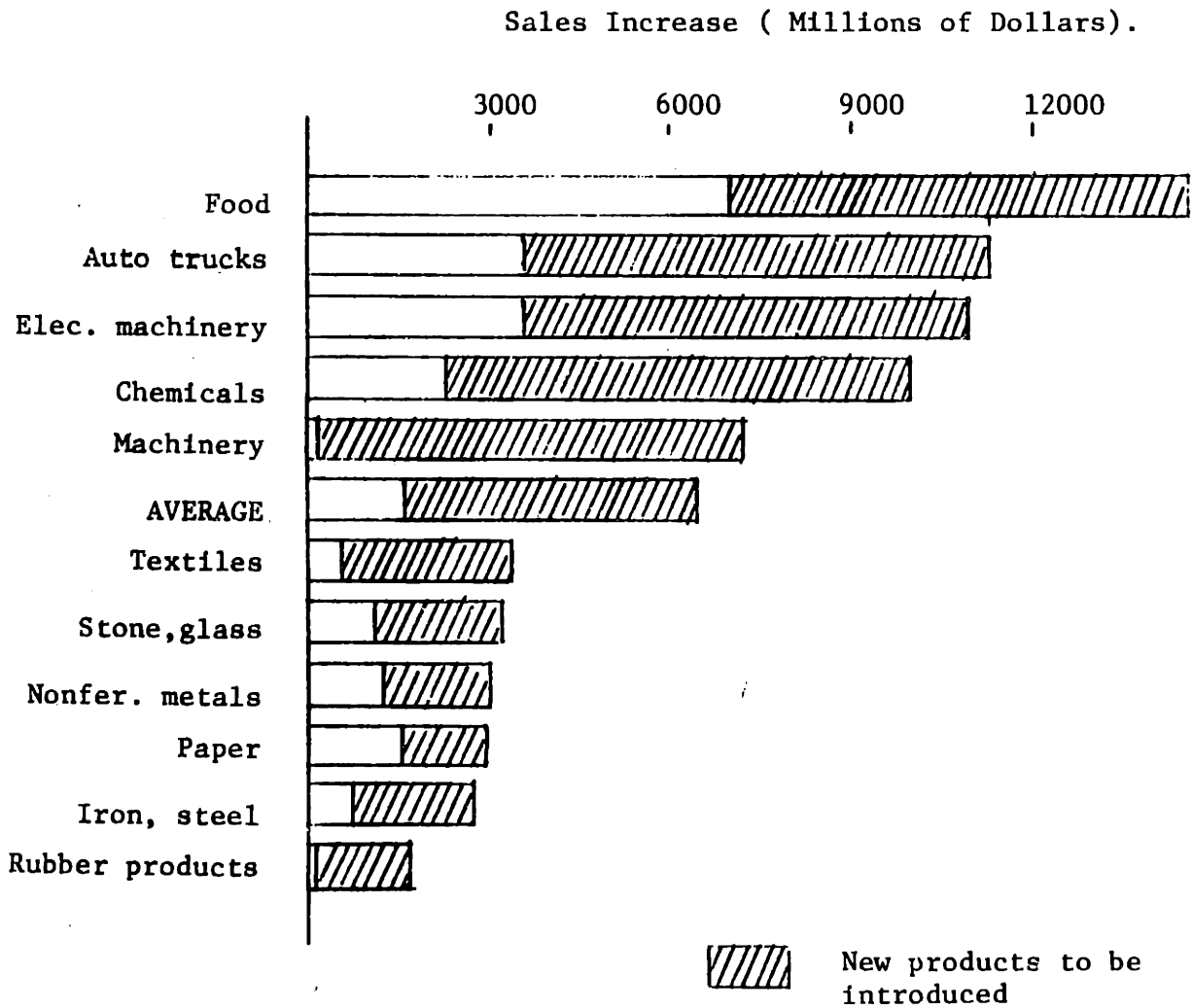


FIGURE 1.1: CONTRIBUTION OF NEW PRODUCTS TO EXPECTED SALES GROWTH

Source : Booz Allen and Hamilton [9]

1.2.2. Risks Associated with New Industrial Products.

New products are not always commercially successful of course. For the industry as a whole, out of three technically successful products that emerge from R & D departments only one is likely to become a commercial success. In terms of expenditures, more than seventy percent of all money spent on new product activities is spent on products that are not commercial successes. These rates differ surprisingly little between industries (Booz, Allen and Hamilton [9]).

A study by Mansfield and Wagner [85] recently investigated the success probabilities of new industrial products at different stages in their development cycle. Figure 1.2. summarizes their results and compares them to those of Booz, Allen and Hamilton [9]. By and large, the results obtained in these two studies show considerable agreement. The slight difference observed in figure 1.2.C. could will be explained by differences in sample sizes and in the definition of commercial success.

1.2.3. Cost of New Industrial Products.

New industrial products are not only risky. Their development and introduction in the market may, in addition, require substantial financial resources. A recent analysis of 38

	Rate of Commercial Success for Product Development Projects	Rate of Commercial Success for New Products Introduced
Chemical	. 18	. 59
Electrical Machinery	. 13	. 63
Metal Fabricators	. 11	. 71
Non Electrical Machinery	. 21	. 59
Raw Material Processors	. 14	. 59
AVERAGE	. 15	. 62

Figure 1.2.a. Rates of Commercial success for New Industrial Product Projects
Source : Booz, Allen and Hamilton [9].

	Probability of Technical Completion (TC)	Probability of Commercialization (C) given TC	Probability of Economic success (ES) given C.
AVERAGE	. 57	. 65	. 74

Figure 1.2.b. Probabilities of Technical Completion, Commercialization and Economic Success of New Industrial Products
Source : Mansfield and Wagner [85].

	Rate of Commercial Success for Product Development Projects	Rate of Commercial Success for New Products Introduced
Booz, Allen and Hamilton [9]	. 15	. 62
Mansfield and Wagner [85]	. 27 (.57x.65x.74)	. 74

Figure 1.2.c. Average Rate of Commercial Success for New Industrial Product Projects.

industrial innovations by Mansfield and Rapoport [84] suggests that the total cost of developing and marketing a new industrial product represents millions of dollars. Losses on this scale, as in the case of a new product failure, could drastically alter a company's future.

An interesting aspect of the Mansfield and Rapoport study is its analysis of the structure of costs associated with the development of new industrial products. Figure 1.3. summarizes this information. These estimates are consistent with those provided by other sources (De Simone [33]).

From figure 1.3. it can be seen that the major component of cost is the development of a prototype plant, new tools and manufacturing facilities, suggesting that both engineering and in depth market studies should be performed before that stage of development is reached.

In sum, it is very risky for an industrial company to restrain from developing new products, as its future may well depend on such products. On the other hand it is also risky and costly to engage in development activities. The solution to this new product dilemma undoubtedly lies in the identification of the causes of new industrial product failures.

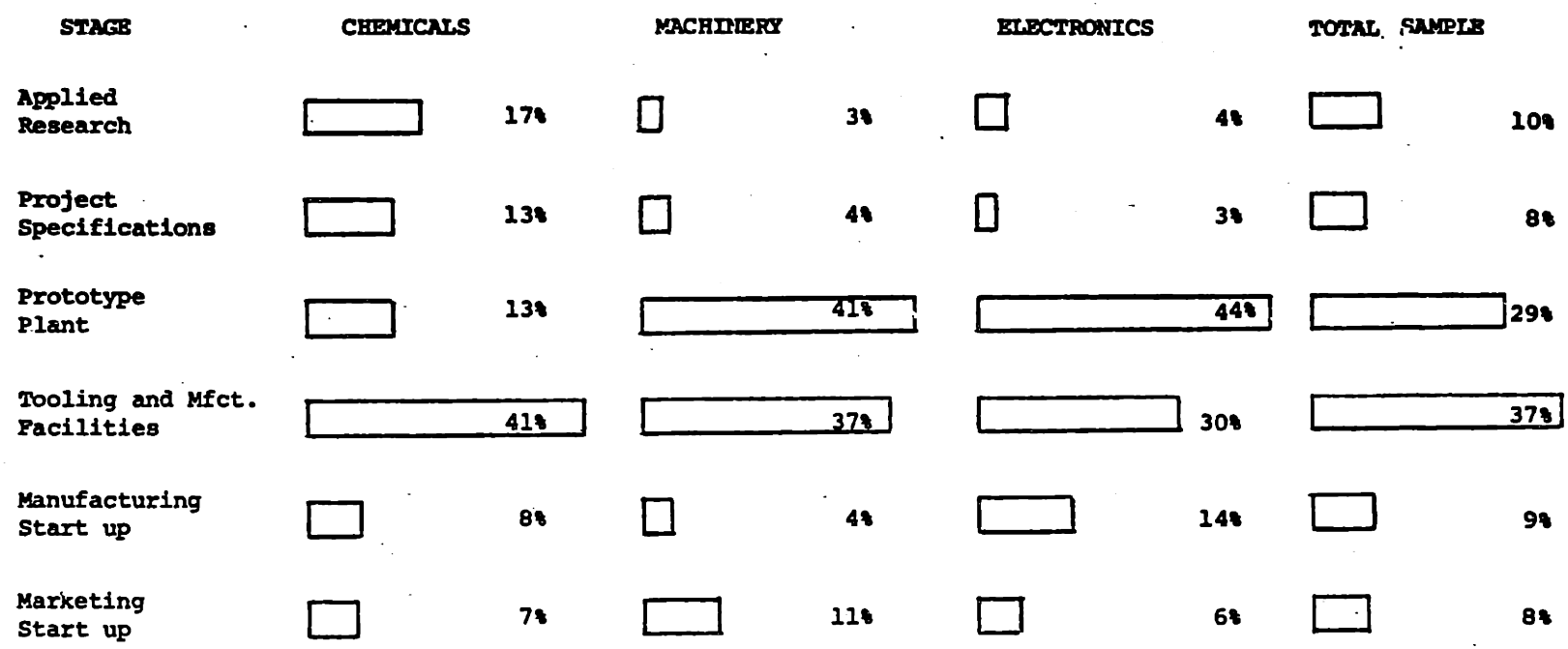


Figure 1.3. : STRUCTURE OF COSTS ASSOCIATED WITH THE DEVELOPMENT OF NEW INDUSTRIAL PRODUCTS.

Source : Mansfield and Rapoport [84].

1.2.4. Reasons for New Industrial Products' Commercial Failures.

Several attempts have made to identify potential causes of new industrial product failures. Briscoe [12] investigated the histories of two new industrial products, from the plastic and the steel industry respectively. Both products emerged successfully from R & D programs only to become total market failures. His analysis points to the following potential causes of new industrial product failures :

- the lack of appreciation for the way in which customers perceive and evaluate the new product.
- the misassessment of the firm's existing stock of resources, especially its marketing skills.
- the lack of specific objectives for the new product in terms of its target market and place in the company's product mix.

Rather than single out any of these factors as the main cause of commercial failure for the two new products that he studied, Briscoe emphasizes the complementarity and interaction between these factors.

A systematic investigation of the differences between successful and unsuccessful industrial innovations was performed in project

SAPPHO [108]. The methodology involved the comparison of pairs of new industrial products competing in the same market with substantially different commercial results.

Five main areas of difference between successful and unsuccessful industrial innovations were discovered. Companies with successfully marketed innovations were marked by :

1. a better understanding of user needs which reduced the expected number of future product modifications

2. a heavier reliance on marketing activities, specially advertising and services such as customers' training.

3. a more efficient product development process which reduced the number of flaws discovered in the production stage.

4. a greater openness to ideas stemming from the scientific community.

5. higher levels of management responsible for new product development.

Cooper [26] recently published the results of a cross-sectional study of new industrial product failures. His results indicate that by far the most important cause of commercial failure, as perceived by management, is of a marketing nature rather than

of a technical nature. Specifically, a lack of understanding of the market place, including competitive forces and customers' needs, was considered of primary importance. A lack of marketing research skills was also perceived as a main cause for commercial failures.

Mansfield and Wagner [85] recently performed an econometric analysis to identify the main variables affecting the probabilities of technical completion, commercialization and economic success of new industrial products. Their model included as predictor variables :

- the speed with which the economic potential of the new product is evaluated,
- the percentage of projects that are "demand pull" as opposed to "technology push", and
- the percentage of projects stemming from R & D departments, as opposed to other sources in the company.

Their results indicate that all three probabilities are positively associated with an early evaluation of the new product's economic potential. Moreover, the percentage of "demand pull" projects is positively related to the probabilities of technical completion and commercialization. The probability of technical

completion, however, is negatively related to the percentage of projects stemming from R & D departments, indicating that projects initiated by these departments tend to be more ambitious, and so less likely to reach technical completion.

The Mansfield and Wagner study also investigated the effect of the degree of integration of R & D and marketing activities, and the degree of formalism of the project selection system on the three probabilities of success. The results indicate that a closer integration of marketing and R & D activities increases the probability of success at all three levels. A more formal project selection system also increases the probability of commercialization, but reduces the probability of economic success. A possible explanation is that the use of tight control systems tends to eliminate risky projects whose potential payoffs are very large.

The results reported by these four studies show considerable consistency. They indicate clearly that more emphasis on industrial marketing activities aimed at understanding the needs and purchasing behavior of organizations as well as a closer integration of market research and engineering activities are likely to reduce the risks inherent in the introduction of new industrial products. The high rate of failure of new industrial products is undoubtedly linked to the policy of many industrial companies of selling the product of their R & D departments rather than satisfy their customers' needs (Levitt [74]).

Recent research by von Hippel [129], [130] on the locus of the innovation process in industrial markets indicates that many commercially successful new industrial products are initially developed by would-be customers who, at their own initiative, communicate the new product idea to manufacturers. In these cases, the manufacturer's role in the innovation process is limited to some additional product engineering work on the user's prototype, the improvement of its reliability, ease of operation etc..., and the production and marketing of the final product.

Independent of the source of an industrial product idea -- internal R&D or customer originated -- full-scale production and commercialization of the new product requires a careful assessment of its market potential. Unfortunately, we are severely limited in this task by our ability to understand and model the purchasing behavior of organizations. As Webster [134] writes: "Nowhere can the need for a more complete understanding of industrial buying be better seen that in the decision to introduce a new product or service".

1.3. The Industrial Adoption Process: What do we know ?

Researchers from several disciplines -- including economics, sociology and marketing -- have investigated the industrial adoption

process. Without disparaging their work, our review of the literature has left us with the impression that :

- not a great deal is known about the industrial adoption process,

- there is a great disparity between research hypotheses and empirical evidence. Many assertions have been made about industrial buying behavior, but few have been investigated in the light of empirical data.

Our review of the literature in this section is purposely selective. It emphasizes those aspects that best illustrate our current knowledge about the industrial adoption process. Interested readers are refered to Zaltman et al [147] for a literature review with special emphasis on the behavioral aspects of the process, and to Baker [5] and Kennedy and Thirlwall [66] for a review of the economists' contribution.

Traditionally we distinguish two main streams of research on the adoption of new industrial products. The first one, called Adoption Research, follows the economics approach and deals mainly with an organization's final choice, that is , its adoption or rejection of a new product or technology. The second stream of research, called Industrial Buying Behavior, is concerned

more with the behavioral aspects of industrial buying and emphasizes the process that leads to an organization's final choice.

1.3.1. Adoption Research.

Research on the adoption and diffusion of innovations began in anthropology and sociology. (See Rogers [106] for a review). According to the classical model of adoption and diffusion of new products and ideas, four elements affect the process of diffusion :

- the innovation, which is
- communicated through certain channels
- over time
- among members of a social system (Rogers and Shoemaker [107]).

The model relates the rate of adoption and diffusion of new products to their characteristics as perceived by the relevant units of adoption. These units of adoption may be grouped on the basis of their "innovativeness", that is the speed with which they adopt new ideas.

Traditionally, adoption research has centered upon the diffusion of technical innovations with relatively short payoffs and for which individuals, rather than groups, are the most likely unit of adoption (Rogers [106], Baldridge and Burnham [6]).

Few attempts have been made to apply the concepts and models proposed in adoption research to industrial markets. A notable exception is the work by Mansfield [82] [83], O'Neal et al [95], Peters and Van Katesan [101], Ozanne and Churchill [96] and Cziepel [30].

Mansfield is undoubtedly the most prolific researcher on the adoption and diffusion of industrial innovations. He has synthesized the findings of years of research in two books [82],[83] which represent the state-of-the-art in this field.

Mansfield studied the speed with which industrial firms respond to new techniques. Specifically, he investigated fourteen innovations in four industries : bitumious coal, iron and steel, brewing and railroads. The speed with which a particular firm begins using a new technique appears to be directly related to its size and the expected return on its investment in the technique (measured by various surrogates). The coefficient of the expected return variable is not generally significant, however, and shows considerable variation across innovations. A number of other variables were also entered in Mansfield's analysis including the firm's growth rate, profitability, liquidity and the age of its president, but no statistically significant relationship was found.

As pointed out by Kennedy and Thirwall [66], not all case

studies conclude that the largest firms are quickest in adopting new techniques. Other factors also affect the speed of adoption including the market structure, the cost of the innovation and the firm's ability to tolerate risk (Webster [134]).

Mansfield also investigated the rate of diffusion of innovations both within an industry and within individual firms. In the first case, he analyzed twelve innovations in the four industries mentioned above and tested the hypothesis that the rate of diffusion from firm to firm is a function of a) expected profitability, b) size of investment, and c) the proportion of firms that have already introduced the innovation. A positive association was found between the rate of diffusion and variables a) and c), and a negative association was found with variable b). Unfortunately, a recent analysis by Gold et al [40] casts serious doubts about the accuracy of the measure of diffusion used by Mansfield.

In the case of intra-firm diffusion of technological innovations, Mansfield investigated the adoption of diesel locomotives by railroads. His results indicate that the intra-firm rate of diffusion is related to the expected profitability of the investment, the firm's liquidity, the size of the investment required, and the length of time the firm takes to adopt the innovation relative to other firms in the industry.

Ozanne and Churchill [96] and Peters and Vankatesan [101] investigated the relationship between the adoption of new industrial products and some characteristics of the adopting firms and of their decision makers. Ozanne and Churchill analyzed the adoption of a new automatic machine tool by a small sample of midwestern industrial firms. Their results are mainly exploratory. No statistically significant relationships were discovered between the characteristics of the industrial adoption process (such as its duration, the number of alternative considered, etc...) and the set of exploratory variables (including various characteristics of the firms and their decision makers).

Peters and Vankatesan [101] analyzed the adoption of a new small computer . They investigated the characteristics of the firm and the decision maker that were associated with an adoption decision. Their results suggest that firm size and prior ownership of tabulating equipment are positively related to the adoption of the new product. Some personal characteristics of the decision maker, including his educational background, previous experience, and professional affiliations were also significantly related to the decision's outcome.

Czepiel [30] investigated the relationship between firm and decision participants characteristics and the speed of adoption of an industrial innovation. The study, based on the diffusion

of continuous casting in the american steel industry, found that the number of participants in the decision process was significantly fewer in early adopting firms. In addition, the participants had more experience with similar innovations. The age of the firm and its structure of organization, but not its size, were also found to affect its speed of response.

Finally, O'Neal et al [95] investigated the adoption of industrial innovations within the framework of a business game. The major factors associated with the adoption of innovations included : the relative advantage of the innovation, its compatibility with present facilities and the availability of information concerning its cost. The firm's competitive environment and its size were not related to its adoption decision.

1.3.2. Evaluation of Adoption Research.

The results reported above suggest the state of confusion that characterizes research on the adoption of industrial innovations. First, available studies cover a heterogeneous set of new industrial products and technologies whose adoption could involve considerably different processes. Second, these studies involve different research designs, ranging from cross-sectional analyses to experimental gaming, which could also account for an important part of the observed differences in their results.

A limitation of these studies is their focus on innovations which were eventually successful. A careful assessment of the variables associated with the adoption and diffusion of industrial innovations would appear to require a study of unsuccessful innovations as well. If not, a sensible discrimination cannot be performed, and no inference can be made about the future adoption of a new industrial product or technology.

The most important limitation of these studies, however, is their reliance on ex-post data to infer primary determinants of industrial adoption decisions. The data used often represent recollections, estimates and guesses subject to substantial margins of error (Gol et al [40]). Moreover, ex-post designs preclude the inclusion in the analysis of important variables such as management perceptions and attitudes toward the new product which are likely to have an important impact on its adoption (Rogers and Shoemaker [107]).

1.3.3. Industrial Buying Behavior Research.

Contrary to adoption research, industrial buying behavior research has a micro-analytic orientation. Its objective is not to account for the firm's final choice, but rather to dissect and understand the decision process that led to the choice.

1.3.3.1. Nature of the Organizational Adoption Process.

The organizational adoption process differs from the consumer adoption process in many respects. First, organizational buying decisions usually involve several people who have different responsibilities in the organization and who play different roles in the buying process. Second, the organizational adoption process can be disaggregated into phases more easily than the consumer adoption process because specific individuals, with different job responsibilities, are usually associated with each decision stage. Finally, organizational decisions typically take longer to make. Consequently, there tend to be significant lags between the application of a marketing strategy and the buying response (see Webster and Wind [136]).

Several conceptual models of industrial buying have been proposed in the literature (see Webster and Wind [136] for a review). Here, we discuss three models known for their comprehensive view of organizational buying.

1.3.3.2. The Robinson and Faris Model.

This model, also known as the "Buygrid" model, is the result of a systematic investigation of thousands of individual buying situations in three large manufacturing companies (Robinson and Faris [105]).

The model identifies eight basic phases in industrial buying whose duration and relative importance depend on the specific buying situation at hand. Hence, the model focuses on the entire decision-making process rather than on one of its specific elements.

Three classes of buying situations are distinguished. They are called "New Task", "Modified Rebuy", and "Straight Rebuy". These situations are found to differ in terms of the newness of the purchasing problem, the amount and kind of information required as the decision process develops, and the extent to which new alternatives are considered.

In New Task situations, the purchasing problem has never before arisen. Decision makers have no relevant past experience upon which to draw. They need a large amount of information and have to consider new alternatives. The adoption of new industrial products usually falls in this category.

The Straight Rebuy situation originates from a requirement for which continuity of supply is a major consideration. Purchases that fall in this category are generally handled routinely by members of the purchasing department. Much relevant experience is available from similar situations so that decision makers' need for information is limited. No new alternatives are considered. Suppliers are chosen from a list of "acceptable" sources that has

been developed either formally or informally on the basis of past experience.

The Modified Rebuy situation arises from internal changes in buying influences, or from a search for cost reduction or quality improvement. This situation is characterized by the availability of past experience from similar purchases, but this time new alternatives and sources of supply are considered.

Assuming that an industrial marketer can identify those of his actual and potential customers that fall in each of these three buying situations, different marketing strategies can be developed, taking the specific information needs of these segments into account (Faris [36]).

1.3.3.3. The Webster and Wind Model.

The fundamental assertion of the conceptual model developed by Webster and Wind [135], [136], is that organizational buying is a decision-making process carried out by individuals in interaction with other people in the context of a formal organization. The organization, in turn, is influenced by a variety of forces in its environment.

Each of these broad classes of variables is further subdivided according to their specific relation to the buying problem at hand.

"Task variables" are directly associated with the solution to the organizational buying problem. "Nontask" variables extend beyond this problem. An example of a task variable at the individual level is the desire of a buyer to obtain the lowest price on the market for the product to be purchased. A nontask variable would be an attempt by the purchasing staff to choose a supplier favored by senior management.

The Webster and Wind model emphasizes the importance of environmental forces as determinants of organizational purchasing behavior. These factors define which goods and services are available at a given time, the general economic conditions of growth and employment in which organizations operate, and the framework within which interorganizational exchanges of goods and services take place. Thus, the environment acts both a source of information and as a source of constraints affecting organizational buying.

The second source of influence on organizarional buying behavior is the organization itself. Members of the buying center - which consists of all individuals and groups who participate in the purchase decision-making process - are motivated and directed by organizational goals and constrained by the financial, technological and human resources of their firms. Moreover, the organizational structure, as characterized by its subsystems of communication,

authority, status, reward and work flow, influences the decision making behavior of members of the buying center.

The third major source of influence distinguished by the model is the network of interpersonal relationships among organizational actors and more specially among members of the buying center. These individuals often have different responsibilities and may play different roles. To understand the nature of their interaction in the decision process, one must identify each individual's "role set" as characterized by his expectations, actual behavior, and relationships with other members of the buying center.

Organizational buying behavior, however, finally reduces to individual behavior. In Webster and Wind's model the individual is at the center of the buying process. Individuals are the targets of the industrial marketer's strategy, not an abstract organization. As a result, the model emphasizes the need to identify the psychological characteristics of members of the buying center, to study their attitudes and preferences toward particular products and suppliers, and to understand the nature of their individual decision processes.

1.3.3.4. The Sheth Model

Sheth's model [115] of industrial buying behavior attempts to

describe all types of industrial buying decisions.
It is similar to the Howard and Sheth model of buyer behavior [115] in both its format and system of variable classification. It includes, however, fewer variables and explicitly describes the joint decision-making process that characterizes many industrial buying situations, including the adoption of new industrial products.

First, the model recognizes the existence of differences between decision participants in their expectations about suppliers and brands. These individuals, who have different responsibilities in the organization, tend to consider different criteria in their evaluation of available alternatives. For instance, product users look for prompt delivery and proper installation, purchasing agents look for maximum price advantage, and engineers look for excellence in quality pretesting and standardization of the product. As specified in the Sheth model the most important determinants of differential perceptions and expectations are the educational background and task orientation of the decision participants, their specific sources of information, and their personal satisfaction with past purchases.

The second aspect of the model concentrates on the conditions which precipitate joint decision-making among the individuals involved in the decision process. The model distinguishes several factors which are either product specific, such as the repetitive

character of the purchase, or company specific, such as its size, and managerial philosophy.

Finally, the Sheth model characterizes the process of joint decision-making in industrial purchasing. It describes the various kinds of inter-party conflicts that may occur in such situations and suggests possible methods of resolution.

In sum, the Sheth model represents an attempt to apply some of the most important concepts developed in the theory of organizational behavior (March and Simon [36]) to the industrial purchasing situation.

1.3.3.5. Empirical Studies of Organizational buying Behavior.

A number of empirical studies dealing with specific aspects of organizational buying behavior have appeared in the literature. These studies are mainly of three types : observations of organizational buying behavior in specific purchase situations, analyses of the aggregate frequencies of involvement of different organizational functions in the purchasing process, and studies of the behavior and decision style of decision participants.

One of the most extensive observational studies of organizational buying behavior is that by Cyert, Simon and Trow [29]. They investigated a firm's purchase of a computer as the decision actually

evolved. Their analysis points to the incremental nature of purchasing decisions and to the complexity of information seeking and product evaluation activities. Several other analyses of industrial purchasing decisions over time are also reported by Brand [11].

The frequency of involvement of different organizational functions in the purchasing decision process has also been investigated (Harding [53], Scientific American [110], Buckner [14], Stevens and Grant [121]). These studies typically involve a survey of a large cross-section of industrial firms, from which aggregate frequencies of involvement are computed on an industry or product category basis. No attempt is made to group and systematically investigate the characteristics of organizations that have similar patterns of involvement in their decision process.

Several studies have also investigated the behavior of individual decision participants. They have concentrated mainly on buyers' product evaluation strategy and choice behavior. For instance, Lehman and O'Shaughnessy [72] have found significant differences in the relative importance of several evaluation criteria, both among industrial buyers and across categories of product purchased. Parket [97] [98], has investigated the effect of the perceived similarity between available alternatives on industrial buyers' behavior.

Recent analyses of the industrial buyers' decision process, however, have been more concerned with understanding risk reduction behavior, identifying general decision-making styles, and modeling the buyers' evaluation process.

Source loyalty has been investigated by Wind [145] who showed its importance in the purchasing decision for industrial components. Cardozo and Cagley [18] analyzed procurement managers' preference for specific bids and bidders that involved different levels of risks. Hakansson and Wootz [48] investigated a similar problem, but in an international environment. The results of these last two studies are quite consistent and indicate that perceived risk affect both the number of bids requested and the way the bids are evaluated. The results did not quite agree, however, on the relative importance of the product's price and quality in purchasing situations involving different levels of risks.

Wilson [143] found evidence of the existence of individual decision-making styles. He distinguishes between a normative style individual who behaves very much according to the expected monetary value maximization principle, and a conservative style individual who strictly avoids risky alternatives. Decision styles were found to be associated with industrial buyers' personality traits such as need for certainty, need for achievement

and level of self-confidence. Different patterns of industrial buyers' risk reducing behavior have also been reported by Sweeney et al [122].

Several attempt have been made to assess the ability of attitude models to explain the way decision participants form preferences for available alternatives. Scott and Bennett [112] report a study of linear attitude models to account for engineers' preference for different brands of widely used resistors. Wildt and Bruno [140] use a linear compensatory model to predict rank preference for capital equipment. Lavin [69] investigates systematically the power of both compensatory and lexicographic models to explain the adoption of data processing equipment. His analysis suggests that even if lexicographic models present a more accurate description of managers' actual decision processes, they are inferior to simple compensatory models in predictive ability. More recently, Scott and Wright [113] analyzed decision participants product evaluation strategy in the case of component parts. Their results suggest that engineers consider more evaluation criteria than purchasing agents when forming preference for products in this class.

1.3.4. Evaluation of Organizational Buying Behavior Research.

The three models of organizational buying reviewed here are a

significant step toward a better understanding of this complex decision process. Unfortunately they raise more questions than they answer.

As noted by Webster and Wind [136], the Buygrid model has little predictive power. Although its distinction of "buying situations" is conceptually useful, much variability in the purchasing process must be expected in each of these broad categories due to product -- and company -- specific factors. Moreover, although the model provides a useful conceptual framework for segmentation of industrial markets, managers do not generally have the necessary information about the buying behavior of their potential customers to perform such a segmentation. Hence, the usefulness of the model is quite limited from the managerial standpoint.

The Webster and Wind model identifies a large number of variables that may potentially affect organizational buying behavior. It is too complex, however, to be quantified and used in the context of an industrial marketing decision system. Moreover, the model rests on many assumptions that have not been tested in an industrial setting.

The Sheth model is a first attempt toward more specificity in the study of industrial buying behavior. The model contains some methodological hints about how certain of its component could be measured. It is still too general, however, and suffers from the

many untested assumptions it makes about specific aspects of industrial buying.

All three models, however, are useful structures for thought and may be used as a primary source for generating research hypotheses. In addition, they provide a framework within which results from empirical studies should be integrated, and their relevance assessed.

In this respect, our review of available empirical studies of organizational buying behavior points to a serious lack of coordination of research in the area. Available studies have covered a broad range of questions, but often very superficially, and have contributed little to the development of a theory of organizational buying behavior.

The main limitation of these studies is of a methodological nature. Usually they rely upon small samples of purchasing agents, whose final role in the decision process is most likely very limited (see Weigand [137]). Moreover, many of these studies have been performed in highly structured experimental settings whose impact on individuals' behavior has not been systematically investigated.

Hence, organizational buying behavior research does not provide us with a much better framework than adoption research for studying the decision process involved in the adoption of new

industrial products. These two approaches, however, are quite complementary, and there is little doubt that further progress in this area will make use of the strenghts of both approaches. As Gold et al [40] emphasized, the scope of traditional research on the adoption of industrial innovations must be broadened to encompass the study of the decision process of organizations. On the other hand, the scope of organizational buying behavior research must also be broadened. An effort must be made to quantify intervening behavioral variables and investigate more formally their relation to organizational buying behavior (Wind [145]).

1.4. The Industrial Adoption Process : What do we need to Know ?

The industrial adoption process has not been investigated as systematically as the consumer adoption process. In the latter, several comprehensive methodologies have been developed to measure consumer response to product innovations (Hauser and Urban [52], Urban [127]).

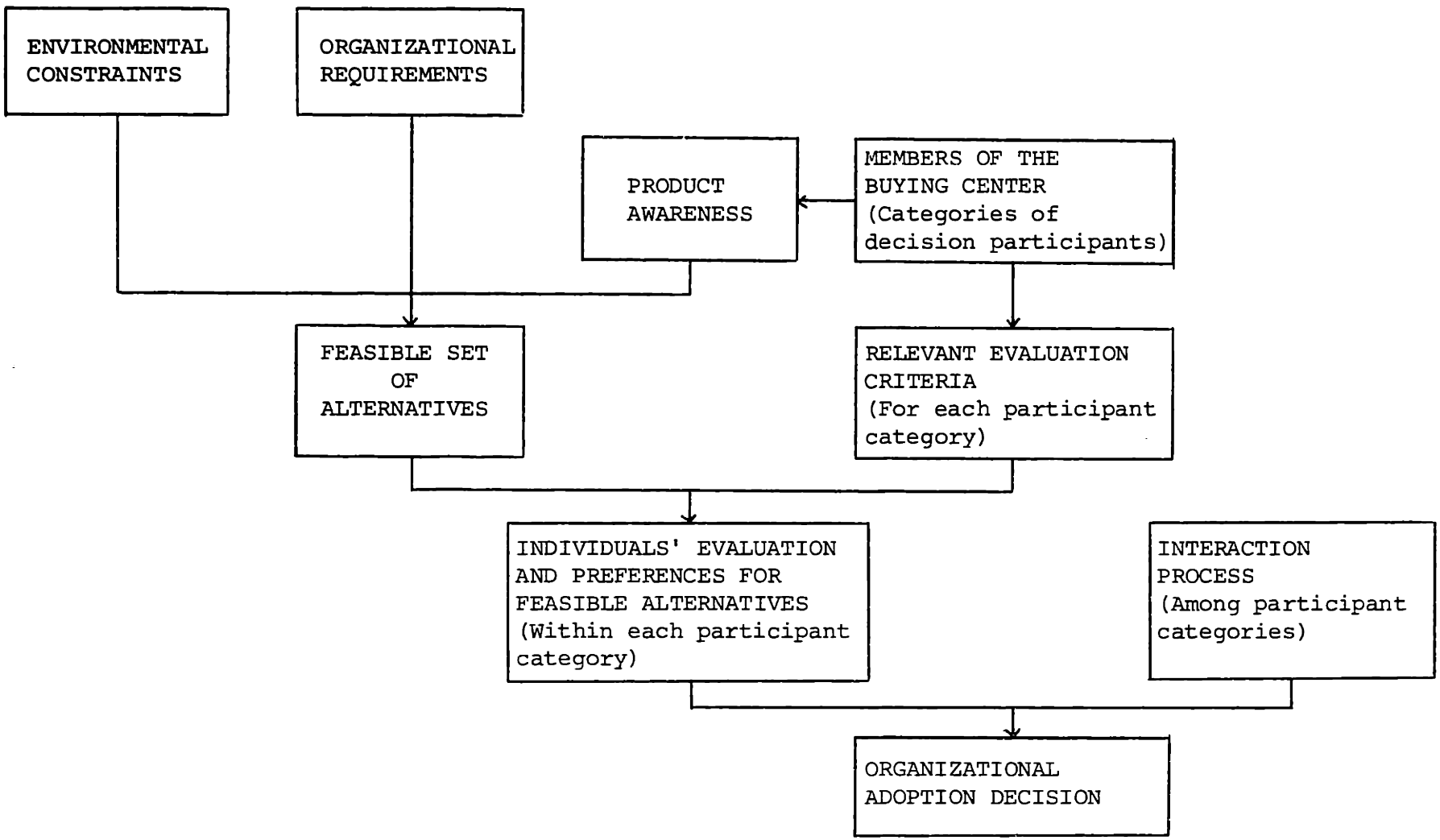
On the industrial side, Choffray and Lilien [21] recently proposed a model of the industrial adoption process that constitutes a first step in the development of a model-based methodology to assess industrial firms response to product innovations. Their model identifies the major classes of intervening variables, and structures them in a way that is consistent with

current knowledge. As opposed to other models proposed in this area, however, the Choffray and Lilien model is meant to provide an operational (as opposed to conceptual) structure to assess industrial market response. Figure 1.4. presents the main components of this model. It is implicitely assumed that organizations have already recognized the need to buy a product from the generic class to which the new product belongs and that the purchase decision is the result of a systematic decision process.

According to this model, decision participants -- or members of the buying center -- in potential customers' organizations are aware of a certain number of alternatives. However, not all of these alternatives are feasible as a result of environmental constraints and organizational requirements. For instance, technical specifications of the new product and customers' requirements in terms of production compatibility might lead to the elimination of the new product from the feasible alternatives.

Of course, organizations differ in the number of people involved in their adoption process as well as in the specific responsibilities of these individuals. In addition, these individuals may exhibit substantial differences in the way they perceive feasible alternatives and in the respective evaluation criteria that they use for assessing them. In order to account for such differences Choffray and Lilien

FIGURE 1.4. : MAJOR ELEMENTS OF AN INDUSTRIAL MARKETS RESPONSE MODEL.



propose to group decision participants into more homogeneous categories on the basis of their background and task orientation. For each of these categories of participants, product evaluation criteria can then be assessed and individuals' perceptions and preferences can be investigated.

Finally, group preferences are linked to individual preferences by making explicit assumptions about the kind of interaction that take place among decision participants. For this purpose, the model requires the identification of segments of organizations homogeneous in the structure of their adoption process in the sense that essentially the same categories of participants are involved in the decision.

Choffray and Lilien identify four aspects of this structure on which additional research is needed before significant progress can be made in the development of a comprehensive methodology to assess response to industrial innovations. They distinguish problems associated with :

- The measurement of environmental constraints and organizational requirements, which define the product alternatives that might satisfy the needs of a company at a given time.

- The analysis of differences in product perception and evaluation criteria among various categories of influential decision participants.

- The development of better measurement instruments to investigate the structure of the industrial adoption process. What is needed is the ability to identify those categories of individuals in an organization who are most likely to be involved in the adoption process.

- The development of formal models of group decision-making.

Choffray and Lilien investigate the last of these questions. They propose several criteria for the development of models of group decisicn-making and suggest several models based on various assumptions about the nature of the interaction among group members.

The first problem, is of less immediate interest. It deals more with the tangible aspects of the industrial adoption process, an area in which some research evidence is already available (See, for instance, Mansfield's [83] analysis of the impact of some aspects of the environment on the adoption of industrial innovations, and Lavin's [69] analysis of organizational selection criteria).

Our research here is specifically concerned with the second and third problems. The study of both is essential to a better understanding of the behavioral aspects of the industrial adoption process and, as noted at the begining of this chapter, the two questions are closely interrelated from a managerial standpoint.

1.5. Objectives and Outline of the Dissertation.

The objective of this research is twofold :

1. develop methodology to assess the nature and extent of differences in product perceptions and evaluation criteria among several categories of decision participants, and investigate the relevance of such differences in the formation of individual preferences.

2. propose new measurement methods to assess the structure of the industrial adoption process, and develop methodology to segment the potential market for a new industrial product on that basis.

The dissertation proceeds as follows. In Chapter 2 we describe the new product investigated in this work and discuss the relevance of the two problems under study. Several methodological aspects of the research are discussed, namely the development of measurement instruments and the data collection procedures. A "decision matrix"

is proposed as a structured instrument to collect information about the most likely pattern of individual involvement in the adoption process in potential customers' organizations. The validity of the measurements obtained with this instrument is also assessed.

In Chapter 3, we present a comprehensive methodology to investigate differences in product perceptions and evaluation criteria among potential decision participants. The methodology extends considerably the most recent approaches used to investigate similar problems in consumer marketing. It logically links several methods of multivariate data analysis and provides objective criteria to investigate the process of perception and evaluation of industrial product alternatives. A new, formal test to assess the similarity between factor analytic solutions obtained with the same set of perceptual scales from different groups of individuals is developed. This test is used to assess whether decision participants differ in the way they combine attributes of industrial products into higher-order evaluation criteria. The relevance of these differences in the formation of individual preferences for available product alternatives is also formally assessed.

Chapter 4 is concerned with the development of a methodology for grouping companies in the potential market for a new industrial product on the basis of the structure of their adoption process. The methodology uses as input the information collected with the decision matrix and addresses more specifically the following questions :

- how many segments should be distinguished in the potential market on the basis of the structure of the adoption process ?

- is the pattern of individual involvement in the adoption process substantially different across these segments ?

- how are these segments related to traditional bases for industrial market segmentation ?

In order to investigate these questions, the methodology logically combines several methods of cluster analysis and provides solutions to the problems of a) determination of the number of clusters to be retained, b) non-randomness of these clusters, and c) stability of their composition.

Chapter 5 puts the results of our research into perspective. The implications of our work for the development of better marketing strategies for new industrial products are discussed. The limitations of our research are also discussed and areas of high potential for future work are identified.

1.6. This Research in Perspective

The research reported in this dissertation represents a substantial step in the development of better market research methods that account for the specific nature of industrial purchasing behavior. The contribution of this research can be assessed at three different levels : theoretical, methodological and managerial.

From a theoretical standpoint, the research reported in this dissertation contributes to a better understanding of some behavioral aspects of the industrial adoption process. First, the existence of differences in product perceptions and evaluation criteria across decision participants is systematically investigated. Second, the hypothesis that organizations differ in the structure of their decision process is formally tested by identifying segments of organizations homogeneous in this respect. Hence, our research fills two substantial gaps in our understanding of industrial buying behavior.

From the methodological standpoint the analysis of differences in product perception and evaluation criteria among potential decision participants leads to the development of a comprehensive methodology which logically combines several multivariate data analysis methods. The latest developments in the theory of factor analysis are incorporated in the methodology and a new test for the equality of factor solutions is proposed. Moreover, our research considerably extends available methods of industrial market segmentation. New developments in the theory of cluster analysis are incorporated in our methodology for segmenting industrial markets according to the structure of the adoption process.

From a managerial standpoint, the research reported in this dissertation has important implications for the design of industrial marketing strategies. First, perceptual differences among decision participants, as well as differences in their respective evaluation criteria can be used most profitably in the development of industrial communication strategies, including advertising copy, and sales presentations. Second, the segmentation methodology developed here provides industrial marketers with accurate information about the composition of the buying center that they consider most relevant for decision-making (Wind and Cardozo [146]), and which they can use effectively for targeting industrial marketing activities.

1.7. Summary

This chapter set the scope of the research reported in this dissertation. First, the importance of new products in industrial markets was stressed as well as the risks associated with their introduction. An analysis of the main causes of commercial failure of new industrial products led to the conclusion that a better understanding of the industrial adoption process, paralleled by the development of better market research methodologies that account for the specific nature of this behavior, could substantially reduce the failure rate.

Our review of the literature pointed to an important lack of research on the industrial adoption process. Four main problems associated with the development of a model to assess response to industrial innovations were identified. The specific objectives of the research were detailed and the plan for its presentation outlined.

The sum total of this effort is to develop:

- a comprehensive methodology which provides objective criteria for investigating the nature and extent of differences in perceptions and evaluation criteria among different categories of individuals involved in industrial adoption decisions, and to propose

- new measurement methods and better tools to segment industrial markets on the basis of the structure of the adoption process which characterizes each organization in the potential market for an industrial product.

CHAPTER 2 : AN EMPIRICAL STUDY OF THE INDUSTRIAL ADOPTION OF SOLAR COOLING SYSTEMS

This Chapter provides an overview of the empirical research performed in the dissertation. The new product whose adoption is investigated here is an industrial cooling system powered by solar energy. In the first section we assert the potential of solar technology as a source of energy for the United States and discuss the prospects for solar cooling of industrial buildings. We then review some problems raised by the adoption of the new system and assess the relevance of the two research questions identified in Chapter 1. Next, we discuss some methodological issues associated with measuring the structure of the adoption process for industrial cooling systems and with measuring decision participants' perceptions of available alternatives. We then review how these problems have been dealt with in the solar cooling study. Finally, a description of our sample is made and the validity of a "decision matrix" as a measurement instrument to investigate the structure of the industrial adoption process is assessed.

2.1. Solar Energy Alternatives

Over 25 percent of the energy used in the United States is consumed for space heating, air-conditioning and water heating

for buildings (Westinghouse phase 0 report [139]). Most of this energy is presently supplied by the combustion of high quality fossil fuels, mainly gas and petroleum, whose cost is expected to rise sharply in the future. Even with a 10 percent utilization efficiency, solar collectors covering 4 percent of the land area of the continental U.S. could supply all energy needs in the year 2000 (Williams [141]). By comparison, at present 15 percent of the U.S. land area is used for growing farm crops. As the efficiency of solar collectors is already much higher than 10 percent and since they can be placed on the walls and roofs of buildings, the 4 percent estimate is an upper limit and the actual land area requirements will be much smaller. In view of ever increasing costs and diminishing supplies of fossil fuels, as well as the country's need for energy independence, solar energy should then be considered as an alternative.

A recent study investigated the market potential and economic feasibility for solar heating and cooling of buildings (Cohen [24]). It indicated that if all buildings that could potentially make use of solar heating and cooling by the year 2000 where indeed equipped with such systems, substantial annual energy savings would result on the order of 1.5 trillion Kwh of electricity and $ 50 billion of fuel. Industrial and commercial buildings only would account for more than 40 percent of these potential annual energy savings (Cohen [24]).

Space cooling is one of the fastest growing areas of U.S. energy use, with an annual growth rate of 15 percent in the residential market and 9 percent in the commercial sector (Williams [141]). By 1980, space cooling is expected to account for over 5 percent of U.S. energy demand (Westinghouse phase 0 report [139]). Thus, a considerable amount of expensive fossil fuel could be saved by wide scale adoption of solar powered cooling systems.

The most promising technology in this respect combines solar energy with a standard absorption cooling machine. Currently, however, these systems are not cost effective. Their best application is as an add-on to a cost effective heating system with high summer cooling loads. A recent study of the economic and technical feasibility of such mixed systems indicate that they will become generally competitive in many regions of the U.S. by 1985 (Weinstein [138]).

The economic and technical considerations hindering the adoption of solar systems have been extensively investigated (see Arthur D. Little [77] report, and de Winter [34]). Considerably less emphasis has been devoted to studying areas of customer resistance to the solar concept, although it has been increasingly recognized that potential adopters' attitude toward such systems will have an important impact on their adoption (Jones [61], Scott [111]). For instance, substantial differences in perception and causes of resistance within different professions can be expected to affect the acceptance of solar technology (Fleming [39]). It is then vital

for this new industry to identify the favorable and unfavorable attitudes toward solar systems and how they are distributed across potential buyers (Scott [111]).

2.2. The Adoption of Solar Cooling Systems.

Solar absorption cooling systems are not currently economically attractive. These systems require substantially higher initial outlays, and although they promise important savings in operating costs, uncertainties concerning their overall reliability and the expected life of solar collectors preclude an accurate estimation of their economic feasibility.

Costs are only one aspect of the problem, however. Lehmann and O'Shaughnessy [72] indicate that price is not the primary determinant of supplier in most industrial purchasing situations. Sheth [116] reviews evidence supporting the importance of so-called "non-rational" factors on industrial purchasing decisions. For capital expenditures such as industrial cooling systems, Lilien [75] emphasizes that it is entirely possible that a solar system be preferred to other conventional systems due to essentially non-economic considerations such as reliability, protection against energy shortage, prestige, environmental concern etc.

A detailed understanding of these issues and of their relative importance for the different individuals involved in the adoption of industrial cooling systems is an essential input to the development of an effective marketing strategy for currently available solar cooling technology. An early identification of potential causes of resistance to the solar concept within certain professions might, for instance, lead to the development of specific communication programs aimed at limiting the potency of these negative feelings or lead to refinements in the system design itself. It is therefore essential to identify which individuals, both inside and outside potential customers' organizations, are most likely to be involved in the adoption process for the new solar system and to understand the nature and extent to which they differ in the way they perceive and evaluate industrial cooling alternatives.

2.3. Outline of Empirical Research

The analysis of the industrial adoption process for solar cooling systems reported here was initiated as part of an E.D.A. funded study to investigate the market potential for industrial solar cooling systems in the United States. The original project, described in Lilien [75], represents a systematic attempt to integrate more closely engineering and market research activities in the development of a new industrial product.

A marketing team, headed by Professor Gary L. Lilien from M.I.T. was responsible for the identification of areas of potential resistance to the industrial solar cooling concept and for the assessment of future demand for such systems. The team worked in close cooperation with an engineering team whose objective was to develop and test an industrial solar cooling system that would best satisfy potential customers' needs.

The work of the marketing team was subdivided into several tasks. First, an extensive review of the engineering and professional literature was performed to improve our understanding of solar heating and cooling of industrial buildings. An accurate description of the new industrial cooling system was made as well as a description of other more conventional systems. An effort was also made to identify areas of potential concern about the adoption of the new system.

Second, a series of personal interviews were conducted with representatives from eight industrial firms that were currently using industrial cooling systems and seven Heating Ventilating and Air Conditioning (H.V.A.C.) consulting firms. These interviews were mainly unstructured. They centered upon the nature of the adoption process for industrial cooling systems and attempted to identify potential sources of resistance to the new solar system.

It was clear that several individuals, both inside and outside a company were involved in the decision to purchase an industrial cooling system for a new plant. Moreover, it appeared that some issues that were of importance to H.V.A.C. consultants in their evaluation of alternative industrial cooling systems were less relevant to company people and vice versa. It was decided that these differences should be taken into account in the development of a sensible survey instrument.

Two questionnaires were then designed : one to be sent to those individuals within potential customers' organizations most likely to be involved in the decision to purchase an industrial cooling system and the other to H.V.A.C. consultants. Both questionnaires were fully pre-tested. First, each questionnaire was administered in a group session to representatives of several industrial companies and to a group of H.V.A.C. consultants. After appropriate modifications, each questionnaire was sent to approximately 100 pre-selected industrial companies and 100 consultants. An in-depth analysis of the questionnaires returned (35 from industrial firms and 32 from H.V.A.C. consultants) was performed and led to the introduction of additional changes. The final version of the company questionnaire appears in Appendix 1.

2.4. The Measurement of Decision Participants Perceptions, Evaluation Criteria and Preferences for Industrial Product Alternatives.

2.4.1. Related Work.

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

Allaire [1], for instance, proposed a methodology to measure heterogeneous semantic, perceptual and preference structures. More recently, Hauser and Urban [51] developed a general methodology to assess response to consumer innovations that explicitely links product perceptions to individual probabilities of choice. A similar approach was also used in Urban's [121] PERCEPTOR model which relates the perceptions of a new product to its ultimate probability of trial and long term repeat purchase rate.

These methodologies share the same theoretical foundations. They all assume the existence of a multidimensional perceptual space as has been suggested often in the psychological literature. (See Howard and Sheth [55] and Allaire [1] for a review). A

consumer's perception of a product may then be thought of in terms of the coordinates of this product on the set of relevant perceptual dimensions. Operationally, an individual's perception of a product is provided by his ratings of the product on a set of perceptual items representing the salient attributes in the product class.

In order to relate individuals' preferences to products' perceptions these methodologies suggest the reduction of the perceptual space to a subspace of lower dimensionality whose coordinate axes represent the basic performance evaluation dimensions (Hauser and Urban [52]) or evaluation criteria (Howard and Sheth [55]) used by individuals to assess products in this class. An individual's evaluation of a product may then be viewed as the projection of this product on his relevant evaluation criteria.

The reason for distinguishing an individual's perception from his evaluation of a product comes from the ample empirical evidence suggesting that man is a good perceiver but poor combiner (Miller [87], Lavin [69]). Although an individual can record with reasonable accuracy his perception of a given product on a set of one-dimensional attribute scales, it is unlikely that he considers all these attributes independently and simultaneously when he forms judgements about these products. In addition, several attributes of a product

class may in fact be interrelated because they satisfy the same underlying motive (Howard and Sheth [55]).

Several authors have suggested that the methodologies developed in the consumer area be applied in industrial markets to investigate how individual decision participants perceive and evaluate product alternatives (Sheth [115], Hauser [51]). Our review of the literature in Chapter 1, however, indicates that little work has been done to date in that direction.

As we discuss in section 3.1., the methodologies developed in the consumer area present limitations when they are transposed in industrial markets to investigate decision participants product perceptions and evaluation criteria. These limitations come from the multiperson nature of industrial purchasing, in which participants can be expected to show substantial differences in the way they perceive and assess product alternatives. In their present state of development, available methodologies do not provide objective criteria to investigate the nature and extent of such differences.

However, these methodologies do provide sound measurement procedures to assess individuals products perceptions and to determine

the set of relevant evaluation criteria common to a group of individuals. Typically, three major steps are involved in the measurement process (Howard and Sheth [55]).

First, the researcher has to ascertain which attributes of the product class under investigation are salient. Several methods have been used successfully for this purpose. They include, for instance, focus group interviews, word association and projective techniques. After a scaling procedure has been choosen -- Howard and Sheth [55] and Allaire suggest the use of the Semantic Differential while Hauser and Urban [52] use likert scales -- an attribute scale is developed for each attribute identified. These attribute scales are then suitably tested.

The second step in the measurement process involves the survey of a representative sample of potential customers. The product investigated is either physically presented or described in a concept statement and individuals perceptions are recorded. Individuals' preferences for product alternatives are also obtained through the use of various methods including rankings or constant-sum paired comparisons.

The final step in the measurement procedure involves the use of analytical techniques to derive the set of relevant evaluation

criteria for all potential consumers. Individual product evaluations are then obtained and linked to preferences.

The ability of the measurement procedures developed in the consumer goods area to assess individuals' product perceptions and to determine the set of relevant evaluation criteria common to a group of individuals is in no way limited to consumer goods. Essentially the same approach is used in this research to measure decision participants' perceptions and evaluation criteria for industrial products.

2.4.2. Measurement of Product Perceptions and Preferences in the Solar Cooling Project.

The measurements obtained in the solar cooling study from individual decision participants closely parallel those described above. In industrial markets, however, it is often more difficult to expose a new product to potential buyers. Indeed, a physical product is not generally available in the early stages of industrial product development, at the time its market potential must be assessed. Moreover, even if a prototype were available it might be very costly and time consuming to introduce it to potential buyers.

For these reasons, in the solar cooling study a concept statement was developed for each available alternative. They included a conventional compression system (COMAIR), a conventional absorption system (ABSAIR) and the new solar absorption system (SOLABS). Members of both the marketing and the engineering research teams participated actively in the development of these concept statements. For the new solar absorption system, special care was taken to avoid the emphasis of any characteristics of these systems that are likely to change in the near future as solar technology evolves, and that might significantly bias current perception of the system. The same concept statements were used in both the company questionnaire and the H.V.A.C. questionnaire. The SOLABS concept statement is reproduced in Figure 2.1.

Due to the complexity of many new industrial products and the technical orientation of potential buyers, the use of concept statements to measure individual product perceptions and preferences is probably as suitable in industrial markets as in consumer markets where it is reported to have been used with success (Hauser and Urban [52]).

More than 150 product attributes were identified in our review of the engineering and professional literature or mentionned in personal interviews with potential decision participants. Many of these attributes were redundant, however, and the list was reduced

FIGURE 2.1. : CONCEPT DESCRIPTION FOR SOLABS

SOLABS consists of a standard absorption chiller as used in ABSAIR and a hot water solar collector which replaces the boiler in a standard absorption a/c system. As it uses solar energy as a power source, SOLABS is less sensitive to fuel shortages and power fluctuations than other industrial a/c systems.

The solar collector used by SOLABS is a flat type that is located on the roof of the building. In some cases, collectors can even replace the roof. Collectors come in panels of various standard sizes that are attached to one another by normal plumbing connections. Two water storage tanks are also part of SOLABS and are generally buried in the ground. One of these tanks is for chilled water, to meet the immediate demands of the absorption system. The other one is for hot water, to meet a/c needs during periods of little sunshine or alternatively to provide heating during these same periods. When the system is used exclusively for a/c, water storage capacity need not be large as more solar energy is available when cooling is most needed. A small backup heating and cooling system can be used to make up for prolonged periods of low sunshine.

Solar energy alone can provide 40% - 60% of all building a/c requirements, significantly reducing energy costs. In addition, warm water produced by the solar collector can be used for manufacturing or domestic water needs. In colder climates, this system can provide 30% - 40% of heating requirements.

The initial cost of SOLABS is at least 50% higher than for non-solar systems, depending on the size of the installation. The operating cost of SOLABS, however, is considerably lower than for other systems due to a reduction of at least 40% in a/c energy consumption (depending on the geographical location). Maintenance costs for SOLABS are similar to those for ABSAIR.

SOLABS produces no pollution. As it requires a minimum of moving parts, SOLABS is also very quiet and vibration free.

The solar a/c concept is not new. Several well-known manufacturers produce components and one such system was in operation at the University of Florida as early as 1960. Currently, there is a new school in Atlanta, Georgia that is air-conditioned by SOLABS and there are several projects to install similar a/c systems in different parts of the U.S.

to approximatively twenty basic attributes whose relevance was assessed during the group sessions with company representatives and H.V.A.C. consultants as well as in the pilot survey. The perceptual scales used in the company survey are reproduced in Figure 2.2.

Likert scales were used to measure the extent of agreement of individual decision participants as to whether a given system incorporated each attribute, thereby providing his perception of the system. Seven-point scales were used for this purpose on the ample evidence that such scales are most satisfactory (Howard and Sheth [55], Green and Rao [46], Lehmann and Hulbert [71]).

Individual preferences for the three systems were obtained by two different methods, ranks and constant-sum paired comparisons. As observed by Wildt and Bruno [140], however, the preferences obtained for industrial product alternatives do not usually represent purchase preferences, but rather preferences conditional to the requirement that these alternatives meet organizational financial constraints. Accordingly, in this study individual preferences should be viewed as preferences for the three systems conditional to their feasibility for the organization. This approach is consistent with the two-step model of the industrial adoption process described in Chapter 1. Moreover, it is consistent with the contention that solar heating and cooling systems will become more generally competitive in the near future, so that is would be unwise to let individual product perceptions and preferences be completely overwhelmed by cost considerations.

FIGURE 2.2. : PERCEPTUAL SCALES FOR COMPANY SURVEY

(Circle one number for each item)

	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 manufacturers 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

2.5. Measurement of the Structure of the Industrial Adoption Process.

2.5.1. Previous Work

Little research has been done to date to measure the role played by different decision participants in industrial buying decisions and to develop effective, inexpensive instruments to identify these decision participants in customers' organizations. Available studies have typically involved the survey of a large cross-section of firms for which aggregate frequencies of involvement in the purchasing process were computed for each of several organizational functions on an industry or product basis (Scientific American [110], Buchner [14], Stevens and Grant [121]). None of these studies, however, have investigated the question of interorganizational variation in the structure of the purchasing process - that is, in the pattern of individual involvement in the various phases of this process - which is of the highest importance to industrial marketers (Webster [133], Wind and Cardozo [146]).

A small number of studies have dealt more specifically with the measurement of the relative influence of different decision participants in the industrial purchasing process. These studies are mainly exploratory, however, and quite limited in scope. Weigand [137], for instance, investigated how purchasing agents appraised their "concern" over various characteristics of an industrial product and how others in the same organization viewed

the purchasing agent's "concern" over these same characteristics. McMillan [80] investigated the degree of involvement of purchasing agents, scientists and managers in the vendor selection process for three chemical intermediate products. And more recently, Grashof and Thomas [41] investigated the relative involvement of Librarians, R & D Managers and Plant managers in the purchase of scientific and technical information. Although important methodological weaknesses exist in all three studies, their results consistently suggest that individuals tend to inflate their personal influence in the decision process. Purchasing agents, for instance, tend to appraise their own "concern" over various characteristics of an industrial product consistently higher than do other executives in their organizations (Weigand [137]).

Some researchers have suggested that breaking the question of global influence into more specific influence areas improve the reliability of the measurements (Patchen [99], Corey [27]). A recent investigation of the structure of the industrial purchasing process by Kelly [65] tends to support that hypothesis and concludes that there is surprisingly little disagreement between decision participants as to who in the organization had performed any of five major functions distinguished in the decision process.

In sum, available research on the structure of the industrial

purchasing process indicates three major ways of improving the design of future studies on the subject :

- First, research should be limited to a single product at a time. This would maximize the possibility of identifying interorganizational variations in the industrial purchasing process without the risk of contamination from differences in product characteristics (Kelly [65]).

- Second, the reliability of self-report data about personal influence in the purchasing process can be improved by breaking the decision process into managerially meaningful areas of influence (Patchen [99], Corey [27]).

- Third, the measurement by self-report of the involvement of each of several decision participants in the purchasing process leads to more reliable results than the measurement of the relative influence of these decision participants (Grashof and Thomas [41]). The task of identifying what individuals are involved in any stage of the purchasing decision is indeed much simpler than the task of specifying their relative influence.

2.5.2. Measuring Involvement in the Adoption Process for a New Industrial Product.

The studies discussed above are mainly concerned with measuring

the involvement and relative influence of different categories of participants in the organizational buying process on the basis of past purchases. For a new industrial product the measurement problem is more complex as a decision has not yet occured and organizations may have little past experience with the product class. In this case, we are then concerned with identifying the most likely structure of the adoption process within potential customers' organizations.

The following criteria are proposed as sensible ones for a measurement instrument designed to assess the structure of the adoption process for a new industrial product :

- Specificity : the instrument should be flexible enough to adapt to different products.

- Simplicity : the instrument should be understandable and unambiguous.

- Robustness : the instrument should prevent non-sensible answers of the type "in our company all divisions would be involved in all stages of the adoption decision for this new product".

- Economical : the instrument should be administrable through standard marketing survey methods.

- Convergent Validity : independent measurements within the same organization should lead to similar estimates of the likely structure of its adoption process for the new product.

In this research, we use a "decision matrix" as a structured measurement instrument to collect information about which categories of individuals are likely to become involved in the major stages of the adoption decision for a new industrial product. A decision matrix is a double-entry table whose rows list the main categories of individuals who might become involved in the decision process in potential customers' organizations and whose columns list the major stages involved in the decision process. The respondent -- who has been identified a priori as an individual likely to be involved in the adoption decision for the new industrial product -- is then requested to indicate what percentage of the task-responsibilities for each stage in the decision process would belong to each category of decision participant in his organization. The request for constant-sum information forces respondents to specify only these decision participant categories that would play a substantial role in each phase of the decision process or whose involvement in a specific phase is certain. A less constraining version of this method -- which did not request constant sum information about decision participants involvement in each phase of the decision process -- has been used in several other studies (See for instance Buchner [14], Scientific American [110]).

2.5.3. Solar Cooling Study.

The accuracy of the measurements obtained with a decision matrix can be expected to depend on the definition of both the stages of the decision process and the categories of decision participants that are included in the analysis.

The disaggregation of the adoption process into phases is a non trivial task. Several authors have proposed possible subdivisions of the industrial purchasing process (see for instance Robinson and Faris [105], Webster and Wind [136]). But the phases distinguished by these authors differ both in the number and in the specific activities they cover, leaving the specifics of the measurement procedure to the researcher.

In the solar cooling study, input from literature and actual practice was used to break the adoption process for such systems into a managerially meaningful set of decision stages. Descriptions of the decision process for industrial cooling systems, provided by the 35 companies in the pilot survey were carefully analyzed. This analysis pointed to five major phases in the adoption process for an industrial cooling system. These phases correspond closely to those used by Kelly [65]. We distinguish:

- evaluation of cooling needs, and specification of system requirements

- preliminary budget approval,
- search for alternatives, and preparation of a bid list
- equipment and manufacturer evaluation
- equipment and manufacturer selection

Although slight differences appeared from one company to another, this sequence of decision stages was found to provide an accurate description of the adoption process for an industrial cooling system within most companies in the pilot survey.

The specification of the main categories of decision participants likely to become involved in the decision process is also difficult. In the solar cooling study, the specification followed analysis of the descriptions of the adoption process provided in the pilot survey. Five major categories of decision participants were distinguished among company personnel. These categories comprise the main job responsibilities of those individuals whose involvement in the adoption process was described in each company surveyed in the pilot study phase. In addition, three main categories of decision participants were distinguished among the personnel external to potential customers' organizations. Figure 2.3. present the resulting decision matrix.

The decision matrix is then product dependent. The purchase of a new industrial product may involve different categories of individuals and/or a different disaggregation of the adoption decision process than another industrial product. These differences must be incorporated in the decision matrix.

FIGURE 2.3. : DECISION MATRIX IN SOLAR 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 *	5 Equipment and manufacturer selection
COMPANY PERSONNEL	Production and Maintenance Engineers	%	%	%	%	%
	Plant or Factory Manager	%	%	%	%	%
	Financial controller or accountant	%	%	%	%	%
	Procurement or purchasing department	%	%	%	%	%
	Top Management	%	%	%	%	%
EXTERNAL PERSONNEL	HVAC/Engineering firm	%	%	%	%	%
	Architects and Building Contractor	%	%	%	%	%
	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.*

2.6. Industrial Solar Cooling Study Sample

Several steps were involved in the selction of the companies surveyed in the solar cooling study. Our objective was to identify companies that presented characteristics most conducive to the adoption of a solar cooling system. Three criteria were used for this purpose: geographic location, S.I.C. code classification and company size as measured by sales.

Geographic location is an important criterion in this study because an absorption solar cooling system is most efficient in those situations where high cooling loads are required and abundant solar energy is available. Accordingly, more than 50% of the companies surveyed were selected from the sun-belt states.

The second criteria, S.I.C. code classification was used to eliminate firms that do not require cooling in their manufacturing operations. Finally, company sales was used as a control for size. Although, as indicated in Chapter 1, empirical studies do not point to the existence of any systematic relationship between firm size and the adoption of new industrial products, it was believed that larger firms would be more likely to adopt the new solar cooling system. Cheston and Doucet [20] give the precise breakdown of the final sample (720 companies) along these three dimensions.

For our purpose, it was necessary to have the questionnaire answered by an individual who would participate in the decision process for a new cooling system in this organization. We used a two-stage sampling strategy. First, a member of senior management was identified within each company in the sample using the most recent information published in the Standard and Poor Register of Corporations. A personal letter was sent to that person stating the purpose of our study and the reasons why participation by his company was essential. A request was then made to return an enclosed postcard giving the name of at least one individual in the organization who would be a key participant in the decision for a new industrial cooling system. Second, a questionnaire was sent to the individuals thus identified along with a personal letter informing them that they had been named by senior management as key persons in a decision to purchase a new industrial cooling system.

As expected, the response rates at the two levels of sampling were different. Approximately 28% of the 720 companies selected returned the postcard. However, 56% of the decision participants identified returned 144 questionnaires of which 130 were sufficiently complete to be included in most of our analysis.

2.7. Formal Assessment of the Validity of the Measurements obtained with the Decision Matrix.

The investigation of the pattern of individual involvement in the adoption process for a new industrial product and the study of interorganizational differences in the adoption process requires a formal assessment of the validity of the measurements obtained with the decision matrix. Ideally, one would like to investigate the external validity of these measurements, that is, the accuracy with which the individuals who are actually involved in the adoption process for the new product can be identified with the decision matrix. This approach was not feasible in this research. Indeed, investigation of the external validity of the measurements obtained with the decision matrix requires a true experimental design in which first the instrument is administered, then the actual involvement in the adoption process is observed and the two results compared. In the context of the solar cooling study, this approach might have required several years, so that other methods of validation had to be used.

A common denominator shared by most validity concepts is that of agreement or convergence between independent approaches. For example, Ayer [4], discussing a historian's belief about a

past event, notes that if his sources of informations are "numerous and independent, and if they agree with one another, he will be reasonably confident that their account of the matter is correct". Our problem is quite similar. Suppose that several decision participants in the same organization filled out the decision matrix separately. The extent of the agreement between these individuals about which categories of individuals are likely to become involved in the major phases of the adoption process for the new industrial product can be taken as a measure of the convergent validity of the measurement procedure. In order to investigate the validity of the measurements obtained with the decision matrix we will then use the information provided in those cases where several decision participants from the same company answered the questionnaire.

In this section we make use of the data provided by the solar cooling project and by a study of the adoption process for a new "intelligent" computer terminal (Bunker [14]). In the latter study, the decision matrix used involved four major decision phases and seven categories of decision participants. In the solar cooling project, 12 companies were identified for which two decision participants answered the questionnaire. In the computer terminal study, 13 companies were identified from the 420 answering the questionnaire.

Two parallel approaches are used to investigate the convergent validity of the measurements obtained with the decision matrix. The first method relies on a simulation to investigate whether the extent of agreement between separate measurements of the structure of the adoption process in the same organization is substantially higher than the extent of agreement between separate measurements of this same process in different organizations. The second method is a variant of the method of convergent and discriminant validation proposed by Campbell and Fiske [16]. This method allows us to assess whether respondents do discriminate between decision phases in terms of the involvement of the different categories of participants included in the analysis. As a result, the method provides a way to assess the relevance of the decision matrix to investigate the pattern of individual involvement in the various phases of the industrial adoption process.

In the next pages we make use fo the following notation :

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

2.7.1. Simulation Approach.

The simulation approach to assess the convergent validity of the measurements obtained with the decision matrix makes use of both the validation sample and the main sample. Its purpose is to assess whether the extent of agreement between separate measurements of the likely structure of the adoption process in the same organization is significantly higher than the extent of agreement between separate measurements of this same process in different organizations.

In this research, we are concerned only with measuring the involvement of different categories of decision participants in the adoption process and not with measuring the extent of their involvement. Hence, we measure the degree of agreement between two separate measurements obtained with the decision matrix with a matching coefficient. These coefficients measure the degree of association or similarity between entities defined on a set of binary variables. In this section, we use the Sokal and Michener [119] coefficient (s hereafter).

Consider the following example drawn from the solar cooling study. Figure 2.4. reproduces the measurements obtained from two decision participants from the same company. The estimation

FIGURE 2.4. : STRUCTURE OF THE INDUSTRIAL ADOPTION PROCESS

	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	33 40 %	%	%	50 5 %	25 5 %
	Plant or Factory Manager	33 %	10 20 %	%	%	%
	Financial controller or accountant	%	30 20 %	%	%	%
	Procurement or purchasing department	%	%	5 10 %	%	25 5 %
	Top Management	%	60 40 %	%	%	%
EXTERNAL PERSONNEL	HVAC/Engineering firm	33 60 %	20 %	25 90 %	50 95 %	25 90 %
	Architects and Building Contractor	%	%	50 %	%	25 %
	a/c equipment manufacturers	%	%	20 %	%	%
	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.*

of the s coefficient involves the computation of the number of times the two respondents agreed on the likely involvement or non-involvement of a given category of decision participant in each phase of the adoption process. In this specific case, it appears that they both agreed 35 our of 40 possible times, leading to a value of .875 for the s coefficient. A more detailed discussion of the properties of this coefficient appears in section 4.3.2.

Figure 2.5. outlines the main steps involved in the simulation approach. 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 in fact vectors of binary variables reflecting the involvement of the various categories of participants in the different phases of the adoption process in company i. Then, we compute the average similarity index : $S = \frac{1}{n_1} \sum_{i=1}^{n_1} s_i$

The next step involves generating the distribution of the statistic S under the null hypothesis (H_0) that measurements of the structure of the adoption process are mutually independent. 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 which represent

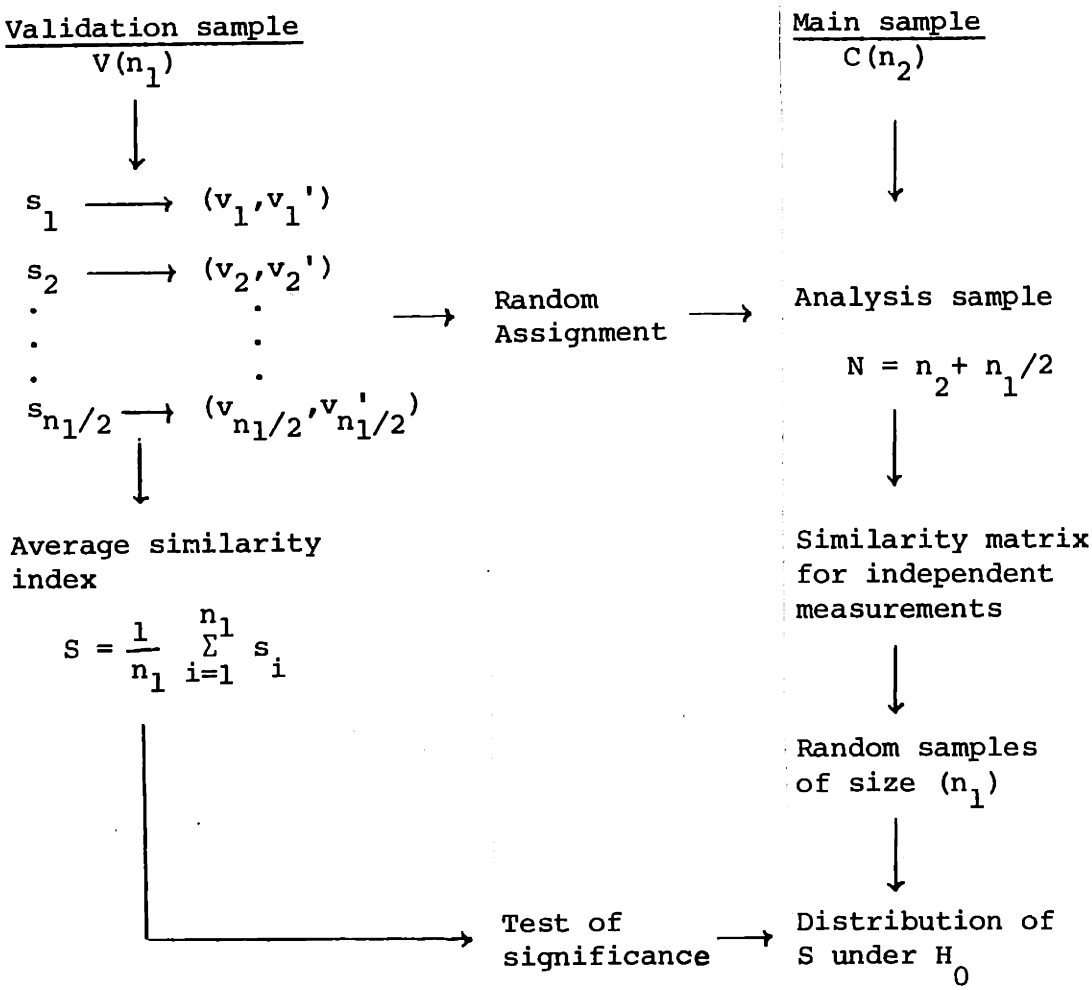


FIGURE 2.5 : OUTLINE OF THE SIMULATION APPROACH TO THE VALIDATION OF THE MEASUREMENTS OBTAINED WITH THE DECISION MATRIX.

independent measurements of the likely structure of the adoption process for the new product because each of these measurements is from a different organization. The similarity coefficient between all different pairs of observations in the analysis sample is computed. There are $\frac{1}{2}$ N (N-1) such similarities from which samples of size n_1 are drawn randomly with replacement. Each of these sample lead to an estimate of S.

The results of our simulation for both the solar cooling data and the intelligent terminal data are reported in figure 2.6. These results are based on 5000 samples of size n_1 drawn randomly under H_0.

The results 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 $\alpha < .001$. 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.

	Solar cooling study	Intelligent terminal study
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	$\sigma(S) = .035$	$\sigma(S) = .037$

FIGURE 2.6 : RESULTS OF THE SIMULATION APPROACH TO THE VALIDATION OF THE MEASUREMENTS OBTAINED WITH THE DECISION MATRIX

2.7.2. Convergent and Discriminant Validation Approach.

In addition to the question of convergent validity of the measurements obtained with the decision matrix, an important issue concerns whether respondents are indeed able to discriminate between decision phases in terms of the involvement of the various categories of participants distinguished in the decision matrix. The second method of validation used here, addresses this question directly.

This second method is a variant of the convergent and discriminant validation approach proposed by Campbell and Fiske [16]. Although this latter approach was initially developed to assess the validity of psychological tests, it is quite general and has been used in a variety of different research settings.

Consider the involvement within each phase of the decision process as a psychological "trait" in the Campbell and Fiske terminology. Also, consider the measurements obtained with the decision matrix from different decision participants in the same organization as the result of different "methods". We can then use the set of criteria proposed by Campbell and Fiske to assess the convergent and discriminant validity of the measurements obtained with the decision matrix.

Figure 2.7. outlines the main steps involved in this approach. A major difference with the methodology proposed by Campbell and Fiske is that, in our case, the degree of association between relevant entities is measured with a matching coefficient instead of a correlation coefficient. The first step is to 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).

Figure 2.8. and 2.9. present the results of these computations for the solar cooling data and the intelligent terminal data respectively.

Following the conditions for validation 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 figure 2.8., .750 is superior to .583, .646 and .562 as well as to .500, .541, .646, and .583. Hence, a hig 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.

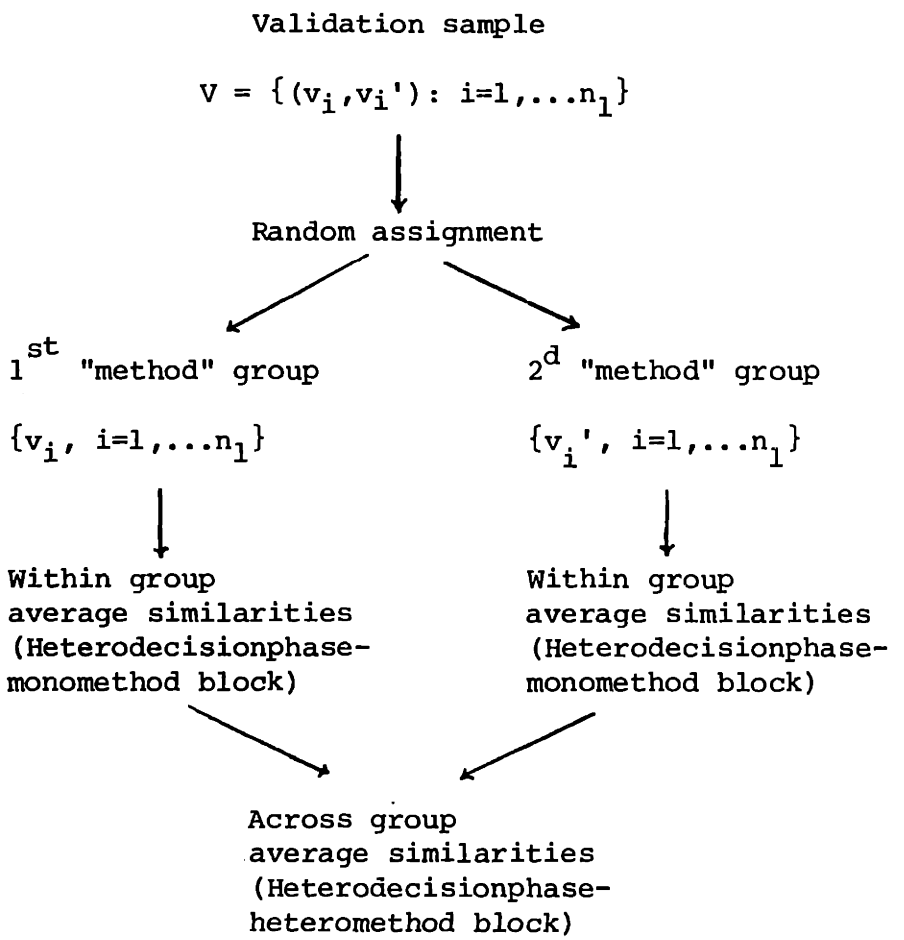


FIGURE 2.7 : CONVERGENT AND DISCRIMINANT VALIDATION OF THE MEASUREMENTS OBTAINED WITH THE DECISION MATRIX

		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	.750	.583	.541	.646	.562	—				
	Ph_2	.500	.854	.521	.583	.562	.562	—			
	Ph_3	.541	.521	.833	.771	.729	.562	.500	—		
	Ph_4	.646	.562	.729	.812	.729	.708	.583	.791	—	
	Ph_5	.583	.625	.729	.792	.875	.604	.625	.770	.770	—

FIGURE 2.8. : CONVERGENT AND DISCRIMINANT VALIDATION MATRIX (SOLAR COOLING STUDY)

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

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

FIGURE 2.9. : CONVERGENT AND DISCRIMINANT VALIDATION MATRIX (INTELLIGENT TERMINAL STUDY)

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

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. The fourth condition that the same pattern of interrelationship appears in all of the heterodecisionphase triangles of both the monomethod and heteromethod blocks, is also satisfied to a large extend by the data.

Two remarks must be made, however. First, the question of the presence of method variance is not relevant in our situation as the measurements were randomly assigned to the two "method" groups. Second, the relatively high average similarities between decision phases in the monomethod and heteromethod blocks should no be taken as a potential sources of invalidation. Rather, it indicates that decision participants who are involved in one phase of the decision process tend to be involved in other phases as well. A similar conclusion was reached by Cheston and Doucet [20].

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

- there exists substantial agreement between separate attempts to measure with the decision matrix the structure of the adoption process in a given company, and that

- the measurements obtained show evidence of discriminant validity across decision phases, suggesting that individuals do indeed discriminate between decision phases in terms of the involvement of the various categories of individuals included in the decision matrix.

A promising area for future research is the analysis of the external validity of the measurements obtained with the decision matrix. Future empirical studies might, for instance, take advantage of the quasi-experimental situations provided by the purchase of established (as opposed to new) industrial products to investigate this question. In such studies, the researcher would administer the decision matrix to a small number of companies. He would then observe the actual purchasing behavior and compare his observations with the measurements initially obtained with the decision matrix.

Another direction for future research involves the confirmation of the results reported here on the convergent and discriminant validity of the measurements obtained with the decision matrix. Such studies would involve the administration of the decision matrix to several decision participants (3-5) in each company in the potential market for an industrial product. The same methods of analysis as those described above could then be used to investigate the extent of agreement between these "independent" measurements.

As noted by Webster and Wind [135], "There are rich research opportunities in defining the influence of different members of the buying center at various stages of the buying process." The validation analysis performed here, however, was limited to an assessment of the ability of the decision matrix to collect information about the involvement or non-involvement of several categories of decision participants in the major phases of the industrial adoption process. Future research might then investigate the ability of the decision matrix to assess the relative influence of these categories of individuals in each phases of the decision process.

2.8. Summary

This chapter provided an overview of the empirical research performed in the dissertation. First, we asserted the potential of solar energy in the United States, and discussed the prospects for solar cooling of industrial buildings. The importance of the problems investigated in the dissertation was stressed.

We then discussed some issues associated with the measurement of decision participants' perception and evaluation of industrial cooling systems as well as some problems associated with assessing the structure of the adoption process for the new solar system. Potential solutions to these problems were proposed. A description of our sample was made and finally we investigated the validity of the decision matrix as a measurement instrument to assess the structure of the adoption process. Results of the validation analysis indicate that the measurements obtained with the decision matrix possess substantial convergent validity. Additional research is needed, however, to assess the external validaty of the measurements obtained by this method.

CHAPTER 3 : A METHODOLOGY TO INVESTIGATE DIFFERENCES IN PRODUCT PERCEPTIONS AND EVALUATION CRITERIA AMONG PARTICIPANTS IN THE INDUSTRIAL ADOPTION PROCESS.

In this chapter, we develop and illustrate methodology to investigate how decision participants involved in the adoption of a new industrial product differ in their perceptions of available alternatives and in their evaluation criteria. The methodology builds upon the work done to date in consumer marketing. It logically combines several multivariate statistical methods and provides objective criteria to investigate the process of perception and evaluation of industrial product alternatives.

The Product Perception Analysis Methodology, provides methods for systematically analyzing how several categories of decision participants -- defined on the basis of job responsibility -- differ in their perceptions of the attributes of industrial products. Multivariate Analysis of Variance (MANOVA) is used to assess whether individuals in each category are able to discriminate between available alternatives on the basis of the set of perceptual scales included in the analysis. Then, Multivariate Profile Analysis (MPA) is used to assess the extent and nature of perceptual differences across groups of decision participants for each product alternative.

The Evaluation Space Analysis Methodology provides methods for systematically investigating how these same categories of participants differ in the way they structure the basic attributes of industrial products into higher-order evaluation criteria. Factor analysis is used to derive the evaluation criteria common to each category of decision participants. A set of procedures is developed that provide objective tests to determine whether decision participants differ in the number and composition of their evaluation criteria. Specifically, a statistical test is proposed to assess the equivalence of factors obtained from the same set of perceptual scales in different populations. The behavioral relevance of the differences in evaluation criteria between groups of decision participants is then investigated through preference regression.

The chapter is organized as follows. First, we review the objectives of the methodology and briefly discuss the work done to date in consumer marketing. Next, we describe the structure of the methodology and the specific tests involved. Then, we assess the importance of differences in perceptions and evaluation criteria across categories of decision participants likely to become involved in the adoption of a new industrial cooling system powered by solar energy.

The end product of this chapter is a comprehensive methodology which incorporates formal tests for investigating differences in perceptions and evaluation criteria between groups of participants in industrial adoption decisions. Results of this analysis provide management with important information on which to develop better industrial marketing programs.

3.1. Purpose of the Methodology

In Chapter 2 we introduced the notions of product perception and evaluation criteria. As different terms have been used in the literature to refer essentially to the same concepts care must be taken in defining exactly what we mean by an individual's perception of a product and by the evaluation criteria common to a group of individuals. In this research we refer to the following definitions for these terms :

- the perceptual space common to a group of individuals is an n-dimensional space defined by the set of salient attributes for the product class under investigation. Following Howard and Sheth [55] these attributes possess "goal-satisfying" capabilities. An individual's perception of a product may then be seen as a vector of coordinates in this space and is provided by his rating of the product on the corresponding attribute scales.

- the evaluation space common to a group of individuals is an m-dimensional subspace ($m < n$) approximately spanning the original perceptual space. The coordinate axes in this evaluation space are independent, and refered to as evaluation criteria. They express how individuals in that group structure the basic product attributes into higher-order evaluation dimensions. An individual's evaluation of a product may then be seen as a vector of coordinates in this reduced space.

As pointed out in section 2.4.1., some research has dealt with how individuals perceive and evaluate product alternatives in the consumer goods area (See Hauser [51] and Allaire [1] for a review). Little work has been done to date, however, on the analysis of perceptual differences, as well as of differences in evaluation criteria between managerially meaningful segments of buyers.

Rogers and Shoemaker [107] have emphasized the importance of perceptual differences among groups of potential adopters in the diffusion of innovations. Some empirical evidence has also appeared. Allaire [1] reports differences between groups of consumers in the way they evaluate each of several brands of beer. Hauser and Urban [52] identify differences between a group of students, staff members and professors in their evaluations of several concepts of Health Maintenance Organization. More recently, research by Urban and Neslin [128] on the design of educational programs

concludes at the existence of important differences in the way students, professors and recruiters evaluate alternative programs.

Typically, these studies have investigated differences in the average positioning of product alternatives -- computed for each of several groups of individuals -- in a common reduced evaluation space. No attempt was made to investigate how these groups differed in their perceptual ratings of each product alternative on the original attribute scales. Such an analysis, however, would have been more likely to identify specific areas of resistance to the new product concept within each group of individuals. For this reason, the perceptual analysis methodology proposed in this research involves the systematic investigation of product ratings on the original attribute scales.

In industrial markets, product perception differences are likely to occur among decision participants as a result of differences in background and job responsibilities (Sheth [115], Choffray and Lilien [21]). Explicit consideration of these differences is necessary in the development of better communication programs that address the specific information needs of these various individuals. As our review of the literature in Chapter 1 indicated, however, little work has been done to date in the study of perceptual differences among participants in industrial purchasing decisions.

The existence of differences in the evaluation criteria used by different groups of individuals has also not received adequate attention. Recent research by Allaire [1] points to the existence of such differences in consumer markets. However, his results are mainly exploratory. Indeed, the methodology Allaire uses for this purpose relies on several subjective criteria -- both for the determination of the number of evaluation dimensions used by each group of consumers, and for the comparison of these evaluation dimensions across groups -- which preclude an in-depth investigation of the reported differences. As Allaire concludes: "The burden of the proof regarding the importance of heterogeneity in [evaluation spaces] lies with further experimental investigation".

Additional evidence suggesting differences in the evaluation spaces harbored by different groups of consumers is provided by Green and Rao [45] and Green and Wind [44]. These researchers use essentially the same methods as Allaire to "abstract" groups of individuals homogeneous in the way they structure basic product attributes into higher-order evaluation criteria. Typically, these studies use the INDSCAL procedure to assess individual differences in the pattern of inter-perceptual scales similarities, obtained either directly from each individual or computed from his perceptual ratings for several product alternatives. Consumers can then be clustered into several groups on the basis of these

differences and the evaluation space is derived for each of these groups.

Although the INDSCAL procedure might prove useful for identifying individuals who share a common evaluation space, this methodology is highly dependent on the ability of cluster analytic methods to abstract a set of homogeneous segments. As we discuss in Chapter 4, this assumption might be overly optimistic. In addition, the INDSCAL procedure does not solve the problem of determination of the number of evaluation criteria (or dimensionality of the evaluation space) common to a group of individuals, nor does it provide adequate tests for the comparison of evaluation criteria across these groups.

The evaluation space analysis methodology developed in this research assumes that the groups of individuals -- whose evaluation criteria are being investigated -- have been defined on the basis of a priori information. For this purpose decision participants are grouped on the basis of their job responsibility. This decision is consistent with Sheth [115] contention that product perceptions and evaluation criteria tend to differ among decision participants as a results of differences in educational background, task orientation, sources of information, and reference groups.

As some variation must be expected across companies in the responsibility corresponding to different job titles, a specific request was made in the industrial solar cooling questionnaire

that the respondent specify his main job responsibility. Four main categories of decision participants were then created : Production Engineers (PE), Corporate Engineers (CE), Plant Managers (PM), and Top Managers (TM).

Then, the problems investigated in this chapter are :

- how do these four categories of decision participants differ in the way they perceive industrial cooling alternatives, including the new solar system ?

- how do these categories of decision participants differ in the way they structure basic product attributes into higher-order evaluation criteria used to assess products in this class ?

3.2. Structure of the Methodology

3.2.1. Perceptual Analysis Methodology

Figure 3.1. outlines the perceptual analysis methodology proposed in this research. The input to the analysis consists of the ratings obtained from a sample of decision participants for each available product alternative -- or concept statement -- on a set of perceptual items representing the salient attributes for the product class. As discussed earlier, decision participants are grouped on the basis of job responsibility.

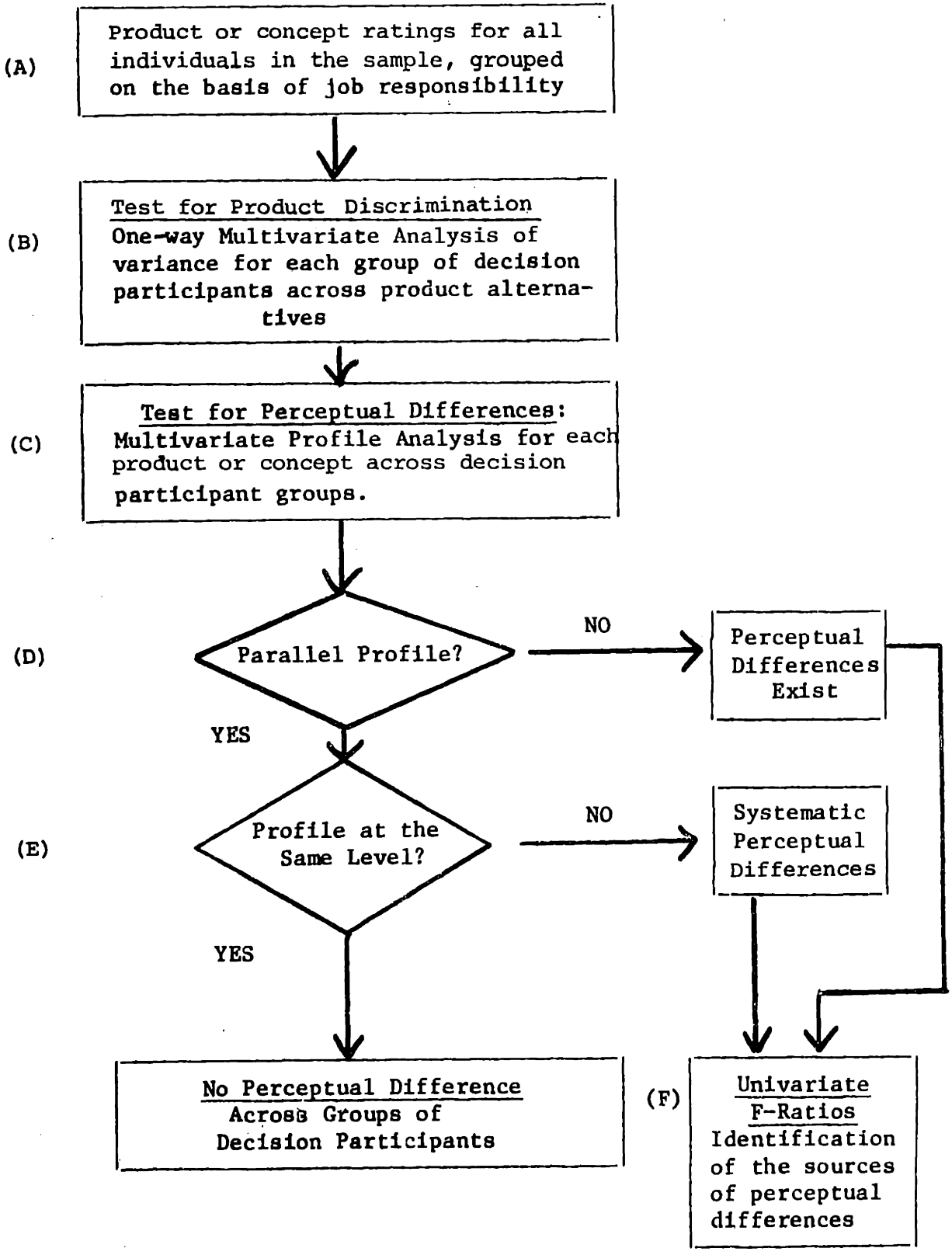


FIGURE 3.1. : OUTLINE OF PERCEPTUAL ANALYSIS METHODOLOGY

The perceptual analysis methodology comprises two main steps. First, a test for product discrimination is performed within each group of decision participants. Next, perceptual differences across categories of decision participants are analyzed for each product alternative.

3.2.1.1. Test for Product Discrimination

The test for product discrimination involves assessing for each category of decision participants whether respondents' perceptions of available alternatives do indeed differ across these alternatives. This test is a necessary step in the perceptual analysis methodology for the following reasons :

- First, the test provides an indirect way to assess the discriminating power of the attribute scales retained in the analysis and on which individuals' perceptions were recorded.

- Second, in those cases where product concept statements are used to expose individuals to available alternatives, the test allows the assessment of whether the concept statements do indeed convey the product characteristics they are supposed to.

- Third, the test provides an objective criteria to assess ambiguity of product perception that is, the extent to which individuals are unable to discriminate between available alternatives in terms of the relevant perceptual scales.

The inexistence of product discrimination has important implications. First, it may suggest the elimination of some perceptual scales from subsequent analyses or require major changes in the concept statements if the researcher wants to use them in future surveys. Second, in case that the product concept statements do convey the right product characteristics and the attributes scales have discriminating power, the inexistence of product discrimination within a given category of participant suggests ambiguity of product perceptions. In this case, as individuals do not discriminate between available alternatives in a meaningful way, it is doubtful that their stated preferences for these alternatives can be trusted.

Methodologies developed to date in the consumer goods area have to a large extent overlooked this last issue. In view of its importance in industrial marketing for the interpretation of perceptual differences between decision participant categories and in view of the emphasis placed on it in the theory of buyer behavior (Howard and Sheth [55]) a formal test for product discrimination is included in the perceptual analysis methodology proposed here.

Multivariate analysis of variance (MANOVA) provides a set of objective criteria to investigate the problem of product discrimination within each group of decision participants. The research issue is whether individuals' perceptions are so volatile that, on an aggregate basis, their perceptions of available alternatives do not substantially differ.

Figure 3.2. depicts a simple MANOVA situation in the case of a 2-dimensional perceptual space. The ellipses represent the variation in the perceptions of each product alternative. The issue involves whether some of the products included in the analysis are centered at different locations in the perceptual space defined in terms of these two salient attributes. In this case the three products are perceived as substantially different.

The case involving an n-dimensional perceptual space is similar. For each group of decision participants we want to test if their perceptions of available alternatives on the n salient attribute scales are significantly different from one another. In order to discuss this question we first briefly describe the MANOVA model. Interested readers are referred to Morrison [90] and Cooley and Lohnes [25] for a complete presentation of this technique.

The MANOVA Model

Consider a situation in which measurements are obtained on a n-vector variable x from a group of individuals submitted

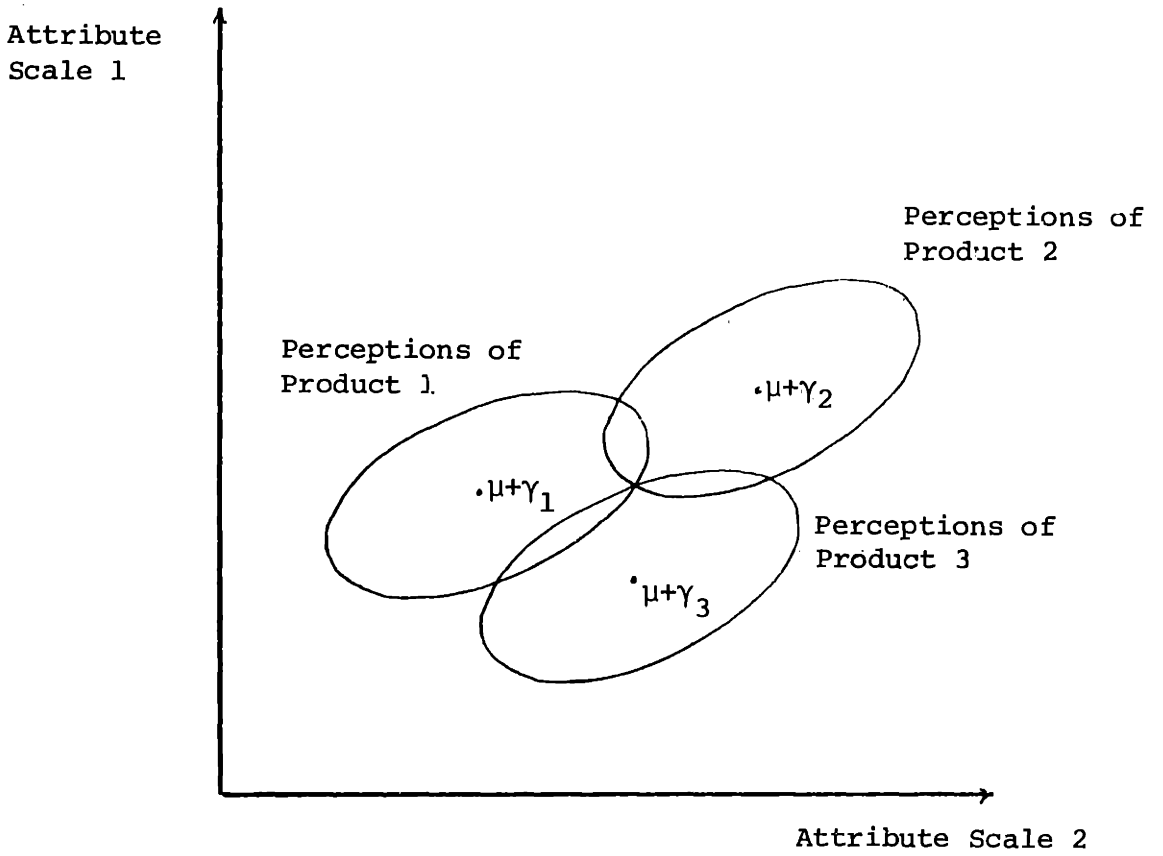


FIGURE 3.2 : MANOVA DESIGN IN THE CASE OF A TWO DIMENSIONAL PERCEPTUAL SPACE.

to several treatments. The MANOVA model assumes that each n-observation is generated by the model:

$$x_{ij}=\gamma_j + \mu + \varepsilon_{ij}$$

where the subscript $i = 1,\ldots\ldots N_j$ refers to a specific individual submitted to treatment j with $j = 1,\ldots\ldots,k$.

In this model, μ is a general level vector parameter whose h component is common to all observations obtained on response variable h; γ_j is a vector whose components represent the effect of experimental condition j on each response variable, and ε_{ij} is a vector of disturbances. The MANOVA model assumes that the disturbance vector ε_{ij} has a multinormal distribution with zero mean vector and some unknown nonsingular covariance matrix Σ common to all experimental conditions.

In terms of this notation, the null hypothesis of no treatment effect in the one-way analysis of variance design can be written :

$$H_0 : \gamma_1 = \gamma_2 =\ldots= \gamma_k$$

This hypothesis can be tested using Wilk's Lambda

$$\Lambda = \frac{|W|}{|T|}$$

where :

W denotes the matrix of squares and cross-products of deviations of subjects from their experimental condition centroid (that is the vector of average ratings) pooled over all experimental populations, and

T denotes the matrix of sums of squares and cross products of deviations of all subjects from the grand centroid.

As $|T|$ increase relative $|W|$, the ratio Λ decreases with an accompanying increase in the confidence with which we reject H_0. Intuitively, we reject H_0 when the proportion of the total variance in the data explained by the k experimental conditions is large.

Under H_0, Wilks' Λ has an approximate F-distribution whose degrees of freedom are function of the design parameters n, k, and N_j's (See Cooley and Lohnes [25]).

Use of the MANOVA Model to perform the Product Discrimination Analysis

The research situation portrayed in the MANOVA model is identical to that found in the product discrimination analysis. For each group of decision participants, individual product perceptions represent observations on an n-dimensional vector variable and the different product alternatives do in fact constitue different experimental treatments. The null hypothesis of inexistence of product discrimination

is then the exact counterpart of the no treatment effect hypothesis in the one-way MANOVA lay-out.

Assuming that the null hypothesis of no-discrimination between product alternatives is rejected, inspection of the univariate F-ratios may suggest which of the original perceptual items are contributing most to the discrimination between the products. Although these individual tests are not independent, this approach has been found most suitable in empirical studies (See Hummel and Slogi [58]).

It should be noted that although the distributional assumptions made by the MANOVA model place stringent requirements upon the data used, the method is quite robust under departure from these assumptions (See Cooley and Lones [25]). Thus MANOVA provides a useful theoretical framework and a set of objective criteria to investigate the existence of product discrimination within each group of decision participants.

3.2.1.2. Testing the Existence of Perceptual Differences Among Several Categories of Decision Participants

The investigation of perceptual differences among several groups of decision participants calls for more sensible criteria than those provided by the one-way MANOVA lay-out. Indeed the issue of differences in groups' perceptions of a specific alternative is not only a question

of difference in location in the n-dimensional perceptual space. Rather, as the alternative presents the same characteristics to all individuals, it is mainly a question of interaction between group membership and perceptual responses.

As depicted in figure 3.1., the methodology proposed in this research to investigate the existence, and specific nature of perceptual differences across groups of decision participants makes use of Multivariate Profile Analysis (MPA). A product profile is simply its vector of average ratings (centroid) on the original set of perceptual items computed for each category of decision participants.

As such, Multivariate Profile Analysis is a specific case of the general multivariate linear model, which allows investigation of response by group interaction in the case where dependent variables are expressed in comparable units. An excellent presentation of the MPA technique is provided by Morrison [90].

As suggested in section 3.3.1.1. individuals' perception of the specific product investigated are taken as observations on an n-vector variable. This time, however, the different categories of decision participants involved in the analysis represent the experimental conditions.

The issue of whether the perception of each product differ significantly across participants categories is investigated in a two-step procedure as shown in figure 3.1. First, a test for profile parallelism (D) is performed. Then, a test for equality of levels is applied (E). Figure 3.3. provides an illustration of the concept of profile parallelism and profile level equality.

The hypothesis of profile parallelism or no interaction between individual product perceptions and group membership involves a simultaneous test on the slope of adjacent segments of the different groups' profiles. In terms of the previous notation this hypothesis can be stated :

$$H_{01} : \begin{bmatrix} \gamma_{11} & - \gamma_{12} \\ & \\ \gamma_{1,n-1} & - \gamma_{1n} \end{bmatrix} = \ldots\ldots = \begin{bmatrix} \gamma_{k1} & - \gamma_{k2} \\ & \\ \gamma_{k,n-1} & - \gamma_{kn} \end{bmatrix}$$

The hypothesis H_{01} can be investigated within the framework of the multivariate general linear model. It is tested by the largest characteristic root criterion using Heck statistic (See Morrison [90]). Rejection of this hypothesis indicates the existence of significant perceptual differences among categories of decision participants for the product investigated.

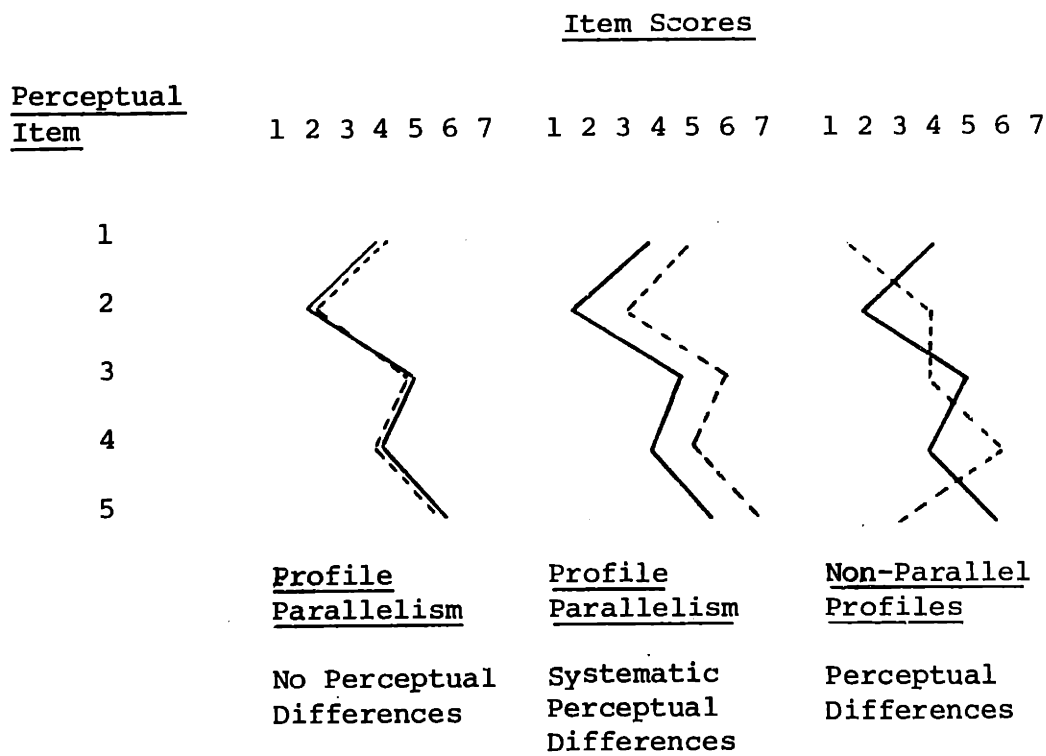


FIGURE 3.3 : THE CONCEPT OF PROFILE PARALLELISM AND PERCEPTUAL DIFFERENCES.

Assuming that the hypothesis of parallel profiles is not rejected, a test is performed to investigate the equality of profiles levels. The test involves a one-way univariate analysis of variance on the sum of the n responses of each individual across all k groups. In terms of the previous notation this hypothesis becomes ;

$$H_{02} : \sum_{h=1}^{n} \gamma_{1h} = \ldots = \sum_{h=1}^{n} \gamma_{kh}$$

Rejection of H_{02} indicates the existence of a systematic perceptual difference among participants categories for the product investigated. This perceptual difference has the nature of an additive constant, suggesting that some participants categories give consistently more extreme perceptual ratings than other participants categories to the alternative investigated.

As in the MANOVA model, rejection of the hypothesis of no perceptual differences across groups of decision participants calls for separate univariate analyses of variance on each of the response variables to assess the exact nature of these perceptual differences.

3.2.2. Product Evaluation Space Methodology

The methodology proposed in this research to investigate possible differences in the evaluation space of different categories of decision participants is based on the assumption that all individuals who belong to a given category -- that is who have similar job responsibilities in their respective company -- 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 number of evaluation criteria in their assessment of available product alternatives ?

- second, assuming that the dimensionality of the evaluation space is the same among different groups of participants, are their evaluation criteria essentially similar ?

Figure 3.4. outlines the evaluation space methodology proposed in this research. The input to the analysis is the ratings obtained for each product alternative from each individual in the sample. These individuals are then grouped on the basis of their job responsibility and the variance-covariance matrix of the ratings

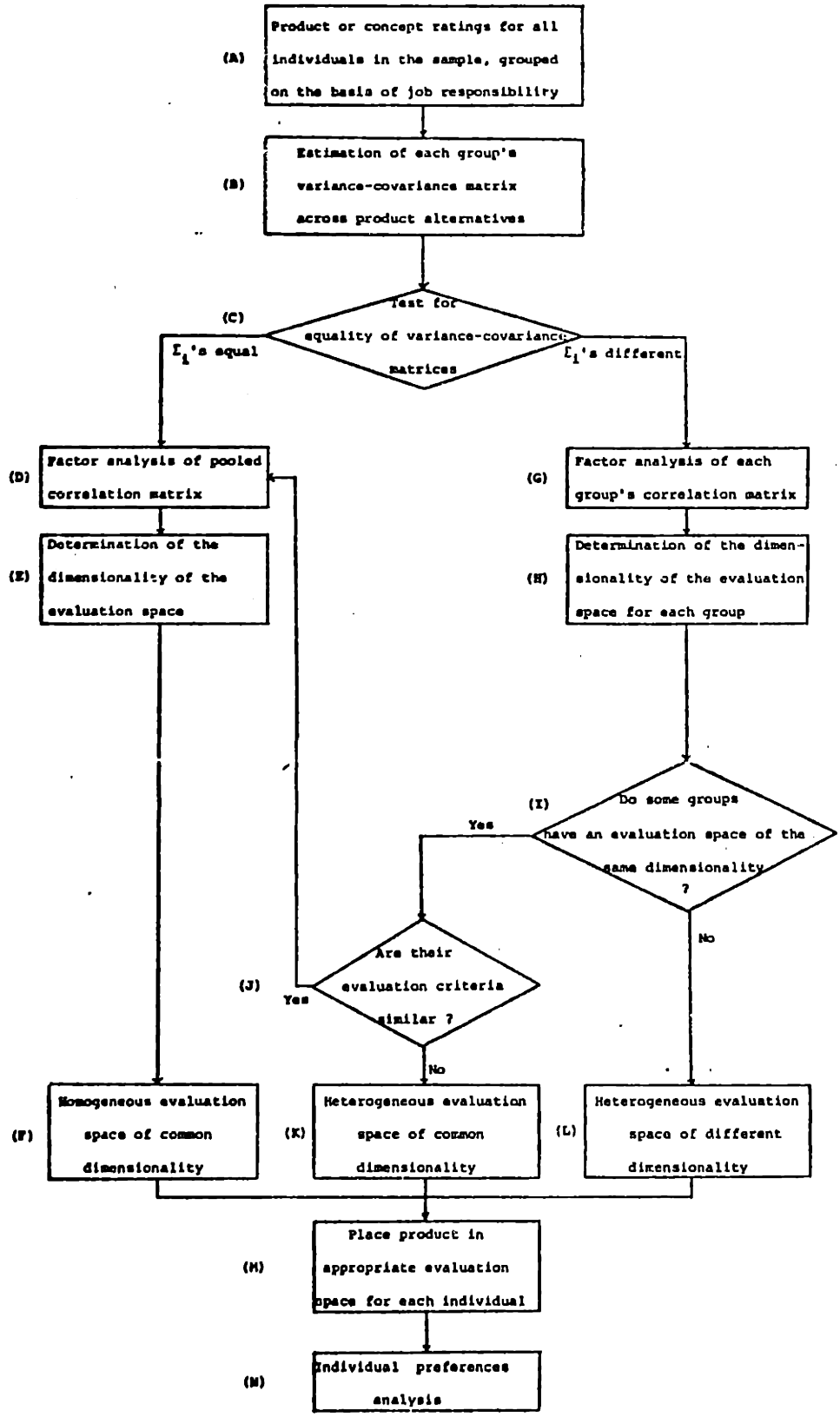


FIGURE 3.4. : OUTLINE OF EVALUATION SPACE METHODOLOGY

obtained on all n-perceptual scales is computed for each of them. These covariance matrices are computed across product alternatives and so, we implicitely assume that the evaluation criteria derived for each group of decision participants are the same for all industrial products in the class investigated. This approach has been suggested and implemented by Urban [127] in the consumer goods area. It has the advantage of increasing the number of degrees of freedom in the estimation of the evaluation criteria common to each group of decision participants.

At the macro-level, the methodology proposed in this research proceeds as follows. First, a test for equality of all decision groups' covariance matrices is performed and allows for an early detection of possible differences in the way individuals in each of these groups structure the relevant product attributes into higher-order evaluation criteria (C). 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 exact composition of the evaluation criteria common to all categories of decision participants is appraised (F). In this case, the analysis concludes at the existence of no substantial differences across categories of decision participants in the evaluation criteria used to assess product alternatives.

Rejection of the hypothesis of equal covariance matrices across decision groups suggests the existence of potential differences in the evaluation space of each groups of decision participants, so that separate factor analyses are justified (G). The dimensionality of the evaluation space is then determined for each group (H). If the number of evaluation criteria is different for each group of decision participants, the analysis concludes at the existence of substantial differences in the evaluation space harbored by different categories of decision participants. On the other hand, when some groups have an evaluation space of same dimensionality, additional tests for the equality of evaluation criteria are necessary (J). If all evaluation criteria are found identical, these groups of individuals have a common evaluation space so that a factor analysis of their pooled correlation matrix is now required (D). If at least one of their evaluation criteria is different, the analysis concludes at the existence of heterogeneous evaluation spaces across those decision groups with the given dimensionality.

The final step in the methodology is concerned with the behavioral relevance of the differences in the evaluation criteria used by each group of decision participants to assess products alternatives. At this level we investigate whether the explicit consideration of the differences in product evaluation criteria harbored by each group of decision participants leads to a better recovery of individual preferences.

3.2.2.1. Test for Equality of Variance Covariance Matrices

In this research we test the hypothesis of equality of the covariance matrices of perceptual ratings obtained for each group of decision participants with the Box [10] criterion, M below. 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

$$H_0 : \Sigma_1 = \ldots\ldots = \Sigma_k$$

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

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

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 [25], and Morrison [90], for a discussion of this test). A computer program to perform the Box test was developed and appears in Appendix 2.

Unfortunately, the Box test is very powerful. A recent Monte Carlo study found that the power of the test increases not only as the inequality of the covariance matrices increases, but also as the sample size increases and as the number of variates increases (Greenstreet and Connor [47]). For this reason, in the methodology proposed here, the Box criterion is suggested mainly as an early detector of the equality of all groups' covariance matrices and as a way avoid the expensive computations involved in steps G through J.

Hence, rejection of the hypothesis of equality of covariance matrices does not ensure the existence of substantial differences in the evaluation criteria harbored by different groups of decision participants, although acceptance strongly points to equality. Indeed, as common factor analysis does not make use of all information present in the covariance matrices, it is possible that the evaluation criteria of some groups of participants are quite similar even though the Box criteria led to the rejection of the equality hypothesis. More discriminating tests must then be devised to study differences between groups of decision participants in such cases.

3.2.2.2. Derivation of the Evaluation Space for any Group of Decision Participants.

In this research, common factor analysis is used to derive the evaluation space of the various groups of decision participants.

This multivariate method of data analysis presents substantial advantages over other possible methods of reduction of the perceptual space. Allaire [1] and Hauser [51] have extensively discussed the characteristics of these methods. Typically factor analysis presents the following advantages :

- first, it provides an analytical framework within which both objective product attributes and subjective product characteristics can be combined into meaningful evaluation criteria.

- second, factor analysis is specially suitable when the number of product alternatives is small and precludes the use of other reduction methods like non-metric multidimensional scaling of similarity judgements.

- third, methods of factor analysis have been increasingly investigated from a statistical standpoint and provide better criteria for comparison than other methods of reduction.

The aim of factor analysis is to represent observed covariances or correlations among many variables in terms of linear dependencies on a reduced number of abstract, conceptual variables. Harman [49], Rummel [109], and Lawley and Maxwell [70] provide excellent reviews of the subject.

At the outset a distinction must be made between the principal component model and the classical factor analysis model. The principal component model, is essentially a closed model. It considers that the total variance in the n original variables is wholly accounted for by a set of n independent factors or components that are linear combinations of the original variables. These are very stringent requirements and as Cattell ([19], p. 177) writes :

> "The components model must be rejected for general scientific investigation because it would be most unlikely that n variables would contain within themselves all the causes for accounting for their own variances. To do this, they would have to lie in a completely self-explanatory subuniverse, self-sufficient as a system entirely isolated from the rest of the universe".

The classical factor analysis model considers that the variance of each variable is partly accounted for by a set of common factors, and partly by a factor specific to each variable. These unique factors might be regarded in some sense as the researcher's "confession of ignorance" (Cattell [19]p.177).

In the evaluation space methodology proposed in this research, the reduction of the perceptual space is done by common factor

analysis. It is doubtful , indeed, that the set of perceptual items included in the analysis represent the exhaustive set of relevant product attributes. For instance some of these attributes may have been omitted out of parsimony in the development of the survey instrument or the researcher may have considered some attributes not sufficiently important to be incorporated in the analysis.

3.2.1.2.1. Classical Factor Analysis : A Brief Overview

The Classical Factor Analysis model may be written :

$$(1) \qquad z_{ji} = \sum_{p=1}^{m} a_{jp} f_{pi} + u_j y_{ji}$$

where $p = 1,\ldots.m$ factors

$i = 1,\ldots.N$ individuals

$j = 1,\ldots.n$ variables.

Each of the n observed variables z_j is described in terms of m (usually $m<n$) common factors f_p and a unique factor y_i. The common factors account for the correlations among the original variables, while each unique factor accounts for the remaining variance in these variables.

The common factor analysis model is based on the following assumptions :

A1. unique factors $\{ y_j : j=1,....n \}$ are mutually independent

A2. unique factors $\{ y_j : j=1,....n \}$ are independent of the common factors $\{ f_p : p=1,....m \}$.

A3. unique factors $\{ y_j : j=1,....n \}$ and common factors $\{ f_p : p=1,....m \}$ have zero means and unit variances.

The common factor analysis model can be written more elegantly in compact matrix notation. Let

Z be the (nxN) matrix of observations suitably normalized

F be the (mxN) matrix of unobserved factor scores

A be the (nxm) pattern matrix or matrix of coefficients of the factors in equation (1)

Y be the (nxN) matrix of unique factors

U be the (nxn) diagonal matrix of coefficients for the unique factors.

Then,

(2) $Z = AF + UY$

Post multiplying both sides by F', we get

$ZF' = AFF' + UYF'$

(3) $ZF' = AFF'$ by A2.

But ZF' is simply N times the factor structure matrix S of correlations between the original variables and the hypothetical common factors. In addition, FF' equals N times the matrix of correlations among common factors Φ. So, the last relation can be written :

(4) $$S = A\Phi$$

This equation expresses the fundamental relationship between the factor pattern A and the factor structure S. Obviously, when the common factors are orthogonal, $\Phi = I$ and the last expression reduces to

(5) $$A = S$$

In turn, the matrix of reproduced correlations may be written :

$$\hat{R} = AFF'A'$$

$$= A\Phi A'$$

(6) $$= SA' \qquad \text{as } S = A\Phi$$

If the common factors are kept orthogonal, the reproduced correlations may be written

(7) $$\hat{R} = AA'$$

This relation expresses the "Fundamental Factor Theorem"

Factor analysis usually comprises two steps. First, a primary solution is obtained which satisfies the factor analytic model in a mathematical sense. Second a rotation is performed to produce a solution most amenable to interpretation. In the case of principal factor analysis, the primary solution is unique as the extracted factors satisfy the common variance maximization criterion. This solution provides a basis that spans the common factor space. Many such bases are equally plausible, however, and can be obtained by rotation of the primary solution. In case of orthogonal factors, this property is straightforward. Indeed, in this situation $A = S$ so that if we multiply each side of relation (2) by itself we get :

$$ZZ' = SS' + UU' \tag{8}$$

Multiplying the structure matrix S by the mxm orthogonal matrix T, relation (8) becomes :

$$\begin{aligned} ZZ' &= STT'S' + UU' \\ &= SS' + UU' \end{aligned}$$

So, although the elements of ST are different from the original loadings S, their ability to generate the correlation matrix ZZ' is unchanged.

Such rotations have a special importance in factor as they offer the analyst with a means to achieve factorial invariance that is, they produce a solution which is not wholly dependent on the particular mix of variables involved in the analysis (Rummel [109]). Thurstone [123] proposed the concept of simple structure as a means of selecting the loadings most interpretable in terms of the original variables. The VARIMAX method proposed by Kaiser [63] most nearly approximate these principles (See Harman [49] , for a discussion).

Factor analysis can be performed by a variety of methods that differ in terms of their computational characteristics, their assumptions about the underlying distribution of the data and their definition of what part of the variance of each variable or communality can be explained by the common factors. In the methodology proposed here, Principal Factor Analysis is used as the method of reduction of the perceptual space of any group of decision participants. The method requires that estimates of the communalities of the original variables be placed on the diagonal of the correlation matrices instead of unit variances. In the absence of any additional information, squared multiple correlation coefficients are often used for this purpose as they provide lower bounds of the communalities (Harman [49]).

The reduced correlation matrix is then iteratively factored and new estimates of the communalities are estimated at each iteration until they converge. Once the primary solution has been obtained, it is rotated to simple structure by the VARIMAX criterion.

3.2.2.2.2. Determination of the Number of Common Factors

When factor analysis is used for exploratory purposes, an important problem which faces the researcher is the determination of the number of factors that should be retained in the analysis. This problem is of crucial importance as the rotation of the factor structure can have distorting consequences if insufficient attention is given to selecting the best number of factors. In other words, the loadings and interpretation of all rotated factors may substantially differ for the same data, primary solution and rotation criterion as a result of a different number of factors retained. Rummel ([109] p. 352-3) provides an illustration of this problem in the case of both oblique and orthogonal rotations.

The number of factors problem has no general solution Some criteria have been proposed in the case of specific models of factor analysis and a number of rules of thumb have been developed from practical experience. Rummel ([109], chapter 15) provides an excellent overview of these criteria. The choice among them, however,

is far from clear-cut. As Humphreys and Montanelli [88] recently summarized this field of research :

> "The application of several criteria typically provides several different answers. Also, many are open to theoretical objections when applied to real data ; e.g., theorems true for the population can not be applied directly to sample data. Others like Cattell's scree test are too subjective. The investigator, as a result, frequently falls back on the meaningfulness of his rotated factors, which is quite inadequate for any scientific purpose other than a primitive form of hypothesis formation"

In this research, the determination of the number of factors to be retained for each group of decision participants is of special relevance. Indeed, these factors represent how individuals in each group structure product attributes into higher order evaluation criteria. The systematic investigation of the dimensionality of the evaluation space of different groups of decision participants thus requires the use of an <u>objective</u> criterion by which to stop factoring.

Such a criterion is provided by the method of parallel analysis which requires the construction of a second correlation matrix, from normally distributed random numbers, using the same number of variables (n) and the same number of observations

(N) as there are in the group investigated (Humphreys and Ilgen [59]. Squared multiple correlations are placed on the diagonal of the original and random matrices, which are factored using the principal axes method. The eigenvalues of both matrices are then plotted and the point at which the two traces intersect indicates the number of factors that should be retained in the analysis. This criterion is based on the very reasonnable consideration that a researcher should not be interested in a factor that accounts for less variance than the corresponding factor obtained from a distribution of random numbers. Empirical investigations of this criterion suggest that it is more accurate than other criteria including the maximum likelihood method (Humphreys and Montanelli [88]).

Recently, Montanelli and Humphreys [88] developed a method for predicting the logarithm of the latent roots of random data correlation matrices, with squared multiple correlations on the diagonal. The following equation was found to predict very accurately the size of these eigenvalues ($R^2 > .99$) :

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

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

The methodology proposed in this research makes use of this criterion. For this purpose, a computer program was developed to compute the expected size of the eigenvalues of random correlation matrices with squared multiple correlations on their diagonal. The program makes use of the smoothed regression coefficients recommended by Montanelli and Humphreys. It is reproduced in Appendix 3.

3.2.2.2.3. Estimation of Factor Scores

Once the appropriate evaluation spaces have been derived for each category of decision participants following the method described above, it is necessary to identify those groups that use the same number of evaluation criteria to assess available alternatives (step (I) in the methodology). A systematic investigation of the differences between these groups in the way they structure the basic product attributes into higher-order evaluation criteria is then performed (J).

The method proposed in this research to test for the existence of differences in the composition of each evaluation criteria between groups of decision participants who have an evaluation space of same dimensionality makes use of some properties of the regression method of estimation of factor scores. As these factors scores - which represent each individual's evaluation of

each product alternative -- are also required for the preference analysis, we review now how they are estimated.

In common factor analysis, as opposed to principal component, it is not generally possible to compute exact factor scores. Rather, these scores have to be estimated indirectly by various methods, most often linear regression on the original variables (Rummel [109] p. 441-4 provides an interesting discussion of some alternative methods).

In this research, factor scores are estimated by regression. This approach is most commonly used in Social Science research (Nie et al [94]) and has been used by Allaire [1] in his investigation of consumers' preferences and perceptions of different brands of a frequently purchased good. In addition, the estimation of factor scores by regression provides some interesting properties upon which we build the test (J) of equality of evaluation criteria between groups of decision participants who have an evaluation space of same dimensionality.

The regression approach

The linear regression of factor f_p, p=1,....m on the n original variables suitably standardized z_j may be expressed as

follows.

$$f_{pi} = \sum_{j=1}^{n} \beta_{pj} z_{ji} + \varepsilon_{pi} \quad , p=1,\ldots.m$$

where i refers to the specific score of individual i and the ε_{pi}'s are disturbances.

From the theory of multivariate linear regression it follows that the normal equations for determining the parameters β's of all m factors are :

$$FZ' = BZZ'$$

where B is the (mxn) matrix of regression parameters to be estimated. The matrix of least squares estimates of the β's is then given by :

$$\hat{B} = FZ' \ (ZZ')^{-1}$$

Although the factor scores F are unknown, the matrix FZ' is the structure matrix S of correlations between the m factors and the n original variables, and is known as a result of the factor analysis. Moreover, ZZ' is the matrix R of correlations among the n original variables, and of course is also known. Hence, the last relation may be written :

$$\hat{B} = SR^{-1}$$

The <u>estimated</u> factor scores of each individual are therefore given by :

$$\hat{F} = \hat{B}Z$$
$$= SR^{-1}Z$$
$$= AR^{-1}Z \text{ (in case the common factors are kept orthogonal)}$$

In regression analysis, it is customary to assess the accuracy with which the response variable is estimated by the linear combination of the predictors. The coefficient of multiple correlation ρ is used for this purpose. This coefficient measures the degree of correlation between the actual values of the response variable and its estimated values. In terms of the more general framework of the analysis of variance, ρ^2 may be viewed as the percentage of the observed variance in the response variable accounted for by the best linear combination of the predictors.

The question of the accuracy with which factor scores are estimated by a linear combination on the original variables deserves as much attention as in regression analysis. Harman [49] provides several important results involving the coefficient of multiple correlation ρ associated with the estimation of factor f . Let the normal equation for this factor be written:

$$(f_p' - \beta_p' Z)\ Z' = 0$$

This relation indicates that the residuals $(f_p' - \beta_p' Z)$ are orthogonal to each of the original variables z_j. Hence they are

also orthogonal to any linear combination of the original variables so that :

$$(f_p' - \hat{\beta}_p' Z)\, Z'\hat{\beta}_p = 0$$

and as $\hat{f}_p' = \hat{\beta}_p' Z$, we get

$$f_p' \hat{f}_p - \hat{f}_p' \hat{f}_p = 0$$

which, upon dividing by N reduces to :

$$\sigma_{\hat{f}_p} \rho_{f_p \hat{f}_p} - \sigma_{\hat{f}_p} = 0 \quad \text{as from A3, } \sigma_{f_p} = 1$$

so,

$$\rho_{f_p \hat{f}_p} = \rho_p = \sigma_{\hat{f}_p}$$

This last expression indicates that the coefficient of multiple correlation ρ_p associated with the estimation of f_p is equal to the standard deviation of the factor score estimates $\hat{f}_{pi}$.

A simpler expression for ρ_p may be obtained by premultiplying both sides of the relation

$$\hat{f}_p = \hat{\beta}_{p1} z_1 + \hat{\beta}_{p2} z_2 + \ldots + \hat{\beta}_{pn} z_n$$

by f_p' the true unobserved factor scores and dividing by N. One obtains :

$$\sigma_{\hat{f}_p} \rho_p = \hat{\beta}_{p1} s_{11} + \ldots \hat{\beta}_{pn} s_{np}$$

where s_{jp} stands for element (j,p) of the factor structure matrix S. As from above $\rho_p = \sigma_{\hat{f}_p}$, one finally gets

$$\rho_p^2 = \sum_{j=1}^{n} \hat{\beta}_{pj} \, s_{jp}$$

Hence, each of the individual products $\hat{\beta}_{pj} \, s_{jp}$ represents the contribution of variable z_j to ρ_p^2 . Harman([49], p. 371) also provides an expression to measure the indirect contributions to ρ_p^2 of any of the original variable z_j through its correlation with each of the other variables.

The coefficient of determination ρ_p^2 is of fundamental importance in common factor analysis as it specifics the extent to which the estimated factor scores are indeterminate. This coefficient provides a lower bound for the expected correlation between any two estimates of the factor scores f_p obtained by the model

$$\sum_{j=1}^{n} \beta_{pj} \, z_j + \varepsilon_p \, ,$$

for any distribution of the ε_{pi}'s ; and ρ_p^2 equals the expected correlation between any two of these estimates under ordinary assumptions of independent symmetric errors (Mulaik [91]). Green [41] recently provided an excellent review of the role of ρ_p^2 in common factor analysis.

In the methodology proposed here, ρ_p^2 has a special importance as it provides the information necessary for the test (J) of equality of evaluation criteria. Before discussing this test, however. a final comment must be made about ρ_p^2 .

Another way to look at ρ_p^2 is in terms of the amount of variance in the true factor scores f_{pi} accounted for by the regression on the n original variables z_j. The coefficient of determination ρ_p^2 may then be written :

$$\rho_p^2 = \frac{\sum_{i=1}^{N} (\hat{f}_{pi} - \bar{f}_p)^2}{\sum_{i=1}^{N} (f_{pi} - \bar{f}_p)^2}$$

$$= \frac{\text{Variance accounted for by the regression model}}{\text{Total variance}}$$

alternatively,

$$\rho_p^2 = 1 - \frac{\sum_{i=1}^{N} (f_{pi} - \hat{f}_{pi})^2}{\sum_{i=1}^{N} (f_{pi} - \bar{f}_p)^2}$$

$$= 1 - \frac{1}{N} \sum_{i=1}^{N} (f_{pi} - \hat{f}_{pi})^2$$

as by A3 : $\frac{1}{N} \sum_{i=1}^{N} (f_{pi} - \bar{f}_p)^2 = 1$

The sum of the squared residuals in the estimation of factor f_p is then given by :

$$\sum_{i=1}^{N} (f_{pi} - \hat{f}_{pi})^2 = (1 - \rho_p^2)\ N$$

This last expression plays a central role in the new test (J) for the equality of evaluation criteria across groups of decision participants, developed in the next section.

3.2.2.3. A Test for the Equality of Evaluation Criteria Across Groups of Decision Participants.

Consider the case where the evaluation spaces of different categories of decision participants have the same dimensionality. Does this fact imply that these decision participants use similar evaluation criteria ? Or is it possible that these different groups of individuals, although using the same number of evaluation criteria, exhibit systematic differences in the composition of at least one of these criteria in terms of the original product attributes ?

This problem can be cast easily in terms of our factor analytic methodology. It refers to the relation between several factor solutions obtained in different samples from the same battery of variables. This problem is receiving increasing attention in the mathematical psychology literature. Some theoretical work

has appeared recently (Joreskog [62], Please [102]) that indicates new directions for the statistical analysis of such variations in factors structures. No general solution to the problem has been found to date, however, and as Harman recently concluded in his excellent review of the literature on the subject ([49]p. 346):

> "The empirical approach, employing indices of proportionality of factors... seems not inappropriate at this time for the identification of factors across different studies... [involving the same set of variables in different samples]".

The approach for testing the equality of evaluation criteria proposed here is different from that typically used in the literature. Instead of attempting to assert the similarity between the factor structure matrix obtained in each sample, we concentrate on the similarity between the predictive equations used to assess factor scores. Our test then compares pairs of factor measurement equations obtained from different samples.

The problem of testing the equality of sets of regression coefficients in two or more regressions arises frequently in econometrics. An excellent discussion of this problem is provided by Chow [23] and Fisher [37].

Consider a situation in which data are available from two samples. The first has N_1 observations and the second N_2.

Let subscripts 1 and 2 denote the first and second sample respectively. We can write the two regression models in the form

$$Y_1 = X_1\beta_1 + \varepsilon_1$$

$$\hat{Y}_1 = X_1 b_1 + e_1$$

$$Y_2 = X_2\beta_2 + \varepsilon_2$$

$$\hat{Y}_1 = X_2 b_2 + e_2$$

Where Y_i and X_i are $(N_i \times 1)$ and $(N_i \times m)$ observation matrices, β_i and b_i are $(m \times 1)$ vectors of coefficients and least squares estimators, and ε_i and e_i are $(N_i \times 1)$ error and residual vectors. The ε_i's are assumed to be normally distributed with mean vector 0 and covariance matrix $\sigma_i^2 I$.

These two regressions can be written jointly as

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix}$$

$$= \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \end{bmatrix}$$

The null hypothesis that $\beta_1 = \beta_2$ gives rise to the reduced model

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

$$= \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} b + e$$

Assume for the sake of simplicity that m is less than min (N_1, N_2), indicating that in each sample the number of observations is larger than the number of parameters to be estimated. Then, the null hypothesis $H_0 : \beta_1 = \beta_2$ can be tested with the statistic

$$C = \frac{e'e - (e'_1e_1 + e'_2e_2) / m}{(e'_1e_1 + e'_2e_2) / (N_1 + N_2 - 2m)}$$

$$= \left\{ \frac{e'e}{e'_1e_1 + e'_2e_2} - 1 \right\} \frac{(N_1 + N_2 - 2m)}{m}$$

Under H_0, C is distributed as an F-variate with m and $(N_1 + N_2 - 2m)$ degrees of freedom respectively. This test, often refered to as the Chow test in the literature, is in fact an immediate result of the general linear test (Neter and Wasserman [ ]).

In this research, a slightly modified version of this test is proposed to investigate the similarity between common factors obtained from different groups of individuals who have a factors space of same dimensionality. The test involves the assessment of whether the factor score coefficients β_j's used to estimate the scores of each individual on a given factor are the same for the two groups.

Before discussing the specific steps involved in the computation of the test statistic C in the context of factor analysis a caution is in order. Indeed, the general linear test, of which Chow test is a specific case, assumes that the error terms are mutually independent and normally distributed with mean zero.

In the case of common factor analysis, the prediction equations are :

$$f_{pi} = \sum_{j=1}^{n} \beta_{pj} z_{ji} + \varepsilon_{pi} \qquad p = 1,\ldots m$$

The distribution of the disturbances ε_{pi}'s, however, is unknown. Moreover, as the true factor scores are unobserved, there are no means of testing any assumption about the distribution of the error terms from the empirical distribution of the residual e_{pi}'s.

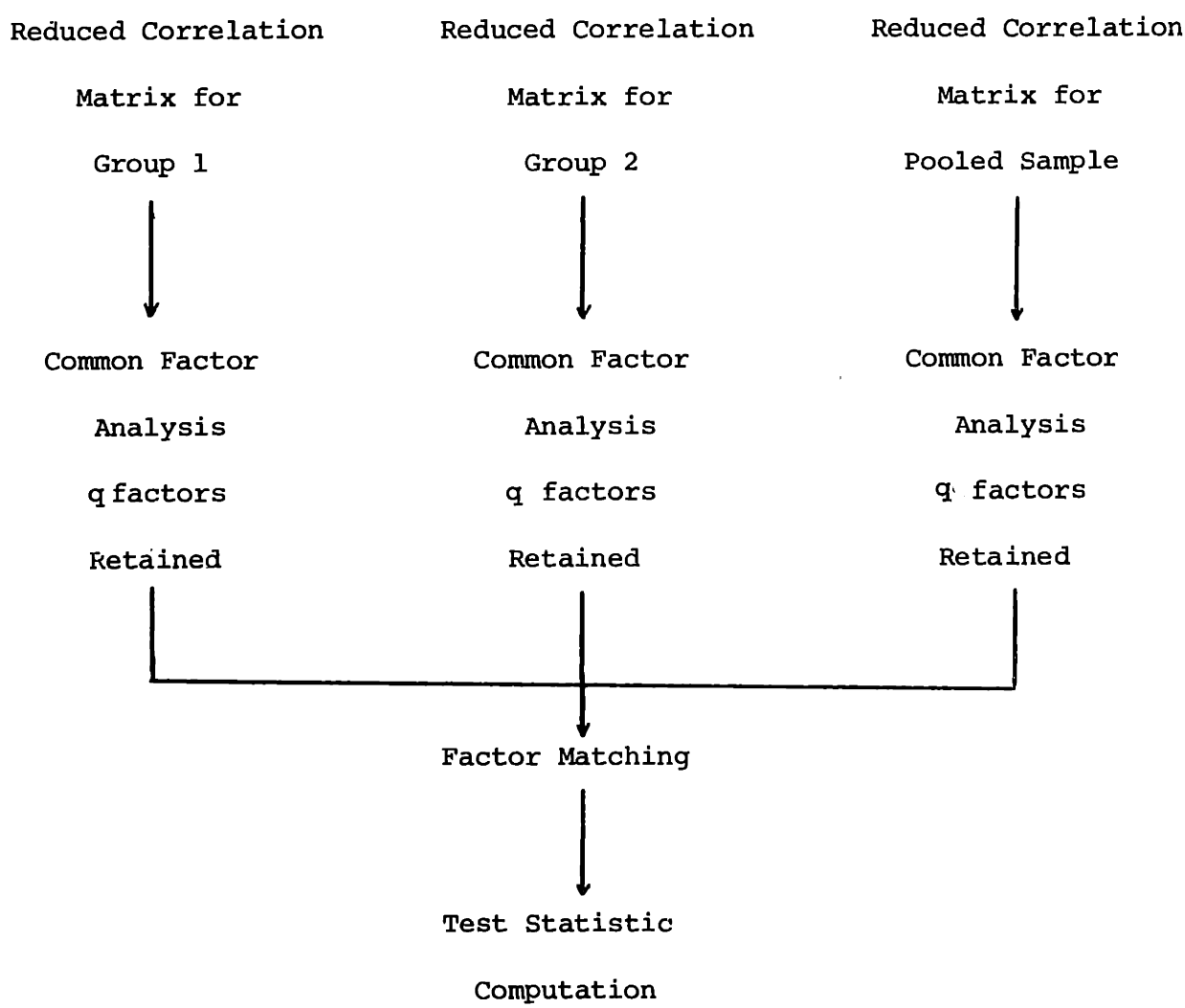
Here, we assume that the ε_{pi}'s are independent and normally distributed with mean zero. This assumption represents the price for development of objective criteria to compare factors. This assumption is intuitively appealing and does not conflict with any of the basic hypotheses of the common

factor model. Moreover, theoretical and empirical investigations have shown that the F-test for the general linear hypothesis is fairly robust under departure from the normality assumption (Hoel, Port and Stone [54]). Recently, Toyoda [125] also showed that the test statistic C was still well behaved under heteroscedasticity conditions. The assumptions we are making here about the distribution of the disturbances ε_{pi}'s are then not as stringent a restriction on the validity of the test proposed as it might first appear.

Figure 3.5. outlines the various steps involved in the computation of the test statistic C 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 quite 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 evaluation criteria harbored by members of each of the two groups of decision participants to assess product alternatives. Call these evaluation criteria f_1^1, f_2^1, f_3^1 and

FIGURE 3.5.: OUTLINE OF THE METHODOLOGY FOR ASSESSING INTER-DECISION GROUPS DIFFERENCES IN EVALUATION CRITERIA



f^2_1, f^2_2, f^2_3, for group 1 and group 2 respectively and let ρ^2_{11}, ρ^2_{12}, ρ^2_{13} and ρ^2_{21}, ρ^2_{22}, ρ^2_{23} denote the coefficients of determination associated with the estimation of these factors.

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

Next, potentially 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. Indeed, if it were not the case, we would readily conclude at the inequality of the evaluation criteria exhibited by these two groups. Let f^1_i, f^2_h and f_k denote such a set of potentially similar factors.

We can then compute the statistic C by the following expression :

$$C = \left[\frac{(1 - \rho^2_k)\ (N_1 + N_2)}{(1 - \rho^2_{1i})\ N_1 + (1 - \rho^2_{2h})\ N_2} - 1 \right] \frac{N_1 + N_2 - 2m}{m}$$

where $(1 - \rho^2_{rp})\ N_r$ represents the sum of the squared residuals associated with factor f_p in group r.

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

3.2.3. Preference Analysis

The final step of the methodology is preference estimation (L). Once products are positioned in the appropriate evaluation space for each category of decision participants, individual preferences for the available alternatives can be linked to the products' coordinates in this space. This step of the methodology thus addresses the question of whether the evaluation analysis, performed at the level of each group of decision participants is behaviorally meaningful. In other words, does the consideration of the specific evaluation criteria of each participant category lead to a better understanding of the way decision participants form preferences.

In this research, the link between individuals preferences for available product alternatives -- as measured by the methods described in section 2.4.2. -- and their evaluation of those

alternatives along the appropriate evaluation criteria is investigated using a linear regression model. This approach provides a more accurate method for assessing the relative importance of the evaluation criteria of each group of decision participants in the formation of individual preferences than measures of importance obtained directly from the respondents (Allaire [1]). Moreover, research by Lavin [69] suggests that simple linear compensatory models provide a better prediction of managers' choices in industrial adoption situations than various classes of lexicographic models that describe more accurately the actual decision process.

Although simple linear regression provides an adequate model to investigate the relevance of the differences in evaluation criteria between groups of decision participants in the formation of individual preferences, it is quite likely that more complex models, including for instance nonlinearities, would give better preference fits. Work by Allaire [1] in the consumer area suggests that several models should be explored and the best one chosen for each segment of consumers. Similar work in the context of the industrial adoption process might lead to the discovery of additional differences between decision participant categories. This task falls outside the scope of this research, however, and will be matter for future work.

3.3. Implementation of the Methodology

In this section we implement the methodology just presented to investigate if different groups of decision participants likely to become involved in the adoption decision for a new industrial cooling system differ in terms of their perception of the major alternatives and in terms of the evaluation criteria they use to assess these alternatives. Three main alternatives are included in the analysis: an industrial compression cooling system (COMAIR), an absorption system (ABSAIR) and the new solar System (SOLABS). Four categories of decision participants are distinguished : Production Engineers (PE), Corporate Engineers (CE), Plant Managers (PM), and Top Managers (TM). The sample size for each of these four decision groups are 35, 23, 20 and 41 respectively.

A fifth decision group was in fact included in our survey and involved H.V.A.C. consultants. This group is not included in the present analysis, however. Our reasons are first, that the perceptual items were not exactly identical in the questionnaire used for company representatives and in that for H.V.A.C. consultants. Inclusion of the latter decision group in the analysis would then have forced the exclusion of some potentially relevant product attributes. Second, the sample size for H.V.A.C. consultants was much larger than for the other four decision groups

so that interpretation of the results should have been carefully weighted for unequal sample sizes. This analysis has then been performed separately and is reported in Choffray and Lilien [22]. We will refer to some of those results in the current presentation.

3.3.1. Product Perception Analysis

3.3.1.1. Product Discrimination Analysis

The first step in the perceptual analysis methodology is a test for product discrimination. As described in section 3.2.1.1. the objective of the test is threefold:

- identify within each group of decision participants if available alternatives are perceived differently ; that is, whether these alternatives are perceived as offerering substantially different attributes

- check if all perceptual items included in the analysis have strong discriminating power.

- identify if decision groups differ in their perception of the relative characteristics of available alternatives ; that is, do the rank ordering of the perceptual ratings of available product alternatives on each perceptual item vary from one decision group to another ?

To answer these questions, a one-way multivariate analysis of variance was performed for each of the four decision groups across product alternatives. Table 3.1. presents the main results of the analysis.

For all four groups, the generalized correlation $\eta^2 = (1 - \Lambda)$ is quite high, indicating strong discrimination between the three alternatives within each group of decision participant. For each group the F-ratio is significant at the .01 level. Thus, the three alternatives COMAIR, ABSAIR and SOLABS appear to offer substantially different characteristics. This result is not surprising as the three alternatives do indeed present important differences. It is however, satisfying to note that these differences have been correctly conveyed through the concept statements.

The results of the univariate analysis of variances for each group of decision participants are reported in tables 3.2. to 3.5. A cursory look at the F-ratios for each perceptual item indicates that they all have strong discriminating power. It is interesting to note, however, that Plant Managers do not strongly discriminate among the three systems on the basis of their perceived complexity (Item 14).

TABLE 3.1. : ONE-WAY MULTIVARIATE ANALYSIS OF VARIANCE FOR PRODUCT DISCRIMINATION

	Wilks Λ	Generalized Correlation η^2	F-Ratio
Production Engineers	.0593	.9407	15.16 *** (34 ; 166)
Corporate Engineers	.0301	.9699	17.36 *** (34 ; 124)
Plant Managers	.0758	.9242	7.28 *** (34 ; 94)
Top Managers	.0655	.9345	16.25 *** (34 ; 190)

*** Significant at .01 level

TABLE 3.2. : UNIVARIATE ANALYSIS OF VARIANCE FOR PRODUCT DISCRIMINATION

(Production Engineers)

	Average Rating for COMAIR	Average Rating for ABSAIR	Average Rating for SOLABS	F-Ratio (2,99)
ITEM 1	5.65	5.39	3.89	22.94***
ITEM 2	1.50	1.91	3.86	27.20***
ITEM 3	3.53	2.73	4.49	9.98***
ITEM 4	6.18	5.12	3.05	56.60***
ITEM 5	4.09	4.09	6.06	27.31***
ITEM 6	5.24	3.21	2.89	24.99***
ITEM 7	3.29	1.82	5.60	44.41***
ITEM 8	3.68	2.67	5.86	32.99***
ITEM 9	4.97	4.09	3.40	8.59***
ITEM 10	3.53	3.42	5.31	17.49***
ITEM 11	1.74	2.73	4.46	29.26***
ITEM 12	2.94	2.27	6.14	76.34***
ITEM 13	3.76	3.33	5.20	10.43***
ITEM 14	3.03	3.64	3.80	2.78
ITEM 15	3.50	2.73	4.91	18.27***
ITEM 16	3.79	3.30	5.03	11.29***
ITEM 17	5.15	2.06	1.66	77.91***

TABLE 3.3. : UNIVARIATE ANALYSIS OF VARIANCE FOR PRODUCT DISCRIMINATION

(Plant Managers)

	Average Rating for COMAIR	Average Rating for ABSAIR	Average Rating for SOLABS	F-Ratio (2,63)
ITEM 1	5.91	4.81	3.91	13.23***
ITEM 2	1.82	2.57	4.57	18.35***
ITEM 3	3.50	3.76	4.91	5.94***
ITEM 4	5.82	5.14	3.35	20.49***
ITEM 5	4.23	4.05	5.83	18.26***
ITEM 6	5.09	3.24	2.48	18.75***
ITEM 7	3.32	2.67	5.78	25.78***
ITEM 8	3.77	3.48	6.04	21.08***
ITEM 9	4.73	3.71	3.61	2.82*
ITEM 10	3.41	3.14	5.26	16.14***
ITEM 11	2.41	2.95	4.74	12.52***
ITEM 12	2.64	3.19	5.70	37.30***
ITEM 13	3.64	3.62	5.30	9.69***
ITEM 14	3.09	3.62	3.61	1.03
ITEM 15	3.23	3.33	4.96	12.39***
ITEM 16	4.45	3.57	5.52	16.48***
ITEM 17	4.86	2.57	1.83	36.98***

TABLE 3.4. : UNIVARIATE ANALYSIS OF VARIANCE FOR PRODUCT DISCRIMINATION

(Corporate Engineers)

	Average Rating for COMAIR	Average Rating for ABSAIR	Average Rating for SOLABS	F-Ratio (2,78)
ITEM 1	5.96	5.25	3.77	22.09***
ITEM 2	1.41	2.18	2.81	5.76***
ITEM 3	3.19	3.14	4.58	5.26***
ITEM 4	6.26	5.18	2.81	57.68***
ITEM 5	4.11	3.57	5.65	17.95***
ITEM 6	5.33	3.54	2.19	30.08***
ITEM 7	4.11	2.04	5.42	27.80***
ITEM 8	3.26	1.86	5.85	60.25***
ITEM 9	4.93	3.64	3.81	5.99***
ITEM 10	3.00	2.54	5.19	22.58***
ITEM 11	1.37	2.04	4.88	58.90***
ITEM 12	3.00	2.82	6.04	44.16***
ITEM 13	2.70	2.71	4.12	10.13***
ITEM 14	2.44	3.21	4.12	8.39***
ITEM 15	3.63	3.18	4.62	5.51***
ITEM 16	4.48	3.64	4.62	3.68**
ITEM 17	4.81	1.61	1.81	99.08***

TABLE 3.5. : UNIVARIATE ANALYSIS OF VARIANCE FOR PRODUCT DISCRIMINATION

(Top Managers)

	Average Rating for COMAIR	Average Rating for ABSAIR	Average Rating for SOLABS	F-Ratio (2,111)
ITEM 1	5.73	5.19	3.95	19.81***
ITEM 2	1.41	1.86	4.22	40.80***
ITEM 3	3.65	3.73	4.25	1.65
ITEM 4	6.05	5.08	2.88	66.00***
ITEM 5	3.78	3.19	5.42	24.94***
ITEM 6	5.35	2.78	2.38	57.33***
ITEM 7	2.97	1.97	5.65	57.88***
ITEM 8	3.35	2.43	5.92	54.68***
ITEM 9	4.51	3.95	3.07	6.75***
ITEM 10	2.97	3.03	5.07	23.27***
ITEM 11	1.70	3.03	4.75	41.28***
ITEM 12	2.68	2.49	5.95	74.09***
ITEM 13	3.35	3.16	5.20	16.22***
ITEM 14	2.59	3.68	3.63	6.54***
ITEM 15	4.03	2.97	4.80	13.33***
ITEM 16	4.08	3.57	4.75	4.29**
ITEM 17	4.76	2.14	1.95	50.15***

A systematic investigation of the rank orderings of the ratings obtained by the three alternatives on each perceptual item does not indicate the existence of any important differences across decision groups. Typically, the rank ordering of the three alternatives is the same, suggesting that product attributes are perceived consistently across decision groups. Only one slight difference is worth mentioning. It concerns Item 3: "Climate Sensibility". Engineers (PE ; CE) perceive COMAIR as more sensitive to climate conditions than ABSAIR, while Managers (PM ; TM) perceive the opposite. In our opinion, this difference is probably due to the technical background and broader experience of engineers who associate COMAIR more readily with roof-top units.

An interesting pattern emerges from the systematic analysis of the average perceptual ratings of the three alternatives on all perceptual scales. Indeed, it appears that most of the time individuals discriminate among alternative industrial cooling systems on the basis of two basic dichotmies :

- Type I : Conventional cooling Systems (ABSAIR, COMAIR) versus. Non-conventional cooling system (SOLABS)

- Type II: Compression cooling System (COMAIR) versus Absorption cooling systems (ABSAIR, SOLABS)

Most perceptual items favor discrimination of either the first or the second type. Moreover, no systematic difference appear across decision groups in terms of the type of discrimination fostered by each perceptual item. So, Item 1 and 12 discriminate mainly between conventional and non-conventional industrial cooling systems. Item 6 and 17, discriminate mainly between compression and absorption industrial cooling systems.

Identification of this pattern of perceptual discrimination between available alternatives is most interesting. It points not only to the existence of differences between these alternatives in terms of the attributes they each offer. But, in addition, it points to the sources of these differences that may have important implications for the development of marketing strategies for the new solar system. For instance, if an item which favors a type I discrimination is found to constitute an area of potential resistance in the formation of individual preferences a repositioning of the solar concept along that attribute should be considered. On the other hand if a type II perceptual item is found to constitute an area of resistance, major re-design of the SOLABS concept might be necessary. In the latter case, a solar rankine cycle cooling system (Burriss [15]) might prove more acceptable than the solar-absorption alternative, even if this first system is not currently technologically feasible.

Thus, the test for product discrimination performed in this analysis suggests that the three alternatives COMAIR, ABSAIR and SOLABS included in our study do indeed present substantial differences and are perceived accordingly by each group of decision participants. No fundamental disagreements were observed across decision groups when the rankings of all three alternatives on each perceptual item were compared. This suggests that products' attributes are perceived consistently across decision groups. Finally, the results of the unvariate analyses of variance suggest that most perceptual items favor a discrimination of one of two basic types. These allow for a more systematic analysis of the areas of potential resistance to the SOLABS concept.

3.3.1.2. Product Perception Differences Across Decision Groups

The second part of the perceptual analysis methodology is concerned with the identification of perceptual differences across groups of decision participants likely to become involved in the purchase of an industrial cooling system. As we described in section 3.2.1.2., perceptual ratings for each product alternative are submitted to a Multivariate Profile Analysis. A computer program developed by Allaire, Silk and Tsang [2] is used for this purpose.

The main results of the analysis are reproduced in table 3.6. As the Heck criterion indicates, the hypothesis of

TABLE 3.6. : MULTIVARIATE PROFILE ANALYSIS FOR PERCEPTUAL DIFFERENCES ACROSS CATEGORIES OF DECISION PARTICIPANTS

Product Concept	Heck Criterion for Profile Parallelism	F-Ratio for Difference in Profile Level
COMAIR	.294 ** (3=3, M=6, N=52)	.905 (3,121)
ABSAIR	.266 * (5=3, M=6, N=51)	2.493 * (3,119)
SOLABS	.254 * (5=3, M=6, N=50)	.808 (3,118)

* Significant at .10 level ** Significant at .05 level

parallel perceptual profiles across decision groups is rejected at the $\alpha<.10$ level for each product alternative. Although the test of equality of profile height assumes that the hypothesis of parallelism has been retained, the F-ratio for ABSAIR suggests the existence of differences in profile level across decision groups.

Hence, our analysis suggests the existence of systematic perceptual differences across participant categories for each industrial cooling alternatives. Our results indicate, however, that these differences might be more important for established products like COMAIR and ABSAIR than for a new product like SOLABS. This phenomenon is not in disagreement with the theory of organizational buying behavior (See, for instance, Webster and Wind [136]). It means that for a new industrial product, decision participants have little experience upon which to draw and so, find it harder to assess its potential to fulfill the needs of their organization and their personnal needs.

In the Choffray and Lilien [22] paper, involving H.V.A.C. consultants as a fifth decision group, the hypothesis of perceptual profiles parallelism was rejected at the $\alpha = .01$ level for all three product alternatives. The increase in degrees of freedom resulting from the addition of H.V.A.C. consultants in this analysis hence obscured the interesting fact that perceptual differences might be less for SOLABS than for the other two systems.

Tables 3.7. - 3.12. present the univariate analyses of variance for COMAIR, ABSAIR, and SOLABS respectively. There are two interesting ways of looking at these results. The first one is to identify for each pair of participant categories the perceptual differences that are statistically significant. The second one is to consider, for each product alternative and perceptual item, the pattern of inter-decision group perceptual differences irrespective of the statistical significance of these differences.

The first approach is exhibited in tables 3.7. - 3.12. Individual F-ratios are reproduced and have been used to test the statistical significance of each perceptual difference. It appears immediately that SOLABS is characterized by the smallest number of significant perceptual differences, emphasizing once again the difficulty that decision participants have to form their opinion about this new alternative. Some interesting perceptual differences can be identified, however. For instance, PE perceive SOLABS more as an energy saving system than PM. They view it more as conveying the image of an innovative company than TM, and as making a fuller use of available unproductive areas than CE. However, PE consider the cost of the new system less acceptable than CE. Other perceptual differences for SOLABS and the two other alternatives -- COMAIR and ABSAIR -- are evident from the tables. The identification of these differences is a major

TABLE 3.7 : COMPARISON OF GROUP MEANS FOR THE THREE PRODUCT CONCEPTS

PLANT MANAGERS VS TOP MANAGERS

	CONAIR			ABSAIR			SOLABS		
	PM	TM	F-RATIO (1,60)	PM	TM	F-RATIO (1,59)	PM	TM	F-RATIO (1,60)
ITEM 1	5.91	5.74	.57	4.83	5.21	1.23	3.83	4.03	.24
ITEM 2	1.83	1.43	4.57**	2.57	1.86	4.20**	4.43	4.36	.02
ITEM 3	3.61	3.76	.16	3.78	3.76	.00	5.00	4.28	2.87*
ITEM 4	5.87	6.05	.46	5.04	5.07	.01	3.22	2.92	.53
ITEM 5	4.30	3.82	2.79*	4.04	3.10	5.61**	5.70	5.51	.29
ITEM 6	5.09	5.30	.40	3.26	2.76	2.85*	2.39	2.43	.01
ITEM 7	3.26	2.94	.46	2.78	2.02	4.00**	5.70	5.74	.02
ITEM 8	3.91	3.33	1.60	3.57	2.47	6.03**	6.04	5.94	.13
ITEM 9	4.83	4.51	.42	3.52	3.97	.97	3.52	3.17	.63
ITEM 10	3.30	3.00	.65	3.09	3.00	.05	5.34	5.08	.43
ITEM 11	2.35	1.79	2.95*	2.96	3.00	.01	4.91	4.67	.35
ITEM 12	2.65	2.74	.06	3.26	2.52	3.56*	5.60	5.95	1.01
ITEM 13	3.78	3.35	.81	3.57	3.18	.83	5.30	5.18	.09
ITEM 14	3.04	2.71	.84	3.57	3.63	.02	3.60	3.56	.01
ITEM 15	3.26	3.92	3.84*	3.30	3.05	.41	4.95	4.90	.02
ITEM 16	4.35	4.12	.29	3.70	3.47	.27	5.39	4.95	1.22
ITEM 17	4.96	4.82	.11	2.52	2.10	1.34	1.78	1.97	.49

* Significant at .10 level ** Significant at .05 level

TABLE 3.8. : COMPARISON OF GROUP MEANS FOR THE THREE PRODUCT CONCEPT

PRODUCTION ENGINEERS VS PLANT MANAGERS

	COMAIR			ABSAIR			SOLABS		
	PE	PM	F-RATIO (1,56)	PE	PM	F-RATIO (1,55)	PE	PM	F-RATIO (1,55)
ITEM 1	5.60	5.91	1.89	5.35	4.83	2.85*	3.85	3.83	.00
ITEM 2	1.54	1.83	1.73	1.88	2.57	4.04**	3.94	4.43	.78
ITEM 3	3.60	3.61	.00	2.79	3.78	5.61**	4.47	5.00	1.47
ITEM 4	6.11	5.87	.93	5.12	5.04	.04	3.06	3.22	.17
ITEM 5	4.09	4.30	.50	4.03	4.04	.00	6.06	5.70	1.20
ITEM 6	5.20	5.09	.11	3.15	3.26	.08	2.91	2.39	1.31
ITEM 7	3.26	3.26	.00	1.79	2.78	7.13***	5.59	5.70	.06
ITEM 8	3.69	3.91	.24	2.68	3.57	3.89*	5.85	6.04	.28
ITEM 9	4.94	4.83	.08	4.12	3.52	1.84	3.44	3.52	.03
ITEM 10	3.60	3.30	.49	3.47	3.09	1.09	5.29	5.35	.02
ITEM 11	1.80	2.35	2.81*	2.71	2.96	.30	4.47	4.91	1.02
ITEM 12	2.94	2.65	.52	2.32	3.26	6.63**	6.15	5.61	2.81*
ITEM 13	3.74	3.78	.01	3.35	3.57	.22	5.18	5.30	.09
ITEM 14	3.03	3.04	.00	3.70	3.57	.10	3.80	3.61	.10
ITEM 15	3.49	3.26	.38	2.74	3.30	2.93*	4.88	4.96	.03
ITEM 16	3.77	4.35	2.96*	3.24	3.70	1.35	5.00	5.39	1.09
ITEM 17	5.11	4.96	.17	2.06	2.52	1.48	1.68	1.78	.23

* Significant at .10 level ** Significant at .05 level *** Significant at .01 level

TABLE 3.9. : COMPARISON OF GROUP MEANS FOR THE THREE PRODUCT CONCEPTS

PRODUCTION ENGINEERS VS TOP MANAGERS

	COMAIR			ABSAIR			SOLABS		
	PE	TM	F-RATIO (1.72)	PE	TM	F-RATIO (1.70)	PE	TM	F-RATIO (1.71)
ITEM 1	5.60	5.74	.45	5.35	5.21	.23	3.85	4.03	.26
ITEM 2	1.54	1.44	.40	1.88	1.87	.00	3.94	4.36	.72
ITEM 3	3.60	3.77	.22	2.79	3.76	6.61**	4.47	4.28	.21
ITEM 4	6.11	6.05	.09	5.12	5.08	.02	3.06	2.92	.15
ITEM 5	4.09	3.82	.80	4.03	3.11	6.60**	6.06	5.51	3.11*
ITEM 6	5.20	5.31	.14	3.15	2.76	1.46	[illegible]	2.44	1.65
ITEM 7	3.28	2.95	.45	1.79	2.02	.76	5.59	5.74	.19
ITEM 8	3.69	3.33	.69	2.68	2.47	.30	5.85	5.95	.09
ITEM 9	4.94	4.51	1.19	4.12	3.97	.14	3.44	3.18	.47
ITEM 10	3.60	3.00	2.82*	3.47	3.00	1.82	5.29	5.08	.38
ITEM 11	1.80	1.79	.00	2.71	3.00	.57	4.47	4.67	.26
ITEM 12	2.94	2.74	.28	2.[illegible]	2.53	.35	6.15	5.95	.55
ITEM 13	3.74	3.36	.78	3.35	3.18	.17	5.18	5.18	.00
ITEM 14	3.03	2.72	1.01	3.[illegible]1	3.63	.04	3.80	3.56	.10
ITEM 15	3.49	3.92	1.[illegible]	2.74	3.05	.87	4.88	4.90	.00
ITEM 16	3.77	4.13	.88	3.24	3.47	.35	5.00	4.95	.02
ITEM 17	5.11	4.82	.73	2.06	2.11	.02	1.68	1.97	1.54

* Significant at .10 level ** Significant at .05 level

TABLE 3.10. : COMPARISON OF GROUP MEANS FOR THE THREE PRODUCT CONCEPTS

PRODUCTION ENGINEERS VS CORPORATE ENGINEERS

	COMAIR			ABSAIR			SOLABS		
	PE	CE	F-RATIO (1.62)	PE	CE	F-RATIO (1,60)	PE	CE	F-RATIO (1,58)
ITEM 1	5.60	5.96	2.85*	5.35	5.25	.10	3.85	3.84	.00
ITEM 2	1.54	1.39	.54	1.88	2.18	.78	3.94	2.77	5.09**
ITEM 3	3.60	3.28	.52	2.79	3.14	.63	4.47	4.50	.00
ITEM 4	6.11	6.25	.47	5.12	5.18	.03	3.06	2.92	.13
ITEM 5	4.09	4.11	.01	4.03	3.57	1.64	6.06	5.77	.81
ITEM 6	5.20	5.29	.07	3.15	3.53	1.00	2.91	2.23	2.86*
ITEM 7	3.26	4.00	2.94*	1.79	2.04	.58	5.59	5.53	.01
ITEM 8	3.69	3.25	.91	2.68	1.86	6.13**	5.85	5.88	.01
ITEM 9	4.94	4.82	.12	4.12	3.64	1.42	3.44	3.80	.69
ITEM 10	3.60	3.00	2.86*	3.47	2.54	7.22***	5.29	5.15	.12
ITEM 11	1.80	1.36	3.60*	2.71	2.04	2.91**	4.47	4.76	.50
ITEM 12	2.94	2.93	.01	2.32	2.82	1.59	6.15	6.15	.00
ITEM 13	3.74	2.71	5.63**	3.35	2.71	2.79*	5.18	4.46	2.97*
ITEM 14	3.03	2.39	3.56*	3.70	3.21	1.51	3.80	4.11	1.66
ITEM 15	3.49	3.61	.09	2.74	3.17	1.73	4.88	4.65	.24
ITEM 16	3.77	4.43	2.90*	3.24	3.64	1.07	5.00	4.76	.39
ITEM 17	5.11	4.71	1.44	2.06	1.60	2.82*	1.68	1.77	.17

* Significant at .10 level ** Significant at .05 level *** Significant at .01 level

TABLE 3.11. : COMPARISON OF GROUP MEANS FOR THE THREE PRODUCT CONCEPTS

CORPORATE ENGINEERS VS PLANT MANAGERS

	COMAIR			ABSAIR			SOLABS		
	CE	PM	F-RATIO (1,49)	CE	PM	F-RATIO (1,49)	CE	PM	F-RATIO (1,47)
ITEM 1	5.96	5.91	.05	5.25	4.83	1.29	3.85	3.83	.00
ITEM 2	1.39	1.83	3.87*	2.18	2.57	.75	2.77	4.43	8.45***
ITEM 3	3.29	3.61	.44	3.14	3.78	1.79	4.50	5.00	1.17
ITEM 4	6.25	5.87	2.85*	5.18	5.04	.13	2.92	3.22	.48
ITEM 5	4.11	4.30	.38	3.57	4.04	1.57	5.77	5.70	.05
ITEM 6	5.29	5.09	.30	3.54	3.26	.43	2.23	2.39	.13
ITEM 7	4.00	3.26	2.93*	2.04	2.78	2.96*	5.54	5.70	.14
ITEM 8	3.25	3.91	1.96	1.86	3.57	18.21***	5.88	6.04	.28
ITEM 9	4.82	4.83	.00	3.64	3.52	.06	3.80	3.52	.34
ITEM 10	3.00	3.30	.58	2.54	3.09	2.83*	5.15	5.35	.17
ITEM 11	1.36	2.35	8.72***	2.04	2.96	4.86**	4.77	4.91	.10
ITEM 12	2.93	2.65	.58	2.82	3.26	.96	6.15	5.61	2.90*
ITEM 13	2.71	3.78	6.00**	2.71	3.57	3.95*	4.46	5.30	3.42*
ITEM 14	2.39	3.04	2.92*	3.21	3.57	.61	4.11	3.61	1.44
ITEM 15	3.61	3.26	.75	3.18	3.30	.11	4.65	4.96	.41
ITEM 16	4.43	4.35	.04	3.64	3.70	.02	4.77	5.39	3.17
ITEM 17	4.71	4.96	.41	1.61	2.52	8.86***	1.77	1.78	.00

* Significant at .10 level ** Significant at .05 level *** Significant at .01 level

TABLE 12. : COMPARISON OF GROUP MEANS FOR THE THREE PRODUCT CONCEPTS

CORPORATE ENGINEERS VS TOP MANAGERS

	COMAIR			ABSAIR			SOLABS		
	CE	TM	F-RATIO (1,65)	CE	TM	F-RATIO (1,64)	CE	TM	F-RATIO (1,63)
ITEM 1	5.96	5.74	.98	5.25	5.21	.01	3.85	4.03	.23
ITEM 2	1.39	1.44	.06	2.18	1.87	.87	2.77	4.36	9.42***
ITEM 3	3.29	3.77	1.38	3.14	3.76	2.70*	4.50	4.28	.24
ITEM 4	6.25	6.05	.85	5.18	5.08	.11	2.92	2.92	.00
ITEM 5	4.11	3.82	.81	3.57	3.11	1.45	5.77	5.51	.62
ITEN 6	5.29	5.31	.00	3.54	2.76	5.05**	2.23	2.44	.31
ITEM 7	4.00	2.95	4.84**	2.04	2.03	.00	5.54	5.74	.32
ITEM 8	3.25	3.33	.03	1.86	2.47	3.41*	5.88	5.95	.05
ITEM 9	4.82	4.51	.53	3.64	3.97	.64	3.81	3.18	2.90*
ITEM 10	3.00	3.00	.00	2.54	3.00	1.70	5.15	5.08	.03
ITEM 11	1.36	1.79	2.81*	2.04	3.00	6.71**	4.77	4.67	.07
ITEM 12	2.93	2.74	.25	2.82	2.53	.52	6.15	5.95	.62
ITEM 13	2.71	3.36	2.84*	2.71	3.18	1.38	4.46	5.18	2.86*
ITEM 14	2.39	2.72	.90	3.21	3.63	1.17	4.12	3.56	2.90*
ITEM 15	3.61	3.92	.77	3.18	3.05	.11	4.65	4.90	.30
ITEM 16	4.43	4.13	.58	3.64	3.47	.17	4.77	4.95	.21
ITEM 17	4.71	4.82	.09	1.61	2.11	2.90*	1.77	1.97	.60

* Significant at .10 level ** Significant at .05 level *** Significant at .01 level

input to the development of better communication strategies aimed at alleviating the defavorable perceptions that some groups of decision participants might have of certain attributes of SOLABS.

The analysis of the patterns of inter-decision group perceptual differences is based on the idea that, irrespective of their statistical significance, some of these differences may appear consistently in a meaningful pattern when several pairs of decision groups are considered. The analysis is then based on the simultaneity of perceptual differences of a specific nature for several pairs of decision groups. Two of these patterns are specially relevant:

- Pattern 1 : for a given product alternative and perceptual item, both PE and PM perceive the alternative as offering more (or less) of this attribute than both CE and TM do.

- Pattern 2 : for a given product alternative and perceptual item, both PE and CE perceive the alternative as offering more (or less) of this attribute than both PM and TM do.

Pattern 1 indicates that decision participants' level in the organization is a main source of perceptual differences. Pattern 2 stresses the importance of decision participants functional area in the organization as a source of perceptual differences.

Table 3.13 summarizes these perceptual patterns for each product alternative and perceptual item. For SOLABS, it is interesting to note that engineers perceptions, when compared to managers , indicate that SOLABS

- offers less protection against power failures and fuel rationing
- reflects more the image of an innovative company
- offers less opportunity to reduce pollution
- is more conducive to energy savings
- results less in low cost a/c
- contributes more to noise reduction in the plant.

On the other hand, plant personnel, when compared to corporate personnel, view SOLABS as :

- more made up of field proven components
- more vulnerable to weather damage
- more state of the art

Similar perceptual differences are exhibited for COMAIR and ABSAIR, and are immediately identifiable from table 3.13.

TABLE 3.13 : PATTERNS OF PERCEPTUAL DIFFERENCES FOR ALL THREE PRODUCT ALTERNATIVES

	COMAIR	ABSAIR	SOLABS
Item 1	-	ENG > MGR	-
Item 2	PLT > CRP	-	ENG < MGR
Item 3	ENG < MGR	ENG < MGR	-
Item 4	ENG > MGR	ENG > MGR	PLT > CRP
Item 5	-	PLT > CRP	ENG > MGR
Item 6	PLT < CRP	-	-
Item 7	-	-	ENG < MGR
Item 8	PLT > CRP	PLT > CRP	ENG < MGR
Item 9	PLT > CRP	-	-
Item 10	PLT > CRP	PLT > CRP	PLT > CRP
Item 11	ENG < MGR	ENG < MGR	-
Item 12	ENG > MGR	-	ENG > MGR
Item 13	PLT > CRP	PLT > CRP	-
Item 14	PLT > CRP	-	-
Item 15	PLT < CRP	-	ENG < MGR
Item 16	-	-	PLT > CRP
Item 17	PLT > CRP	ENG < MGR	ENG < MGR

PLT = Plant Personnel (PE & PM)

CRP = Corporate Personnel (CE & TM)

ENG = Engineer (PE & CE)

MGR = Managers (PM & TM)

In sum, our perceptual analysis establishes that definite perceptual differences exists between categories of decision participants likely to become involved in the purchase of an industrial cooling system. These differences point to areas of potential resistance to the solar concept in specific decision groups, and provide input to the development of more diversified marketing strategies for the new product.

3.4. Product Evaluation Space Analysis

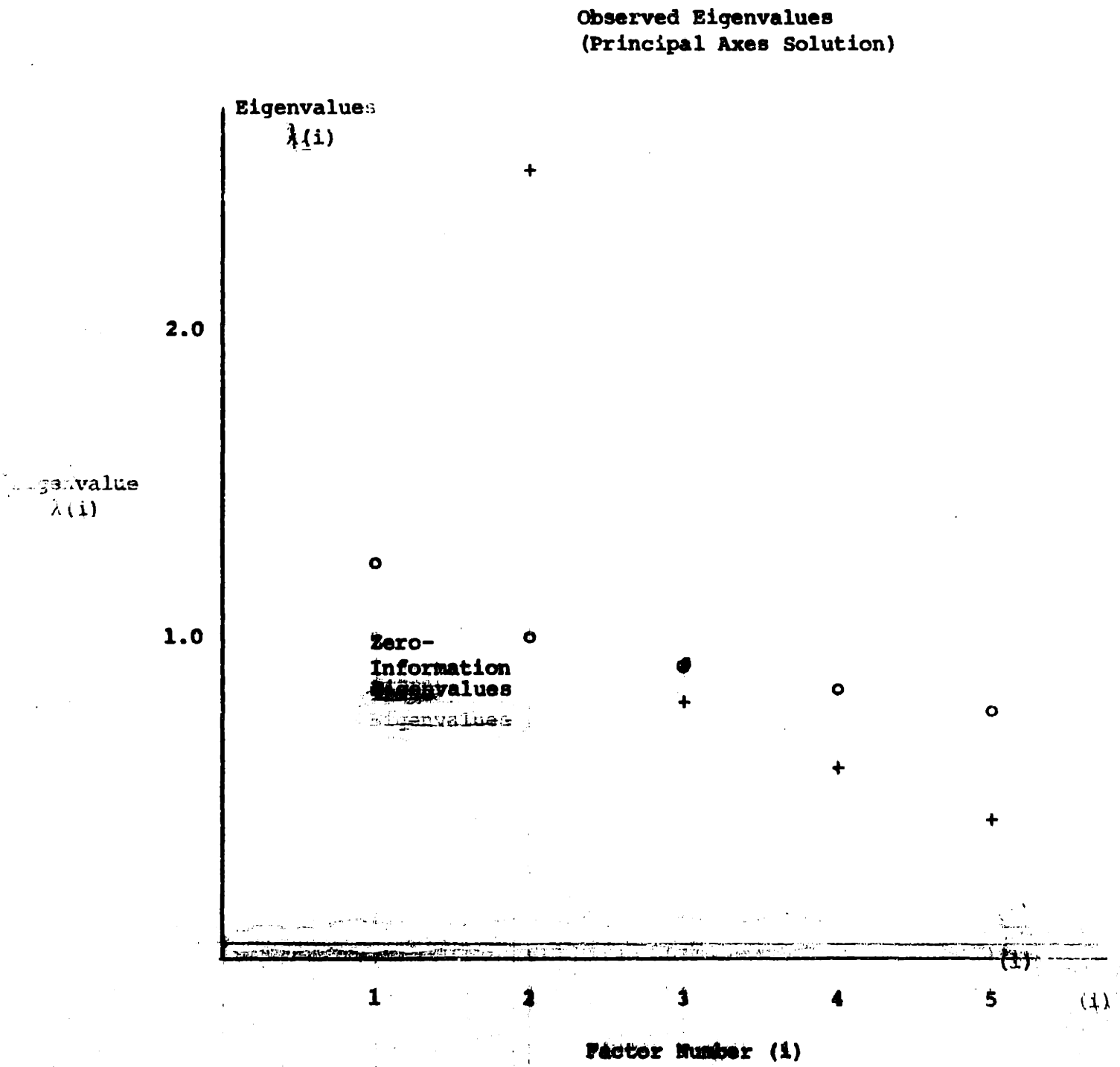
In the previous section, we established that decision groups present substantial differences in the way they perceive industrial products. Now, we are concerned with whether these same decision groups differ in the way they structure basic product attributes into higher-order evaluation criteria. We then assume that all individuals within a given group use the same evaluation criteria. The final part of our analysis assess the relevance of these differences in the formation of individual preferences.

3.4.1. Identifying the Evaluation Criteria of Each Group of Decision Participants

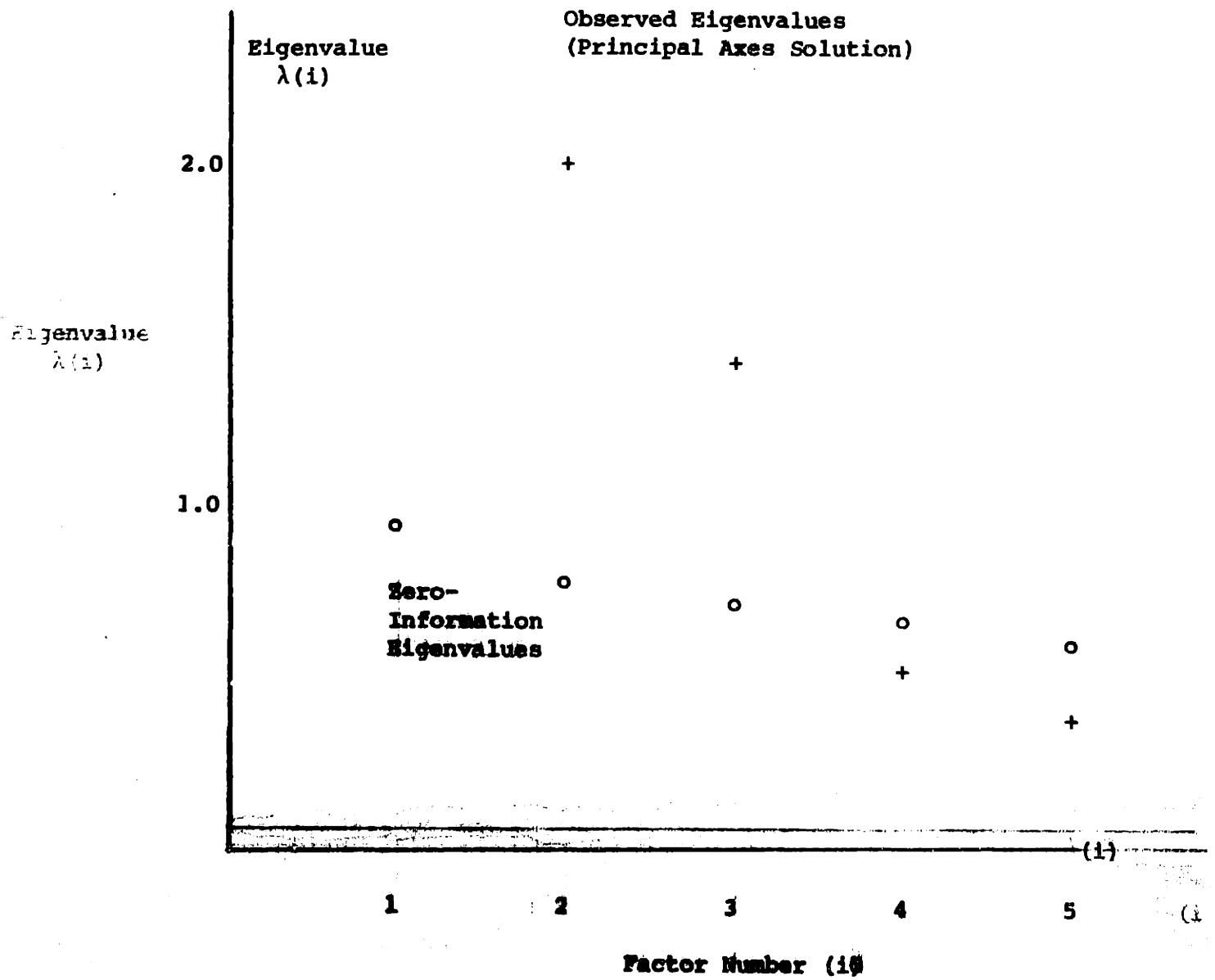
Following the product evaluation methodology proposed in section 3.2.2. individual covariance matrices were estimated for each

of the four decision groups (PE, PM, CE, TM) using the ratings obtained for all three product alternatives on the 17 perceptual scales. The Box Criterion was used to test the equality of these covariance matrices, giving an F-ratio of 1.72 for 452 and 218,201 degrees of freedom. The hypothesis of equal covariance matrices was then rejected and a separate Principal Factor Analysis was performed for each decision group. Squared multiple correlations (SCM) 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 3.6. - 3.9. present the trace of observed eigenvalues and the trace of eigenvalues expected from randomly generated correlation matrices with SMC on the diagonal for the four decision groups. The point at which the two traces intersect indicate the maximum number of factors that should be retained. Indeed, we are not interested in a factor that does not account for more variance than the corresponding factor obtained from random correlation matrices. The number of evaluation criteria retained for each decision group is given in table 3.14.



[illegible] 3.6. [illegible] OF DIMENSIONALITY OF EVALUATION SPHERE [illegible] FOR [illegible] MANAGERS (PM)



[redacted] OF DIMENSIONALITY OF EVALUATION SPACE [redacted] (PE).

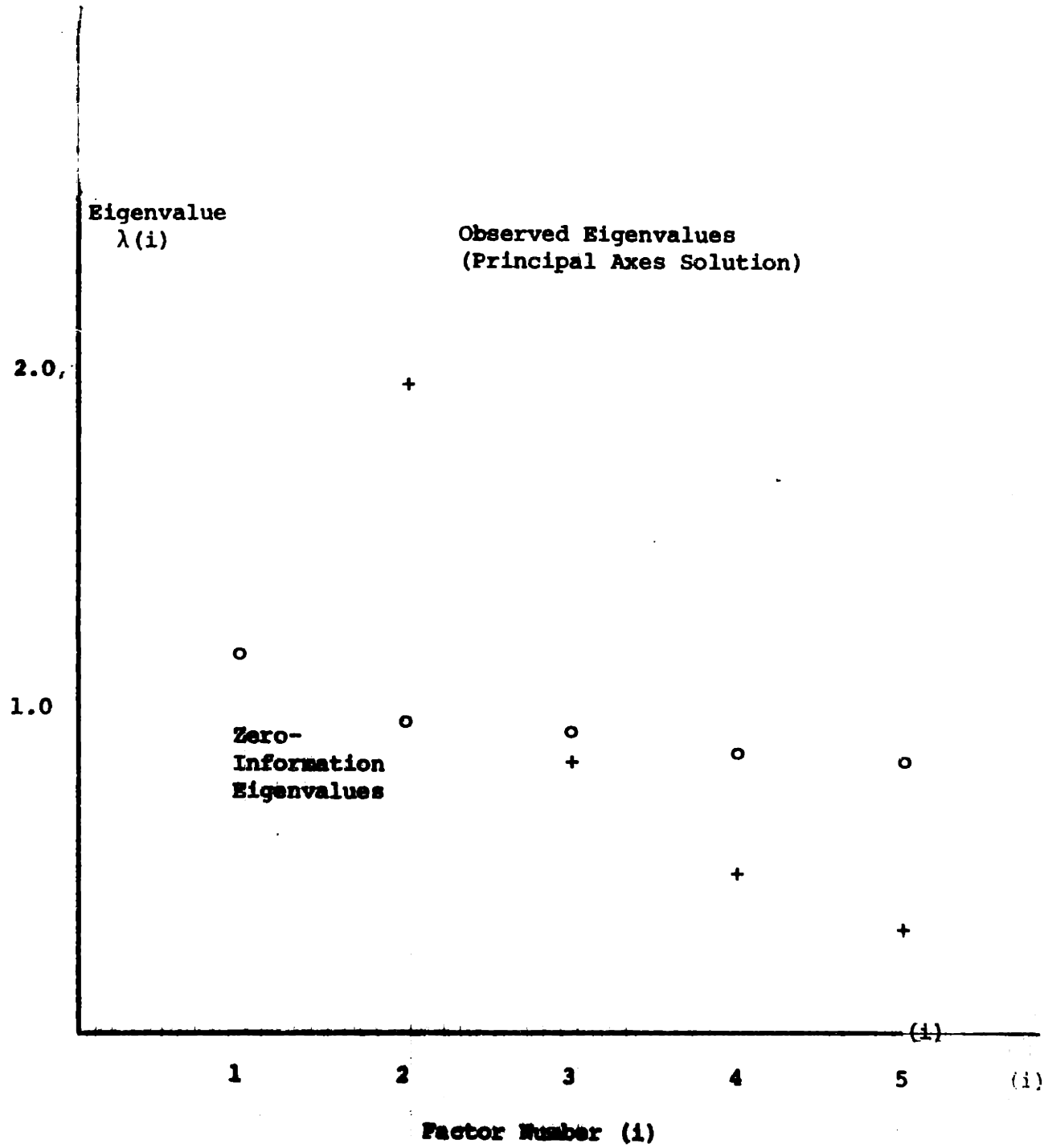


FIGURE 3.8. : DETERMINATION OF DIMENSIONALITY OF EVALUATION SPACE FOR CORPORATE ENGINEERS (CE).

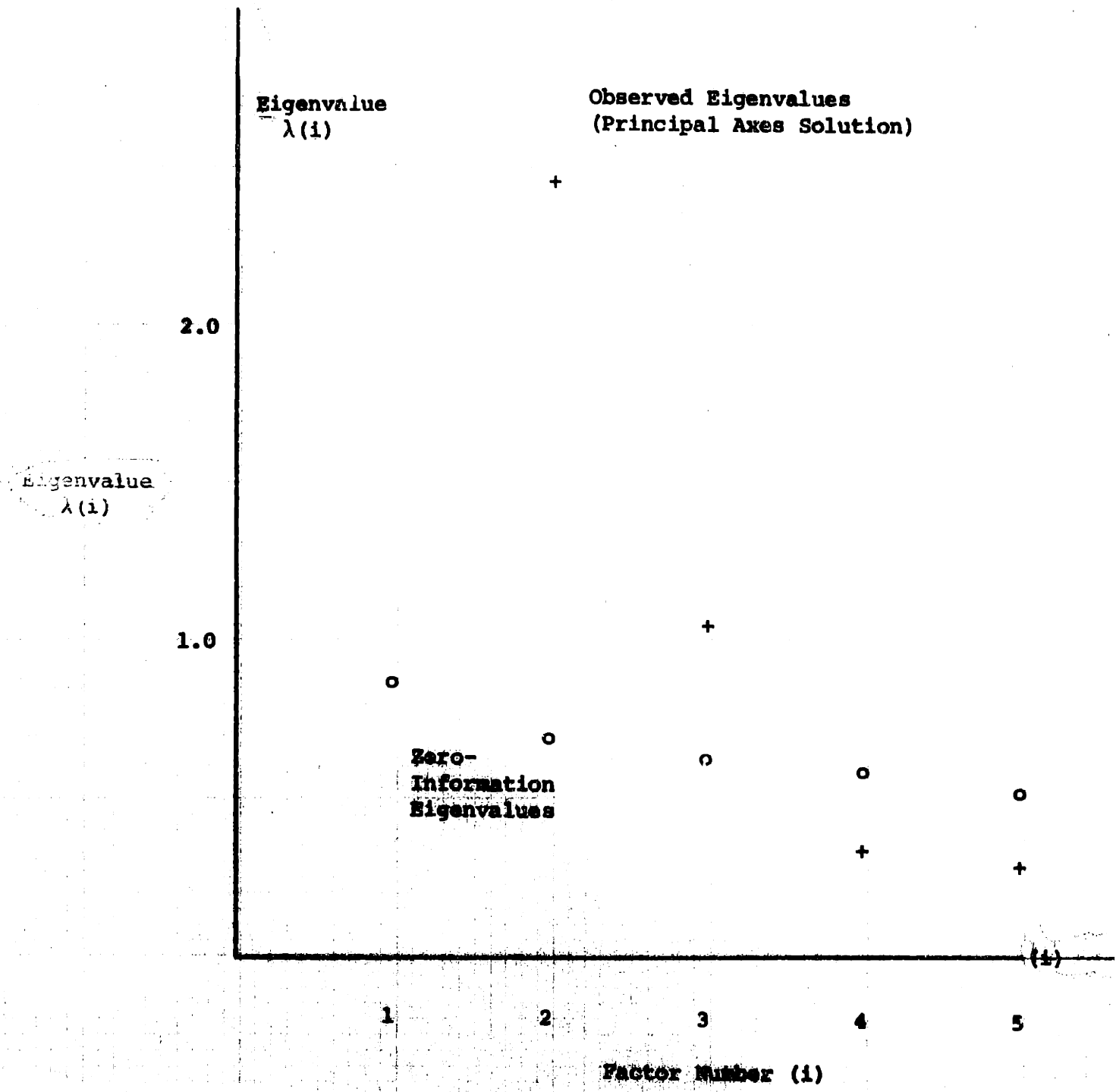


FIGURE 1.2. : [illegible] OF DIMENSIONALITY OF EVALUATION SPACE [illegible] (EM).

TABLE 3.14 : EVALUATION SPACE DIMENSIONALITY FOR VARIOUS GROUPS OF DECISION PARTICIPANTS

Decision Participants	Dimensionality of Evaluation Space
Production Engineers (PE)	3
Corporate Engineers (CE)	2
Plant Managers (PM)	2
Top Managers (TM)	3

Production Engineers and Top Managers have a three dimensional evaluation space. The other two groups (CE and PM) have an evaluation space of dimensionality two. These results are consistent with those reported by Choffray and Lilien [22] for the same decision groups but with a smaller set of perceptual items (n=14). The number of evaluation criteria used by these different decision groups thus shows substantial invariance. This suggests that Production Engineers and Top Managers, who are reported to exert considerably more influence in the purchase of industrial cooling systems (see Cheston and Doucet [20]), use more evaluation criteria to assess these alternatives.

Separate Principal Factor Analyses were run for CE, PM, and (CE & PM). A varimax rotation was performed for each of them, and the coefficient of determination associated with each factor was computed. Table 3.15 - 3.17 reproduce these factor structures. Most similar factors were identified and their equivalence tested one at a time using the test described in section 3.2.2.3. Table 3.18 gives the result of this analysis.

Factor B is significantly different for the two groups and Factor A is nearly so. Hence the hypothesis of equality of the evaluation criteria used by CE and PM is rejected.

TABLE 3.15 : VARIMAX ROTATED FACTOR MATRIX FOR PLANT MANAGERS

	FACTOR 1	FACTOR 2
Item 1	-0.037	-0.798
Item 2	0.521	0.366
Item 3	0.165	0.595
Item 4	-0.287	-0.877
Item 5	0.589	-0.026
Item 6	-0.208	-0.352
Item 7	0.750	0.327
Item 8	0.633	0.321
Item 9	0.127	-0.620
Item 10	0.420	0.407
Item 11	0.227	0.727
Item 12	0.788	0.284
Item 13	0.703	-0.062
Item 14	-0.227	0.445
Item 15	0.772	-0.047
Item 16	0.604	0.057
Item 17	-0.312	-0.487
Percentage of Common Variance*	.57	.26
Coefficient of Determination	.897	.915

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

TABLE 3.16 : VARIMAX ROTATED FACTOR MATRIX FOR CORPORATE ENGINEERS

	FACTOR 1	FACTOR 2
Item 1	-0.726	-0.169
Item 2	0.338	0.135
Item 3	0.439	0.208
Item 4	-0.776	-0.307
Item 5	0.166	0.612
Item 6	-0.781	0.027
Item 7	0.011	0.750
Item 8	0.237	0.779
Item 9	-0.388	0.202
Item 10	0.571	0.408
Item 11	0.830	0.407
Item 12	0.320	0.692
Item 13	0.253	0.351
Item 14	0.537	0.134
Item 15	0.082	0.471
Item 16	-0.180	0.458
Item 17	-0.486	0.079
Percentage of Common Variance*	.59	.23
Coefficient of Determination	.902	.845

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

TABLE 3.17 : VARIMAX ROTATED FACTOR MATRIX FOR CORPORATE ENGINEERS AND PLANT MANAGERS

	FACTOR 1	FACTOR 2
Item 1	-0.783	-0.102
Item 2	0.336	0.355
Item 3	0.476	0.221
Item 4	-0.810	-0.305
Item 5	0.087	0.616
Item 6	-0.603	-0.081
Item 7	0.130	0.734
Item 8	0.250	0.738
Item 9	-0.483	0.148
Item 10	0.496	0.418
Item 11	0.780	0.344
Item 12	0.293	0.729
Item 13	0.126	0.513
Item 14	0.490	0.011
Item 15	0.031	0.584
Item 16	-0.093	0.533
Item 17	-0.476	-0.090
Percentage of Common Variance*	.59	.24
Coefficient of Determination	.879	.841

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

TABLE 3.18 : TEST FOR FACTOR EQUALITY FOR PLANT MANAGERS (PM) AND CORPORATE ENGINEERS (CE)

	F-RATIO	Degrees of Freedom
A. Matched Factors (PM_1, CE_2)	1.46	(17,119)
B. Matched Factors (PM_2, CE_1)	2.14***	(17,119)

*** Significant at .01 level.

Note : PM_i represents the ith factor in the original varimax solution for PM.

Similarly, a Principal Factor Analysis, followed by a varimax rotation, was run for PE, TM, and (PE & TM). The results are reported in table 3.20 - 3.22 . Most similar factors were matched and tested for equivalence. Table 3.23 gives the results of these computations. Factor A and B show significantly different compositions between the two groups. Thus, we reject the hypothesis of equality of the evaluation spaces of PE and TM.

As both pairs of decision groups show significantly different evaluation criteria the next step involves the examination of these differences from a more qualitative standpoint. For the CE and PM groups, which have an evaluation space of dimensionality 2, we summarized and interpreted their respective product evaluation criteria in table 3.24.

From this table, it is apparent that substantial differences exist between the two groups of decision participants PM and CE in the way they structure the basic attributes of industrial cooling systems into higher-order evaluation criteria. Plant Managers appear especially concerned about 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.

TABLE 3.20 : VARIMAX ROTATED FACTOR MATRIX FOR TOP MANAGERS

	FACTOR 1	FACTOR 2	FACTOR 3
Item 1	-0.065	-0.662	0.354
Item 2	0.602	0.189	-0.306
Item 3	0.074	0.588	0.116
Item 4	-0.288	-0.526	0.636
Item 5	0.662	0.086	-0.064
Item 6	0.074	-0.245	0.716
Item 7	0.807	0.202	-0.141
Item 8	0.803	0.287	-0.096
Item 9	-0.145	-0.234	0.364
Item 10	0.281	0.718	-0.133
Item 11	0.252	0.584	-0.515
Item 12	0.702	0.257	-0.234
Item 13	0.512	-0.020	-0.298
Item 14	-0.174	0.452	-0.235
Item 15	0.698	-0.016	0.137
Item 16	0.575	-0.214	0.106
Item 17	-0.105	0.092	0.782
Percentage of Common Variance*	.56	.26	.11
Coefficient of Determination	.892	.795	.814

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

TABLE 3.21 : VARIMAX ROTATED FACTOR MATRIX FOR PRODUCTION ENGINEERS

	FACTOR 1	FACTOR 2	FACTOR 3
Item 1	-0.192	0.479	-0.558
Item 2	0.469	-0.406	0.039
Item 3	0.313	0.046	0.536
Item 4	-0.229	0.726	-0.518
Item 5	0.662	-0.248	0.060
Item 6	-0.007	0.528	-0.280
Item 7	0.705	-0.013	0.388
Item 8	0.728	-0.051	0.354
Item 9	0.000	0.542	-0.040
Item 10	0.422	-0.064	0.456
Item 11	0.297	-0.421	0.649
Item 12	0.749	-0.263	0.291
Item 13	0.456	-0.168	0.127
Item 14	-0.119	-o.161	0.517
Item 15	0.776	0.128	0.049
Item 16	0.621	-0.024	-0.107
Item 17	-0.120	0.639	-0.010
Percentage of Common Variance*	.60	.21	.10
Coefficient of Determination	.875	.812	.740

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

TABLE 3.22 : VARIMAX ROTATED FACTOR MATRIX FOR PRODUCTION ENGINEERS AND TOP MANAGERS

	FACTOR 1	FACTOR 2	FACTOR 3
Item 1	-0.107	0.454	-0.591
Item 2	0.543	-0.349	0.111
Item 3	0.160	0.042	0.592
Item 4	-0.257	0.715	-0.466
Item 5	0.654	-0.130	0.088
Item 6	0.034	0.662	-0.191
Item 7	0.748	-0.101	0.297
Item 8	0.762	-0.094	0.328
Item 9	-0.070	0.427	-0.140
Item 10	0.311	-0.136	0.621
Item 11	0.260	-0.530	0.563
Item 12	0.724	-0.257	0.279
Item 13	0.487	-0.224	0.052
Item 14	-0.157	-0.257	0.434
Item 15	0.725	0.127	0.043
Item 16	0.597	0.078	-0.127
Item 17	-0.128	0.715	0.111
Percentage of Common Variance*	.58	.24	.10
Coefficient of Determination	.868	.793	.730

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

TABLE 3.23 : TEST FOR FACTOR EQUALITY FOR PRODUCTION ENGINEERS (PE) AND TOP MANAGERS (TM)

	F-RATIO	Degrees of Freedom
A. Matched Factors (PE_1, TM_1)	1.59*	(17,194)
B. Matched Factors (PE_3, TM_2)	1.96**	(17,194)
C. Matched Factors (PE_2, TM_3)	1.29	(17,194)

* Significant at .10 level

** Significant at .05 level.

TABLE 3. 24 : COMPARISON OF FACTOR SOLUTIONS FOR PLANT MANAGERS AND CORPORATE ENGINEERS

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

Notes :

- Our interpretation is 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.
- Items appearing between parentheses have a complexity higher than 1.
- The sign appearing on the left hand side is the loading's sign.

Similarly, table 3.25 presents our interpretation of the 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 specially 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 about the system's complexity and the substituability of its major components.

In sum, our analysis of the evaluation criteria of the different groups of decision participants likely to become involved in the purchase of an industrial cooling system, clearly establishes that these groups not only differ in the number of evaluation criteria that they use to assess product alternatives but, that substantial variations exist in the composition of these criteria. Different marketing strategies, including product postioning and salesmen presentations, can be targeted at these different groups to take advantage of these differences.

The next question is whether the product evaluation space analysis, performed at such a disaggregate level, is behaviorally meaningful : does the consideration of these specific, and different evaluation criteria lead to a better understanding of the way decision participants form preferences ?

TABLE 3.25 : COMPARISON OF FACTOR SOLUTIONS FOR TOP MANAGERS AND PRODUCTION ENGINEERS

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

3.4.2. Behavioral Relevance of the Differences in Evaluation Criteria used by Different Categories of Decision Participants.

In order to assess the relevance of the different evaluation criteria identified for each of the four categories of participants included in this analysis, we link individuals' preferences for the three available alternatives to their evaluation of these alternatives on the appropriate evaluation criteria (See section 3.2.3.).

For this purpose, we use a linear regression model[1]. We refer to the coefficients of this model as the preference parameters. Following the approach suggested by Urban [127], 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 : The 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 different for each of these groups

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

---

1. Allaire [1] reviews evidence which indicates that statistical methods provide better estimates of the importance of evaluation criteria than more direct methods which involve explicit measurement of importance weights from subjects.

Under assumptions A1 and A2 it is necessary to derive the 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. Table 3.26 gives this common factor solution. A qualitative interpretation appears in table 3.27.

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. Table 3.28 summarizes this step of our analysis. Inconsistency of preferences was more frequent than we expected for a highly technological product like an industrial cooling system. Although not statistically significant, our results suggest that corporate people (TM, CE) are less consistent in their preference judgements than people working at the plant level (PM, PE).

Two set of regressions were run. First, the actual rank-order preferences was used as a dependent variable. Although this dependent variable is only ordinal, available empirical evidence suggests that least squares regression closely approximates monotone regression for integer rank order preference variables (Hauser and Urban [52]). Second, the constant-sum paired comparison preference data were tranformed to a ratio-scale

TABLE 3. 26 : VARIMAX ROTATED FACTOR MATRIX FOR ALL DECISION GROUPS

	FACTOR 1	FACTOR 2	FACTOR 3
Item 1	-0.100	0.504	-0.560
Item 2	0.484	-0.335	0.112
Item 3	0.156	-0.032	0.611
Item 4	-0.268	0.683	-0.476
Item 5	0.659	-0.088	0.072
Item 6	-0.013	0.640	-0.209
Item 7	0.742	-0.049	0.246
Item 8	0.753	-0.099	0.281
Item 9	0.007	0.400	-0.146
Item 10	0.316	-0.118	0.640
Item 11	0.299	-0.537	0.561
Item 12	0.739	-0.267	0.211
Item 13	0.471	-0.125	0.138
Item 14	-0.106	-0.262	0.425
Item 15	0.670	0.056	0.010
Item 16	0.586	0.068	-0.124
Item 17	-0.147	0.724	0.112
Percentage of Common Variance*	.60	.24	.09
Coefficient of Determination	.862	.788	.725

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

TABLE 3.27 : FACTOR SOLUTION FOR ALL DECISION GROUPS :

HOMOGENEOUS EVALUATION SPACE

Factor 1	Factor 2	Factor 3
(+) Reduce Pollution	(+) Noise Level	(+) Vulnerability to Weather
(+) Fuel Rationing Protection	(+) Field Proven	(+) Climate Sensitivity
(+) Energy Savings	(+) System's Cost	(+) (Not Fully Tested)
(+) Low Cost a/c	(-) (Not Fully Tested)	(-) (Reliability)
(+) Modern Image	(+) (Reliability)	
(+) State of the Art Solution		

TABLE 3.28 : ANALYSIS OF INDIVIDUAL PREFERENCES INCONSISTENCIES

	PE	PM	CE	TM	TOTAL
Consistent Preferences	29	19	21	30	99
Inconsistent Preferences	3	3	6	7	19
Total	32	22	27	37	118

χ^2 (3) = 2.14

via Torgerson's [124] 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 and have been extensively reported in the literature (Hauser and Urban [52], Wildt and Bruno [140]). 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 3.29 summarizes the preference recovery results under all three sets of assumptions. It appears that preference recovery - both when rank and ratio-scaled preferences are used - 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

TABLE 3.29 : PREFERENCE RECOVERY ANALYSIS

	Homogeneous Evaluation Criteria Homogeneous Preference Parameters		Homogeneous Evaluation Criteria Heterogeneous Preference Parameters		Heterogeneous Evaluation Criteria Heterogeneous Preference Parameters	
	Rank Order Preferences	Cste. Sum Preferences	Rank Order Preferences	Cste. Sum Preferences	Rank Order Preferences	Cste. Sum Preferences
1st. Preference Recovery	.65	.63	.61	.60	.69	.66
Full Rank Order Preferences Recovery	.42	.44	.41	.39	.49	.47

that although A2 is a reasonable assumption in consumer marketing research (Allaire [1], Hauser [51]) it might not be reasonable in industrial markets, where different groups of decision participants exhibit substantial divergence in their perceptions 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.

The preference parameters estimated from ratio-scaled preferences and from rank-order preferences are quite similar. As the latter are slightly better in terms of preference recovery, we have summarized the results of the rank-order preference regressions under all three sets of assumptions in tables 3.30 - 3.32.

From table 3.30 it appears that under assumption A1 Factor 1 is most important on a aggregate basis. Although separate regressions indicate that some shifts may occur in the preference parameters (see Table 3.31), 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 equal preferences parameters in the four groups can not be rejected at the .05 level.

More interesting findings come from a comparison of the results obtained under assumption A2 and under assumption A3. These results

TABLE 3.30 : 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)

TABLE 3. 31 : 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 3.32: 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 Managers	2.00	-.26 (2.29)	.18 (1.69)	-	.23	5.78 (2;51)
Top Managers	1.99	-.35 (4.40)	-.27 (3.22)	.14 (1.45)	.25	9.73 (3;90)

are reproduced in table 3.31 - 3.32 respectively. It appears that Production Engineers weight reliability and complexity issues very heavily. This was not observable under assumption A2, as the issues of system's complexity and substituability of components did not even come out in the common evaluation space (See table 3.49). 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 TM are in fact willing to make trade-offs between a) the reliability of industrial cooling systems and b) the better efficiency in energy use and the added protection they offer against irregularities of traditional sources of energy supply.

Hence, the preference regression run under assumption A2 - common evaluation space and heterogeneous preference parameters - not only led to a poorer recovery of individuals preferences but, it also overlooked (1) the issues of system's complexity and substituability of components that are essential to Production Engineers, and (2) the issues of protection against power failures and use of improductive areas that significantly affect Plant Managers

as well as Top Managers preferences. In addition, the regression results under assumption A2 did not isolate the important trade-offs that Top Managers seem willing to make. The explicit consideration of heterogeneous evaluation criteria across decision groups therefore leads to a better understanding of how individual decision participants form preferences for industrial product alternatives.

3.5. Summary

Industrial adoption decisions typically involves several individuals who differ in their background and organizational responsibilities. In this chapter, methodology was developed to investigate perceptual differences as well as differences in evaluation criteria between several categories of decision participants likely to become involved in the adoption of an industrial product. These categories were defined on the basis of job responsibility.

The methodology is comprehensive. It addresses the problems of:

- within decision participant category product discrimination,
- across participant categories differences in perceptions for each industrial product alternative, and
- across participant categories differences in evaluation criteria.

In order to investigate these questions, the methodology logically combines several multivariate statistical methods. Multivariate Analysis of Variance (MANOVA) is used to assess whether decision participants in each category do discriminate between industrial product alternatives on the basis of the perceptual scales included in the analysis. Multivariate profile analysis (MPA) provides objective criteria to assess the existence and exact nature of perceptual differences across groups of decision participants for

each alternative. Factor analysis is used to derive the evaluation criteria common to each category of decision participants. A set of procedures is developed that provide objective tests to determine whether decision participants differ in the number and composition of their evaluation criteria. Specifically, a statistical test is proposed to assess the equivalence of factors obtained from the same set of perceptual scales in different populations.

Implementation of the methodology for the new industrial cooling system powered by solar energy reveals the existence of definite perceptual differences between decision participants categories. Substantial differences are also registered in the way these groups of individuals structure the basic attributes of industrial cooling systems into higher-order evaluation criteria. Preferences regressions indicate that the explicit consideration of these differences not only leads to a better preference recovery but also provides a better understanding of how individual decision participants form preferences for industrial product alternatives.

The existence of meaningful differences in product perceptions and evaluation criteria between categories of decision participants involved in the adoption of an industrial product offers new opportunities for the development of better communication programs that address the specific needs and requirements of these categories

of individuals. A well integrated industrial marketing strategy will tap these differences both in a product development and communication program.

CHAPTER 4 : MICROSEGMENTATION OF THE POTENTIAL MARKET FOR A NEW INDUSTRIAL PRODUCT: ISSUES, SOLUTIONS, AND IMPLEMENTATION.

The analysis performed in Chapter 3 pointed to differences in the way groups of individuals involved in the purchase of a new industrial product perceive and evaluate available alternatives. These differences have immediate implications for the development of industrial marketing programs addressing the specific needs and requirements of these individuals, as well as for the development of better tools to assess response to industrial product innovations. These uses are most powerful, however, if the potential market for an industrial product can be segmented into groups of organizations homogeneous in the structure of their adoption process, that is, homogeneous in the pattern of individual involvement in the major phases of this decision process. The development and implementation of methodology to perform such an analysis to the focal point of this chapter.

First, we discuss the present state of the art in the classification of organizations and review the few studies that are available about industrial market segmentation. Next, we specify the objectives of the methodology and review its structure. Four problems associated with the use of cluster analytic methods for industrial market segmentation are identified. They include a) the

impact of extreme observations on cluster analytic results, b) the non-randomness of a dissimilarity structure c) the determination of the number of clusters in a hierarchical classification and d) the invariance of the clustering solution retained.

The methodology developed here addresses each of these problems and provides solutions for all them. Single linkage cluster analysis is proposed as a way to identify organizations whose adoption process shares little similarity with other organizations represented in the sample. Simulation is used as a method to investigate the non-randomness of the data structure. A sensible measure of intra-cluster homogeneity is also introduced which provides a more objective criteria for determining at what level in the hierarchical classification should the clustering solution be chosen. The invariance of this solution is then investigated by the use of parallel methods of cluster analysis that substantially differ from one another in their assumptions and mathematical logic. The end product of this effort is a better framework for systematically analyzing inter-organizational differences in the structure of the adoption process, which provides additional input for the targeting of industrial marketing activities.

Implementation of this methodology to segment the potential market for the new solar cooling system leads to the identification of several groups of organizations that exhibit substantial similarity in their adoption process. The systematic analysis of the adoption process within each of these segments, as well as the analysis of the characteristics

of the organizations comprised in each of them, contribute significantly to a better understanding of the adoption process for this new industrial product.

4.1. The Classification of Industrial Organizations.

A fundamental element of the marketing concept is the grouping of potential buyers into groups relatively homogeneous in buying behavior. Implementation of this concept in industrial market, however, leads to problems. In fact, although consumer markets can be segmented on the basis of demographic and psychographic variables that correlate with purchasing behavior (See Kotler [67]), our review of the industrial marketing literature in Chapter 1 showed little evidence of the impact of many observable characteristics of industrial organizations on their purchasing behavior.

In addition, existing classification schemes proposed in organization theory are not of much help for industrial market segmentation. They lack comprehensiveness and usually rely on variables that have little managerial relevance. As Mc Kelvey [79] recently wrote :

> "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" (p. 509).

Few comparative analyses of organizations are available. Most often, they reflect exploratory analyses rather than hypothesis testing (Udy [126]) and are based on a small number of field studies (Scott [114]). Improvements in the methods of collecting information about large cross-sections of organizations, and in the methods of analysis of such information are needed for developing better and more useful classification schemes.

The segmentation of industrial markets is an area in need for more research (Sheth [116], Cardozo [17]); few studies are available in the literature. Wilson et al [144] propose segmenting industrial markets on the basis of the decision-making styles of individual buyers. Faris [36] suggests grouping industrial organizations on the basis of "buying situations". Typically, however, these studies pay little attention to the problems of implementing industrial market segmentation. As a result, they are of limited managerial usefulness.

Wind and Cardozo [146] recently reviewed segmentation practice in industrial markets. Their results suggest that segmentation strategies are used, but primarily to explain past performance rather than to develop more effective industrial marketing programs. Their study also stresses the need for new segmentation methodologies that address the characteristics of industrial purchasing Decision Making Units (DMU's).

It is the aim of this chapter to propose and critically appraise methods to perform such a segmentation. The characteristic investigated is the composition of the "DMU" or "Buying Center". Our objective is to group industrial organizations in the potential market for a new industrial product on the basis of the structure of their adoption process, that is, on the basis of the pattern of individual involvement in the various phases of this decision process.

4.2. Structure of the Microsegmentation Methodology

The industrial market segmentation methodology proposed in this research may be viewed as a two-step procedure. Given an industrial product, we first determine its potential market. This step has been sometimes called macrosegmentation (Wind and Cardozo [146]). Its purpose is to characterize those companies that, on an a priori basis, are more likely to adopt the product because, for instance, of their particular activity or geographic location.

The second step involves the formation of microsegments of organizations that exhibit a substantial degree of similarity in the structure of their adoption process. The methodology proposed here specifically addresses this type of segmentation.

The following criteria are proposed to assess the relevance of the microsegments identified in the potential market for an industrial product :

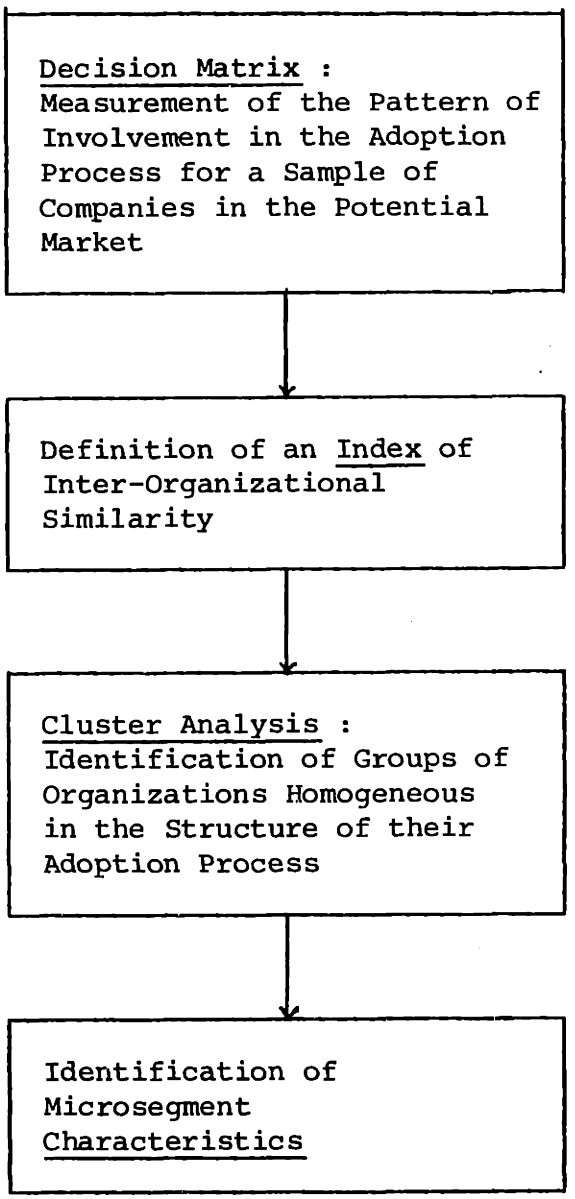
- Homogeneity : companies that comprise a specific microsegment should exhibit a high degree of similarity in the structure of their adoption process. Each microsegment might then be characterized by an overall pattern of involvement in the adoption process.

- Parsimony : an extreme microsegmentation strategy might involve the consideration of every company as a unique target Such a segmentation of industrial markets would not be managerially meaningful nor economically feasible in most instances. For this reason, the methodology proposed here attempts to identify a parsimonious set of microsegments which are substantial enough to be worth considering in the formulation of an industrial marketing strategy.

- Accessibility : microsegments should be characterized in terms of observable variables that allow for the development of differentiated industrial marketing strategies.

Figure 4.1. outlines the general structure of the methodology proposed in this research. The first step involves the measurement of the structure of the adoption process for a sample of organizations

FIGURE 4.1. : OUTLINE OF THE MICROSEGMENTATION METHODOLOGY.



in the potential market for the industrial product under investigation. In Chapter 2 we described the "decision matrix" as a structured survey instrument to collect that information, and systematically investigated the convergent validity of the measurements obtained. The microsegmentation methodology proposed here uses these measurements as basic input.

The second step in the methodology concerns the selection of an appropriate index to measure inter-organizational similarity in the structure of the adoption process. The choice of this index is of importance as different indices may imply different assumptions about the scaling properties of the data. Different indices might also affect the composition of the microsegments identified or lead to different interpretation for these microsegments.

The third step in the methodology uses cluster analysis to identify microsegments of organizations homogeneous in the structure of their adoption process. The methodology suggests new approaches to investigate some currently unresolved problems associated with the use of cluster analytic methods. For instance, it addresses the question of determination of the number of clusters to be retained in the microsegmentation analysis. It also addresses the issue of invariance of these clusters.

The final step in the methodology is concerned with the identification of the overall pattern of involvement in the adoption process within each microsegment, that is, it identifies those categories of individuals that are most likely to become involved in the adoption process for the companies that comprise each microsegment. In addition, an attempt is made to characterize each microsegment in terms of directly observable variables. In view of the present state of the art in the classification of industrial organizations, our analysis at this stage is mainly exploratory.

The aim of the microsegmentation methodology proposed here is therefore to contribute to a better understanding of the structure of the adoption process for a new industrial product. The methodology builds upon existing differences across organizations to identify microsegments of similar entities. The end product of this effort is a better framework for systematically analyzing the industrial adoption process that provides additional input for targeting industrial marketing activities.

4.3. Development of the Microsegmentation Methodology : Issues and Solutions.

This section is devoted to a discussion of some technical aspects of the methodology just described. Our discussion centers upon the

three last steps in the methodology, as the use of a decision matrix to collect information about the structure of the industrial adoption process has already been discussed in Chapter 2.

As pointed out earlier, this research is concerned with studying the pattern of involvement of different categories of influencers in the main phases of the adoption process for an industrial product. No attempt is made to investigate the relative "influence" of each of these categories of individuals in the decision process. This latter question is more complex, as we have seen in Chapter 2, and falls beyond the scope of the present methodology.

4.3.1. Notation and Definitions

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 $h:\{h=1....p\}$ that are part of the role of category of participant j $j:\{j=1....g\}$ in the adoption process for company $i:\{i=1....N\}$.
We have :

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

$$\sum_{j=1}^{g} x_{ijh} = 1.0 \text{ for all } i,h$$

A category of decision participant, say j, is said to be <u>involved</u> in phase h of the adoption process for company i whenever $x_{ijh} > 0$. This definition is reasonable in view of the request for constant-sum estimates of involvement in each phase of the decision process made in the decision matrix, as this request actually forces respondents to mention only those categories of participants whose involvement they are sure of. Moreover, the analysis of the convergent validity of the measurements obtained with the decision matrix tend to support the adequacy of this definition.

Let δ_{ijh} denote a binary variable representing the involvement or non-involvement of participant j in decision phase h for company i. We have :

$$\delta_{ijh} = \begin{cases} 1 \text{ if } x_{ijh} > 0 \\ 0 \text{ if } x_{ijh} = 0 \end{cases}$$

In this research, we propose to view the pattern of involvement of various groups of participants in the adoption process for a given organization i as a (gxp)-dimensional vector Δ_i containing only 0's and 1's :

$$\Delta_i = \{\delta_{i11},\ldots,\delta_{ig1} \; ; \; \delta_{i12},\ldots,\delta_{ig2} \; ;\ldots; \; \delta_{i1p},\ldots,\delta_{igp}\}$$

One such vector characterizes each organization in the sample. As the measurements obtained are less than perfectly accurate, Δ_i is in fact a random vector. In the rest of this chapter, however, we treat Δ_i as the actual pattern of involvement in the adoption process for company i.

4.3.2. Selection of an Index of Inter-Organizational Similarity.

The choice of an index to measure the degree of similarity or dissimilarity between organizations in the structure of their adoption process is an important empirical question. Indeed, this choice can influence the composition of the microsegments identified, as well as their interpretation.

The consideration of the pattern of individual involvement in the adoption process as a vector of binary variables Δ_i, reduces this problem significantly. In this case, the selection of an index of interorganizational similarity is to a large extent limited to coefficients of association or "matching coefficients". Such coefficients have been widely used in Numerical Taxonomy. Sokal and Sneath [120] and Bijnen [7] provide thorough discussions of the characteristics and properties of many of these coefficients.

One of the simplest matching coefficient is the Sokal and Michener [119] coefficient introduced in Chapter 2 to investigate

the validity of the measurements obtained with the decision matrix. Consider two organizations -- say r and s -- characterized by the following vectors of individual involvement :

$$CO_r : \Delta_r = \{1\ 0\ 1\ 0\ 1\ ;\ 0\ 1\ 0\ 1\ 1\}$$

$$CO_s : \Delta_s = \{1\ 1\ 1\ 0\ 0\ ;\ 1\ 1\ 1\ 0\ 0\}$$

where for the sake of simplicity we have assumed only two decision phases (p=2) and five categories of participants (g=5).

The Sokal and Michener coefficient of similarity between company r and company s is given by :

$$S_{rs} = \frac{\text{Number of ACTUAL Matches}}{\text{Number of POSSIBLE Matches}}$$

$$= \frac{A}{P}$$

$$= .4$$

where P equals the number of actual matches A plus the number of misses M. In terms of the above example, A=4, P=10, and M=6. Obviously,

$$S_{rs} \rightarrow 0 \text{ as } \frac{A}{M} \rightarrow 0 \quad \text{, and}$$

$$S_{rs} \rightarrow 1 \text{ as } \frac{M}{A} \rightarrow 0$$

The coefficient S_{rs} has a nice intuitive interpretation. It measures the probability that an agreement will occur between company r and s in a randomly chosen cell of the decision matrix.

Numerous coefficients of associations have been proposed in the literature. Some give different weights to matches and non-matches respectively. Others consider only positive or 1-matches. In this research, we have no a priori information that justifies the use of differential weighting coefficients of association. Indeed, from a marketing standpoint, agreement between organizations about the non-involvement of a specific category of participant in a given phase of the adoption process provides as much information as their agreement about involvement. We thus include both 0- and 1-matches in the computation of a measure of inter-organizational similarity in the structure of the adoption process.

The cluster analysis methodology proposed in this research makes it preferable, from the standpoint of interpretation, to use dissimilarity measures rather than similarity measures. The relationship between the S coefficient of association and the Euclidean distance is straightforward. If we let D^2_{rs} denote the square of the Euclidean distance between the vectors Δ_r and Δ_s, we get :

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

$$D^2_{rs} = (1 - S_{rs})\ P$$

= number of ACTUAL non-matches.

Consequently, we have :

$$0 \leq D^2_{rs} \leq (pxg)$$

The dissimilarity measure D^2_{rs} may be viewed as a specific case from a more general class of distance functions involving the relationships between sets of (0-1) entities (Curry [28]). As such, D^2_{rs} still satisfies the properties of non-negativity, symmetry and the triangle inequality required of true distances (Restle [103]). It may therefore be used as metric input in any subsequent analyses.

In view of the insensitivity of cluster analysis results to linear transformations of the type above, and in view of the substantial gain in interpretability of the derived microsegments, D^2_{rs} is recommended here as a measure of dissimilarity.

A largely unexplored question in the development of similarity and dissimilarity indices on the basis of binary data is the statistical significance of the estimates obtained. Sokal and Sneath [120] provide an excellent discussion of this problem. they conclude that researchers "have to put general faith in the validity of the [similarity or dissimilarity] matrices [obtained with

coefficients of association]" (p. 155). Personnally, we tend to disagree with this position. As we describe in section 4.3.3.2., simulation provides an adequate framework to investigate the non-randomness of dissimilarity matrices.

4.3.3. Cluster Analysis as a Method of Microsegment Formation.

The general problem addressed by cluster analysis is how to partition a heterogeneous set of entities -- in our case industrial organizations -- 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 most available methods of cluster analysis is provided by Hartigan [50].

The microsegmentation methodology proposed here makes use mainly of agglomerative hierarchical clustering methods. These methods use as input a dissimilarity -- or similarity -- matrix in which each cell discribes the degree of dissimilarity between any two entities in the sample, as measured for instance with the index D^2_{rs} introduced earlier. From this matrix, agglomerative clustering methods gradually form clusters by grouping most similar entities in the same cluster.

These methods generate solutions which can be graphically presented as hierarchical trees or dendograms.

Agglomerative hierarchical clustering methods present two substantial advantages over other clustering methods that make them worth considering for market segmentation purposes. First, agglomerative methods do not require any a priori information about the actual number of clusters in the population nor do they require any a priori information about their respective composition : no initial clustering solution has to be provided by the researcher. Second, agglomerative methods provide a visual representation of intra-cluster formation that may be of significant value in the interpretation of the clusters retained.

From a technical viewpoint, at each stage in the clustering process agglomerative methods form new clusters that minimize some function of inter-clusters distance. The dissimilarity matrix is then re-computed to express the relationships between the new clusters and the remaining entities. The major difference between agglomerative clustering algorithms is found at this stage. Some of the available methods define inter-cluster distances that assume only ordinal dissimilarity measures (See for instance Johnson [60]). Other methods assume an underlying metric and manipulate algebraically inter-cluster distances(See for example Ward [131]). Both classes of methods will be introduced in the next few sections.

The number of applications of clustering methods in marketing research appears to be increasing. Green and Tull [43] review more than a score of articles and papers in which cluster analysis was the primary tool of investigation. Applications encompass a wide variety of problems including the improvement of marketing experiments (Day and Heeler [32]), the study of consumer interests and opinion leadership (Montgomery and Silk [89]), the development of consumer typologies (Myers and Nicosia [93]), and market segmentation (Lessig and Tollefson [73]).

The use of cluster analysis to perform meaningful industrial market microsegmentation, however, requires that satisfactory solutions be provided to several problems associated with clustering methods. These problems include :

1. The sensitivity of cluster analysis results to extreme observations or outliers.

2. The non-randomness of the structure observed in a dissimilarity matrix.

3. The determination of the number of clusters to be retained for subsequent analysis.

4. The non-uniqueness of the clustering solution retained.

In the next sections we investigate these problems and suggest solutions for each of them. We then specify the cluster analytic methodology proposed here to perform industrial markets microsegmentation.

4.3.3.1. The Sensitivity of Cluster Analytic Solutions to Extreme Observations.

In the cluster analytic framework, extreme observations or "outliers" refer to entities that do not belong to the same populations as the other entities in the data set. For instance, outliers might be the result of errors in the earlier stages of data collection and coding.

The impact of outliers on the results of some statistical techniques, like regression, has been extensively investigated (Huber [56]). Recognition of this problem has led to the introduction of the concept of "robustness" of the solutions obtained.

There is increasing concern among cluster analysis practitioners about the impact that extreme observations might have upon cluster analytic results (Blashfield [8]). In view of the fact that most cluster analysis methods are misled by outliers -- and in particular those methods that assume an underlying metric for the

dissimilarity measures -- Kanal [64] suggested that these points should be removed from a data set prior to clustering.

The presence of outliers has implications beyond the cluster analysis results. In terms of the microsegmentation methodology proposed here, outliers might represent industrial organizations that have a substantially different pattern of involvement in their adoption process. Inclusion of such organizations in any of the segments retained would therefore reduce intra-segment homogeneity with the consequence that :

- it would be harder to get a precise description of the overall pattern of involvement within every microsegment, and
- it would be more difficult to investigate the link between microsegment membership and other observable characteristics of organizations.

Intelligent microsegmentation of industrial markets thus requires the elimination of outliers from the data set.

Following the suggestion of Blashfield [8], the method proposed here to identify outliers in a dissimilarity matrix is Single Linkage cluster analysis. This method is also known as "minimum method" (Johnson [60]), "Linkage Analysis" (Mc Quitty [81]) and "Nearest Neighbor Cluster Analysis" (Lance and Williams [68]).

The method of single linkage cluster analysis is conceptually among the simplest of all agglomerative clustering methods. At each stage in the clustering process, after two clusters -- say u and v -- have been merged into a new cluster t, the dissimilarity between the new cluster and some other cluster w is defined as :

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

Hence, the quantity d_{tw} is the distance between the two closest members of cluster t and w. If clusters t and w were to be merged next, for any entity in the resulting cluster, the distance to is nearest neighbor would be at most d_{tw}.

A cluster identified by single linkage analysis is then 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 serpantine clusters that are weakly connected. This property called "chaining" has been, and still is, a main criticism of the method.

From our standpoint, however, that same property of single linkage analysis makes it a very powerful tool to identify entities that share little similarity with the rest of the data set. Typically, in a single linkage analysis solution, any point

that exhibits the following characteristics might conceivably be considered as an outlier :

1. The point is isolated or is a member of a very small cluster (2 or 3 entities maximum), and

2. it clusters with the rest of the data set only in the final stages of the clustering process.

After careful examination of these points, and if they do not make-up a substantial portion of the data, the researcher should remove them from his data set. An example of the sensitivity of cluster analytic solutions to extreme observations appears in section 4.4.1.

4.3.3.2. Non-Randomness of the Structure Observed in a Dissimilarity Matrix.

Prior to determining the number of clusters that should be distinguished in a data set, it is essential to investigate if the structure observed in the dissimilarity matrix is non-random. By structure of a dissimilarity matrix, we mean the pattern of cluster formation at various stages in the clustering process.

Indeed, cluster analysis methods, which have been designed to discover groups of similar entities in a data set, are very

successful at that task even in the presence of completely unrelated entities. A careful strategy -- after removal of extreme observations -- is therefore to investigate the non-randomness of the number of clusters formed at various stages in the clustering process.

As noted by Fleiss and Zubin [38], a key defect in almost all 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 [57]). Ling [76] proposes a probability theory of cluster analysis. He recognizes, however, that no compelling argument justifies his particular choice of a model, and that in most real situations the conditions required by his model are not entirely satisfied. Moreover, the model proposed concerns only single linkage cluster analysis. Attempts to extend this theory to more complex clustering methods have consistently failed to date. As Ling concludes : "it is quite impossible to work out analytically the distribution theory of k-[connected] clusters under any reasonable model for the distribution of the points to be clustered, except for trivial cases".

In the absence of any satisfactory statistical model, simulation is recommended here to investigate the non-randomness of the structure observed in a dissimilarity matrix.

The idea behind the simulation approach is that a researcher is not interested in a pattern of clusters formation which does not substantially differ from that which would be obtained if the dissimilarities had been generated completely independently from one another that is, if there were no relations whatsoever between pairs of entities in the data set.

Fast cluster analysis programs (Dalziel [31]) 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.

The difference between the clustering structure obtained from the observed dissimilarity matrix and the clustering structure obtained under the null hypothesis of independence between pairs of dissimilarities can then be investigated through a comparison of the number of clusters identified at various levels under both hypothesis. This method also provides ranges for the number of non-random clusters in a given analysis, and so, can be of some help in the determination of the clustering solution that should be retained.

4.3.3.3. An Approximate Criterion for Determining the Number of Clusters to be retained in the analysis

A substantial problem in performing a cluster analysis is deciding upon the number of clusters in the data. This difficulty comes from the lack of precise definition of what a "cluster" is. Agglomerative clustering methods give a configuration for every number of clusters from the number of entities (each cluster has only one member) to a unique cluster (containing the entire data set). That gives the researcher a broad range of possible choices.

Several rules of thumb have been proposed in the literature to address this problem. Curry [28] notes that the determination of an appropriate cut-off level in a hierarchical clustering classification is a matter of analyst judgement and depends on the ultimate use to which the results will be put. He suggests that an attempt should be made to identify clusters which have attained nearly their entire membership at low levels in the clustering process and remain stable through higher levels. This view is also shared by Green and Tull [43], who suggest identifying a set of "fairly compact" clusters. Anderberg [3] suggests that a data set may be characterized by different clustering solutions. Within a classification hierarchy there may be several meaningful levels of aggregation that could all be further investigated. Finally, the simulation approach suggested in the previous section does not

usually prove very useful to find a "best" set of clusters. Indeed, whenever a data structure is non-random, there is usually a range of clustering levels for which a significant departure from the random model is registered.

It is our opinion that the determination of the number of microsegments in the potential market for an industrial product should not totally result from the application of subjective rules of thumb. Rather it should result from the application of criteria derived from the specific objective of the microsegmentation methodology. This objective being to find the smallest possible set of microsegments of organizations such that within each of them, organizations are maximally similar in the structure of their adoption process. The criterion proposed next makes use of the trade-off between these two conflicting objectives.

As discussed in section 4.3.1., the structure of the adoption process for organization r can be viewed as a (gxp)-dimensional vector of binary variables :

$$\Delta_r = \{\delta_{rjh} : j = 1....g,\ h = 1....p\}$$

$$\{\delta_{rk} : k = 1....(gxp)\}$$

Consider a specific cluster q_α, identified at clustering level α and containing n_α entities. We define the homogeneity $H^2_{kq_\alpha}$ of this cluster on the kth binary variable as :

$$H^2_{kq_\alpha} = 1 - (S^2_{kq_\alpha}/S^2_k)$$

where : $S^2_{kq_\alpha}$ is the variance of scores on variable k in cluster q_α

S^2_k is the variance of scores on variable k in the complete sample.

Alternatively, $H^2_{kq_\alpha}$ can be seen as the proportional lack of contribution of cluster q_α to the total variance in variable k. This expression approaches 1.0 as the within cluster variance $S^2_{kq_\alpha}$ falls to zero relative to the total variance S^2_k.

Considering all variables simultaneously, we define the overall homogeneity of cluster q_α as :

$$H^2_{q_\alpha} = \sum_{k=1}^{(pxg)} (S^2_k - S^2_{kq_\alpha}) \Big/ \sum_{k=1}^{(pxg)} S^2_k$$

This quantity represents the portion of the total variance in the data not accounted for by cluster q_α. It is a weighted average of the homogeneities of cluster q_α over all variables, where the weight of variable k is :

$$W_k = \frac{S^2_k}{\sum_{k=1}^{(pxg)} S^2_k}$$

Similar definitions for the homogeneity of a cluster have been proposed by Curry [28].

At level α in the clustering process, we then define the total homogeneity of a particular set of clusters as :

$$H_\alpha^2 = \sum_{z=1}^{n_\alpha} H_{q_{\alpha z}}^2$$

where n_α is the number of clusters identified at this level. We also define the average homogeneity of the clustering solution α as :

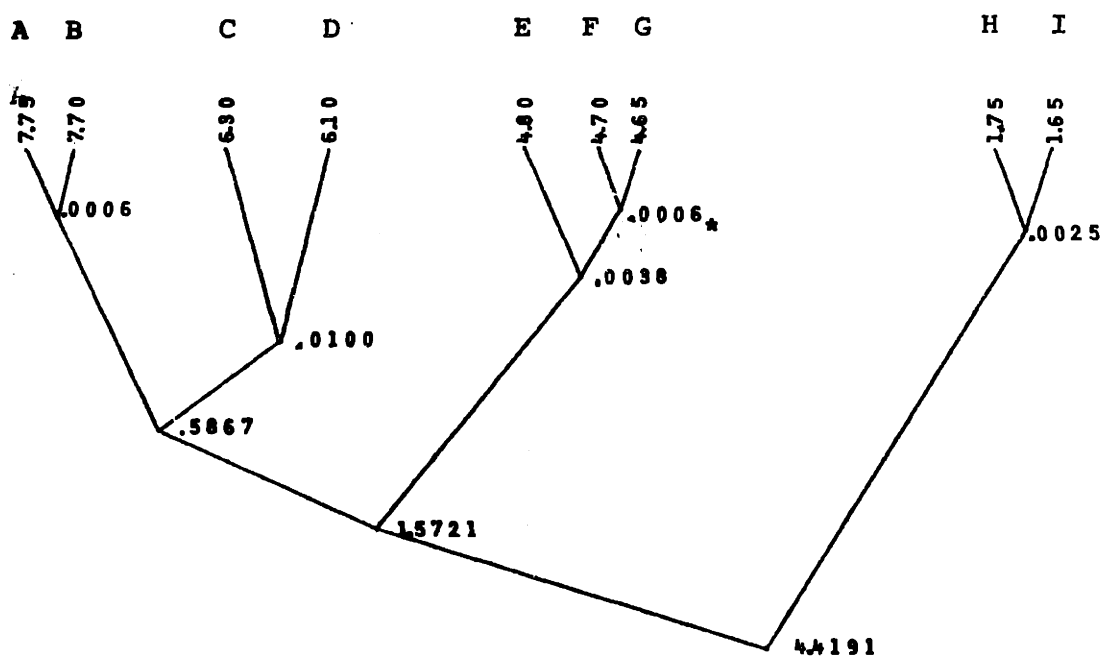
$$\overline{H_\alpha^2} = \frac{1}{n_\alpha} H_\alpha^2$$

This last expression provides a common basis to compare the adequacy of clustering solutions obtained at different levels in a hierarchical classification. It is less sensitive to small changes in the within clusters homogeneities than H_α^2 and expresses more directly the trade-off between the two conflicting objectives of the microsegmentation methodology.

Consider the example reproduced in figure 4.2. and involving nine entities defined on a single continuum. Entity C, for example has the value 6.30, while entity H has for value 1.75. A four Cluster solution appears natural in this case and would include the

FIGURE 4.2. : A SIMPLE EXAMPLE OF THE BEHAVIOR OF THE MEASURES OF CLUSTERS HOMOGENEITY H_α^2 AND $\bar{H}_\alpha^2$.

a. Data and Clustering Solution



b. Analysis of Clusters' Homogeneity

α	n_α	H_α^2	$\bar{H}_\alpha^2$
0	9	9.0	1.0
1	7	6.998	.999
2	6	5.996	.999
3	5	4.992	.998
4	4	3.982	.995
5	3	2.406	.802
6	2	.425	.212
7	1	.0	.0

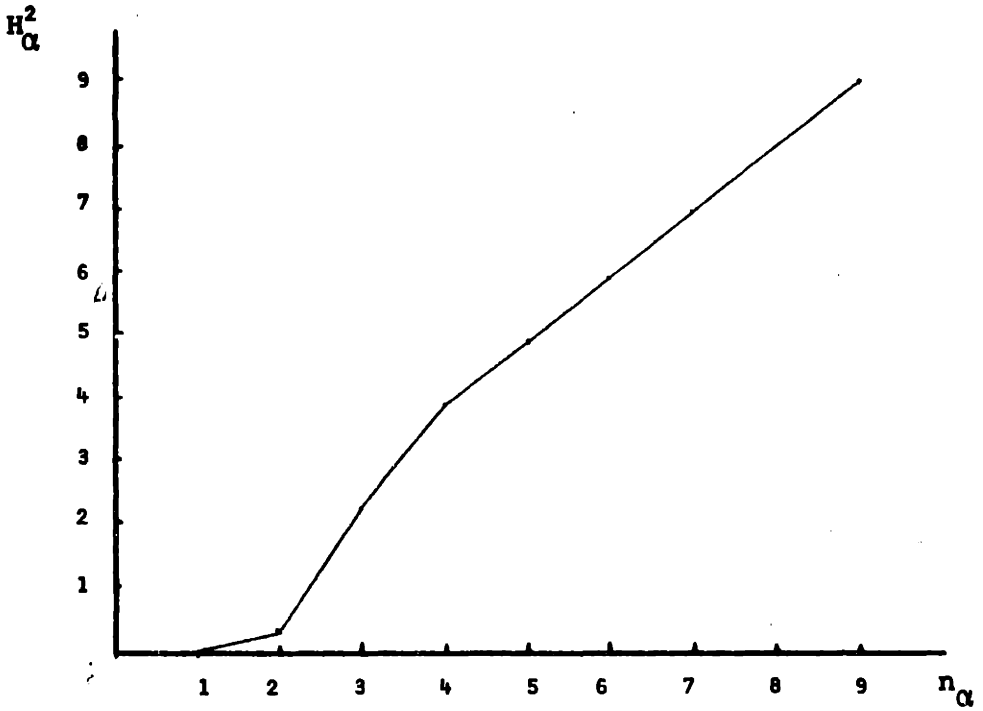
* Within cluster variance

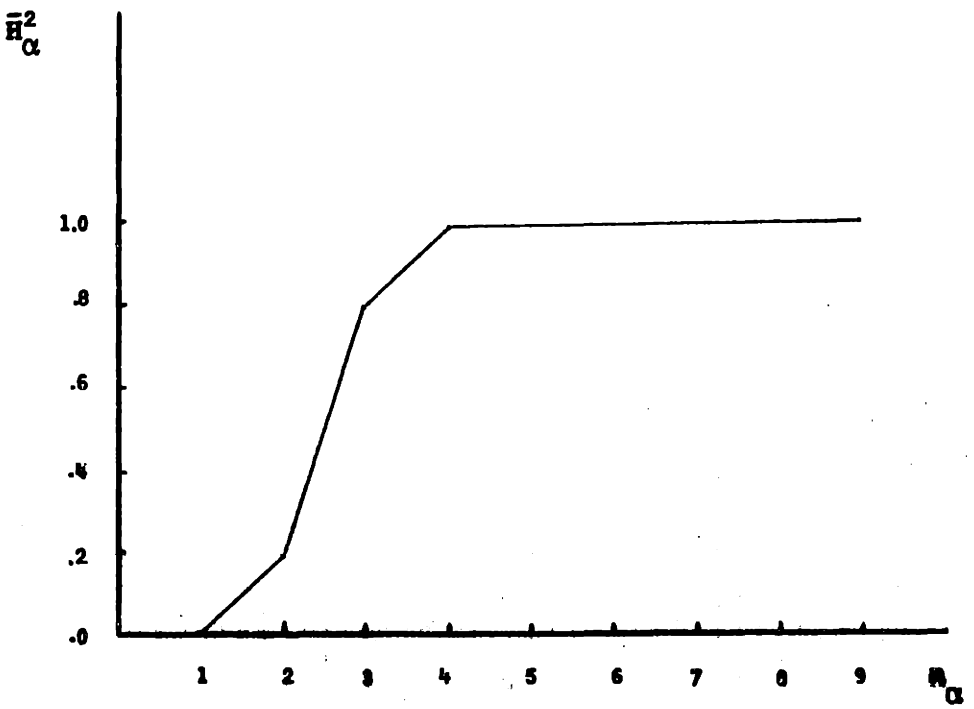
(Continued on next page)

* Within cluster variance.

(Continued on next page)

c. Behavior of H_α^2 and $\bar{H}_\alpha^2$





grouping (A,B) (C,D) (E,F,G) and (H,I). A complete linkage clustering analysis was performed and led the hierarchical structure reproduced in figure 4.2. A description of this clustering method appears in section 4.3.3.4.

At the level $\alpha=0$ in the clustering process, each of the nine entities forms an independent cluster. The homogeneity of each of these clusters is 1.0, so that $H_0^2 = 9$. This particular clustering therefore accounts for all the variance in the data.

As the clustering classification proceeds to higher levels, entities are grouped into gradually less homogeneous clusters, so that H_α^2 decreases. At the level $\alpha=7$, the last level in this hierarchy, all entities are grouped into one cluster. The overall homogeneity $H_7^2 = 0$, implying that this last clustering accounts for no variation in the data.

Unless there is no link whatsoever between the entities represented in the data set, in which case H_α^2 would drop abruptly for small values of α, the function H_α^2 is usually concave. Figure 4.2.C depicts this situation.

At level $\alpha=5$ in the clustering process, one notes a substantial change in the slope of H_α^2. This indicates a reduction in the total homogeneity of the clustering solution more serious than at

previous levels. It thereby confirms our expectations concerning the existence of a four clusters solution in this specifc case.

The average homogeneity $\bar{H}^2_\alpha$ presents a very stable pattern over the first five levels in the classification. Its value is almost constant over that range, indicating that groupings occur within fairly homogeneous clusters. At level α=5, however, a substantial drop occur in the average homogeneity of the clusters extracted, pointing to the loss of information of grouping the data in less than four clusters.

Given the present state of development of cluster analysis, a systematic investigation of the behavior of the average homogeneity of the clustering solutions obtained at all levels in a hierarchical classification provides an additional basis for inference. The presence of a systematic change in the slope of the $\bar{H}^2_\alpha$ trace, or the presence of an "elbow" in this trace, for instance, might be used as an approximate criterion for determining the number of clusters in a data set. Use of this criterion, when combined with the results of the simulation analysis outlined earlier, provides a sound basis on which to make a decision concerning the number of clusters.

4.3.3.4. The Non-Uniqueness of the Composition of Clusters

The fourth problem associated with the use of cluster analysis concerns the indeterminacy of cluster analytic solutions. 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 reason has to do with the particular way a clustering method handles tied dissimilarities that may occur at various levels in the clustering process. Consider the simple example involving four entities reproduced in figure 4.3. The dissimilarity between each pair of different entities was computed using the measure D^2_{rs} introduced earlier. Although some of the dissimilarities violate the ultrametric inequality[1], this situation is quite common in real life situations involving large data sets.

Complete linkage analysis was used for clustering these entities and the solutions appear in figure 4.3.c-f. Stage one and two in the clustering process are characterized by the presence of tied

---

1. The Ultrametric inequality (Johnson [60]) requires :

$$d(x,z) \leq \max \{d(x,y), d(y,z)\},$$

where x,y and z are any three entities.

This is a much stronger condition that the triangle inequality :

$$d(x,z) \leq d(x,y) + d(y,z),$$

required of true distance functions.

FIGURE 4.3. : NON-UNIQUENESS OF CLUSTERS' COMPOSITION IN THE PRESENCE OF TIED DISSIMILARITIES

a Original Data

Δ_1 :	1	1	1	1	1	1	1	1	0	0
Δ_2 :	1	1	1	1	1	1	1	1	1	1
Δ_3 :	0	1	1	1	1	1	1	0	1	1
Δ_4 :	0	0	0	1	1	1	1	0	1	1

b. Dissimilarity Matrix

	Δ_1	Δ_2	Δ_3	Δ_4
Δ_1	—	—	—	—
Δ_2	2	—	—	—
Δ_3	4	2	—	—
Δ_4	6	4	2	—

(Continued on next page)

FIGURE 4.3. : (Continuation)

c. Solution 1

	(Δ_1,Δ_2)	Δ_3	Δ_4
(Δ_1,Δ_2)	—	—	—
Δ_3	4	—	—
Δ_4	6	2	—

	(Δ_1,Δ_2)	(Δ_3,Δ_4)
(Δ_1,Δ_2)	—	—
(Δ_3,Δ_4)	6	—

d. Tree Diagram

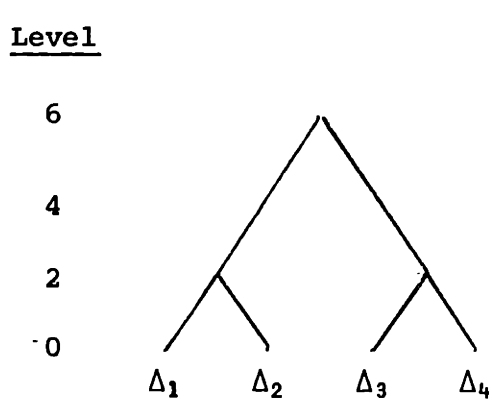


FIGURE 4.3. :(Continuation)

e. Solution 2

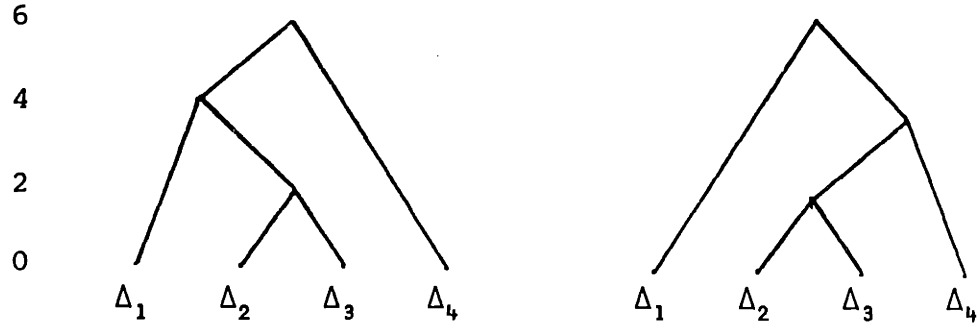
	Δ_1	(Δ_2, Δ_3)	Δ_4
Δ_1	–	–	–
(Δ_2, Δ_3)	4	–	–
Δ_4	6	4	–

	$(\Delta_1, \Delta_2, \Delta_3)$	Δ_4
$(\Delta_1, \Delta_2, \Delta_3)$	–	–
Δ_4	6	–

	Δ_1	$(\Delta_2, \Delta_3, \Delta_4)$
Δ_1	–	–
$(\Delta_2, \Delta_3, \Delta_4)$	6	–

f. Tree Diagrams

Level



dissimilarities. From the solutions provided, it is clear that the final clusters' composition is strongly affected by the choices made at these two stages.

The non-uniqueness of clusters' composition is not specific to complete linkage analysis. Examples can be built easily around most other clustering methods. Which of the possible tree diagrams should we therefore take as the real representation of a data structure ?

One way to alleviate the impact of tied dissimilarities on cluster analytic solutions would be to introduce a small random perturbation whenever tied dissimilarities occur in the clustering process. The exact nature that this perturbation should have, however, is unknown. Common sense suggests that this perturbation be linked to the variability of individual dissimilarity estimates. Unfortunately, the statistical properties of distance measures defined on sets of objects are not established (Sokal and Sneath [120]).

The second reason for the indeterminacy of cluster analytic solutions comes from the fact that different clustering algorithms make different assumptions about the scaling properties of the dissimilarity measure used, and compute distances between clustered entities differently. As a result, different methods usually lead

to different clusters' composition except in the case of extremely stable clusters. Which of the many algorithms available should then be used ?

To date, no answer has been provided to this question. Each of the available clustering techniques has its advocates and its critics (See the discussion by Anderberg [3]). Very few empirical studies are available that compare their relative performance. A recent analysis by Blashfield [8], 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.

In terms of the microsegmentation methodology, the question of indeterminacy of cluster analytic solutions is of considerable importance. Indeed, from the nature of dissimilarity measures defined over a finite set of binary variables -- typically (pxg) such variables for the decision matrix -- we know that ties are bound to occur in any data set of reasonable size, thereby contaminating the clustering solutions. In addition, it is a prerequisite that the microsegments identified be very stable if one wants the investigation of the general structure of the adoption process within each microsegment, as well as its correlation with other characteristics of industrial organizations, to make sense.

The approach we suggest is to use several clustering algorithms in parallel and analyze the composition of the resulting clusters. If the set of clusters retained are indeed "real", one would expect their composition to vary little across clustering methods. This criterion of clusters' composition invariance across clustering models has also been proposed by Everitt [35].

For this purpose, three agglomerative clustering models are used in our empirical research and deserve some attention now. Interested readers are refered to Hartigan [50], Anderberg [3], and Dalziel [31] for more complete descriptions of these algorithms.

Complete Linkage Cluster Analysis

According to this method, a cluster is defined as a group of entities in which each member is more similar to all members of the same cluster than it is to all members of any other cluster. At each clustering stage, after cluster u and v have been merged, the dissimilarity between the new cluster -- say t -- and some other cluster w is determined by :

$$d_{tw} = \max\ (d_{uw}, d_{vw}).$$

A substantial advantage of complete linkage analysis over most other clustering methods, is that it requires only ordinal dissimilarity measures. The solution provided is therefore invariant under monotonic transformation of the dissimilarity matrix.

A main criticism of complete linkage analysis, however, is that as an entity can not join a cluster until it obtains a given similarity level with all members of this cluster, the probability of a cluster obtaining a new member becomes smaller as the size of the cluster increases. This property, known as "space-diluting" (Lance and Williams [68]), means that the effective distance between a particular cluster and some non member increases as the size of the cluster increases.

Average Linkage Cluster Analysis

Average linkage analysis represents a compromise between single linkage analysis -- which characterize a cluster by the longest link needed to connect any of its member to some other one -- and complete linkage analysis -- which characterize a cluster by the longest link needed to connect all of its members. In average linkage analysis, a cluster t is characterized by the mean of the

distances between all pairs of distinct items within the cluster :

$$\text{size of cluster}(t) = \frac{2}{n_t\ (n_t-1)} \sum_{r \neq s \in t} d(r,s)$$

where n_t is the number of entities in t and the summation is over all pairs of points $r \neq s$ in t. A cluster is then defined as a group of entities in which each member has a greater mean similarity with all members of the same cluster than it does with all members of any other cluster.

Sneath and Sokal [117] claim that average linkage cluster analysis is the most preferable of many hierarchical methods which have been proposed. Available evidence suggests, however, that this method is more likely than some other clustering methods to form "non-conformist" groups as the sizes of clusters increases (Williams, Clifford, and Lance [142]).

Minimum Variance Cluster Analysis

Ward [131] and Ward and Hook [132] have described a very general method of hierarchical clustering which attempts to maximize at each step an objective function which refects an investigator's purpose in a particular problem. Although the method is quite general and encompasses most other hierarchical methods, Ward illustrated it with an error sum of squares objective function which came to be better known than his general procedure.

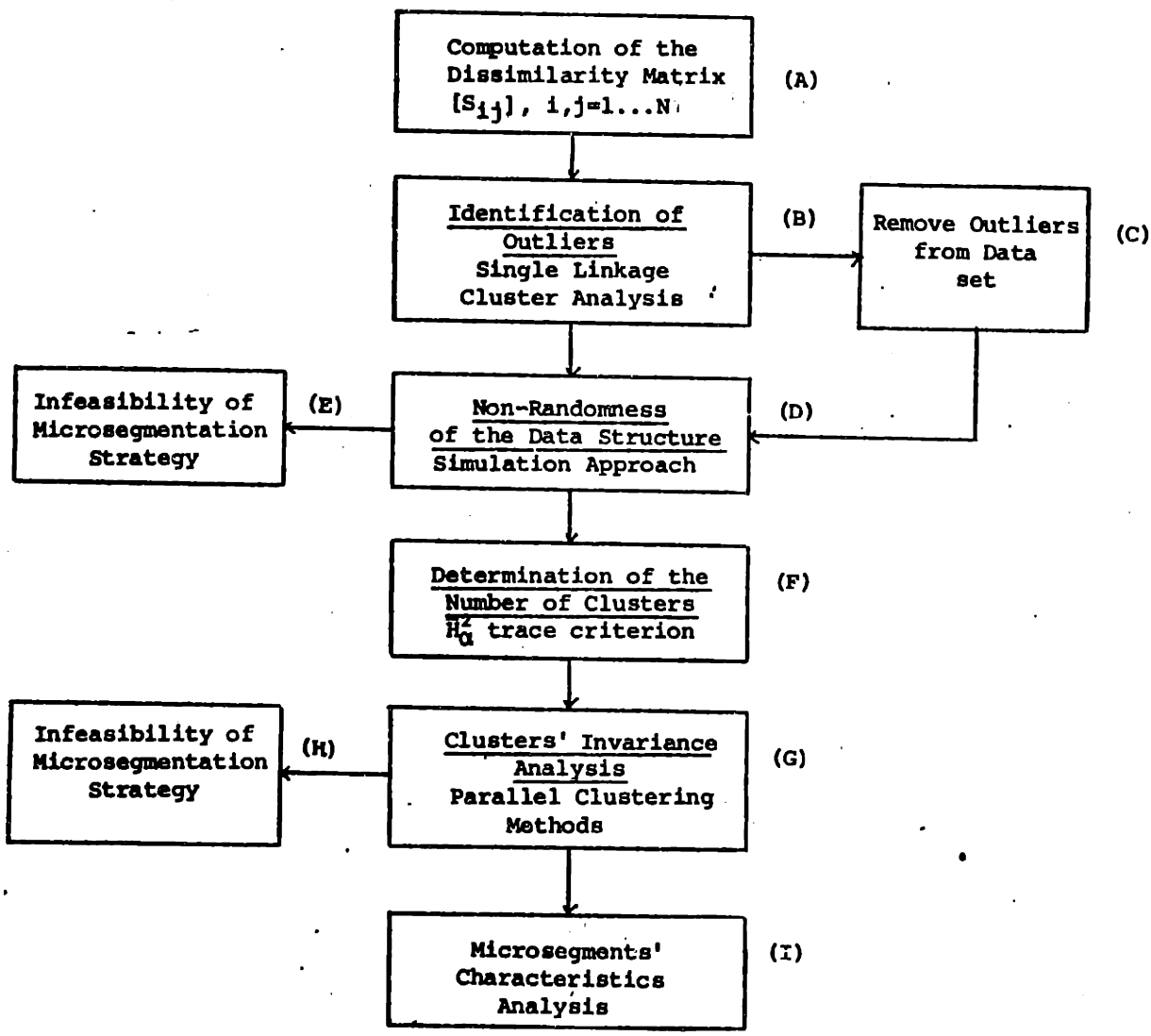
The objective of this latter method is to find at each stage of the classification process the two clusters that minimize the increase in the total within clusters error sum of squares. A recent analysis of the relative performance of alternative cluster analytic methods by Blashfield [8] suggests that this technique is consistently most accurate in recovering data generated under a mixture model involving several different populations.

4.3.4. Analytical steps involved in the Microsegmentation Methodology

The previous sections were devoted to a presentation of the main problems associated with the use of cluster analytic methods and to the presentation of reasonable solutions for each of them. The purpose of this section is to incorporate these suggestions within the microsegmentation methodology outlined earlier.

Figure 4.4. presents the micro-structure of the methodology proposed here to identify segments of organizations homogeneous in the structure of their adoption process in the potential market for an industrial product. Step (A) of the methodology involves the computation of the dissimilarity matrix $[S_{ij}]$. Each entry in this matrix expresses the dissimilarity between organization i and organization j in the structure of their adoption process for the

FIGURE 4.4. : MICRO-STRUCTURE OF THE INDUSTRIAL MARKET SEGMENTATION METHODOLOGY



product investigated. The distance measure D^2_{ij} introduced in section 4.3.2. is used for this purpose.

The next step in the methodology (B) involves the identification of outliers, that is, organizations whose adoption process shares little ressemblance with that of other organizations in the potential market. As suggested in section 4.3.3.1., single linkage analysis is used for this purpose. If extreme observations are identified, they are removed from the data set (C) and the adoption process of the corresponding companies is the object of a separate analysis.

After the dissimilarity matrix $[S_{ij}]$ has been freed from extreme observations, the non-randomness of the structure observed is investigated (D). For this purpose, the trace of the actual number of clusters formed at different levels in the clustering process is compared with the trace of the number of clusters expected under the null hypothesis of completely unrelated entities, and obtained by simulation. A range of meaningful clustering solutions is also determined.

In those cases where the observed data structure does not significantly depart from the random model at <u>any</u> clustering level, no attempt is made at microsegmenting the potential market (E).

On the other hand, if the data structure significantly differs from that expected under the random model, a microsegmentation

is performed. In view of the established superiority of the Ward [131] minimum variance method to recover actual clusters (Blashfied [8]), and in view of its accurate transposition of the microsegmentation objective to maximize within clusters' homogeneity, microsegmentation of the potential market is performed with this method. An objective function which attempts to minimize within-cluster's variance rather the total error sum of squares is used for this purpose. The trace of the average homogeneity of the hierarchical classification obtained is then examined and used as an aid in determining the number of microsegments (F). If the number of microsegments identified by this method also departs significantly from the random model in the simulation analysis, these microsegments are analyzed for invariance across clustering methods (G).

The analysis concludes at the existence of meaningful microsegments of organizations only in those cases where several clustering algorithms -- which substantially differ in their assumptions and mathematical logic -- converge in terms of the composition of the clustering solution retained. For this purpose, the same number of clusters as identified in step (F) is extracted through the use of different clustering methods and a systematic analysis of the invariance of their composition is performed.

When a substantial degree of agreement in the composition of the clustering solution retained is observed across clustering methods, one can be confident of the significance of the microsegments identified.

The last step in the methodology (I) investigate the structure of the adoption process within each of the microsegments retained and assesses the relationship between microsegment membership and other characteristics of industrial organizations.

4.4. Implementation of the Microsegmentation Methodology

The analysis reported in the next sections concerns the microsegmentation of the potential market for a new solar industrial cooling system on the basis of the likely structure of the adoption process for such a product. The data used, and the way they were collected are described in Chapter two.

One hundred and seventeen industrial companies are included in our analysis. The reduction of the sample is due to the elimination of one observation -- chosen at random -- for each company (12) from which two questionnaires were returned. This avoids contamination of the results of the microsegmentation analysis by artificially inflating within-cluster homogeneity.

First, the dissimilarity matrix $[S_{ij}]$ between all 117 companies was computed using the D^2_{rs} measure described in section 4.3.2. and the information on the structure of the adoption process obtained with the decision matrix from each company. This dissimilarity matrix is the basic input to the microsegmentation analysis.

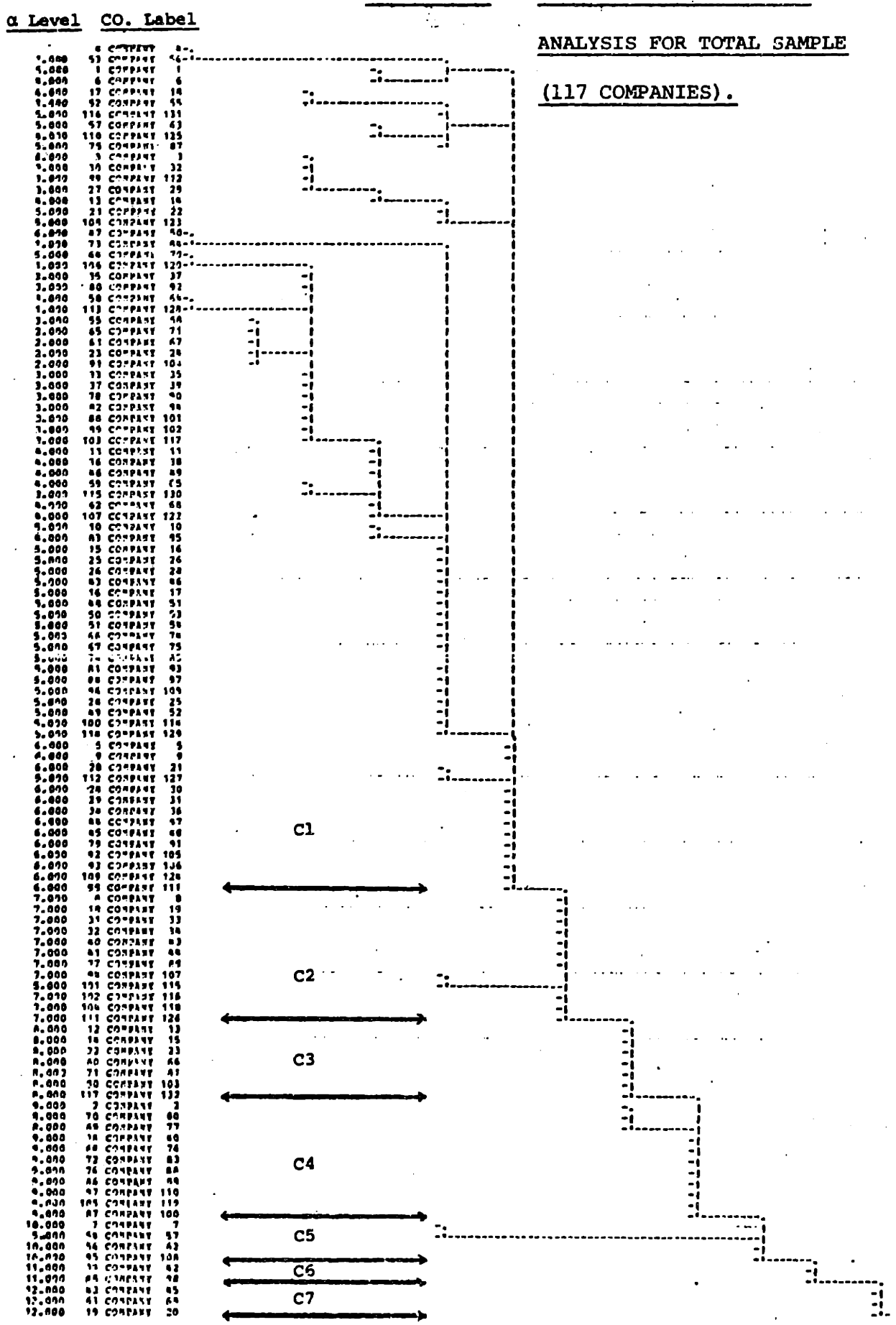
4.4.1. Identification of Extreme Observations

The matrix $[S_{ij}]$ was first submitted to a single linkage cluster analysis for identification of potential outliers. Figure 4.5. presents the results of this analysis.

Seven major clustering levels are identified and labelled C1 to C7. As one moves higher in the hierarchical classification, from cluster C1 to cluster C7, companies become increasingly dissimilar in the structure of their adoption process. For instance, the distance from any company in cluster C5, C6 or C7 to the most similar company in the rest of the sample is more than 10, that is, there is a minimum of 10 non-matches between the pattern of individual involvement in the adoption process of a specific company in cluster 5 and the pattern of involvement of any other company in the sample.

The first substantial fragmentation of the data set occurs with cluster C2. This cluster, however, contains a large number of observations (12) which can not reasonably be considered as outliers.

FIGURE 4.5. : SINGLE LINKAGE CLUSTER ANALYSIS FOR TOTAL SAMPLE (117 COMPANIES).



Elimination of these companies from our sample could significantly affect the validity of the microsegmentation results. The same observation can be made for cluster C3 and cluster C4 which contain 7 and 11 companies respectively.

The problem is quite different for the three last clusters C5, C6 and C7. These clusters typically comprise a small number of organizations. Moreover, in the case of cluster C5, there exists substantial within cluster heterogeneity, as evidenced by the fact that two of the four companies are quite similar (Companies 7 and 57) but weakly connected to the other two companies from the same cluster.

The structure of the adoption process for the companies belonging to clusters C5, C6, and C7 was therefore investigated independently from the rest of the sample. This analysis led to the identification of three main causes of divergence between these companies and the rest of the sample :

- Emphasis on the role played in the adoption process by categories of decision participants external to the organization (cluster C5)

- Emphasis on the role played by members of the purchasing department relative to other categories of decision participants (cluster C6)

- Lack of discrimination in answering the decision matrix. In company 20, for instance, all categories of decision participants were mentionned as being involved in all phases of the decision process.

To summarize, it appears that companies in clusters C5, C6 and C7 are characterized by an atypical emphasis on the role played by a few categories of decision participants in the adoption process. In addition, for some of the companies, the decision matrix failed to provide a meaningful framework for characterizing their adoption process. In view of these problems, these 9 companies were removed from subsequent analyses.

As an illustration of the impact of extreme observations on a hierarchical classification obtained by cluster analysis, we have reproduced in figure 4.6. and 4.7. the complete linkage solution obtained with the total sample of 117 companies and the solution obtained by the same method with the reduced sample of 108 companies. Although this clustering method assumes only ordinal dissimilarities -- and is therefore quite robust -- substantial differences are registered between the two solutions in terms of the <u>number</u> of clusters identified at any given level and in terms of the <u>composition</u> of these clusters. For example, at level $\alpha=24$ in the clustering process, figure 4.6. shows 4 clusters while figure 4.7. shows 3 clusters. Moreover, these clusters differ substantially in their composition. For the purpose of industrial markets microsegmentation it is therefore a wise precaution to remove potential outliers from the data set.

FIGURE 4.6. : COMPLETE LINKAGE CLUSTER

ANALYSIS FOR COMPLETE SAMPLE

(117 COMPANIES)

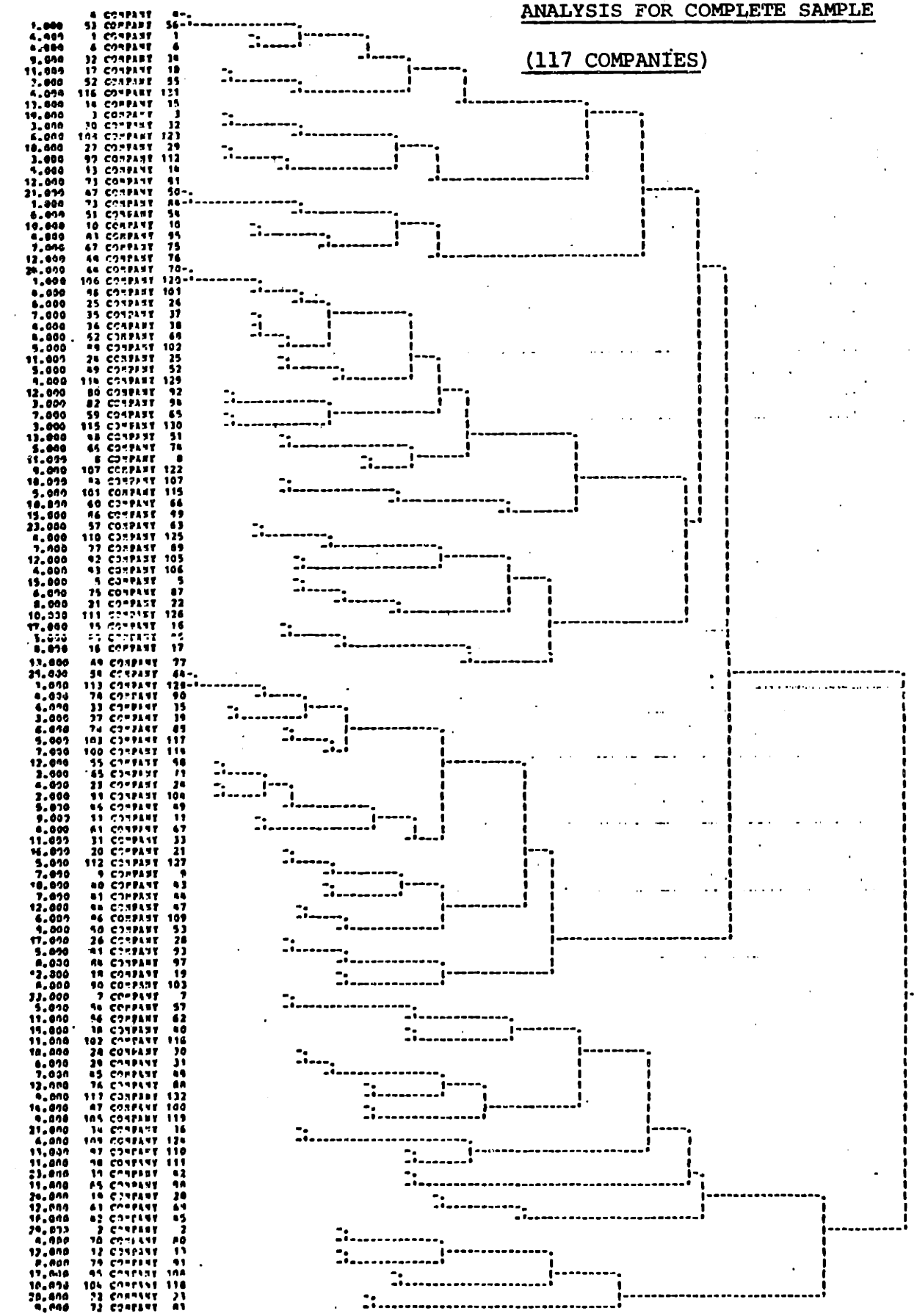
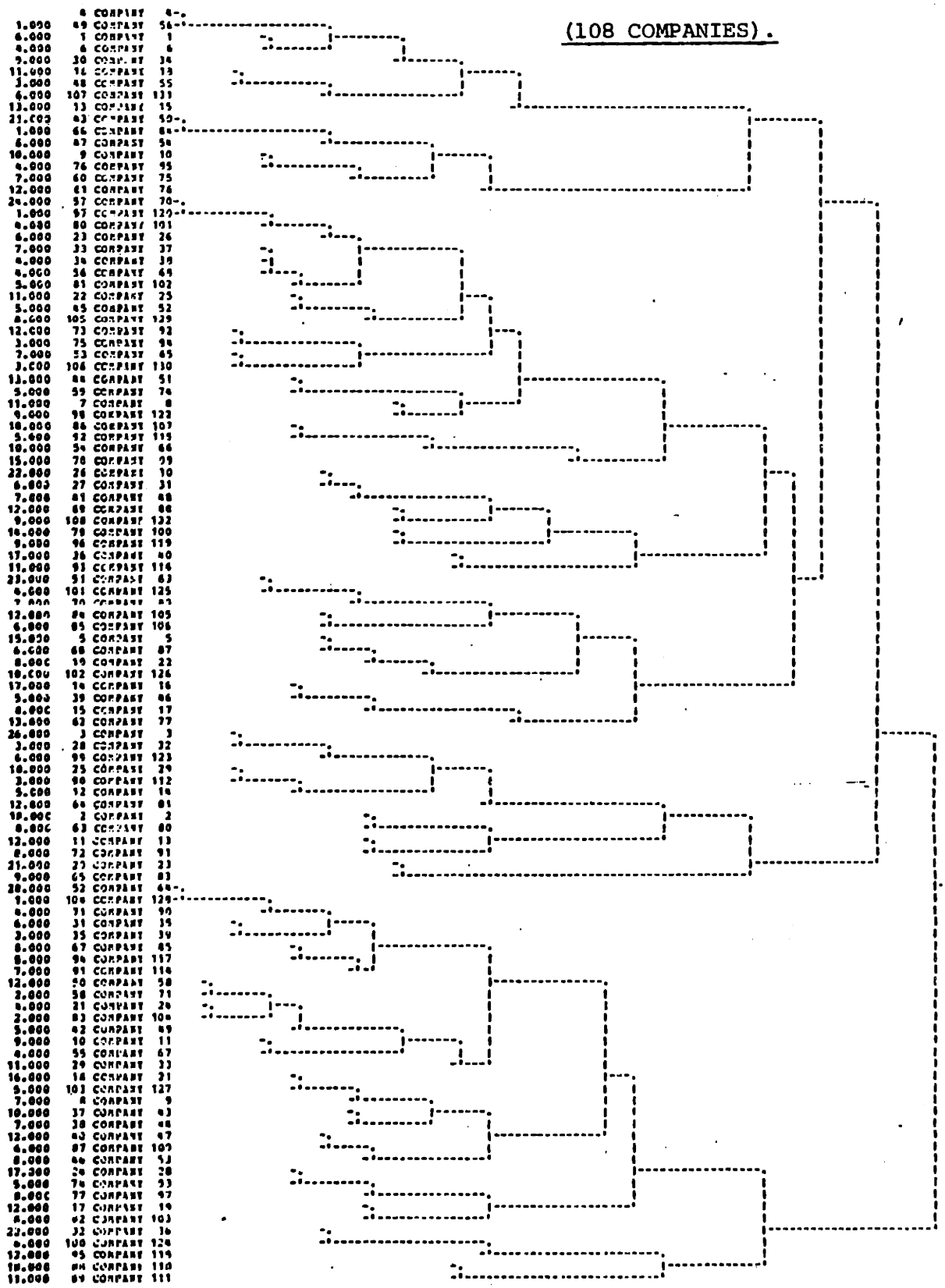


FIGURE 4.7. : COMPLETE LINKAGE CLUSTER ANALYSIS FOR REDUCED SAMPLE (108 COMPANIES).



4.4.2. Non-Randomness of the Data Structure reflected in the Dissimilarity Matrix

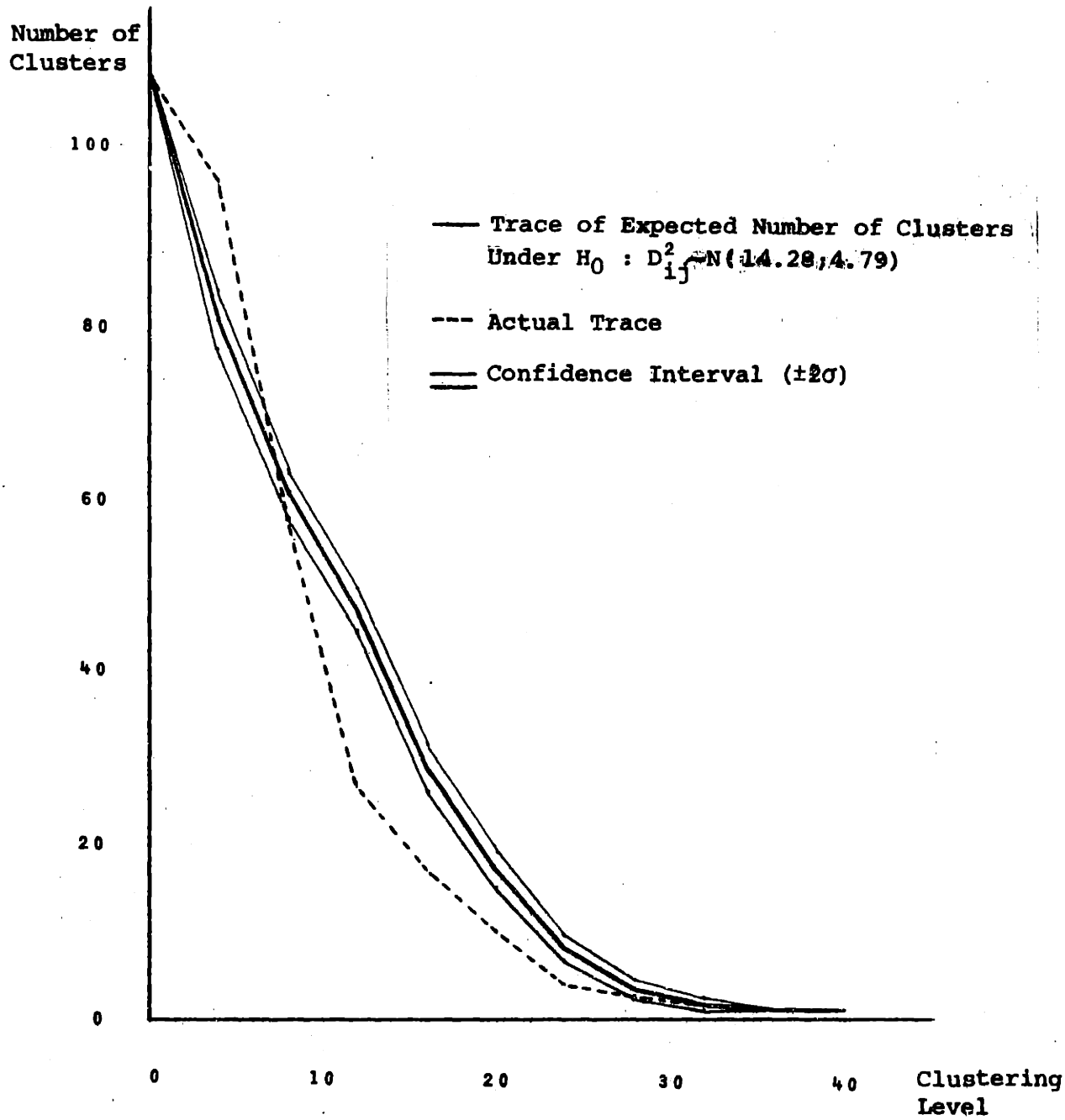
In order to investigate the non-randomness of the data structure reflected in the dissimilarity matrix for the reduced sample, a similation was performed. This simulation involved cluster analyzing 10 dissimilarity matrices whose individual entries were generated randomly from a normal distribution with parameters $\mu=14.28$ and $\sigma=4.79$, as observed in our sample.

The method of cluster analysis used for this purpose is complete linkage analysis. This algorithm -- which is very fast to run on a computer -- is particularly well suited for simulation purposes. Moreover, as noted elswere (Anderberg [3]), cluster analytic methods usually achieve a high degree of consistency in those cases where either true clusters exist in the data, or no clusters exist at all.

Figure 4.8. reproduces the results of the simulation analysis. The number of clusters obtained from the dissimilarity matrix at various clustering levels departs significantly from the number that would be observed at these levels under the null hypothesis $H_0 : D^2_{ij} \sim N(14.28;4.79)$. Interestingly enough, the zero-information trace intersects the observed trace, indicating that :

- the actual data are characterized by a significantly larger number of small, closely connected clusters, and that

FIGURE 4.8. : RESULTS OF THE SIMULATION STUDY OF THE NUMBER OF CLUSTERS



- 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 does exist in our data. Decision process similarities between industrial organizations in our sample 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 contains substantially more connected clusters -- as evidenced by the smaller clustering level -- than under the null hypothesis.

4.4.3. Determination of the number of microsegments to be retained

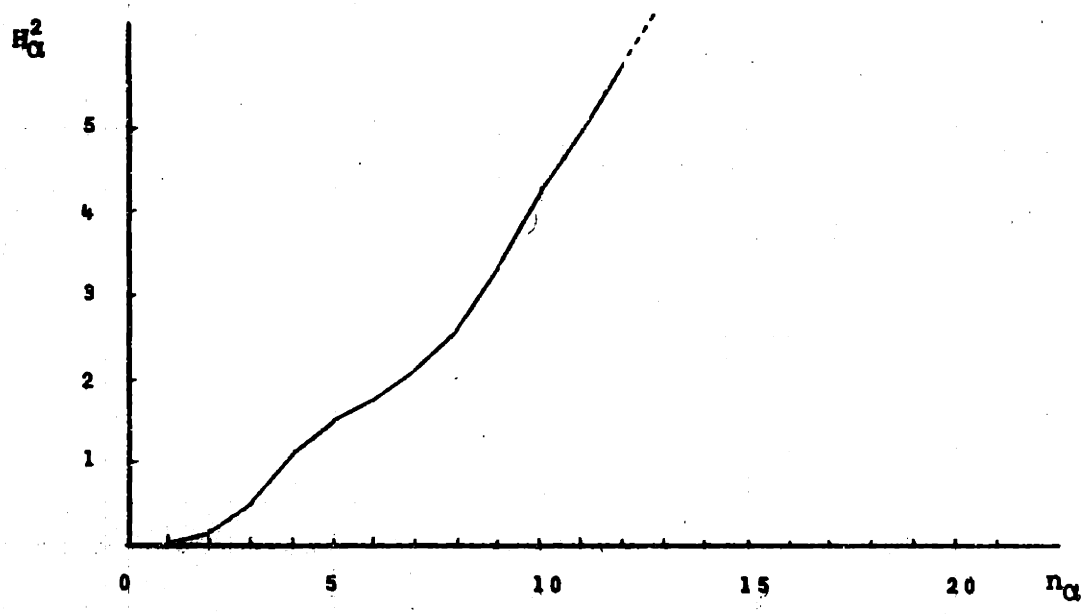
An additional source of information in the determination of the number of microsegments to be retained for subsequent analysis is provided by the behavior of the measures of clusters' homogeneity H_α^2 and $\bar{H}_\alpha^2$ as the hierarchical classification proceeds. Our investigation is based on the results obtained with a variant of the Ward [131] method which uses a within cluster variance objective function. As discussed in section 4.3.4. this particular method forms clusters that are maximally homogeneous at each step in the classification process, and therefore closely reflects the objective of the microsegmentation methodology.

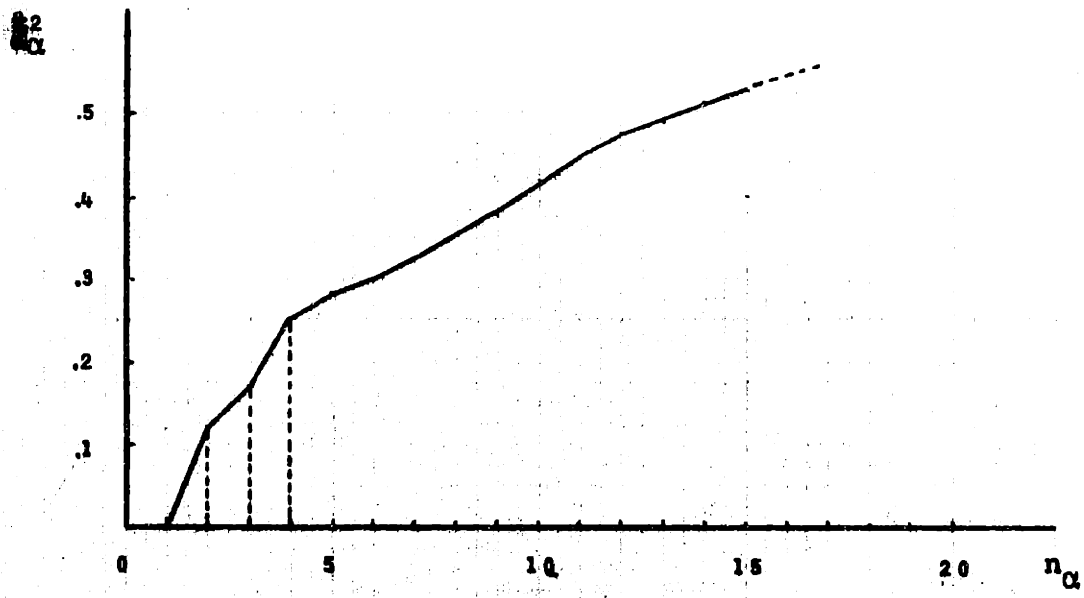
Figure 4.9. reproduces the behavior of H_α^2 and $\bar{H}_\alpha^2$ as the minimum within cluster variance algorithm proceeds. These graphs were derived from the hierarchical classification reproduced in figure 4.13. in the next section.

Consider first the behavior of H_α^2. An interesting pattern emerges in the range ($5 < n_\alpha < 10$). Within that range, indeed, H_α^2 behaves as a convex function, indicating that as companies are grouped into a smaller number of microsegments the total within cluster homogeneity decreases at a <u>decreasing</u> rate. In view of the second objective of the microsegmentation methodology -- to find the <u>smallest</u> possible set of meaningful microsegments -- the behavior of H_α^2 suggests that clustering should be continued in that range. Over the range ($3 < n_\alpha < 5$), however, H_α^2 decreases first slightly (at level $n_\alpha = 4$) and then more drastically (at level $n_\alpha = 3$). The rate of decrease H_α^2 then tapers off. It should be noted in this respect that at level (N-2) when the algorithm passes from two clusters to one, the decrease in total homogeneity is completely driven by the variance in the data. Indeed, at this stage in the clustering process, no degrees of freedom are left to minimize total within clusters' variance and the algorithm simply group all 108 companies together.

The examination of the average homogeneity trace $\bar{H}_\alpha^2$ as the classification progresses is more revealing. The decrease in average clusters'

FIGURE 4.3. : BEHAVIOR OF THE MEASURES OF HOMOGENEITY H_α^2 AND $\bar{H}_\alpha^2$ FOR THE ACTUAL DATA INVOLVING 108 COMPANIES





homogeneity in the range ($4 \leq n_\alpha$) is fairly constant, suggesting that as the algorithm proceeds, no subtantial <u>incremental</u> decrease in average homogeneity occurs until four clusters are formed. At this stage, a substantial drop in $\bar{H}^2_\alpha$ is associated with the passage from a four clusters solution to a three clusters solution, indicating that any decrease in the number of microsegments can only be made at the expense of substantially higher losses in average homogeneity.

If we consider these observations along with the results of the simulation approach -- which indicates that a four cluster solution represents the smallest number of clusters that significantly depart from the random model -- it appears that the four cluster solution is a reasonable choice in terms of the two conflicting objectives of the microsegmentation methodology. We thus retain this solution for subsequent analysis.

4.4.4. Invariance of Cluster Composition

The stability of the four cluster solution was investigated by the use of parallel methods of cluster analysis. Our purpose is to determine how invariant the composition of each cluster is when the same number of clusters is derived by methods that differ in their assumptions about the scaling properties of the dissimilarities and in their mathematical logic.

Three clustering algorithms were used to investigate the stability of the clustering solution retained from the hierarchical classification obtained with the minimum variance method. These algorithms include :

- Complete Linkage analysis,
- Average Linkage analysis, and
- minimum increase in total error sum of squares.

The latter method corresponds to the typical objective function of the Ward [131] method.

The clustering classifications obtained with each of these three algorithms and with the minimum variance method are reproduced in figure 4.10, 4.11, 4.12, and 4.13 respectively. These results were obtained for the reduced dissimilarity matrix, comprising 108 industrial companies. A four clusters solution was retained in each case. The arrows placed in the hierarchical classifications represent the boundaries of these clusters.

In order to investigate the invariance of the four clusters solution, we crosstabulated clusters' membership for all pairs of methods. The results of this analysis appear in table 4.1. to 4.6. respectively. A summary table of this comparative analysis is given in table 4.7.

FIGURE 4.10 : COMPLETE LINKAGE CLUSTER ANALYSIS FOR REDUCED SAMPLE (108 COMPANIES).

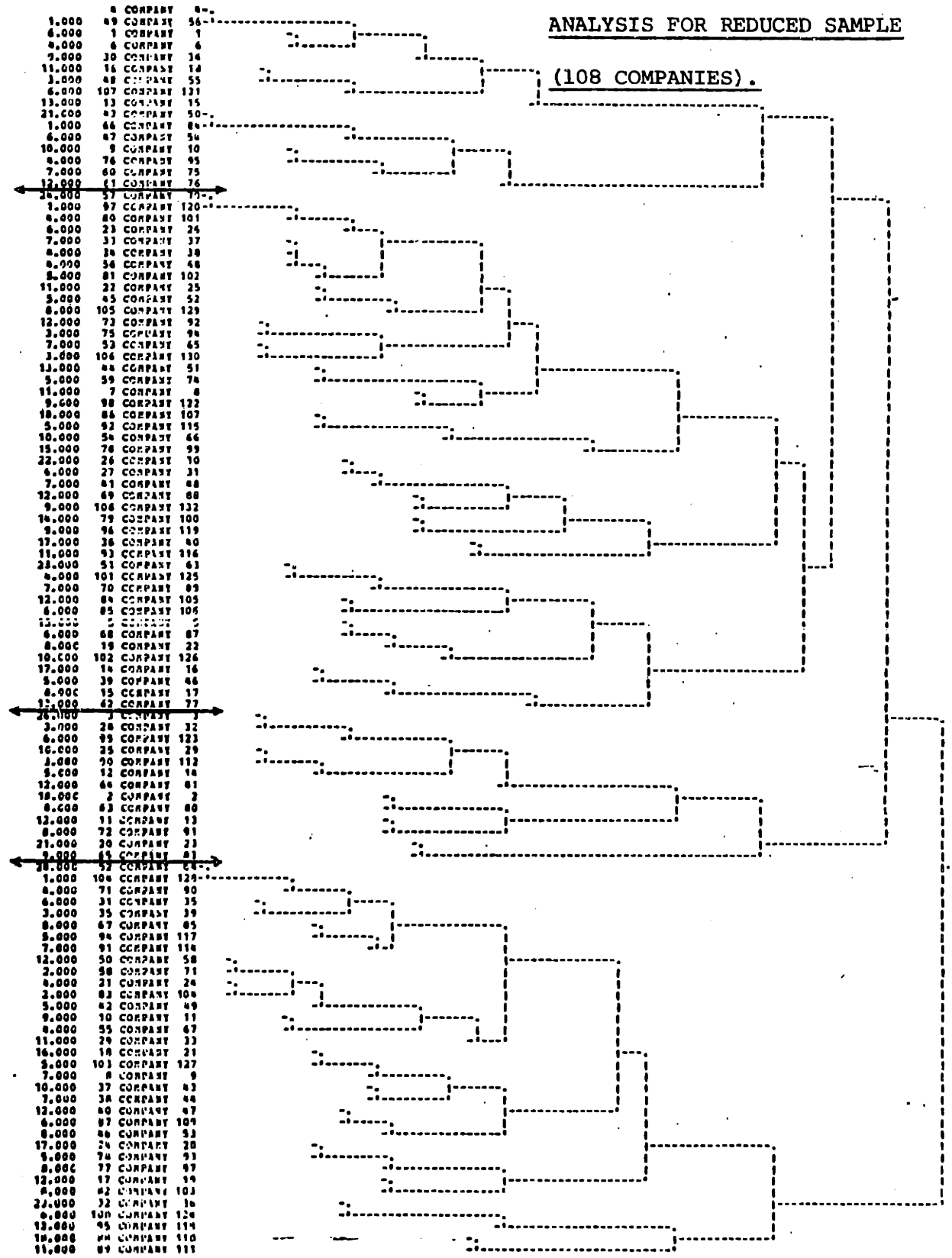


FIGURE 4.11 ; AVERAGE LINKAGE CLUSTER

ANALYSIS FOR REDUCED SAMPLE

(108 COMPANIES).

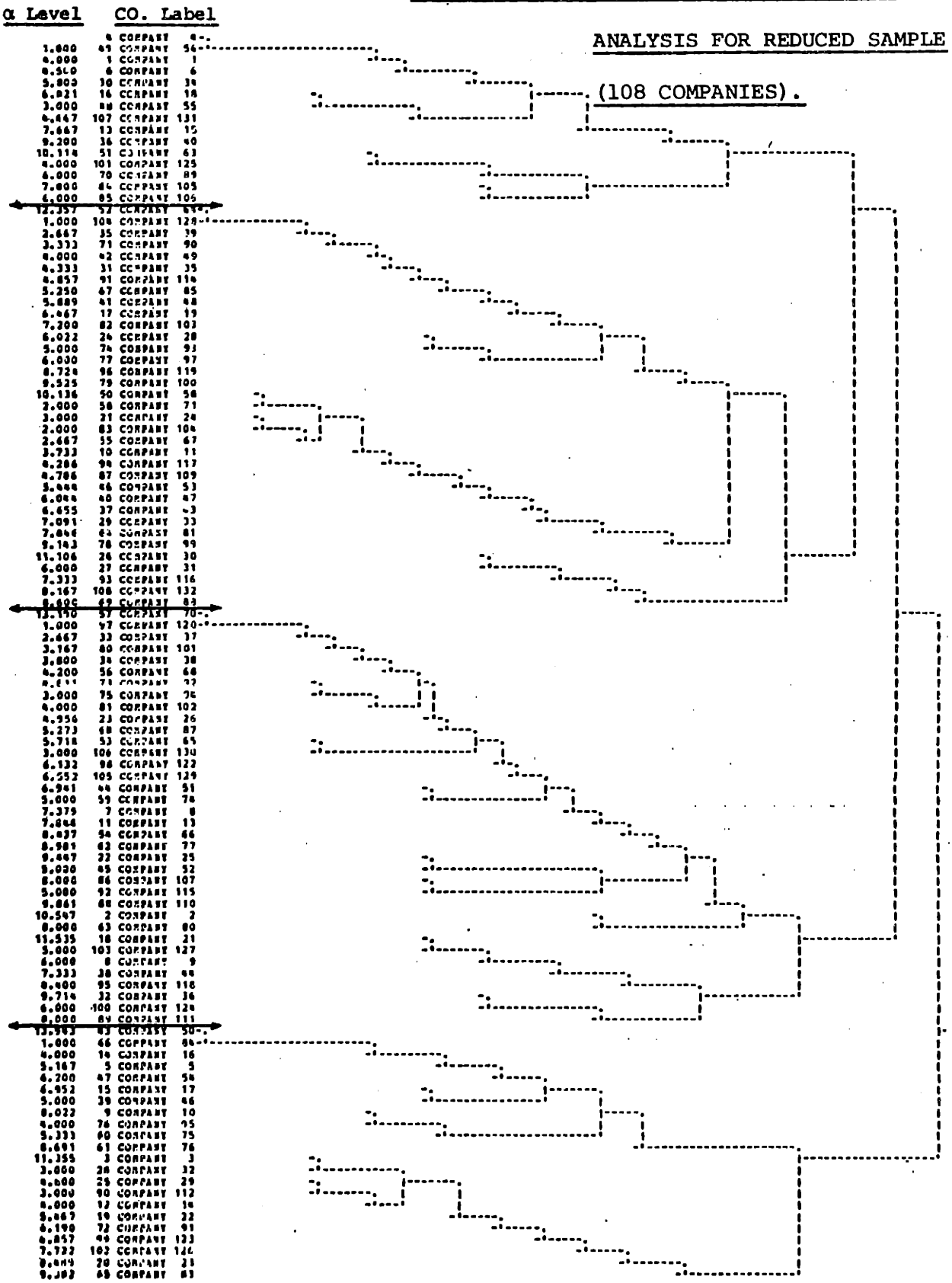
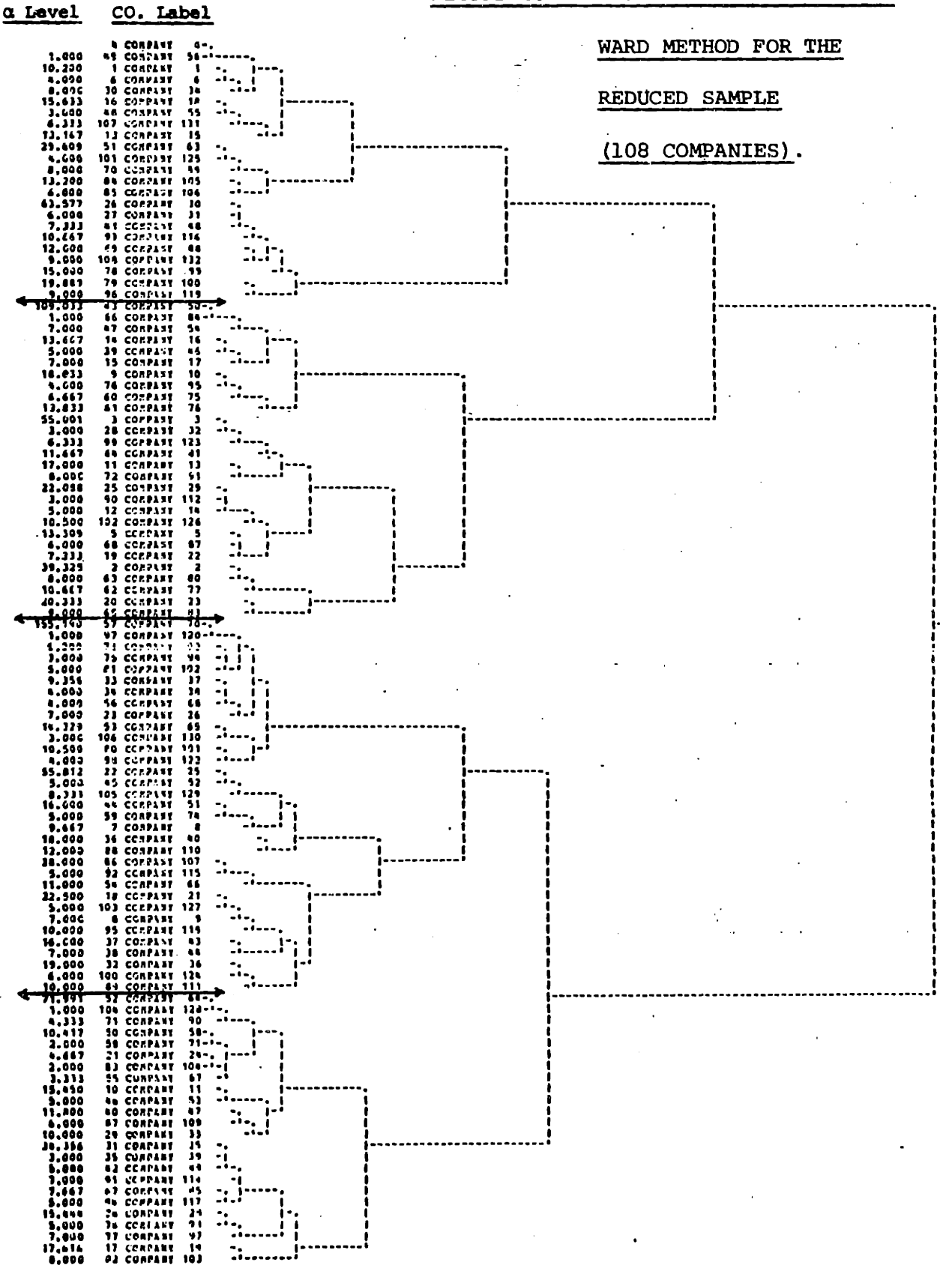


FIGURE 4.12: CLUSTER ANALYSIS BY THE WARD METHOD FOR THE REDUCED SAMPLE (108 COMPANIES).



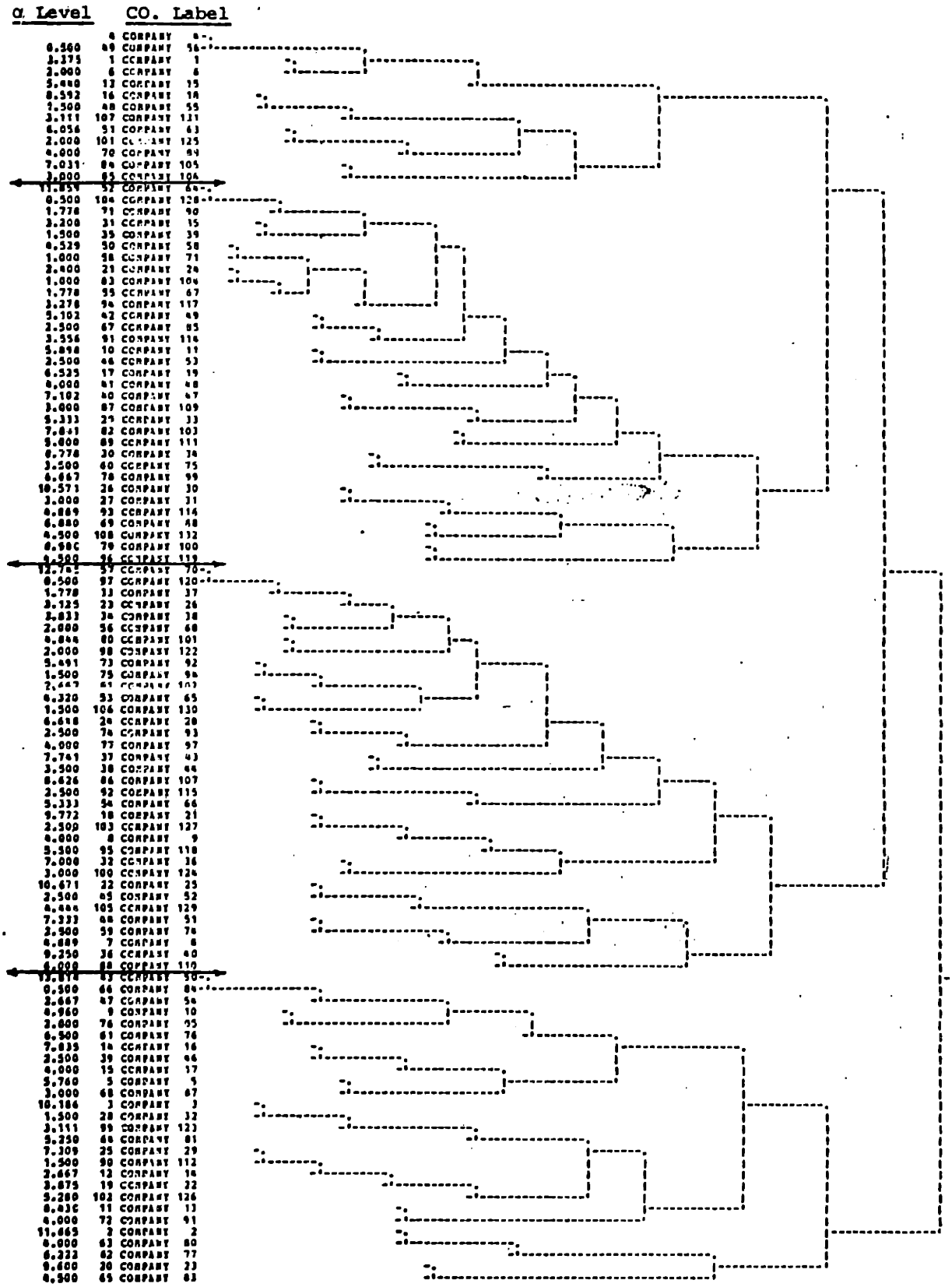


FIGURE 4.13. : MINIMUM WITHIN CLUSTER VARIANCE ANALYSIS FOR THE REDUCED SAMPLE (108 COMPANIES).

TABLE 4.1.: CONFUSION MATRIX BETWEEN COMPLETE LINKAGE RESULTS AND AVERAGE LINKAGE RESULTS.

Average Linkage Clustering Method

		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Complete	Cluster 1	9	0	0	7
Linkage	Cluster 4	0	25	9	0
Clustering	Cluster 2	6	9	24	6
Method	Cluster 3	0	1	3	9

TABLE 4.2.: CONFUSION MATRIX BETWEEN COMPLETE LINKAGE RESULTS AND WITHIN CLUSTER VARIANCE RESULTS

Within Cluster Variances Clustering Method

		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Complete	Cluster 1	8	2	0	6
Linkage	Cluster 4	0	22	12	0
Clustering	Cluster 2	5	9	23	8
method	Cluster 3	0	0	0	13

TABLE 4.3. : CONFUSION MATRIX BETWEEN COMPLETE LINKAGE RESULTS AND TOTAL WITHIN CLUSTERS SUM OF SQUARES RESULTS

		Total Within Clusters Sum of Squares Clustering Method			
		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Complete	Cluster 1	9	7	0	0
Linkage	Cluster 3	0	13	0	0
Clustering	Cluster 2	14	8	23	0
Method	Cluster 4	0	0	10	24

TABLE 4.4.: CONFUSION MATRIX FOR AVERAGE LINKAGE RESULTS AND WITHIN CLUSTER VARIANCE RESULTS

Within Cluster Variance Clustering Method

		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Average	Cluster 1	13	1	1	0
Linkage	Cluster 2	0	30	4	1
Clustering	Cluster 3	0	1	30	5
Method	Cluster 4	0	1	0	21

TABLE 4.5. : CONFUSION MATRIX BETWEEN THE AVERAGE LINKAGE RESULTS AND THE TOTAL WITHIN CLUSTERS SUM OF SQUARES RESULTS

Total Within Clusters Sum of Squares

Clustering Method

		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Average	Cluster 1	14	0	1	0
Linkage	Cluster 4	0	22	0	0
Clustering	Cluster 3	0	5	31	0
Method	Cluster 2	9	1	1	24

TABLE 4.6.: CONFUSION MATRIX BETWEEN WITHIN CLUSTER VARIANCE RESULTS AND TOTAL WITHIN CLUSTERS SUM OF SQUARES RESULTS

		Total Within Clusters Sum of Squares Clustering Method			
		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Within Cluster Variances Clustering Method	Cluster 1	13	0	0	0
	Cluster 4	0	27	0	0
	Cluster 3	0	0	32	3
	Cluster 2	10	1	1	21

TABLE 4.7. : COMPARATIVE ANALYSIS OF THE DEGREE OF CONVERGENCE BETWEEN THE FOUR CLUSTERING METHODS

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

Upper Number : Percentage of Consistent Classification

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

As indicated in table 4.7. there exists substantial agreement across clustering methods in the composition of the four cluster solution. All χ^2 coefficients are significant at the level $\alpha<.001$, thereby leading to the rejection of the hypothesis of independence between clustering solutions. An investigation of the percentage of consistent classification, however, reveals that both the average linkage method and the Ward method perform substantially better than complete linkage analysis in recovering the clusters identified by the minimum variance method. A potential reason for the poorer performance of complete linkage analysis to identify clusters of organizations that are maximally homogeneous in their adoption process might be its "space-diluting characteristic discussed earlier (See section 4.3.3.4.).

Therefore, a high degree of consistency exists between the four cluster solution obtained by average linkage analysis, by the Ward method and by the minimum within cluster variance method. In view of the fact that this latter method most accurately transposes the microsegmentation objective to maximize within clusters' homogeneity, we retain the solution obtained with the minimum within cluster variance method as the basis for the analysis of microsegments' characteristics.

4.4.5. Analysis of Microsegment Characteristics

An important aspect of the microsegmentation of the potential market for an industrial product is the analysis of the characteristics of the segments identified and their use for marketing decision-making. This represents also an indirect way to validate the results of the microsegmentation methodology proposed here. Indeed, given the objective of the methodology to identify groups of organizations homogeneous in the structure of their adoption process, the microsegments retained should be tested against the purpose for which they were generated.

In this section we investigate systematically the characteristics of the four microsegments identified. Two questions must be answered :

- how do these microsegments differ in terms of the overall pattern of involvement in the adoption process for the companies that comprise each of them ?

- how does membership in a particular microsegment relate to other characteristics of organizations traditionnally used for industrial market segmentation ?

Each of these questions is investigated in the next sections for the case of the new industrial cooling system powered by solar energy.

4.4.5.1. Structure of the Adoption Process within Each Microsegment

Three different types of analysis are performed to investigate differences in the general structure of the adoption process across the four segments. First, we investigate the number of decision phases in which each category of decision participant is involved. This will allow us to identify categories of individuals that are consistently involved throughout the various phases of the decision process within each microsegment. Second, we analyze the number of participant categories involved in each phase of the adoption process. This analysis addresses the question of "heterogeneity" of the interaction process involved in each phase of the decision process. Finally, we investigate the overall structure of the adoption process within each microsegment in terms of the frequency of involvement of each category of participants in each phase of the decision process.

Table 4.8. summarizes the results of the univariate analyses of variance performed across microsegments on the number of decision phases in which each category of participants is involved. Important differences are registered among the four microsegments, most of them being statistically significant at the level $\alpha<.01$.

In microsegment C1, plant managers (PMGR) and top manager (TMGT) are involved in most decision phases, while production engineers (PENG) and other categories of participants tend to be involved in

TABLE 4. 8. : AVERAGE NUMBER OF DECISION PHASES IN WHICH EACH CATEGORY OF PARTICIPANTS IS INVOLVED

	Segment C1	Segment C2	Segment C3	Segment C4	F-Ratio (3;104)
PENG	1.91	1.54	4.39	4.67	40.82***
PMGR	4.39	.57	1.57	2.83	49.29***
FCON	1.13	.50	.69	.50	3.30**
PROC	1.43	.71	1.79	.79	4.36***
TMGT	2.91	3.68	1.45	1.29	26.61***
HVAC	1.48	2.89	3.30	.62	18.29***
ARCH	1.35	2.25	1.64	.70	3.79**
ACEQ	.35	.68	.36	.29	1.31

*** Significant at the Level $\alpha \leq .01$

** Significant at the Level $\alpha \leq .05$

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

a substantially smaller number of phases. In microsegment C2, the adoption of industrial cooling alternatives requires the almost continuous involvement of TMGT. Interestingly, in segment C2 decision participants outside the organization, including mainly H.V.A.C. consultants (HVAC) and Architects (ARCH) tend to be involved in several phases. In segment C3, production engineers (PENG) are involved in practically all phases of the decision process. HVAC consultants are also deeply involved suggesting that companies in segment C3 rely heavily on engineers for the adoption of such products. Finally, in segment C4, people at the plant level, including PENG and PMGR tend to exert influence on the largest number of decision phases.

Thus, substantial differences exist across microsegments in terms of the number of decision phases in which each category of participant is involved. This, however, should not be confused with the actual impact of these categories of participant on the final decision. Indeed, some participants who are involved in only one or a small number of decision phases may in fact place constraints on the decisions taken by others in subsequent stages.

As pointed out earlier, the question of the relative influence of the various categories of participants involved in the decision process is beyond the scope of this study. However, it is intuitively

appealing to consider that those categories of participants that are involved in most decision phases have also the most chance to influence the final decision and therefore deserve special consideration in the design of industrial marketing programs.

Table 4.9. gives the results of the univariate analyses of variance performed across microsegments on the number of categories of participants that are involved in each phase of the decision process. This number provides a rough estimate of the heterogeneity of the interaction process within each phase of the adoption decision. Here too, important differences are registered across microsegments.

An interesting pattern emerges from table 4.9. First, for most decision phases, the number of categories of participants involved is consistently larger in segments C1 and C3 than in segments C2 and C4. Second, it appears that the number of categories of participants involved in the adoption process does not typically reduce as this process moves closer to its final phase -- a contention often made in the industrial marketing literature -- but rather that substantial differences exist in this respect across microsegments. Phase I, the identification of industrial cooling needs, however, does almost consistently involve the largest number of decision participant categories.

TABLE 4.9. : AVERAGE NUMBER OF CATEGORIES OF PARTICIPANTS INVOLVED IN EACH PHASE OF THE ADOPTION PROCESS

	Segment C1	Segment C2	Segment C3	Segment C4	F-Ratio (3;104)
Phase 1	3.56	3.04	3.42	2.75	1.65
Phase 2	2.52	2.11	3.45	2.71	6.85***
Phase 3	2.69	2.46	2.69	2.08	1.71
Phase 4	3.04	2.75	2.91	2.12	2.73*
Phase 5	3.13	2.46	2.72	2.04	4.03***

*** Significant at the Level $\alpha \leq .01$

* Significant at the Level $\alpha \leq .10$

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

Hence, substantial differences exist across the four microsegments in the number of individuals involved in each phase of the adoption process for an industrial cooling system. As we discuss in the last chapter, intelligent use can be made of such differences in the development of more meaningful industrial marketing strategies.

Finally, a careful analysis of the frequency of involvement of each category of participants in each phase of the decision process has been performed and is reported in table 4.10. As we are dealing with proportions, the assumptions of the ANOVA model are violated. In order to examine if the individual frequencies of involvement vary across microsegments, we thus perform a variance test for homogeneity of the binomial distribution (Snedecor and Cochran [118]).

Substantial differences across the four microsegments are readily apparent from the statistical significance of the individual χ^2 tests. The only cases in which non significant differences are registered concern those categories of decision participants that are seldom involved in a particular decision phase, for instance, purchasing officers in the evaluation of industrial cooling needs.

It is interesting to note that, for all microsegments, there exists an important variation across decision phases in the pattern of individual involvement. This provides additional evidence of the discriminating power of the measurements obtained with the decision matrix.

TABLE 4.10.: OVERALL STRUCTURE OF THE ADOPTION PROCESS IN EACH MICROSEGMENT

(Frequencies of Involvement)

		Segment C1 $n_1 = 13$	Segment C2 $n_2 = 33$	Segment C3 $n_3 = 35$	Segment C4 $n_4 = 27$	Total N =108	$\chi^2(3)$
	PENG	.23	.94	.91	.41	.71	42.29***
	PMGR	.92	.76	.49	.11	.53	34.20***
	PCON	.00	.18	.06	.07	.09	5.08
Phase 1	PROC	.00	.15	.11	.04	.09	3.87
Need	TMGT	.46	.42	.26	.74	.45	14.54***
Evaluation	HVAC	.38	.24	.91	.74	.60	36.78***
	ARCH	.38	.36	.51	.67	.49	6.14
	ACEQ	.08	.30	.20	.26	.23	3.00
	PENG	.00	.55	.74	.07	.43	39.62***
	PMGR	.38	.79	.66	.22	.56	22.36***
	PCON	.46	.58	.54	.30	.48	5.43
Phase 2	PROC	.08	.06	.11	.04	.07	1.45
Preliminary	TMGT	1.00	.88	.91	.96	.93	2.71
Approval	HVAC	.00	.00	.26	.19	.13	12.63***
	ARCH	.08	.03	.11	.26	.12	7.69*
	ACEQ	.00	.00	.03	.07	.03	3.45
	PENG	.08	.54	.80	.33	.64	45.56***
	PMGR	1.00	.42	.17	.00	.31	46.57***
	PCON	.00	.00	.03	.04	.02	1.57
Phase 3	PROC	.46	.55	.46	.37	.46	1.84
Search for	TMGT	.08	.15	.03	.44	.18	19.68***
Alternatives	HVAC	.46	.09	.74	.67	.49	33.40***
	ARCH	.31	.15	.40	.48	.31	8.32**
	ACEQ	.00	.06	.06	.15	.07	3.43
	PENG	.15	1.00	1.00	.41	.75	64.21***
	PMGR	.92	.61	.20	.15	.40	33.69***
	PCON	.08	.06	.00	.00	.03	4.24
Phase 4	PROC	.23	.27	.40	.19	.29	3.78
Equipment	TMGT	.23	.33	.06	.63	.31	24.00***
Evaluation	HVAC	.38	.18	.86	.74	.56	36.97***
	ARCH	.15	.18	.37	.52	.32	9.78**
	ACEQ	.00	.03	.06	.15	.06	4.67
	PENG	.00	.94	.97	.22	.66	74.62***
	PMGR	1.00	.70	.20	.04	.41	51.95***
	PCON	.00	.18	.03	.04	.07	8.21**
Phase 5	PROC	.15	.33	.46	.00	.30	10.26**
Equipment	TMGT	.23	.45	.20	.85	.44	29.04***
Selection	HVAC	.38	.06	.60	.67	.43	28.84***
	ARCH	.38	.09	.26	.41	.26	9.02**
	ACEQ	.00	.03	.00	.07	.03	3.52

*** Significant at the Level $\alpha < .01$
** Significant at the Level $\alpha < .05$
* Significant at the Level $\alpha < .10$

The information available in table 4.10. can be used to give a precise characterization of the adoption process within each microsegment. In microsegment C1, PMRG appears to play a particularly important role throughout the decision process. In addition, TMGT is involved in the early phases of the decision when the need for industrial cooling is assessed and a preliminary budget is approved. In later phases, the role played by categories of participants outside the organization -- mainly HVAC and ARCH -- keeps increasing.

The pattern of involvement in segment C2 is substantially different. Typically, PENG and PMGR appear to play the major role, except in phase 2 where the influence of TMGT is greatest. In segment C3, engineers -- including PENG and HVAC -- are potentially most influencial. Only in phase 2 does TMGT play a substantial role. Finally, in segment C4, TMGT and HVAC are consistently most influent. Only in phase 2 is some influence exerted by financial people (FCON).

The microsegmentation methodology proposed here therefore lead to the identification of a number of meaningful microsegments. Important differences exist across these microsegments in terms of the pattern of individual involvement in the adoption process. These differences, as we discuss in the next chapter, provide new insights into the industrial adoption process, as well as an

important input to the development of more meaningful industrial marketing strategies.

4.4.5.2. Analysis of the external characteristics of the companies comprised in each microsegment

The microsegmentation results reported thus far have important implications for the development of better industrial marketing strategies independent of our ability to characterize the organizations within each microsegment on the basis of external variables. Identification of such external characteristics, however, would be another step toward the development of better theories of industrial classification that could have significant impact for industrial marketing strategy.

Traditionnally, segmentation bases in industrial markets have included (Wind and Cardozo [146]) :

- the size of firms,
- their geographic location,
- the type of industry, and
- the relative importance of the product in the firms' productive activities.

Table 4.11. presents the general characterisitics of the four microsegments retained in terms of these variables. No strong

TABLE 4.11. GENERAL CHARACTERISTICS OF THE ORGANIZATIONS COMPRISED IN EACH MICROSEGMENT

	Segment C1	Segment C2	Segment C3	Segment C4
Company Sales* ($ millions)	100	200	130	40
Production Area* In Southern States	<30%	<15%	<15%	<50%
Main Activity**	Food Processing	Electronics	Electronics	Electronics
Percentage of Plant* Area Requiring Air Cooling	<50%	<30%	<30%	<30%

* median of the empirical distribution

** mode of the empirical distribution

relationship was found between microsegment membership and any of these traditional bases for industrial market segmentation. In the case of company size, however, the univariate analysis of variance led to an F-ratio of 2.16 with 3 and 93 degrees of freedom respectively. This value is significant at the level α=.10.

In order to formally assess the relationship between microsegment membership and these variables as well as some other characteristics of industrial organizations, 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 : Organizational consequences if a newly adopted cooling system proved less economical than projected
- X_6 : Organizational consequences if a newly adopted cooling system proved less reliable than projected

Two discriminant functions were retained in this analysis using Wilks criterion (See Nie et al [94]). We have reproduced in table 4.12 the standardized discriminant coefficients for each of these functions.

TABLE 4.12.: STANDARDIZED DISCRIMINANT FUNCTION COEFFICIENTS

	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

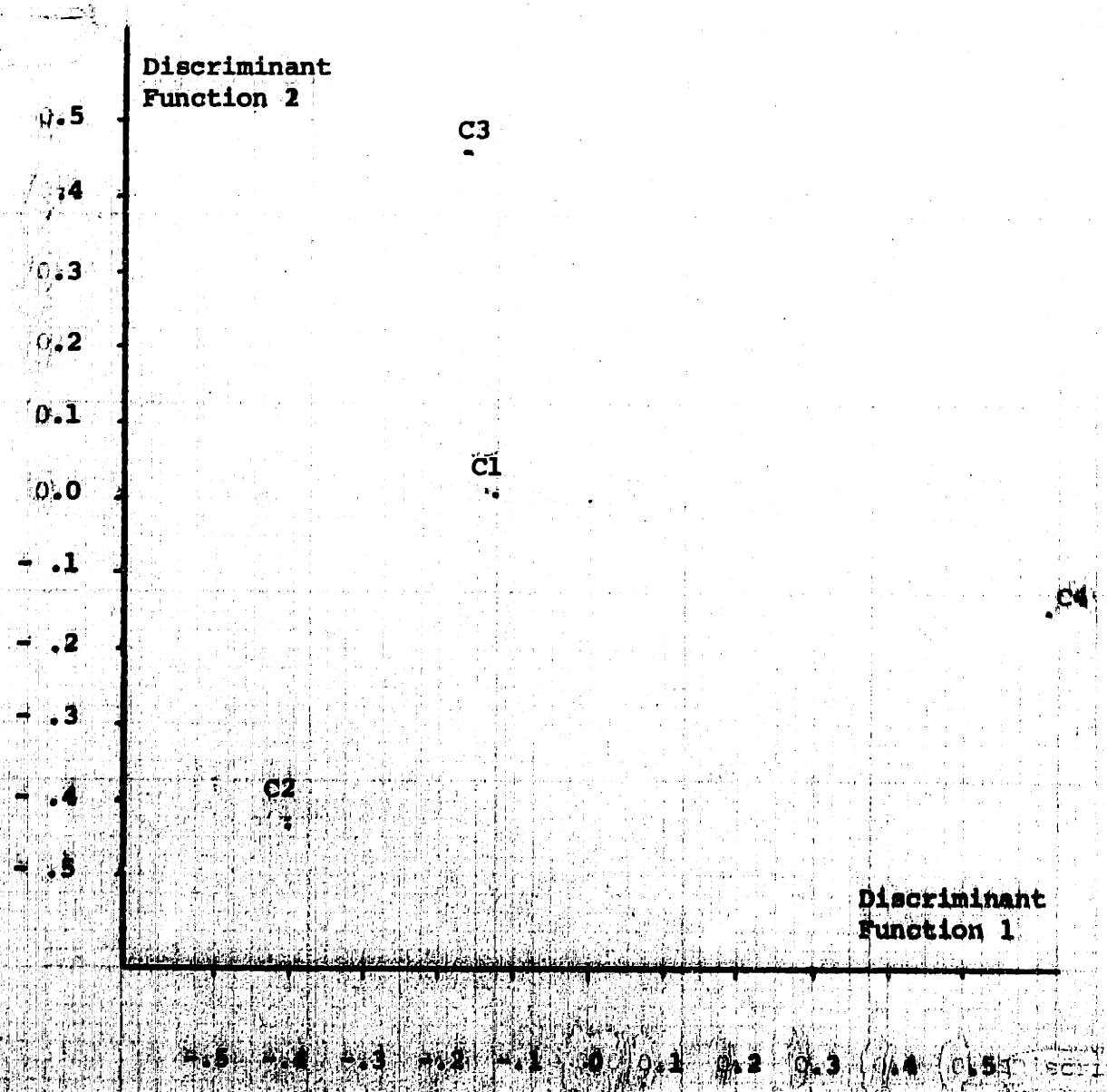
No statistical inference can be made concerning these functions, however, as the assumptions of multinormality of the predictor variables and of equality of within group covariance structures are not satisfied by our data.

From a predictive standpoint, our analysis led to 47% correct classification. This percentage is considerably 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 [91]). Future studies, involving larger samples should address the issue of statistical significance of the discriminant functions and allow more accurate predictive tests.

Although our results are mainly exploratory, they point to some interesting relationships between microsegment membership and company characteristics. To illustrate these points, we have reproduced in figure 4.14. the microsegments centroids in the reduced discriminant space.

Companies in segment C4 tend to be smaller, more satisfied with their current cooling system and more concerned with the economics aspects of industrial cooling. In terms of their adoption

FIGURE 4.14.: MICROSEGMENTS' CENTROIDS IN REDUCED DISCRIMINANT SPACE



process, these companies are characterized by a more frequent involvement of managerial functions (PMRG and TMGT). Moreover, they rely more heavily on external sources of expertise such as HVAC and ARCH to assist them in the assessment of cooling needs, the search for alternatives and the selection of a particular equipment. On the contrary, larger companies represented in segment C2 and C3 make use of their own engineering capabilities for these same tasks.

The comparison between segment C1 and C3 is most interesting because these two segments do not substantially differ in terms of size of companies. However, the discriminant analysis results suggest that companies in C3 tend to have more plants, larger cooling needs and are more concerned with the reliability of industrial cooling systems than companies in C1. It is therefore not surprising to note that companies in C3 rely mainly on engineering functions (PENG and HVAC) in the process of adopting a new industrial cooling system. On the contrary, companies in segment C1 involve mainly managerial functions (PMGR and TMGR) in most phases of their adoption process.

The case of companies in cluster C2 is also interesting. Typically, this segment groups large companies with a small number of plants. Moreover, these companies view little risk in the adoption of a

new industrial cooling system. As a result, they let these decisions be taken more at the plant level, involving mainly PMGR and PENG.

In sum, the microsegmentation methodology has led to the identification of groups of organizations that exhibit substantial homogeneity in their adoption process. The analysis of the external characteristics of these industrial companies suggest new relationships between a firm's adoption process and its size, its needs for industrial cooling, its satisfaction with past purchase and the risks associated with the adoption of such products. Larger samples, however, are needed to both validate and extent these results

From the standpoint of developing better marketing programs for industrial products, these results are most powerful when considered along with the important differences in product perceptions and evaluation criteria among categories of decision participant noted in Chapter 3. When considered jointly, these results have implication for both the design and the targeting of industrial communication programs.

In the case of the new industrial cooling system powered by solar energy, for instance, an efficient communication program addressed at smaller, more cost-conscious companies should be directed mainly at TMGR and HVAC. The program should concentrate on these issues that are most relevant for each of these two categories of decision participant . From our results in Chapter 3, communication

to TMGR should emphasize the added protection against power failures and energy shortages offered by the new solar system, its efficient use of currently unproductive areas, its moderness and low operating cost. Communication to HVAC, as pointed in Choffray and Lilien [11], should emphasize the trade-offs between the new system's first cost and its lower operating expenses, its high reliability and its contribution to lowering the noise level. Similar implications can be drawn for the other microsegments.

4.5. Summary

In this chapter methodology was proposed to identify segments of organizations homogeneous in the structure of their adoption process. The methodology relies on the information collected with the decision matrix from companies in the potential market for an industrial product.

The methodology involves the definition of an appropriate index of inter-organizational similarity in the structure of the adoption process. It uses cluster analytic methods to identify segments of organizations homogeneous in that respect. Several problems associated with the use of cluster analysis are identified. They include a) the impact of extreme observations on cluster analytic results, b) the non-randomness of a dissimilarity structure c) the determination of the number of clusters in a hierarchical classification and d) the invariance of the clustering solution retained. Methods are proposed to deal with each of these problems.

Implementation of the methodology for a new industrial cooling system powered by solar energy leads to the identification of four segments of organizations substantially homogeneous in their adoption process. Important differences, however, exists between these segments in terms of :

- the number of decision phases in which each category of decision participants is involved,

- the number of categories of participants involved in each phase of the decision process, and

- the frequency of involvement of each category of participant in each phase of the decision process.

Analysis of the relationship between microsegment membership and external characteristics of organizations points at the inadequacy of traditional bases of industrial market segmentation to describe the new segments. But the results suggest interesting relationships between the structure of the adoption process and more generic characteristics of industrial organizations that comprise, company size, urgency of the need for the new product, satisfaction with past purchase and the nature of the risks associated with such purchases. These results are exploratory. They should be validated and extended in future research. Significant contributions to the theory of organizational buying behavior can be expected from future analyses of the characteristics of organizations that are similar in their adoption process.

CHAPTER 5: UNDERSTANDING THE INDUSTRIAL ADOPTION PROCESS: THIS RESEARCH IN PERSPECTIVE.

The objective of this dissertation was to develop methodology for the measurement of differences in product perceptions and evaluation criteria across several groups of influencers in industrial adoption situations, and to propose new measurement tools as well as analytical methods to systematically investigate involvement in the industrial adoption process.

In this last chapter, we review this research, discuss its implications for industrial marketing management and suggest areas of high potential for future work.

5.1. Summary and Conclusions

Chapter 1 introduced our research and reviewed other research on the adoption of new industrial products and technologies. The importance of new products in industrial markets was stressed as well as the risks associated with their introduction. A review of the literature was performed, suggesting that a better understanding of the industrial adoption process, paralleled by the development of new market research methodologies accounting for the nature of this behavior,

could substantially reduce new industrial product failure rate. A conceptual framework to assess response to industrial innovations was proposed pointing to the need for research on the two questions investigated in the dissertation.

In Chapter 2, we provided an overview of the empirical research performed in the dissertation. First, we reviewed the potential of solar energy in the United States and discussed the prospects for solar cooling of industrial buildings. We then discussed issues associated with the measurement of decision participants perceptions of available industrial cooling systems and with the measurement of their evaluation criteria. Problems related to the assessment of the structure of the adoption process for such systems were also discussed. New measurement procedures were proposed. They involve the use of a decision matrix which is administered to a sample of target industrial firms in the context of a two-stage sampling process. Results of the validation analysis indicate that the measurement obtained by this method show substantial convergent validity.

In Chapter 3, a methodology was proposed to investigate the nature of perceptual differences, as well as differences in evaluation criteria between several categories of decision participants involved in the purchase of an industrial product. The methodology builds upon some of the latest approaches used in marketing research.

It logically links several methods of multivariate data analysis and provides more objective criteria to investigate the process of perception and evaluation of industrial product alternatives.

Implementation of the methodology for the new industrial solar cooling system, led to the identification of definite perceptual differences among the four groups of decision participants investigated. Substantial differences were also noted between these groups in the way they structure the basic attributes of industrial cooling systems into higher-order evaluation criteria. Consideration of these differences leads to a better understanding of how individual participants form preferences for industrial product alternatives. The results of our empirical study thus support important assumptions made in most recent models of organizational buying behavior concerning the existence of different product perceptions and evaluation criteria among members of the buying center (Sheth [115], Webster and Wind [136]).

In Chapter 4, methods were presented to identify segments of industrial organizations -- within the potential market for a new industrial product -- homogeneous in the structure of their adoption process. The methodology uses as input the information collected with the decision matrix on the pattern of involvement

in the adoption process for each company in the sample. An index of interorganizational dissimilarity is defined and provides information to group industrial organizations on the basis of the structure of their adoption process. Several problems associated with the use of cluster analysis methods are identified and solutions proposed.

Implementation of this new method of market segmentation for the industrial solar cooling system led to the identification of four segments of organizations. Important differences in the structure of the adoption process were registered across these segments which were not readily observable from an analysis of the total sample. The investigation of the relationships between microsegment membership and external characteristics of organizations showed the inadequacy of traditional bases of industrial market segmentation to describe the new segments. Interesting relationships were found between the structure of the adoption process and more generic characteristics of industrial organizations 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.

5.2. Uses for the Methodology

5.2.1. Implications for Industrial Marketing Strategy

The two specific results of the empirical analysis performed in this dissertation are that:

- there are substantial differences between categories of decision participants in the way they perceive and evaluate industrial product alternatives, and that

- companies in the potential market for an industrial product can be characterized in terms of the structure of their adoption process.

The microsegmentation methodology provides information about what categories of decision participants in potential customer organizations are most likely to be involved in the adoption of an industrial product. By isolating homogeneous microsegments of organizations, the methodlogy provides a more accurate description of the adoption process for the new product than is possible from an analysis of the aggregate frequencies of involvement of the various categories of decision participants in the total sample. This information allows industrial marketers to develop differentiated communication strategies that aim more directly at those categories of individuals most influential in the various microsegments.

The microsegmentation methodology proposed here can be used when the potential market for an industrial product contains only a small number of customers. Then, the decision matrix might be administered to each customer individually and provide the information necessary for the development of a meaningful account strategy. For instance, this information could be used to develop salesman call strategies or to send promotional material that addresses the specific needs of the various categories of individuals involved in the adoption process.

In the case of larger industrial markets, the decision matrix might be administered to a representative sample of industrial organizations. Implementation of the microsegmentation methodology would then provide information about the relative size of the various microsegments along with an accurate description of the overall structure of the adoption process within each of them. This information could be used to:

- eliminate from a communication program categories of individuals that are involved in the adoption process less often than management expected on an a priori basis. This might be the case, for instance, for financial people and members of the purchasing department in the adoption of the new industrial solar cooling system,

- concentrate communication efforts on those categories of individuals that are most often involved in the adoption process in the largest microsegments. In the case of the new solar cooling system, this might lead to a concentration of communication expenditures on Production Engineers and HVAC consultants that are most influential in microsegment C3.

- predict the structure of the adoption process for a specific firm on the basis of its external characteristics. This presupposes a meaningful relationship between microsegment membership and external characteristics of industrial organizations. Promotional material or salesmen calls could then be directed at these categories of individuals most influential in the microsegment predicted. For the new industrial solar cooling system, for instance, before calling upon a given company, the general structure of its adoption process could be predicted on the basis of its external characteristics. Although the accuracy of predictive classifications in this specific study was not perfect, such classifications still provide important additional information about a firm's adoption process.

Results of the microsegmentation analysis, however, have implications beyond the definition of a target audience for industrial communication programs. As the various categories of individuals involved

in the adoption process may be expected to differ in their specific sources of information and communication consumption, results of the microsegmentation analysis may be of considerable help in the selection of communication vehicles. In terms of the solar cooling study, for example, it was found that in microsegment C3, plant engineers and HVAC consultants were most influential. As a result of their common educational background, a substantial overlap may be expected in the sources of information and communication consumption characteristics of these two categories of decision participants, suggesting the use of the same communication channels for both of them. In segment C2, Production Engineers and Plant Managers were found most influential. As these two categories of participants may be expected to differ substantially in their sources of information, a communication strategy involving the simultaneous use of several vehicles might be justified.

The results of the microsegmentation methodology are most powerful when they are considered along with the differences in product perception and evaluation criteria across categories of decision participant noted in Chapter 3. Indeed, if the microsegmentation analysis forces recognition of different patterns of involvement in the adoption process for an industrial product, the perceptual analysis elicits specific needs for information within each of these microsegments. The perceptual methodology therefore provides input to the design of communication messages -- including advertising copy and sales

presentation -- that addresses the needs and requirements of each category of decision participants.

Analysis of the differences in product perceptions across categories of decision participants allows :

- the identification of those attributes of a new product which are not perceived by certain categories of decision participants as management wants, so that corrective action can be taken in a product re-design or re-positioning strategy.

- the development of a communication strategy which addresses the specific needs of each group of decision participants.

In the case of the solar cooling system, differences in product perceptions between the four categories of individuals investigated were summarized in table 3.13. These differences provide information about areas of potential resistance to the solar cooling concept within each category of decision participants, and might be used as a basis on which to develop a positioning strategy for the new product. It appears, for instance, that both Production Engineers and Plant Managers perceive SOLABS as less field proven, more vulnerable to weather damage, and more state-or-art than do the other categories of decision participants. It also appears that Managers including both PMGR and TMGR view the new system as offering more protection against power failures and fuel rationing,

less modern, more economical to use and more noisy than do Engineers (including both PENG and CENG).

Differences in evaluation criteria between categories of decision participants provide information about how individual preferences are affected by product characteristics. Typically, the analysis of the evaluation criteria of each category of participant allows:

- the identification of weaknesses in a new product's design by assessing its position relative to that of competitors on the relevant evaluation criteria of each category of decision participants.

- the development of salesmen's presentation strategies that address the specific requirements of each category of decision participant.

- the simulation of the impact of changes in the new product design or positioning on the preferences of each category of individuals.

For the new solar cooling system, substantial 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. Production Engineers, for instance, weight reliability and complexity of industrial cooling systems particularly heavily.

The issues of protection against power failure and of use of improductive areas are of significant importance to Plant Managers and Top Managers. Other substantial differences were also noted in Chapter 3.

Depending on who he is talking to, a salesman should adapt his sales presentation to the specific requirements of this individual. Knowledge of the evaluation criteria usually harbored by this category of participant might considerably help him in this task. Moreover, from the standpoint of predicting individual preferences for industrial product alternatives, the consideration of differential evaluation criteria allows trade-offs in the design and positioning of an industrial product according to the relative frequency with which various categories of decision participants are involved in its adoption.

5.2.2. Implications for the development of a Methodology to Assess Response to Industrial Marketing Strategy.

In addition to the implications of this work discussed above, an important result of our research is its contribution to the development of a methodology to assess response to industrial marketing strategy. Choffray and Lilien [21] have discussed the overall structure of such a methodology. In this section, we review that structure and show how the methods developed in this research contribute to operationalizing it.

Figure 5.1. presents the general structure of an industrial market response model which closely parallels the conceptual model discussed in Chapter 1. The industrial adoption process is formalized as a four element model. The first element, the Awareness model links the level of marketing support for the industrial product a_o under investigation -- measured in terms of spending rates for such activities as Personal Selling (PS), Technical Service (TS), and ADversiting (AD) -- to the probability that a decision participant belonging to category i, say production engineers, will evoke a_o as a potential solution to the organizational purchasing problem. Let

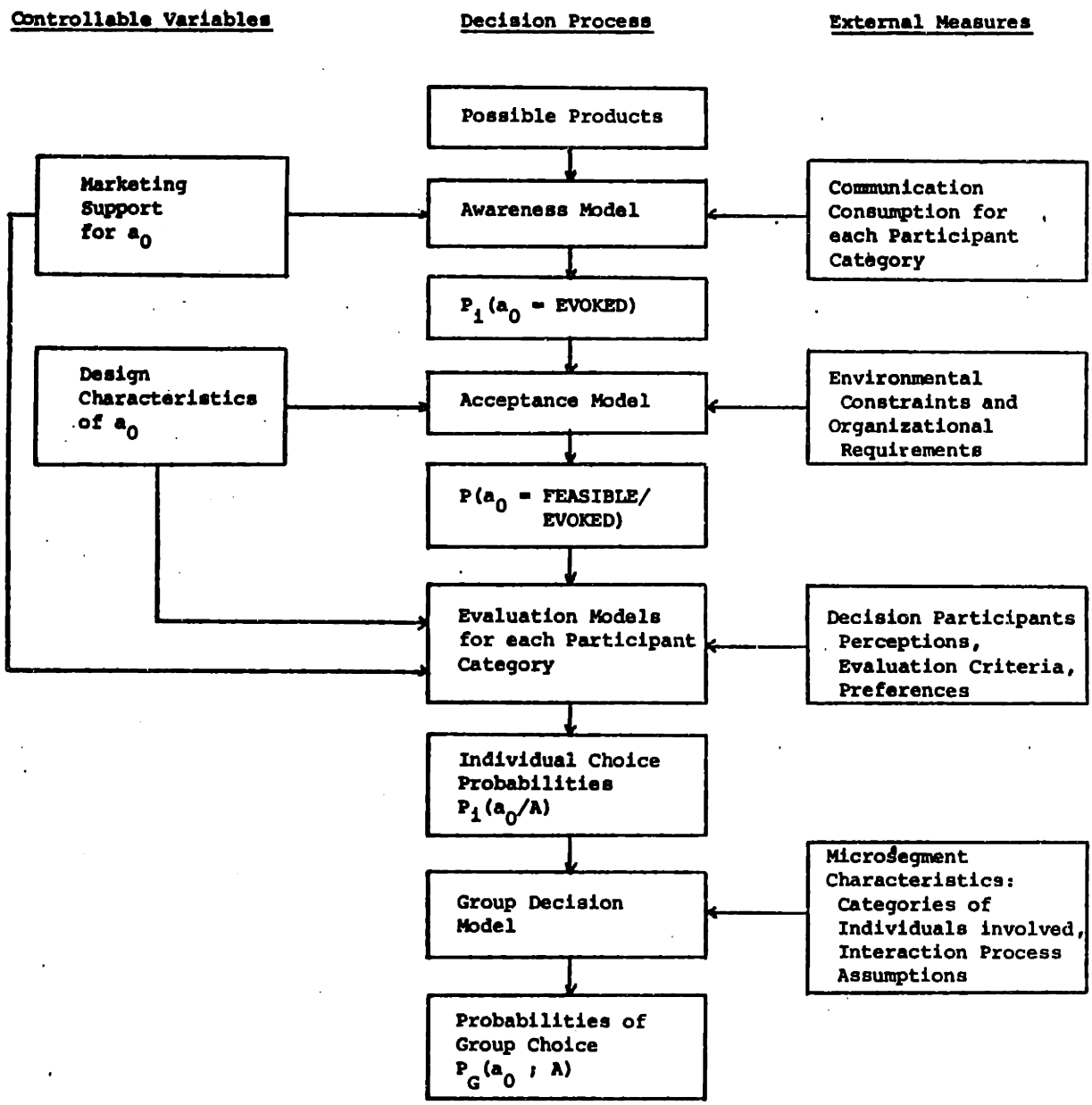
$$P_i \ (a_o = \text{EVOKED})$$

denote this probability. Hence, we assume that

$$P_i \ (a_o = \text{EVOKED}) = f_i \ (\text{PS, TS, AD}).$$

where the functional form of f_i (.) is empirically estimated or provided by the manager in charge of product a_o on the basis of his personal experience with this market. It is reasonnable to consider that the functions f_i(.) will exhibit substantial differences across categories of decision participants as a result of the different sources of information and communication consumption characteristics of these individuals.

FIGURE 5.1.: GENERAL STRUCTURE OF AN INDUSTRIAL MARKET RESPONSE MODEL



If several categories of participants are involved in the adoption decision in a specific microsegment S_q of the potential market, the probability that product a_o will be evoked as an alternative is given by

$$P_G\ (a_o = \text{EVOKED}) = 1 - \prod_i [1 - P_i\ (a_o = \text{EVOKED})]$$

where the index i covers all decision participant categories in microsegment S_q.

The second element of the response model is the Acceptance sub-model which relates the design characteristics $\underline{X}_o$ of product a_o to the probability that it will fall in the feasible set of alternatives -- A -- of any organization. This sub-model accounts for the process by which organizations in the potential market screen out "impossibles" by setting product selection requirements (e.g. limits on price, reliability, payback period, number of successful installations, etc...). Let this probability be denoted by

$$P_G\ (a_o = \text{FEASIBLE/EVOKED}) = g(\underline{X}_o)$$

The specification of g(.) usually requires a survey of companies in the potential market. For instance, in the case of an established industrial product for which design or positioning modifications are contemplated, the function g(.) might be specified from an

ex-post analysis of the requirements of companies that have purchased similar products. A Probit Model could then be used as an approximation for the lexicographic process by which organizations eliminate infeasible alternatives. In the case of a new industrial product the specification of g(.) is more complex as companies have never before purchased the product and so, have no established selection requirements. This situation asks for a survey of potential adopters in which information about their maximum requirements would be obtained. The empirical distribution of these extremes might then be used to assess the probability that an alternative with certain design characteristics is feasible for any organization in the potential market.

The third element, called Individual Evaluation models, relate individuals' evaluation of feasible products characteristics to preferences for each category of decision participants involved in the adoption process. These models are essential when managers want to perform a sensitivity analysis on industrial market response to changes in product design or positioning. They allow consideration of trade-offs in the design of industrial products as they explicitely recognize differences between categories of decision participants in their evaluation criteria. Let

$$P_i\ (a_o\ ;\ A/\text{FEASIBLE AND EVOKED}).$$

denote the probability of choice for a_o in participant category i.

It is assumed that:

$$P_i\ (a_o\ ;\ A/FEASIBLE,\ EVOKED) = h_i\ (\underline{E}_{oj})$$

where $\underline{E}_{oj}$ refers to individual j's evaluation of alternative a_o in decision participant category i. Considerable research has been done on models to relate choice probabilities to products' evaluations (See Hauser [51]). Any of these models can potentially be used to formalize the individual choice process within each category of decision participants.

The last element of the industrial market response model is the Group Decision model that maps individual choice probabilities into an estimate of the group probability of choice within each microsegment :

$$P_G\ (a_o\ ;\ A) = z\ \{P_i\ (a_o\ ;\ A/FEASIBLE,\ EVOKED),\ i=1,\ldots r\}$$

Choffray and Lilien [ ] propose four classes of descriptive probabilistic models of group decision that can be used at this stage. They distinguish a Weighted Probability Model, a Proportionality Model, a Unanimity Model and an Acceptability Model. These models encompass a wide range of possible patterns of interaction between decision participant categories and offer representation of this process for most industrial buying decisions.

Combining these sub-models, we get the expression for the unconditional probability of organizational choice

$$\Pr\ [a_o = \text{ORGANIZATIONAL CHOICE}] =$$

$$\Pr\ [a_o = \text{GROUP CHOICE/ INTERACTION, FEASIBLE, EVOKED}]$$

$$\times \Pr\ [a_o = \text{FEASIBLE/EVOKED}]$$

$$\times \Pr\ [a_o = \text{EVOKED}]$$

Suppose a new industrial product has been proposed and management wants to refine its design and develop an appropriate communication strategy. Several steps are involved in the implementation of the proposed structure.

Macrosegmentation

The first step, called Macrosegmentation following the terminology proposed by Wind and Cardozo [146], consists in specifying the target market for the new product. Bases for segmentation, at this level, might be as general as S.I.C. code, geographic location etc... The main purpose of this segmentation is to reduce the cost and effort involved in subsequent stages, and narrow the scope of the analysis to those organizations most likely to purchase the new product.

Measurement of Organizations' Selection Requirements

Step two is concerned with the measurement of organizational "established policies" and requirements to select products from the class investigated. This information is the main input to calibrate the acceptance sub-model. As discussed earlier, however, the measurement of organizational requirements for new industrial products raise interesting methodological issues that have remained largely unexplored.

Disaggregation of the Industrial Adoption Process

Step three, is concerned with an analysis of the structure of the purchasing decision process for the product investigated. Microsegments of organizations homogeneous in the categories of decision participants that are involved in their decision process are identified and their relative importance in the potential market is assessed. Let these microsegments be denoted by : $S_1 \ldots S_N$ and the percentage of companies in the potential market that fall in each of them by : $V_1 \ldots V_N$.

Within each microsegment, the general structure of the adoption process is described. Microsegment S_q, for example ,is characterized by the set of decision participant categories $DEC_q = \{D_i, i=1,\ldots r_q\}$ that are usually involved in the adoption process for the companies it comprises. For instance, in segment S_1,

Top Management along with Purchasing Officers might be the main categories of decision participants involved. In S_2, Production Engineers are also involved, etc. This information provides an essential input to calibrate the awareness sub-model and the group choice sub-model. Chapter 4 presented methodology to perform such an analysis.

Measurement of Product Perceptions, Evaluation Criteria and Preferences for each Category of Decision Participant.

For each category of decision participant, product evaluation criteria and individual perceptions and preferences are measured. Differences in evaluation criteria across categories of participants are formally investigated and incorporated in the calibration of models of individual choice. The main focus of Chapter 3 has been to develop methodology to investigate systematically differences in product perceptions and evaluation criteria across categories of participant involved in the purchase of an industrial product. This methodology should be of considerable help here.

Managerical Input

At this stage, the industrial marketing manager is asked to specify for each microsegment what models of multiperson interaction best reproduce his understanding of the purchasing decision process for the companies that belong to each microsegment.

In terms of the models proposed by Choffray and Lilien [21], his estimates might be for microsegment S_q:

Weighted Probability Model	: α_{1q}
Proportionality Model	: α_{2q}
Unanimity Model	: α_{3q}
Acceptability Model	: α_{4q}

with $\Sigma\alpha_{eq} = 1$ for each microsegment q. If managers consider that the companies within a particular microsegment -- in addition to being homogeneous in the structure of their adoption process -- exhibit considerable homogeneity in the nature of their interaction process, only one $\alpha_{eq} = 1$, and the others = 0.

This information can be used to assess response at the microsegment level. Let $M_q(a_o)$ denote the estimated share of microsegment S_q that finally adopt product a_o. Hence,

$$M_q(a_o) = \sum_e \alpha_{eq} \Pr[a_o; A/MOD_e, DEC_q]$$

where $\Pr[a_o; A/MOD_e, DEC_q]$ is the probability that a_o is the <u>organizational</u> choice given the involvement of decision categories DEC_q and an interaction model MOD_e.

If we let Q denote the potential Sales for new product a_o, we can estimate actual sales of a_o by computing:

$$\text{SALES } (a_o) = Q \left[\sum_{q=1}^{s} V_q M_q(a_o) \right].$$

This methodological structure provides a new way to formalize our understanding of the industrial adoption process. It explicitely addresses the issues of organizational feasibility, decision participants' perceptions, evaluations and preferences for industrial product alternatives, as well as the issue of involvement in the organizational purchasing process that are of considerable importance in the development of better industrial marketing programs.

Industrial markets, however, involve a wide range of possible products, from sulfuric acid to computer software to nuclear power plants. It is therefore important to specify the portion of the universe of industrial products for which use of the new methodological structure is most promising.

Several assumptions were made in the development of the industrial market response model presented in this chapter. These assumptions delimit the range of new industrial products for which the model might be most useful. These assumptions include:

- Potential market size. The new product is to be used in a number of different industries or by many firms in a single industry.

- Characteristics of customer needs. The new product manufacturer has an accurate understanding of the set of relevant dimensions along which organizations define their requirements for products in this class. This information is necessary to collect accurate data about potential customers' needs and to calibrate the acceptance submodel.

- Characteristics of the decision process. The purchasing process for the new product typically involves several people who have different responsibilities in potential customer organizations. Identification of these individuals is a prerequisite to the formation of meaningful categories of participants that are used for calibrating individual evaluation models as well as for performing the microsegmentation analysis.

- Competitive characteristics. Several products, produced by different manufacturers compete directly with the new product in some portion of the potential market. It is therefore essential to assess areas of resistance to the new product concept for each category of influential decision participant.

These assumptions imply that the new methodological structure is most promising in the case of new industrial products that represent extensions or modifications of a currently existing line rather than in the case of innovations that provide a solution to some previously unsatisfied organizational needs. The methodology appears particularly suitable in the case of multipurpose capital equipment or accessory equipment that embody new technologies or new design features. In its present stage of development, however, the industrial market response model presented here does not provide an adequate framework for investigating the adoption of new industrial products made to customers' specifications. Such

products might include, for instance, special-duty manufacturing equipment of laboratory equipment that provide a unique solution to some previously unsatisfied customer needs.

5.3. Direction for Future Research

Several directions for future research were suggested in the dissertation. In this last section, we briefly reviews the most promising of these areas.

Decision Participant Perceptions and Evaluation Space Analysis

An important result of this research is that participants in industrial adoption decisions differ in their perceptions of available product alternatives as well as in their evaluation criteria.

A limitation of the perceptual analysis performed here is that decision participants perceptions are likely to change as a result of their interaction with other people involved in the decision process . In some sense, the results reported in the dissertation present a "snapshot" of perceptual differences across categories of decision participants at a specific point in time. Moreover, the models of multiperson choice included in the industrial market response assessment methodology do not account for the time dependence of decision participants product perceptions nor do they account for

the interdependence between decision participants perceptions. There are rich research opportunities in the analysis of how the perceptions of different categories of participants change as the decision process moves closer to its final stage. Future empirical studies might for example, involve the systematic investigation of decision participants perceptions of the same set of alternatives at different points in time in the adoption process.

The analysis of the relationship between industrial product evaluations and individual preferences also needs additional research. This dissertation has shown that decision participants differ in the way they structure basic product attributes into higher-order evaluation criteria. Future research might concentrate on the analysis of the decision process typical of each of these categories of participants. New insights into the decision process within each of these groups might be gained through a systematic investigation of several models linking individuals' product evaluations to preferences. These models might include non-linearities and risk aversion considerations. Such an investigation would provide a natural development to the study of individual decision-making styles in industrial buying situations, initiated by Wilson and others ([143], [144]).

Industrial Market Microsegmentation Methodology

The understanding of the industrial purchasing process requires the development of better measurement tools to characterize the

involvement of various categories of actors in the major phases of this process. In this research, a modified version of the decision matrix was proposed and the convergent validity of the measurements obtained by this method was systematically investigated.

As discussed in Chapter 2 future studies might involve the assessment of the external validity of the decision matrix by comparing the measurements obtained with independent observations of the actual decision process. Future studies might also investigate the convergent and discriminant validity of these measurements -- using the methodology proposed in Chapter 2 -- on the basis of a large sample of companies in which all influential decision participants would be surveyed. Such studies would, in addition, allow investigation of decision participants self-inflation of involvement in the decision process.

Finally important research opportunities lie in the analysis of the characteristics -- both external and internal -- of organizations that are similar in the structure of their adoption process. Future studies might for instance make use of the microsegmentation methodology developed in this research to identify groups of organizations homogeneous in the structure of their adoption process. Multiple discriminant analysis could then be used to systematically analyze a large number of characteristics of these organizations. These studies would lead to the definition of better predictors for industrial market segmentation and would indirectly contribute to the validation of the measurements obtained with the decision matrix.

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APPENDIX A1

COMPANY QUESTIONNAIRE

ISOLAC* Questionnaire

*Industrial SOLar Air Conditioning Study

The questionnaire is divided into the following sections:

Section 1: Company information
Section 2: Investment information
Section 3: Attitudes toward alternative a/c systems
Section 4: Preference questions
Section 5: Decision process information
Section 6: Decision maker information

In this questionnaire we ask you for information about your company and the process you use to purchase air conditioning equipment. This information is vital for our nation's energy planning and all responses are completely anonymous. Throughout the questionnaire a/c refers to air conditioning and one ton of a/c equals 12,000 BTU/hr.

Some of the information requested may not be immediately available to you. *Please use any sources (people, reports) within your company that you need to complete the questions.*

Section 1: Company Information

1.1 What were the sales for your company last year (± 10%)? _____ *$ Millions*

1.2 About how many separate plants does your company have? _____

1.3 a. About how many total ft^2 of plant area does your company have? _____

b. About what percent of this space is *owned* by the company (not rented or leased). _____ %

c. Of the area in (a) about what % is in Southern California, Florida, Texas, New Mexico, Arizona or in tropical or sub-tropical areas (Puerto Rico and the Caribbean, e.g.)?

_____ less than 15%
_____ 15-30%
_____ 30-50%
_____ 50-70%
_____ 70-85%
_____ Over 85%

d. Of the area in (a), about what % is for production or storage of items requiring air cooling or humidity control?

_____ less than 15%
_____ 15-30%
_____ 30-50%
_____ 50-70%
_____ 70-85%
_____ Over 85%

e. In what product categories do the items in (d) fall? (Check all categories which apply.)

_____ electronics/electrical components
_____ mechanical equipment
_____ pharmaceuticals
_____ apparel/fabrics
_____ printing
_____ food processing
_____ other (Please specify)_____
_____
_____

1.4 What is your expected growth rate in *new* plant area as a *PERCENT* of your current plant floor area (Do *not* subtract plant area that is being vacated).

_____ % Annual growth rate

1.5 About what fraction of your company's product line (in $sales) requires steam or hot water in production?

_____ none

_____ less than 15%

_____ 15-30%

_____ 30-50%

_____ 50-70%

_____ 70-85%

_____ over 85%

1.6 Consider *one* air conditioned plant location, if you have one.

a. Does your system consist of

_____ one central unit

_____ more than one independent unit

b. What type of air conditioning system is used?

_____ compressor

_____ absorption

_____ both

_____ Other (please specify) _____

_____ _____

c. Suppose the a/c of your plant breaks down *during the summer*. How long would it then be possible to operate your plant without having to shut down any production area?

_____ Not at all

_____ Less than 5 hours

_____ 5 hours to one day

_____ More than one day

d. How satisfied are you with your current air conditioning system. Circle *one* number.

Very Dissatisfied						Very Satisfied
1	2	3	4	5	6	7

e. Who maintains it?

_____ equipment manufacturer

_____ outside service company

_____ internal maintenance crew

Section 2: Investment Information

The questions below concern the characteristics an industrial a/c system must have to represent an acceptable alternative for your company. Some of the questions may be difficult to answer, but *the information is of extreme importance for our study*. Please use whatever sources you need within your company to answer these questions.

2.1 Suppose your company has decided to install an a/c system in a *new* plant and has identified several different systems for consideration. In screening these alternatives, your company *will eliminate* any system,

a. If its expected life is *less than* ____ years.

b. If its initial investment cost is *more than* ____ $/ton of cooling.

c. If it is covered by a complete warranty of *less than* ____ months.

d. If it is successfully operating in *less than* ____ other industrial installations.

e. If its annual operating cost (maintenance included) is *more than* _____ % of its initial investment cost.

2.2 In evaluating industrial equipment such as a/c systems, what financial criteria does your company use?

a. *Payback Period*, balancing differences in investment cost with differences in operating and maintenance cost. _____ YES _____ NO

If yes, what is the *maximum* payback period that your company considers acceptable for this type of equipment? _____ YEARS

b. *Net present value* of the investment and future operating and maintenance costs. _____ YES _____ NO

If yes, what does your company currently use as its internal rate of return? _____ %

c. *Initial investment cost* only _____ YES _____ NO

d. *Other* methods (please specify).

_____

_____

_____

_____

2.3 Question 2.1 and 2.2 mention several criteria typically used to evaluate industrial equipment such as a/c systems. Please indicate how important these criteria are in your company's evaluation of such systems. Circle *one* number for each criterion.

	Unimportant			Moderate Importance					Highest Importance	
a. system's expected life	1	2	3	4	5	6	7	8	9	10
b. initial investment cost	1	2	3	4	5	6	7	8	9	10
c. warranty period	1	2	3	4	5	6	7	8	9	10
d. operating & maintenance cost	1	2	3	4	5	6	7	8	9	10
e. number of successful installations	1	2	3	4	5	6	7	8	9	10
f. payback period	1	2	3	4	5	6	7	8	9	10
g. net present value of all current and future expenditures	1	2	3	4	5	6	7	8	9	10

Section 3: Attitudes Toward Alternative Systems

Now we would like to learn your reaction to three industrial air conditioning systems. Two of the systems use the absorption cycle; one uses the compression cycle. The summary description of each system is followed by a list of statements which you will be asked to agree or disagree with.

We are interested in how you FEEL about these systems, based on their one page description, rather than your quantitative evaluation of the systems. There are NO RIGHT OR WRONG ANSWERS so feel free to register your opinion about the product described.

1. Conventional Absorption A/C System: ABSAIR

ABSAIR consists of an absorption chiller, a boiler, piping, pumps and control equipment.

In order to provide cooling, an absorption chiller utilizes a refrigerant (e.g. water) and an absorbent (e.g. lithium bromide) in conjunction with an evaporator, absorber, generator and condenser as diagrammed below. In the evaporator, the refrigerant, in a vacuum, is vaporized by a sprayer. As it evaporates, the refrigerant absorbs heat from the water that is used to cool the building. The refrigerant vapor is then absorbed by the solution in the absorber. The resulting solution is heated in the generator to drive off the refrigerant. At the condenser, the refrigerant vapor condenses and rejects heat to the environment. The refrigerant then returns to the evaporator to start the cycle again.

The boiler uses oil, natural gas or electricity for power. The system can also be driven by commercially produced steam. The absorption chiller is then independent of the heating system unless both use a common boiler.

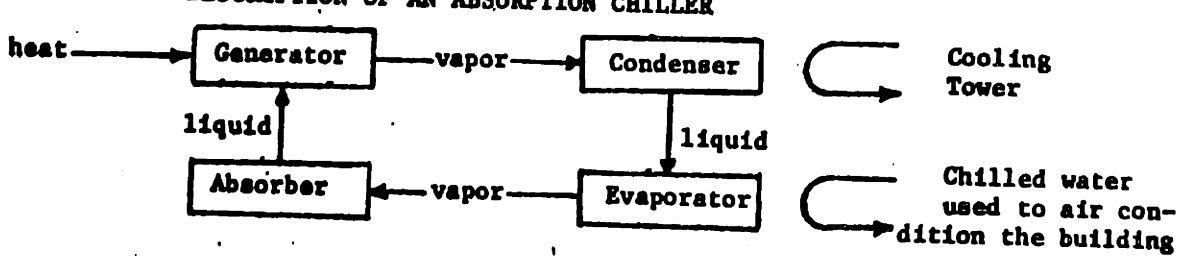
The absorption chiller may be located on the roof or within a mechanical space in the building. Maintenance costs for ABSAIR are approximately 20% lower than those of compressor a/c systems. It is less efficient that compression a/c systems in that to cool a given load, ABSAIR requires between 15-20% more energy. The absorption chiller has a longer expected life than the other a/c systems, so ABSAIR's economic life is around 25 years. In addition, as it has almost no moving parts, an absorption chiller is relatively quiet and vibration free.

The other elements of ABSAIR: fans, pumps, piping and control equipment are generally the same as those in compressor a/c systems.

The initial investment cost of ABSAIR may be significantly more than for compressor systems. This difference however tends to reduce as the installation size increases.

ABSAIR appeals to companies who need a large amount of a/c or who use steam for other industrial processes and want to make additional use of that steam. ABSAIR has been typically used by hospitals and pharmaceutical plants where abundant steam exists. Currently, there are between 3,000 and 5,000 of those industrial a/c systems in use.

DESCRIPTION OF AN ABSORPTION CHILLER



Ratings for ABSAIR (Circle one number for each item)

	Strongly Disagree						Strongly Agree
1. The system provides reliable air condit. ing.	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	[illegible]	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 manufacturers 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

2. Conventional Compression A/C System: COMAIR

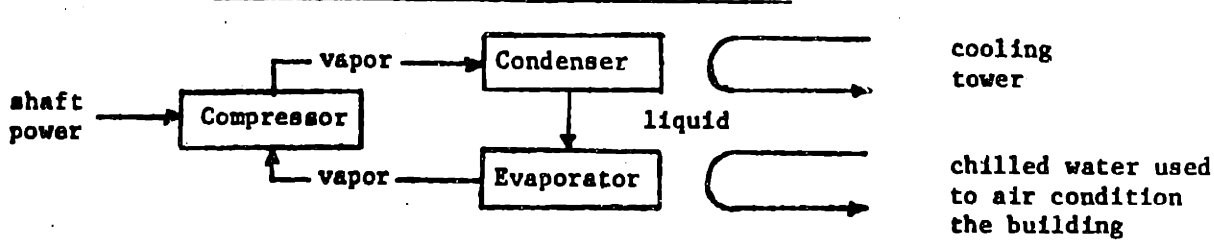
COMAIR consists of a vapor compression system, an electric motor, piping, pumps and control equipment.

In order to produce cooling, the system utilizes a refrigerant in conjunction with an evaporator, compressor and condenser as diagrammed below. In the evaporator, the refrigerant, under pressure, passes through an expansion valve and vaporizes. As it evaporates, the refrigerant absorbs heat from the water that is used to cool the building. The refrigerant vapor is then compressed and sent to the condenser where it rejects heat to the environment. Finally, the refrigerant returns to the evaporator to start the cycle again.

COMAIR may be located on the roof or within a mechanical space in the building. The system typically uses electricity as a power source and is completely independent of the heating system. It is mechanically complex and tends to produce more noise and vibration that an absorption a/c system, sometimes requiring a separate area for housing. Maintenance costs are well established and tend to be higher than for absorption a/c systems. Repair time is usually short due to the system's modularity and the standardization of its components. The entire COMAIR system has an expected economic life of approximately 15-17 years. Although COMAIR does not produce on-site pollution, environmental pollution usually occurs at the point of electric power generation.

The initial cost of COMAIR is among the lowest available in the market. It is the most popular system on the market and strongly appeals to those companies that are first-cost oriented.

DESCRIPTION OF A COMPRESSION A/C SYSTEM



Ratings for COMAIR (Circle one number for each item)

	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 manufacturers 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

3. Solar Absorption a/c System : SOLABS

SOLABS consists of a standard absorption chiller as used in ABSAIR and a hot water solar collector which replaces the boiler in a standard absorption a/c system. As it uses solar energy as a power source, SOLABS is less sensitive to fuel shortages and power fluctuations than other industrial a/c systems.

The solar collector used by SOLABS is a flat type that is located on the roof of the building. In some cases, collectors can even replace the roof. Collectors come in panels of various standard sizes that are attached to one another by normal plumbing connections. Two water storage tanks are also part of SOLABS and are generally buried in the ground. One of these tanks is for chilled water, to meet the immediate demands of the absorption system. The other one is for hot water, to meet a/c needs during periods of little sunshine or alternatively to provide heating during these same periods. When the system is used exclusively for a/c, water storage capacity need not be large as more solar energy is available when cooling is most needed. A small backup heating and cooling system can be used to make up for prolonged periods of low sunshine.

Solar energy alone can provide 40% - 60% of all building a/c requirements, significantly reducing energy costs. In addition, warm water produced by the solar collector can be used for manufacturing or domestic water needs. In colder climates, this system can provide 30% - 40% of heating requirements.

The initial cost of SOLABS is at least 50% higher than for non-solar systems, depending on the size of the installation. The operating cost of SOLABS, however, is considerably lower than for other systems due to a reduction of at least 40% in a/c energy consumption (depending on the geographical location). Maintenance costs for SOLABS are similar to those for ABSAIR.

SOLABS produces no pollution. As it requires a minimum of moving parts, SOLABS is also very quiet and vibration free.

The solar a/c concept is not new. Several well-known manufacturers produce components and one such system was in operation at the University of Florida as early as 1960. Currently, there is a new school in Atlanta, Georgia that is air-conditioned by SOLABS and there are several projects to install similar a/c systems in different parts of the U.S.

Ratings for SOLABS

(Circle one number for each item)

	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 manufacturers 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

Section 4: Preference Information

4.1 You have just rated three alternative industrial air conditioning systems. Now we would like to know your overall preferences for these systems, listed below. *Assume that all three systems satisfy the requirements you stated in question 2.1.* Write a "1" next to the one which would be your first choice, a "2" next to your second choice and a "3" next to your third choice.

Conventional Absorption a/c system	ABSAIR	_____
Conventional Compression a/c system	COMAIR	_____
Solar Absorption a/c system	SOLABS	_____

4.2 Assume your company has reduced the choice of system alternatives to two, *both meeting the requirements you stated in question 2.1.* For each of the pairs listed below, allocate 11 points between the alternatives in a way which reflects your relative preference for the two systems.

a. COMAIR vs. SOLABS

Conventional Compression a/c system	COMAIR	____
Solar Absorption a/c system	SOLABS	____
Total	=	11

b. ABSAIR vs. COMAIR

Conventional Absorption a/c system	ABSAIR	____
Conventional Compression a/c system	COMAIR	____
Total	=	11

c. SOLABS vs. ABSAIR

Solar Absorption a/c system	SOLABS	____
Conventional Absorption a/c system	ABSAIR	____
Total	=	11

4.3 How likely do you feel it is that an a/c equipment manufacturer can currently produce

	Very Unlikely									Very Likely
a) a *cost-effective* solar absorption system?	1	2	3	4	5	6	7	8	9	10
b) a *reliable and dependable* solar absorption system?	1	2	3	4	5	6	7	8	9	10

4.4 Suppose your company chose an a/c system which did not fully meet its expectations. How significant would it be for *your organization* if the system proved

	Of little consequence to the organization									potentially catastrophic to the organization
a. less *economical* than projected?	1	2	3	4	5	6	7	8	9	10
b. less *reliable and dependable* than projected?	1	2	3	4	5	6	7	8	9	10

4.5 Suppose you *actively* supported adoption of an a/c system which did not fully meet expectations. How significant would it be for *you personally* if the system proved

	Would not affect my position and credibility									Would highly endanger my position and credibilit
a. less *economical* than projected?	1	2	3	4	5	6	7	8	9	10
b. less *reliable and dependable* than projected?	1	2	3	4	5	6	7	8	9	10

Section 5: Decision Process Information

5.1 The purchase of an industrial a/c system for a *new* plant typically involves several participants. In this question, we would like to know more about who would be involved in the important phases of the decision-making process -- both company personnel and people external to the firm.

For each of the five "decision phases" in the chart below, please indicate approximately what percentage of the task-responsibilities is that of each category of participants. For instance, Phase 1 may be the responsibility of the architect (25%), the HVAC consulting firm (25%), and top management (50%).

Of course, a given decision-making phase might be the responsibility of only one category of participants, in which case, you should write 100% in the appropriate box and leave all of the other boxes in that column blank.

	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 Manager	%	%	%	%	%
	Financial controller or accountant	%	%	%	%	%
	Procurement or purchasing department	%	%	%	%	%
	Top Management	%	%	%	%	%
EXTERNAL PERSONNEL	HVAC/Engineering firm	%	%	%	%	%
	Architects and Building Contractor	%	%	%	%	%
	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.

5.2 Suppose your firm is going to hire an HVAC consultant to aid in selecting an a/c system.

How would your firm decide which one to hire? (check one)

a) leave the decision to an architectural firm ____
b) hire the HVAC contractor who was responsible for installing and servicing the system of an existing company building. ____
c) use a closed bid system involving preselected HVAC firms ____
d) use an open bid system for any HVAC firm interested in making a bid ____
e) other. Please specify ____

_____

_____

Section 6: Decision Maker Information

6.1 Your age: ____ Years

6.2 Education:

____ High School

____ 1-4 years of college Major area:_____

____ Masters or higher Major area:_____

6.3 How many years have you been working for your present company? _____ Years

6.4 Where is the plant you are associated with located?

____ ZIP CODE

6.5 Please check the category corresponding most closely to your job responsibility.

Production or Maintenance Engineer ____

Plant or Factory Manager ____

Financial controller or accountant ____

Procurement or purchasing officer ____

Top management ____

Others: _____ ____

_____

_____

6.6 For each of the following, please circle the one number that best describes your feelings about the statement.

	Strongly Disagree						Strongly Agree
New products are generally more trouble than they are worth.	1	2	3	4	5	6	7
Managerial performance should be evaluated on immediate results.	1	2	3	4	5	6	7
It is better to let other companies purchase new products first.	1	2	3	4	5	6	7
My way of life has changed little in the last five years.	1	2	3	4	5	6	7
Computers create more problems for management than they solve.	1	2	3	4	5	6	7

Thank you very much for your cooperation!

APPENDIX A2

A COMPUTER PROGRAM TO PERFORM BOX TEST

```
C       ***************************************************************
C       *    PROGRAM TO PERFORM BOX TEST OF EQUALITY OF COVARIANCE    *
C       *    STRUCTURE OF NG NV-DIMENSIONAL MULTINORMAL POPULATIONS   *
C       *    REFERENCES:                                              *
C       *      BOX,"A GENERAL DISTRIBUTION THEORY FOR A CLASS OF      *
C       *      LIKELIHOOD CRITERIA", BIOMETRIKA VOL. 36 (1949)        *
C       *      COOLEY AND LOHNES, "MULTIVARIATE DATA ANALYSIS",       *
C       *      WILEY (1971) P 227-229.                                *
C       *    PROGRAM LIMITATIONS:                                     *
C       *      NUMBER OF GROUPS NG<=5                                 *
C       *      NUMBER OF VARIABLES NV<=17                             *
C       *    PARAMETER CARDS                                          *
C       *      CARD 1      NG IN COL 1                                *
C       *                  NV IN COL 2-3                              *
C       *      CARD 2      ANALYSIS TITLE IN COL 1-72                 *
C       *      CARD 3      SAMPLE SIZE IN GR 1 IN COL  1- 5           *
C       *                  SAMPLE SIZE IN GR 2 IN COL  6-10           *
C       *                  SAMPLE SIZE IN GR 3 IN COL 11-15           *
C       *                  SAMPLE SIZE IN GR 4 IN COL 16-20           *
C       *                  SAMPLE SIZE IN GR 5 IN COL 21-25           *
C       *      CARD 4      NAME OF GR 1 IN COL  1- 8                  *
C       *                  NAME OF GR 2 IN COL  9-16                  *
C       *                  NAME OF GR 3 IN COL 17-24                  *
C       *                  NAME OF GR 4 IN COL 25-32                  *
C       *                  NAME OF GR 5 IN COL 33-40                  *
C       *      CARD 5      DATA INPUT FORMAT COL 1-72                 *
C       ***************************************************************
C
      IMPLICIT REAL*8(A-H,O-Z)
      DIMENSION CO(20,20),POCO(20,20)
      COMMON GR(5)
      DIMENSION NS(5),FMT(9),AC(20),X(20),D(5),XNS(5),TIT(9)
      READ(5,100) NG,NV
      READ(5,110) (TIT(I),I=1,9)
      READ(5,105) (NS(I),I=1,NG)
      READ(5,106) (GR(I),I=1,NG)
      READ(5,110) (FMT(I),I=1,9)
```

```
C
  100 FORMAT(I1,I2)
  105 FORMAT(5I5)
  106 FORMAT(5A8)
  110 FORMAT(9A8)
C
C         TOTAL SAMPLE SIZE AND DEGREES OF FREEDOM
C
      NTS=0
      DO 5 I=1,NG
      NTS=NTS+NS(I)
    5 CONTINUE
      NTDF=NTS-NG
C
      XNTDF=NTDF
      DO 7 J=1,NG
      XNS(J)=NS(J)
    7 CONTINUE
C
C         INITIALIZE POOLED COV. MATRIX POCO
C
      DO 6 J=1,NV
      DO 6 I=1,NV
      POCO(I,J)=0.0
    6 CONTINUE
C
C         WRITE TITLE
C
      WRITE(6,250)
      WRITE(6,251) (TIT(J),J=1,9)
      WRITE(6,252) (GR(J),J=1,NG)
      WRITE(6,253) NV
      WRITE(6,254) ((GR(I),NS(I)),I=1,NG)
```

```
C
  250 FORMAT('1','BOX TEST FOR THE EQUALITY OF COVARIANCE MATRICES',//)
  251 FORMAT('0','TITLE FOR THIS ANALYSIS:',1X,9A8)
  252 FORMAT('0','GROUP NAMES:',5(5X,A8))
  253 FORMAT('0','NUMBER OF VARIABLES FOR THIS ANALYSIS:',I5)
  254 FORMAT('0','SAMPLE SIZES:',5(2X,A8,'=',I5))
C
      DO 25 L=1,NG
      N=NS(L)
      XN=XNS(L)
C
C        INITIALIZE COV. MATRIX CO AND ACCUMULATOR VECTOR AC
C
      DO 10 J=1,NV
      AC(J)=0.0
      DO 10 I=1,NV
      CO(I,J)=0.0
   10 CONTINUE
C
C        COMPUTE MATRIX OF CROSS PRODUCTS
C
      DO 15 K=1,N
      READ(5,FMT) (X(J),J=1,NV)
      DO 15 J=1,NV
      AC(J)=AC(J)+X(J)
      DO 15 I=1,NV
      CO(I,J)=CO(I,J)+X(I)*X(J)
   15 CONTINUE
C
C        COMPUTE COVARIANCE MATRIX
C
      DO 20 J=1,NV
      DO 20 I=1,NV
      CO(I,J)=(CO(I,J)-AC(I)*AC(J)/XN)/(XN-1.0)
      POCO(I,J)=POCO(I,J)+(XN-1.0)*CO(I,J)/XNTDF
   20 CONTINUE
```

```
      CALL MATPRT(CO,NV,L)
      CALL MATINV(CO,NV,DET)
      D(L)=DET
      WRITE(6,200) D(L)
   25 CONTINUE
  200 FORMAT(///,' DETERMINANT =',D15.6)
      L=99
      CALL MATPRT(POCO,NV,L)
      CALL MATINV(POCO,NV,DPOCO)
      WRITE(6,200) DPOCO
C
C        COMPUTATION OF THE STATISTIC M
C
      SUMCO=0.0
      DO 30 I=1,NG
      SUMCO=SUMCO+(XNS(I)-1.0)*DLOG(D(I))
   30 CONTINUE
      SM=XNTDF*DLOG(DPOCO)-SUMCO
      WRITE(6,600) SM
  600 FORMAT('1','STATISTIC M=',F20.10)
C
C        COMPUTATION OF CORRECTION FACTORS
C
      SIDF=0.0
      SIDF2=0.0
      DO 35 I=1,NG
      SIDF=SIDF+(1.0/(XNS(I)-1.0))
      SIDF2=SIDF2+(1.0/((XNS(I)-1.0)**2))
   35 CONTINUE
      WRITE(6,400) SIDF,SIDF2
  400 FORMAT('0','SUM 1/DF =',F10.8,5X,'SUM OF 1/(DF**2) =',F10.8)
C
      XNG=NG
      XNV=NV
      A1=(SIDF-1.0/XNTDF)*(2.0*(XNV**2)+(3.0*XNV)-1.0)/(6.0*(XNV+1.0)
     1*(XNG-1.0))
```

```
      A2=(SIDF2-1.0/(XNTDF**2))*((XNV-1.0)*(XNV+2.0))/(6.0*(XNG-1.0))
      WRITE(6,500) A1,A2
  500 FORMAT('0','CORRECTION FACTOR A1 =',F10.8,5X,'CORRECTION FACTOR A2
     * =',F10.8)
C
C        COMPUTATION OF TEST STATISTICS
C
      C1=1-A1
      XN1=(XNG-1.0)*XNV*(XNV+1.0)/2.0
      X2=C1*SM
      WRITE(6,250)
      WRITE(6,251) (TIT(J),J=1,9)
      WRITE(6,205) X2,XN1
  205 FORMAT('0','CHI-SQUARE TEST      X2=',F10.4,5X,'DF=',F10.0,/////)
      IF(A2.GT.(A1**2)) GO TO 1000
      XN2=(XN1+2.0)/((A1**2)-A2)
      B=XN2/(1.0-A1+2.0/XN2)
      F=XN2*SM/(XN1*(B-SM))
      WRITE(6,210) F,XN1,XN2
      GO TO 999
 1000 XN2=(XN1+2.0)/(A2-A1**2)
      B=XN1/(1.0-A1-XN1/XN2)
      F=SM/B
      WRITE(6,210) F,XN1,XN2
  210 FORMAT(' ','F-TEST      F=',F10.4,5X,'DF1=',F10.0,2X,'DF2=',F10.0)
  999 CONTINUE
      END
```

```
      SUBROUTINE MATPRT(X,N,L)
C        ***********************************************************
C        *     THIS SUBROUTINE PRINTS THE COV MATRIX X             *
C        ***********************************************************
      IMPLICIT REAL*8(A-H,O-Z)
      COMMON GR(5)
      DIMENSION X(20,20)
      IF(L.GT.90) GO TO 7
      WRITE(6,300) GR(L)
  300 FORMAT('1','COV MATRIX FOR GROUP',2X,A8,/////)
      GO TO 10
    7 WRITE(6,305)
  305 FORMAT('1','POOLED COV MATRIX',/////)
   10 DO 5 I=1,N
      WRITE(6,310) (X(I,J),J=1,N)
    5 CONTINUE
  310 FORMAT('0',17F7.2)
      RETURN
      END
```

```
      SUBROUTINE MATINV(A,M,DET)
C        ***************************************************************
C        *     INVERSE AND DETERMINANT OF A BY THE GAUSS-JORDAN METHOD     *
C        *     M IS THE ORDER OF THE SQUARE MATRIX A                       *
C        *     A-INVERSE REPLACES A                                        *
C        *     DETERMINANT OF A IS PLACED IN DET                           *
C        ***************************************************************
      IMPLICIT REAL*8(A-H,O-Z)
      COMMON GR(5)
      DIMENSION A(20,20),IPVT(20),PVT(20),IND(20,2)
C
      DET=1.0
      DO 1 J=1,M
    1 IPVT(J)=0
      DO 10 I=1,M
C
C        SEARCH FOR THE PIVOT ELEMENT
C
      AMAX=0.0
      DO 5 J=1,M
      IF(IPVT(J)-1) 2,5,2
    2 DO 5 K=1,M
      IF(IPVT(K)-1) 3,5,20
    3 IF(DABS(AMAX)-DABS(A(J,K))) 4,5,5
    4 IROW=J
      ICOL=K
      AMAX=A(J,K)
    5 CONTINUE
      IPVT(ICOL)=IPVT(ICOL)+1
C
C        INTERCHANGE THE ROWS TO PUT THE PIVOT ELEMENT ON THE DIAGONAL
C
      IF(IROW-ICOL) 6,8,6
    6 DET=-DET
      DO 7 L=1,M
```

```
      SWAP=A(IROW,L)
      A(IROW,L)=A(ICOL,L)
    7 A(ICOL,L)=SWAP
    8 IND(I,1)=IROW
      IND(I,2)=ICOL
      PVT(I)=A(ICOL,ICOL)
      DET=DET*PVT(I)
C
C        DIVIDE THE PIVOT ROW BY THE PIVOT ELEMENT
C
      A(ICOL,ICOL)=1.0
      DO 9 L=1,M
    9 A(ICOL,L)=A(ICOL,L)/PVT(I)
C
C        REDUCE NON-PIVOT ROWS
C
      DO 10 L1=1,M
      IF(L1-ICOL) 11,10,11
   11 SWAP=A(L1,ICOL)
      A(L1,ICOL)=0.0
      DO 12 L=1,M
   12 A(L1,L)=A(L1,L)-A(ICOL,L)*SWAP
   10 CONTINUE
C
C        INTERCHANGE THE COLUMNS
C
      DO 20 I=1,M
      L=M+1-I
      IF(IND(L,1)-IND(L,2)) 13,20,13
   13 IROW=IND(L,1)
      ICOL=IND(L,2)
      DO 20 K=1,M
```

```
      SWAP=A(K,IROW)
      A(K,IROW)=A(K,ICOL)
      A(K,ICOL)=SWAP
   20 CONTINUE
      RETURN
      END
```

APPENDIX A3

A COMPUTER PROGRAM TO ESTIMATE EIGENVALUES OF RANDOM CORRELATION MATRICES WITH SQUARED MULTIPLE CORRELATIONS ON THE DIAGONAL

```
C         ***********************************************************************
C         *    PROGRAM TO COMPUTE REGRESSION ESTIMATES OF THE                   *
C         *    EIGENVALUES OF RANDOM CORRELATION MATRICES WITH                  *
C         *    SQUARED MULTIPLE CORRELATIONS ON THE DIAGONAL                    *
C         *    REFERENCES:                                                      *
C         *      R.G. MONTANELLI AND L.G. HUMPHREYS,PSYCHOMETRIKA,              *
C         *      VOL. 41 NO. 3 (SEPTEMBER 1976) P.341-349                       *
C         *    ANALYSIS RESTRICTIONS                                            *
C         *      NO-NUMBER OF OBSERVATIONS 25<=NO<=1533                         *
C         *      NV-NUMBER OF VARIABLES  6<=NV<=90                              *
C         *      NE-NUMBER OF EIGENVALUES REQUESTED  NE<=30                     *
C         *    PARAMETER CARDS:                                                 *
C         *      CARD 1  TITLE IN COL  1-72                                     *
C         *      CARD 2  NO IN COL  1- 5                                        *
C         *              NV IN COL  6-10                                        *
C         *              NE IN COL 11-15                                        *
C         *      CARD 3 TO CARD 33                                              *
C         *              ROOT 1       .460-.613 .356                            *
C         *              ROOT 2       .248-.613 .415                            *
C         *              ROOT 3       .168-.620 .439                            *
C         *              ROOT 4       .143-.624 .441                            *
C         *              ROOT 5       .046-.627 .470                            *
C         *              ROOT 6       .011-.629 .477                            *
C         *              ROOT 7      -.015-.637 .486                            *
C         *              ROOT 8      -.064-.647 .506                            *
C         *              ROOT 9      -.078-.649 .507                            *
C         *              ROOT10      -.094-.649 .509                            *
C         *              ROOT11      -.105-.654 .518                            *
C         *              ROOT12      -.173-.656 .531                            *
C         *              ROOT13      -.174-.666 .532                            *
C         *              ROOT14      -.187-.666 .532                            *
C         *              ROOT15      -.187-.668 .532                            *
C         *              ROOT16      -.173-.673 .528                            *
C         *              ROOT17      -.164-.688 .528                            *
C         *              ROOT18      -.135-.690 .525                            *
C         *              ROOT19      -.129-.695 .525                            *
```

```
C         *                ROOT20      -.110-.708 .526                          *
C         *                ROOT21      -.097-.713 .526                          *
C         *                ROOT22      -.080-.715 .518                          *
C         *                ROOT23      -.097-.715 .525                          *
C         *                ROOT24      -.103-.714 .525                          *
C         *                ROOT25      -.081-.718 .510                          *
C         *                ROOT26      -.081-.718 .510                          *
C         *                ROOT27      -.081-.718 .510                          *
C         *                ROOT28      -.081-.718 .510                          *
C         *                ROOT29      -.118-.744 .464                          *
C         *                ROOT30      -.195-.712 .536                          *
C         ***********************************************************************
      IMPLICIT REAL*8(A-H,O-Z)
      DIMENSION B(30,3),XLEIG(30),EIG(30),TIT(9)
C
      READ(5,100) (TIT(J),J=1,9)
      READ(5,105) NO,NV,NE
      DO 5 I=1,30
      READ(5,110) (B(I,J),J=1,3)
    5 CONTINUE
C
  100 FORMAT(9A8)
  105 FORMAT(3I5)
  110 FORMAT(35X,3F5.3)
      DO 50 I=1,30
      WRITE(6,250) (B(I,J),J=1,3)
   50 CONTINUE
  250 FORMAT(' ',3F10.3)
C
      XNO=NO
      XNV=NV
C
      A1=DLOG10(XNO-1.0)
      DO 10 I=1,NE
      XI=I
      A2=DLOG10((XNV*(XNV-1.0)/2.0)-((XI-1.0)/XNV))
```

```
      XLEIG(I)=B(I,1)+A1*B(I,2)+A2*B(I,3)
      EIG(I)=10.0**(XLEIG(I))
   10 CONTINUE
C
      WRITE(6,200) (TIT(J),J=1,9)
      WRITE(6,205) NE,NV,NO
      DO 15 I=1,NE
      WRITE(6,210) I,EIG(I)
C
  200 FORMAT('1','TITLE FOR THIS ANALYSIS: ',9A8,//)
  205 FORMAT(' ','ESTIMATION OF THE FIRST ',I2,1X,'EIGENVALUES OF RANDOM
     * DATA CORRELATION MATRICES OF ',I2,' VARIABLES COMPUTED FROM ',I4,
     *' OBSERVATIONS',/////)
  210 FORMAT(' ','ESTIMATED EIGENVALUE NO. ',I2,'=',F10.5)
C
      END
```

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