A Business Market Segmentation Procedure for Product Planning

Grahame R. Dowling
Gary L. Lilien
Praveen K. Soni

ABSTRACT. This paper demonstrates a market segmentation procedure that responds to the information needs associated with business product marketing. We outline several important criteria that such a procedure should meet, and then propose a procedure that addresses those criteria. We illustrate use of the procedure by applying it to the US information processing market with considerable success. We close with a discussion of the uses and limitations of the procedure and the need for further research.

INTRODUCTION

Customers in both consumer and business markets vary in their basic needs and preferences. Kotler (1991) defines segmentation as

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Grahame R. Dowling is Associate Professor at the Australian Graduate School of Management in the University of New South Wales, Australia. Gary L. Lilien is a Distinguished Research Professor of Management Science and Co-Founder and Research Director of the Institute for the Study of Business Markets at Penn State. Praveen K. Soni is Associate Professor of Marketing at California State University, Long Beach.

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"the act of dividing a market into distinct groups of buyers who might require separate products and/or marketing mixes" (p. 263). Market segmentation is a vital element in market strategy development as it enables marketers to target their offerings to meet the diversity of customer needs most efficiently. The choice of target segments also selects the firm's competitors.

This paper focuses on the use of segmentation in the area of product planning in business markets. Product managers in business markets must identify organizations that are the most likely to evaluate and try new offerings, i.e., the innovator and early adopter segments of a market (Rogers, 1983). The emerging focus on "lead users" as co-developers of new products (von Hippel, 1986, 1988), and as targets for understanding customer needs, requires both identification of early adopters and an appropriate market segmentation procedure based on that identification. One way of identifying segments of early or lead users is to study past purchase behavior: previous early adopters of new products are likely to be early adopters of similar products in the future (Rogers, 1976; von Hippel, 1988). Also, reliable data on past purchase behavior is often available in business markets, permitting such a procedure to be readily implemented.

In this paper, we develop and operationalize a strategic segmentation procedure to identify potential early adopters of new technologies. Our procedure synthesizes the methodological and technological advances in this area. We illustrate this procedure by using organizational needs *revealed by actual purchasing behavior* as the basis for segmentation. This discussion proceeds as follows: first we review past research on segmentation and summarize some of the shortcomings of that research. Next, we develop criteria for evaluating segmentation models and then propose an alternative segmentation procedure. Lastly, we illustrate the use of the procedure by applying it to the US information processing market and evaluate its performance. Our contention is that a systematic, defensible needs-based segmentation procedure is an important component of a firm's marketing tool kit. Our illustration in the second part of the paper demonstrates both the value of the procedure to practitioners, and some of the additional developments needed by the academic community.

BUSINESS MARKET SEGMENTATION RESEARCH: USES, LIMITATIONS, AND NEEDS FOR DEVELOPMENT

The theory and practice of segmentation research in business markets lags behind similar research in consumer markets (Choffray and Lilien, 1980; Moriarty and Reibstein, 1986; and Wind, 1978). This lag has several causes, including the lack of agreement about which criteria should be used to segment markets (e.g., needs), and which should be used to describe these segments (e.g., media usage). Other causes include the heterogeneity of organizations, the complexity of buying decisions, and the difficulty of reaching business markets (Plank, 1985; and Webster, 1991); the dependence of business marketing on other business functions such as manufacturing, R&D, inventory control, and engineering (Ames, 1970); and the difficulty business marketers have identifying variables useful for segmentation (Doyle and Sanders, 1985; and Shapiro and Bonoma, 1984).

Even with the lack of a clear framework for segmenting business markets, managers have benefited from segmentation analysis. For example, Doyle and Saunders (1985) show how segmentation and positioning were useful for a rosin manufacturer in making the switch to specialty chemicals. Moriarty and Reibstein (1986) in the nonintelligent data terminal market, and DeKluyver and Whitlark (1986) in a study of the air compressor market, demonstrate that benefit segmentation is very suitable for industrial applications. Schuster and Bodkin (1987) found that about 74% of the exporting companies surveyed differentiated their marketing activities between international and domestic customers. Berrigan and Finkbeiner (1992) discuss some key uses of needs-based studies performed by National Analysts for such business clients as the Electric Power Research Institute, Pacific Bell, US West and IBM. However, the proprietary nature of most business market segmentation studies has slowed progress in bridging the theory-practice gap.

Doyle and Saunders (1985) and Webster (1991) argue that although the basic concept of segmentation remains the same, the complexity of using a business organization as the unit of analysis calls for significant modifications in the segmentation approaches that are typically applied to consumer marketing. In his review of the segmentation approaches used in business markets, Plank (1985) found that the approaches could be classified by the number of stages used to segment the market. Single stage procedures tended to use a single base to segment the market, e.g., the firm's buying decision typology (Robinson, Faris and Wind, 1967), information processing strategies (Feldman and Cardozo, 1967), customers' perception of value and benefits (Yankelovich, 1964), or purchasing agenda decision styles (Wilson, Matthews and Sweeney, 1971). Multi-stage procedures use several bases in a series of stages to segment a market. Bonoma and Shapiro (1984) and Shapiro and Bonoma (1984) developed a procedure where the number of stages is determined via a tradeoff between the amount of information available about a market and institutional and managerial constraints.

Perhaps the most widely cited approach is a two stage procedure (Hutt and Speh, 1989; Wind and Cardozo, 1974). Here *macrosegmentation*, the first stage, centers on the characteristics of the buying organization such as size, location, industry, and end-use markets. *Microsegmentation*, the second stage, focuses on the characteristics of decision making units within each macrosegment, e.g., individual characteristics of buyers, decision criteria, type of purchase situation, and perceived importance of the purchase (Reeder, Brierty, and Reeder, 1987). Choffray and Lilien (1980), and Moriarity and Reibstein (1986) have applied this approach.

The appropriate number of stages or levels in the segmentation procedure will depend upon the purpose for which the results will be used, and the availability of suitable data with which to segment markets. For example, at the corporate strategy formulation level, where decisions on production technology and type of product offering are made, a one or two stage segmentation procedure should be sufficient. At the marketing program level, however, where customer response to marketing mix variables is crucial and detailed information on target segments is necessary, further stages may be appropriate. These further stages may result in a few or even a single organization being matched with an appropriate marketing program–so-called "customized marketing" (Kotler, 1991).

In reviews of the market segmentation field, Wind (1978), and Moriarty and Reibstein (1986) conclude that advancement in segmentation research requires narrowing the gap between academically oriented research and real world applications. Also Plank's (1985) review of industrial market segmentation, indicates that a sound, normative procedure for business market segmentation is not yet available, and that user requirements should eventually be incorporated in such a procedure.

Thus, while business marketing managers generally recognize the need to develop an appropriate segmentation procedure for their markets, academic research has yet to adequately satisfy this need. There are at least four reasons for this theory-practice gap.

a. Lack of Generalizability. Academic research in segmentation often employs small convenience samples of respondents (Rangan, Moriarty, and Swartz, 1992). Also, in business markets, case studies of particular firms in a restricted number of industries are common (Bennion, 1987; DeKluyver and Whitlark, 1986; Doyle and Saunders, 1985; and Rangan, Moriarty and Swartz, 1992). Few published business market studies have used probability sampling to achieve representativeness (Moriarty and Reibstein, 1986). These factors, combined with a lack of comparable conceptual and empirical approaches to segmentation, make reliable comparison between studies difficult.

b. Product Related Segmentation. Much segmentation research is narrowly focused on either a single product within an industry or market, such as the steel forging industry (Bennion, 1987); the air compressor market (DeKluyver and Whitlark, 1986); the specialty chemicals market (Doyle and Sanders, 1985); the livestock chemical business (Roberts, 1961); or the market for printing services (Woodside and Wilson, 1986). Similar customer needs, however, may be satisfied by products stemming from different technologies. Also, product specific segmentation is myopic (Levitt, 1960), since it neglects need satisfaction through substitute products. For example, segmentation based on the adoption of a specific product like a typewriter may miss the need–word processing–that can be satisfied by personal computers, terminals connected to a central processing unit, and other technologies.

c. Instability of Segments. Most segmentation studies employ cross sectional data and researchers rarely attempt to determine if segments change over time. Segment instability can be of two types: the number and/or nature of the segments can change, and/or firms may change from one segment to another. Roberts (1961) signaled this as an important issue in segmentation research many years ago. Indeed, research in consumer markets (Calantone and Sawyer, 1978) shows that after two years, a household had better than a 50% chance of being classified in a segment other than in its previous group. We signal this as an issue for future research.

d. Use of Mixed Bases for Segmentation. Moriarty and Reibstein (1986) argue that the theoretical objective of segmentation is to produce groups of firms that are homogeneous within and heterogeneous between with respect to benefits sought. Segmentation researchers, however, have yet to agree on appropriate criteria for the clustering of firms in a market. Plank's (1985) review illustrates that the most prevalent criteria are: industry, geographic location, product use, company buying practices, type of buying situation, individual characteristics of buyers, product usage level, type of organization, and needs. (In consumer markets, needs-based or benefit segmentation has become widely accepted.)

Choffray and Lilien (1980a) argue that two broad types of variables should be used to create (needs-based) segments, viz., a set of variables to *segment* firms, and a different set of variables to *describe* the firms in the various segments. The segmentation variables are needed to analyze and understand the structure of the market, while the descriptor variables are vital for implementing marketing strategy. Wind (1978) argues for linking the selection of these variables to the business decision under consideration, a tack we support. Statistical methodology issues are also important here because they can affect the number and character of segments derived from the segmentation variables.

To bridge the theory-practice gap, we advocate the selection of different sets of variables to segment and then describe markets. The segmentation variables must also help to identify target markets and develop marketing strategy. Also, the segments formed must exhibit varying propensity to buy a seller's product or service offering. Thus customer benefits or needs form the most logical segmentation bases (Haley, 1968; Moriarty and Reibstein, 1986; and Urban and von Hippel, 1988).

Customer needs can be classified into benefits sought and solutions to problems. When developing a positioning strategy this distinction becomes important because it affects the advertising copy strategy (Rossiter and Percy, 1987). Each of these categories of need can be further subdivided using a functional or a psychological dimension. For example, consider the early success of IBM in the mainframe computer market. They offered a better combination of functional benefits and/or solutions to customer information processing problems than their competitors. Also, their market dominance allowed them to supplement these functional attributes with the psychological benefit of buying from the market leader.

Needs can be measured either directly or through the use of surrogates such as past purchase behavior, type of industry, or size of firm. Needs-based segments, however, provide managers with only part of the information necessary for target market selection and the development of marketing strategy. To be able to *access* firms in these benefit segments, the firms must be identified (described) in terms of their buying practices, media usage, and demographic characteristics. These descriptor variables then provide insight into finding potential customers and selling products and services to them.

We now outline a needs-based approach to business market segmentation that addresses the limitations above. We then provide an illustrative application in the information processing/telecommunications industry.

A THREE STAGE SEGMENTATION PROCEDURE

In order to address the shortcomings of current work and to evaluate our procedure for business market segmentation, we suggest five criteria for a business market segmentation model:

1. Segments should be need based. The procedure should be able to split a market into naturally occurring *need* segments such that the resulting groups of firms exhibit a significant degree of within-group homogeneity and between-group heterogeneity. These segments may then be targeted with segment-specific marketing strategies (Dickson and Ginter, 1987; Wind and Cardozo, 1974). Our focus on needs rather than characteristics of the buying group (traditional microsegmentation criteria) reflects our contention that, particularly in business markets, needs, or surrogate indicators of needs, are the primary determinants of purchase behavior. Also, unlike consumer markets, business market participants buy or adopt products or services to meet the derived demand for their own products and services most profitably. These need-based segments are likely to exhibit similar price and product feature elasticities, i.e., respond similarly to changes in the marketing mix (Moriarty and Reibstein, 1986).

2. *Segments should be robust and generalizable.* Accurate and reliable market data should be used and appropriate statistical techniques employed to form the segments (Wind, 1978). Merely surveying the opinions of buying group members about their firm's needs may not provide suitable data. Also, the use of "simple" cluster analysis procedures often fails to produce robust groups of firms. To permit generalization, the sample should be representative of the total market, and the subjects of the study should be respondents who are engaged in actual decision making and product usage (Wind, 1978). Hence, the segments formed should be robust and generalizable, i.e., replicable and not an artifact of variability of the sample chosen or of the specific technique used for data analysis (Dowling and Midgley, 1988).

3. *Segments should be testable for time dependence.* The procedure should be capable of detecting intertemporal shifts in segments (Calantone and Sawyer, 1978; Wind, 1978). Needs-based segments allow assessment of segment stability over time by detecting shifts in segment preferences, and customer switching between segments. When segments are based solely on descriptor variables, it may be quite difficult to link changes in these variables to changes in needs. This criterion is important for markets characterised by technological innovation where customer needs can be influenced by new technologies. (Our data however, do not permit us to meet this criterion in the following illustration.)

4. *Segments should be identifiable.* The success of a differentiated marketing strategy depends upon the ability of the firm to reach its target markets (Choffray and Lilien, 1980a). Therefore, segments should be identifiable by easily measured and/or available segment descriptors to allow this accessibility (Kotler, 1991).

5. *The segments should be managerially usable.* The segments

should incorporate institutional and resource constraints to facilitate the determination of useful target markets (Plank, 1985). Segment profiles should also reflect substantive developments in marketing knowledge such as the adoption and diffusion of new products. In addition the segmentation procedure should be adaptable to a variety of situations.

We now outline a three stage segmentation procedure, evaluate it against the above mentioned criteria and illustrate its application (Exhibit 1).

Step 0: Set strategy objectives for segmentation. This preliminary but vital step (implied but rarely cited formally in the literature) suggests that the segmentation procedure is a means to satisfy information needs for developing corporate and/or marketing strategy (Chéron and Kleinschmidt, 1985). For example, if the strategic objective is to "develop and market new information technology products," then the segmentation must group customers based on their (different) propensity to adopt such technologies; indicate who those customers are (type of firm, size, industry, location, and the like), and how best to reach them (information needs, media usage, etc.). This preliminary step guides the specifics of the three stage procedure.

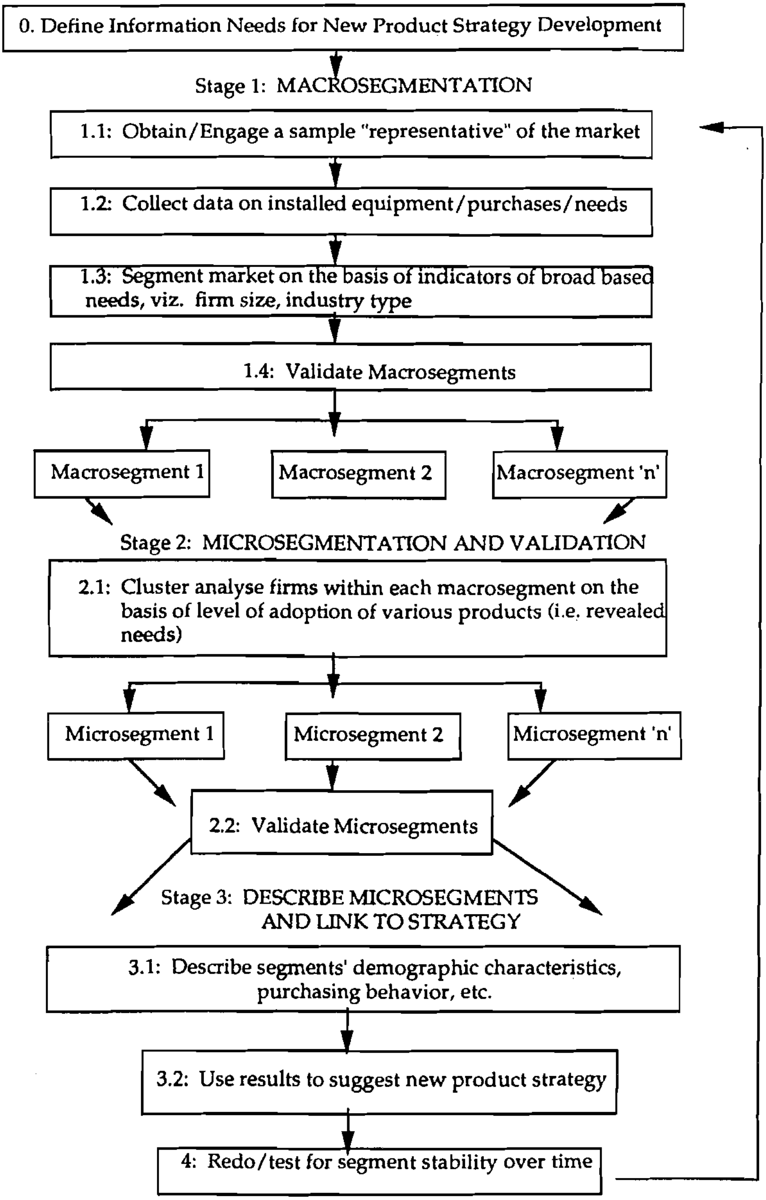
Stage 1: Macrosegmentation

Step 1.1: Obtain/engage a sample "representative" of the industry. Many lists of businesses are available from which samples may be drawn. A representative sample of firms that use a range of products to solve a particular set of needs is needed to make reliable and valid market estimates. Probability sampling methods and weighting procedures can be used to ensure that sample data can be generalized to the total market. A secondary sampling within the sample unit may be needed to address the heterogeneity of needs within an organization so that the appropriate members of the decision-making unit (DMU) can be identified and measured (Brown and Brucker, 1990).

Step 1.2: Collect data on installed equipment, purchases or future customer needs. The collection of data on the equipment in use and date of acquisition will indicate both the time and level of adoption of the equipment by the organization. The consumption

Exhibit 1

Proposed Market Segmentation Process



and ownership of various portfolios of products represent a firm's way of solving its problems. Product ownership data also have other desirable characteristics: (a) they are the result of decision making and represent actual behavior; (b) they are an objective measure that does not depend upon self-reports of respondents, upon their behavioral intentions, or upon the perceived benefits and criteria employed in product selection; (c) they are the result not only of benefits and solutions to problems sought, but also of the impact of other factors such as financial and organizational constraints, variables that are often neglected in studies of purchase potential, and (d) these data allow monitoring of the adoption of complementary and substitute products.

Note that methods like conjoint analysis and value-in-use analysis (Anderson, Jain and Chintagunta, 1993) provide direct and indirect methods for inferring customer values and needs. Ideally, one should combine such need-based data (past purchase data plus stated and inferred need-data) in the segmentation procedure. In practice, such multiple data sources are rarely available; hence we will focus on the use of past purchases and installations data in this paper.

Step 1.3: Implement macrosegmentation. Macrosegmentation is designed to delineate firms that have broadly similar needs and reduce the total market to generally manageable segments. Wind and Cardozo (1974), Choffray and Lilien (1980a), and Shapiro and Bonoma (1984) suggest a macrosegmentation of the total market based upon easily identifiable variables that are significantly related to the benefits and/or solutions to problems sought. Size of firm/establishment and type of industry are often two such variables. (Other variables that may be relevant in certain circumstances are: plant characteristics, location, economic factors, the nature of competition, etc.)

The type of industry as a basis for macrosegmentation is important since the need for various types of products often depends upon their usefulness to a particular industry. The size of a firm as a basis is also important because different size firms will typically have different usage requirements for products. Segmentation by size can also help to eliminate scale effects when it is important to know about the level of adoption of a particular product, process or technology. Moriarty and Reibstein (1986) illustrate, however, that the use of these variables alone is not as effective as more direct measures of need. Hence, there is an added necessity for microsegmentation.

Step 1.4: Validate macrosegments. A macrosegmentation scheme can be validated by showing that the resulting macrosegments differ from each other on the basis of the level (or timing) of adoption of various products and services. (Analysis of Variance can be used to detect such differences.) If some macrosegments are not different then they can be combined prior to the search for microsegments.

Stage 2: Microsegmentation and Validation

Step 2.1: Implement microsegmentation. This step involves further segmentation of each macrosegment based on benefits and/or needs. Operationally, firms should be grouped on the basis of time or level of adoption of relevant new products, resulting in microsegments of firms employing similar solutions to satisfy the same types of need. (The data on level of adoption is obtained from Step 1.2 and a cluster analysis procedure employed to develop microsegments.)

Step 2.2: Validate microsegments. As in Step 1.4, the microsegmentation results should be assessed for their face validity and the statistical significance of differences between the resulting microsegments on the basis of timing or level of adoption. If perceptions of future needs data has been collected, they can also be used to help validate the microsegments.

Stage 3: Describe Microsegments and Link to Strategy

Step 3.1: Characterize microsegments. In this step managerially relevant demographic, purchase decision making, media and organizational variables (segment descriptors), should be identified that characterize the segments. Analysis of variance-based methods or multiple discriminant analysis should be used to test for segment-specific differences here.

Step 3.2: Use the results to suggest strategy. Reflecting the objective in Step 0, Steps 1.1 to 3.1 indicate the number of firms in each market segment, the various levels of adoption of products, and the demographic, media and organizational characteristics of the different segments. This information should then be incorporated in a firm's marketing planning procedure as the basis for developing segment-specific strategies. Berrigan and Finkbeiner (1992) describe in detail, how following the earlier steps, the results should be used to analyze market opportunities and threats such as areas of growth, rapid adoption, penetration by competitors, switching behavior, etc. These results can then be used to guide new product marketing programs.

Step 4: Redo/Test for segment stability over time. Markets and customer needs evolve, so the stability of the segmentation results should be evaluated over time. Differences may occur at both the macro and microsegmentation levels of analysis. For macrosegments, change could be a function primarily of the size of the firm or its growth strategy (e.g., diversification). For microsegments, the rate of technological change within an industry should be one prime determinant of the rate of segment change. Other variables that could cause segment instability include: the entrance or exit of a major new supplier, a change in the concentration ratio of the suppliers or the buyers, a dramatic change in economic conditions (e.g., a recession), etc. The appropriate time period for testing segment stability depends upon the significance of changes occurring in these market related and technological variables.

The procedure outlined in this section has been designed to deal with three of the major shortcomings of past research: the lack of generalizability of many segmentation studies, product specific segmentation, and a potential lack of segment stability over time. The usefulness of Stages 1 and 2 of our approach is best illustrated through an application using commercially available data. (Unfortunately, data to illustrate Steps 3.2 and 4 was not available.)

AN ILLUSTRATIVE APPLICATION OF THE PROCEDURE TO THE INFORMATION PROCESSING MARKET

Step 0: Identifying information needs for new product strategy development. The firm under consideration operates in the telecommunications/information processing market. It is considering a number of product strategies and wants to identify firms that have been either early or heavy adopters of previous generations of telecommunications or information processing equipment. Such organizations also tend to adopt other technologies early, and their behavior can be used to identify emerging needs. Alternatively, they might serve as appropriate targets for the early selling effort for other new products (Rogers, 1976; von Hippel, 1986, 1988). Such a firm could follow up this research with a conjoint analysis study as the product development process proceeds to allow an updating and refinement of the segmentation.

Steps 1.1, 1.2: Collection of a representative sample of data. The data we used is from COMTEC, available from Computer Intelligence, Inc. The COMTEC database on information processing equipment is obtained as a result of surveys at approximately 8000 US public and private sector establishments, involving interviews with approximately 35,000 executives. The survey covers a range of information handling products including computers, telephone systems, reprographic products, typewriters and word processors, facsimile and telex systems. The data collected includes product make and model, number installed, features, applications/usage, and time of adoption.

The COMTEC sample represents all US establishments that are current and potential users of information processing equipment. It achieves representativeness by stratified random sampling, using size of establishment and industry type as the stratifying variables. COMTEC samples a disproportionate number of medium and larger size firms because they acquire more information processing equipment. The sample, broken down by industry type and establishment size, is shown in Appendix 1.

Step 1.3: Macrosegmentation. The need for information processing depends on size of establishment and type of industry. To illustrate our procedure and to develop manageable macrosegments, we combined the size categories into three groups (less than 100 employees, 100-499 employees and greater than 500 employees), and the industry categories into four broad economic sectors (manufacturing, services, non-profit, and other). The combination resulted in 12 macrosegments, two of which we display here to illustrate the procedure for creating microsegments. The twelve macrosegments along with the sample sizes are shown in Exhibit 2. In a practical application, the number of macrosegments to be formed would be a direct consequence of the decision made in Step 0. The other alternative is to search through various logical combinations of size and industry groupings to derive the most parsimonious set of macrosegments.

Step 1.4: Validate macrosegments. We used analysis of variance to verify that the macrosegments reported in Exhibit 2 were different from each other in terms of their use and ownership of information processing products. Exhibit 3 describes the product variables. Note that items 1 through 7 simply represent adoption, while variables 8 through 11 represent indicators of substitution phenomena (fax machine for telex machine, for example) that are critical to identifying early-adopting sectors. To keep our illustration as simple as possible, Exhibit 4 displays the results of separate ANOVAs for each product variable using industry and size as blocking variables. (The use of separate ANOVAs can create a problem when trying to control the overall error rate or when a linear combination of the dependent variables provides evidence of inter-group differ-

Exhibit 2

Macrosegmentation of 1985 COMTEC Data

Size	Industry Sector				
Number of Employees	Manufacturing	Services	Non Profit	Other, Multi-Industry	TOTAL
Less than 100	781	2644	1094	807	5326
100-499	757**	417	374	171	1719
Greater than 500	348	161	209	63**	781
TOTAL	1886	3222	1677	1041	7826*

* These 7826 establishments include those noted in the Appendix less those with data missing that we needed for our analyses.

** Macrosegments chosen for in-depth analysis.

Exhibit 3

Product Variables

1. Number of phones at establishment.
2. Number of copiers--duplicators.
3. Number of machines used for word processing (e.g., electric, electronic, and manual typewriters, etc.).
4. Number of personal computers.
5. Number of (mainframe) computer terminals.
6. Number of dedicated telex machines.
7. Number of fax machines.
8. Personal computers as a percentage of the total number of machines used for word processing.
9. Number of word processing workstations as a percentage of the total number of machines used for word processing.
10. Personal computers as a percentage of the total number of computer outlets.
11. Fax machines as a percentage of the total number of fax and telex machines.

ence. MANOVA is a more appropriate procedure to use in these circumstances.)

All 11 ANOVAs were significant with strong main effects and we found a significant two-way interaction for six product variables. This analysis shows that the macrosegments in Exhibit 2 differ from each other in their adoption and/or use of information technology. We now focus on two macrosegments for further analysis. The 63 large firms in the "other" or multi-industry macrosegment illustrate our procedure for a difficult macrosegment to analyze, while the 757 firms in the 100-499 employee manufacturing industry segment represent a more homogeneous group (and a less difficult test for the procedure). A profile of average values of the 11 product variables for these two macrosegments compared to the overall averages for the total sample is shown in Exhibit 5.

Step 2.1: Creating microsegments. We used a k-means clustering

Exhibit 4

Macrosegmentation Validation:

This exhibit demonstrates that industry and size are significant macrosegment variables except for fax machines, where size has no significant main effect.

ANOVA Summary Results

	Product Variable	Overall F (Total df = 7825)	Level of Significance (p-value)		
			Industry	Size	Interaction
1.	Phones	37	.00	.00	.67
2.	Copiers - Duplicators	42	.00	.00	.06
3.	Word Processors	42	.00	.00	.00
4.	Personal Computers	7	.00	.00	.15
5.	Mainframe Terminals	26	.00	.00	.00
6.	Telex	4	.00	.00	.59
7.	Fax	2	.00	.51	.46
8.	Ratio Personal Computer to Word Processing	6	.00	.00	.00
9.	Ratio Workstation to Word Processing	28	.00	.00	.00
10.	Ratio PCs to Mainframe Terminals	16	.00	.00	.01
11.	Relative use of Fax to Fax plus telex	228	.00	.00	.00

algorithm (Hartigan, 1975) and the segmentation procedure suggested by Dowling and Midgley (1988) to obtain a number of homogeneous microsegments from each macrosegment. K-means is a clustering algorithm that is robust to many of the problems inherent in cluster analysis (Punj and Stewart, 1983). The overall clustering of firms into reliable and robust microsegments is out-

Exhibit 5

Profile of Two Illustrative Macrosegments:

Product Variable	Large Multi-industry Firms	Medium Size Manufacturers	Overall Sample
1. Phones*	.63	.38	.69
2. Copiers - Duplicators*	.02	.02	.07
3. Word Processors*	.22	.10	.29
4. Personal Computers*	.03	.02	.04
5. Mainframe Terminals*	.17	.07	.07
6. Telex*	.00	.00	.00
7. Fax*	.00	.00	.00
8. Ratio Personal Computers to Word Processing	.14	.14	.11
9. Ratio Workstations to Word Processors	.09	.04	.04
10. Ratio PCs to Mainframe Terminals	.18	.23	.22
11. Relative Use of Fax to Fax plus telex	.51	.29	.14
Number of Firms in Segment	63	757	7826

* Variable reported on a per-employee basis

lined in Appendix 2. Sufficient numbers of firms were contained in each segmentation scheme to proceed to validate the output from this phase of the data analysis: namely a five-group solution for the "large size, multi-industry firm" segment (n = 15, 9, 13, 13, 12), and a nine-group solution for the "medium size manufacturing" segment (n = 22, 57, 49, 88, 224, 54, 90, 109, 49).

Step 2.2: Validate microsegments. We conducted three types of validation procedures: First, we ran the k-means algorithm five times with five different start points to test whether the starting partition affected the ultimate assignment of firms to clusters. Dowling and Midgley (1988) advocate this type of validity check after outliers have been deleted from the data set to provide protection against finding a local, versus global solution (or a local optimum value of the Marriott statistic, see Appendix 2). For both optimal solutions, the firms were always assigned to the same cluster. (This however was not the case for the eight and ten group solutions in the large firm, multi-industry macrosegment which had similar Marriott statistics to the nine group solution.)

Our second validity test was an assessment of the robustness of the k-means clustering algorithm. For both optimal solutions we compared the results derived from the k-means procedure with Anderberg's (1973) nearest centroid sorting algorithm available in SPSS. When the k-means cluster center values of the clustering variables were used as the initial starting values for the SPSS Quick Cluster algorithm, both approaches assigned firms to the same two sets of microsegments. However, when the SPSS Quick Cluster algorithm selected its own starting partition (the default option) only 90% of firms were assigned to the same large size, multi-industry firm microsegments, and 86% to the same medium size manufacturing microsegments. The question of which set of assignments is better is answered by the third validity test.

We used multiple discriminant analysis to assess the power of (a linear combination of) the clustering variables to predict microsegment membership. For the two k-means sets of microsegments, the clustering variables correctly predicted 98.4% of the large size, multi-industry firms and 94.7% of the medium size, manufacturing firms. The equivalent figures for the SPSS clustering algorithm were 93.6% and 91.1%, suggesting that the k-means algorithm outperforms the nearest centroid sorting algorithm.

More extensive validation procedures should be conducted before the specific microsegments developed in this case study are used for theory testing or commercial application. However, the work described here illustrates the essence of our validation step.

Step 3.1: Describe the microsegments. A profile of each microsegment can be developed using the clustering variables and a supplementary set of descriptor variables. Descriptor variables should provide information relevant for a company's strategy formulation and implementation. Here we provide a brief description of the five large size, multi-industry firm microsegments simply to illustrate how this stage of our segmentation procedure would be applied. (Note that while we have similar results for the microsegments derived from the other larger macrosegment, this small macrosegment is the easiest to describe and understand.)

Exhibit 6 shows the eight segmentation variables that were significant discriminators between the five groups. The lower part of the exhibit displays four descriptor variables that are significantly different across the microsegments (determined using ANOVA). These are the types of variables that may be used to supplement the microsegment profile constructed from the segmentation variables. We see from this profile that the 12 firms in segment E have the smallest existing investment in information technology and low forecasts for future expenditure. This segment is comprised mostly of construction and transport companies. Segment D, on the other hand, has the highest overall investment in information technology. Eleven out of the thirteen firms in this segment are telephone/utility companies. This type of interpretation provides a face validity check on the microsegments and can be combined with other information to suggest which microsegments may be more innovative and/or susceptible to new products (e.g., probably not segment E). Firms in segments A and D are most likely to be early/heavy adopters and should be targeted for in-depth analysis of needs (i.e., candidates for a conjoint analysis or value-in-use study) and/or heavier than average new product promotional effort.

Ideally, the set of descriptor variables should include direct or surrogate measures of the buying process and sources of information used by typical firms in each segment. (The COMTEC data base did not include this information.) The geographic location and the SIC industry classification of firms (not reported here) are also important descriptors. These variables can be used to help locate networks of organizations that interact with each other in the diffusion of innovations.

Step 3.2: Use results to suggest strategy. From the previous data

Exhibit 6

Profile of Five Microsegments
in Illustrative, Large Multi-Industry Macrosegment

Discriminating Segmentation Variables[1]	Segment A	B	C	D	E
1. Phones	++[2]	– –	0	++	– – –
2. Copiers - Duplicators	+++	– –	–	+	– – –
3. Word Processors	0	– –	0	++++	– – –
4. Personal Computers	–	–	0	++++	–
5. Mainframe Terminals	–	–	0	++++	– – –
7. Fax	++++	– –	– – – –	0	– – –
9. Ratio Workstation to Word Processing	++	+++	– –	0	– –
11. Relative Use of Fax to Fax plus Telex	+	+++	– –	++	– – –
<u>Discriminating Descriptor Variables</u>					
* Percentage White Collar Workers	+	–	0	+	– –
* Desk workers as % of White Collar	0	0	0	0	–
* Data processing budget	–	– – –	– –	++++	– – –
* Number of PCs planned for installation over next 2 years	– –	– – –	– –	++++	– – –
Percentage of Macrosegment	24%	15%	21%	21%	19%

Notes: 1. Numbers correspond to Exhibit 3, including the 8 (of 11) variables significant in discriminating between segments.

2. Legend: '0' = average, '+' = 25-50% above average, '++' = 50-75% above average, '+++' = 75-100% above average, '++++' > 100% above average.

Negative signs interpreted the opposite way to the positives.

analysis we have a basic description of the various microsegments. This information can be used to select target segments of firms and to develop segment specific marketing strategies for equipment manufacturers and resellers. For example, von Hippel (1986, 1988) has proposed that data from the analysis of the needs of "lead user" firms can improve the success rate of new products. The formation of microsegments using this type of data can help isolate such lead user segments. These firms may be approached to help manufacturers generate new product concepts and act as test sites for new product evaluation. Their strong need for innovation also identifies them as the first firms that should be approached by sales people selling new products. However, we do not have the detailed information on the reasons for such needs or for the best ways to reach these early adopters. Such data are not available in the COMTEC data base; however the research results reported here suggest which (types of) firms may be contacted to provide such information. Thus while the segmentation procedure has been used in a rough way by itself, it can also be used as a sample frame to identify those establishments that should be subjected to further in-depth research and analysis. (See Berrigan and Finkbeiner, 1992 for more extensive discussion and Sinha, 1989 for an illustration of using segmentation data in this way.)

Step 4: Redo/Test for segment stability over time. As suggested earlier a number of factors could cause the basic market structure to change over time, or cause firms to migrate from one macro or microsegment to another. Indeed, we view segmentation as an evolving process that a firm must engage in over time, rather than a definitive study. Measuring change in such a situation can be quite subtle (Dowling, 1991). At the macrosegment level of analysis, measurements are likely to be more reliable because the selection and definition of the segmentation variables (e.g., size, industry, etc.) could remain unchanged from one data collection period to another. With a constant measurement instrument it is relatively straightforward to identify if a firm has shifted from its previous macrosegment. For example, further study of characteristics that can help identify and describe firms like those in microsegments A and D would seem quite valuable here (e.g., Sinha (1989)).

Measuring microsegment change, however, may be more tricky.

The simplest case would occur when both macro and microsegments are measured using the same set of variables and the optimal number of microsegments (as determined by the Marriott statistic) remains the same. If a firm is a member of its previous microsegment (as defined by the profile of segmentation variables and not its association with other firms) then no change has occurred. Alternatively, the most complex case would occur when the measurement structure changes and, hence, microsegmentation membership changes by definition. Between these two extreme cases are a variety of alternatives.

Testing for segment stability over time is thus a two stage process. First, stable "measurement rulers" for macro and microsegmentation must be developed. These measurement rulers are a combination of the segmentation variables and the statistical procedures used to form segments. The second stage entails assessing whether the individual firms have changed segments. Given a set of stable measurement rulers this stage requires only a simple comparison of pre and post segment membership. The COMTEC data base, which is essentially an independent sample of firms collected each year, does not permit us to test for segment stability.

CONCLUSIONS

We illustrated the proposed segmentation procedure by segmenting the U.S. information processing market. We used a representative sample of the industry and obtained a range of different microsegments based on purchasing behavior. Identification of these segments by available descriptor variables was possible so that product-marketing programs could be developed for these segments. The procedure could be adapted easily to fit the needs of a particular organization by changing the definitions of economic sectors, levels of adoption, and the like. Hence, the procedure is transportable. Also, due to the regular nature of the collection of the underlying data base by COMTEC, the procedure can be repeated over time.

Our major contribution is one of synthesis and technology transfer. We have outlined a systematic procedure for developing and testing the validity of a business market segmentation procedure that is aimed at supporting product decisions. We then demonstrated the viability of substantial parts of this procedure by applying it to a commercially available set of data. While we have used some of the conceptual structure and methodology from Choffray and Lilien (1980a,b), we have extended it to deal with revealed customer solutions. We have also developed the important issue of validation.

Our procedure is far from a final solution to this problem, however. First, researchers must collect or gain access to data on past-purchase behavior or needs as we did here from a representative industry sample. While we argue that such data are relevant for meaningful segmentation, they may be difficult and/or costly to obtain.

Second, while we propose a cluster-analytic solution to the microsegmentation problem that incorporates a number of tests for robustness and validity, there is no comprehensive theory and associated accepted operational procedure to solve the problem of what constitutes the "optimal" segmentation structure for a market. The solution we recommend is state-of-the-art now, but it requires comprehensive testing and further development.

Third, while we alluded to the need to measure and test for cluster stability over time, we also outlined some conceptual and operational problems inherent in such a task. Further research in this area is clearly needed.

In sum, while more work would clearly be desirable, the integrated structure we propose here can provide a useful procedure for academics interested in business market segmentation research and those practitioners in need of a sound and useful procedure to address their business market segmentation problems in the new product arena.

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APPENDIX 1. Correlation Matrices

This exhibit shows the COMTEC Wave II (1985) sample size broken down by industry type and establishment size

Industry Type		Establishment Size, Number of Employe				
	Total	0-9	10-19	20-49	50-99	100-249
Agricultural, Mining, Construction	536	227	112	81	45	46
Manufacturing, Durable	1040	80	82	114	112	235
Manufacturing, Non-Durable	888	81	71	116	119	226
Transportation & Utilities	467	83	77	93	56	70
Retail	1006	485	184	16	94	52
Wholesale	523	200	109	107	30	38
Finance	592	166	95	99	53	74
Business & Professional Services	803	312	128	99	54	89
Miscellaneous Services	661	324	95	83	42	60
Health	434	172	32	30	32	70
Educational Services	412	46	27	104	99	71
Government - Federal, State, Local	560	100	65	92	58	91
TOTAL	7923	2276	1077	1179	794	1122

APPENDIX 2

Cluster Analysis to Create Microsegments

Prior to using the k-means procedure, we needed to identify and remove outliers because of the detrimental effects that such observations have on the performance of the clustering algorithm (Punj and Stewart, 1983). We used single linkage clustering for this purpose (Choffray and Lilien, 1980b). Single linkage clustering links an observation to a cluster based on the *minimum* distance between that observation and *any* observation in a cluster.

A high value of the distance associated with an observation connecting to a cluster means it is unlike *any* of the other observations in any cluster. Exhibit A2-1 plots, for each of the two macrosegments, the value of the similarity measure (euclidean distance here) against the order in which the firm (observation) joined a cluster. This exhibit makes it simple to identify and discard outliers. After examining the raw data for the last firms joining these chains, one extreme firm was deleted from the large firm, multi-industry macrosegment (n now equal to 62) and 15 extreme firms were deleted from the medium size firm, manufacturing macrosegment (n now equal to 742).

We now used the k-means clustering algorithm to group the firms in each macrosegment into microsegments. A crucial issue here is to select the appropriate number of segments. Marriott (1971) recommends a sound way to identify an appropriate solution from a range of possible alternatives. He defines:

$MS(g) = g^2|W_g| / |T|$ where

$MS(g)$ = Marriott Statistic as a function of g^2

g = number of groups in the solution

$|W_g|$ = determinant of within-group variance/covariance matrix for g-groups

$|T|$ = determinant of total variance-covariance matrix

and suggests that an optimal number of groups is that value of g that minimizes MS(g) in the equation above.

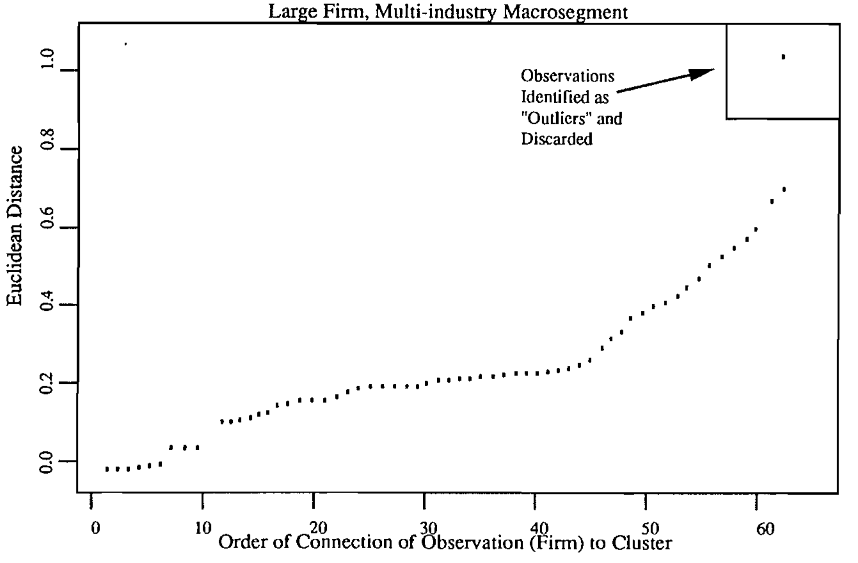
MS(g) trades off within-group homogeneity against the number of groups and focuses on both the isolation of clusters and their internal homogeneity. It indicates one group for a unimodal distribution of inter-item distances and will remain at a constant value for a uniform distribution of inter-item distances as g varies. (These two cases imply that the data is not suitable for cluster analysis.) While there is no test of significance for a Marriott statistic, Everitt (1974) suggests that the selection of the lowest value of this statistic computed over a range of alternative segmentation schemes (i.e., different values of g) is an appropriate and defensible solution to the "numbers of clusters" problem.

Exhibit A2-2 reports the Marriott statistics for the two macrosegments and indicates that the optimal number of microsegments are: five for the multi-industry segment and nine for the medium size manufacturing segment. (While the ten group solution had a similar Marriott statistic for the manufacturing segment it produced a less reliable solution, an issue noted in Step 2.2.)

Exhibit A2.1

Single Linkage Clustering Outlier Detection:

Observations in upper right corner of the plot are for (in euclidean distance terms) from all for other observations and are noted as outliers.



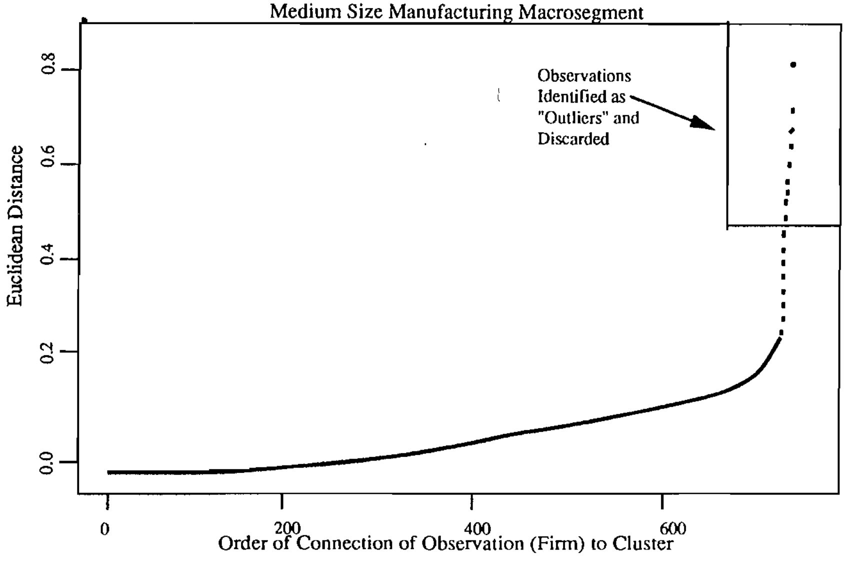


Exhibit A2.2

K-means Clustering Results in Two Illustrative Macrosegments

Number of Groups	Marriott Statistic: Large Firm, Multi-Industry Segment	Marriott Statistic: Medium Size Firm Manufacturing Segment
2	.808	.669
3	.521	.498
4	.316	.499
5	$\boxed{.182}$	.472
6	.264	.421
7	NA	.261
8	NA	.182
9	NA	$\boxed{.177}$
10	NA	.178

NA = not available

$\boxed{}$ Solution choice