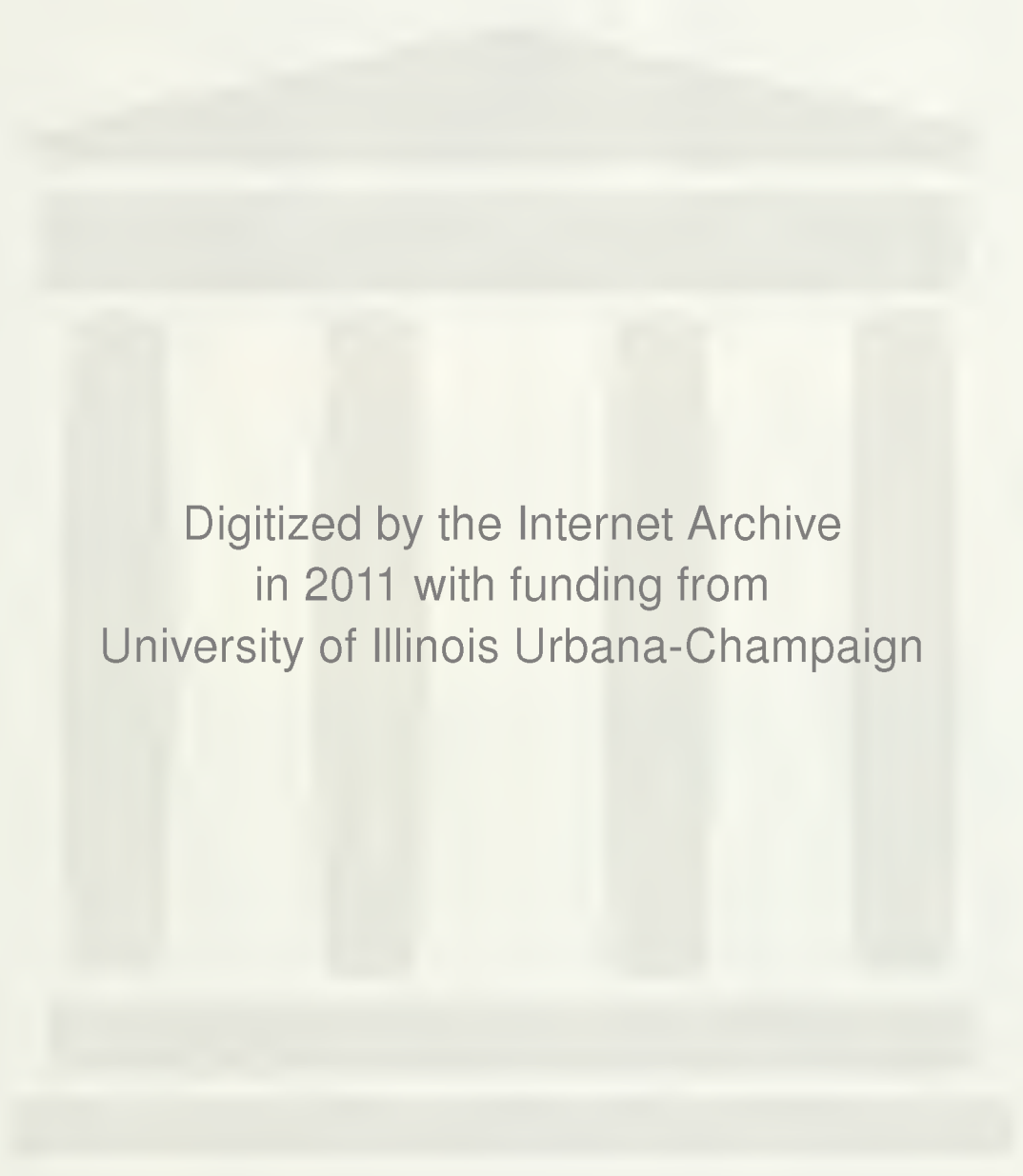


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AN APPLICATION OF THE MULTIVARIATE PROBIT MODEL
FOR MARKET SEGMENTATION AND PRODUCT DESIGN

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ABSTRACT

The tradeoffs among product attributes are typically determined from preferential data on a number of product concepts. The "No-Yes" data on intentions to buy a product concept relative to a previously intended purchase of an existing brand are perhaps more useful for computing these tradeoffs. These measurement concepts are explored using the multivariate probit model, which is ideally suited to the analysis of the dichotomous data. Results of a pilot application indicate that procedures can be developed which can convert data into probability response coefficients applicable to each product attribute. This paper demonstrates the feasibility of applying this model to the two substantive problems of product design and market segmentation.

AN APPLICATION OF THE MULTIVARIATE
PROBIT MODEL FOR MARKET
SEGMENTATION AND PRODUCT DESIGN

1. INTRODUCTION

The fundamental premise of the theory of market segmentation is that the responses of consumers to the marketing mix is divergent. Since the early beginning of market segmentation by Smith [13] marketers have embraced this concept and have geared attempts to understanding innovativeness, deal proneness, price sensitivity, and advertising elasticities of alternative subsets of the market [2]. It is now accepted practice to attempt to identify the characteristics of those consumers in an attempt to channel our marketing efforts and programs to a select few of the consumer market.

Although we have come a long way in the methodology of market segmentation, one of the areas long avoided by market researchers has been a method to design products to meet the needs of the divergent market segments. Issues include the actual determination of products to meet the needs of the market as well as the number of brands/models/product variations necessary to exploit the true potential of the market.

Past approaches to product design have left the manager with a number of useful concepts. Johnson's [7] article illustrates the potential of discriminant analysis in deriving perceptual spaces of homogeneous subsets of consumers. This combined with ideal points may indicate voids in terms of unfulfilled needs and wants or areas of limited competition. By employing Hayley's [6] concept of benefit segmentation, it may be possible to derive another space based on benefits or importances of alternative product attributes. Although measuring and modeling the individual is no problem, it is apparent that in

most methods the respondents must first be clustered for homogeneity in responses before ideal points can be clustered. Next, we must assume that the weights of these attributes are similar within each cluster or go back to individual analysis. The potential for large numbers of clusters within clusters is great.

Recent methodological developments such as multidimensional scaling and conjoint measurement enabled use of preferential and perceptual data for existing products. Typically, these methods provide estimates of implicit or subjective tradeoffs among the product attributes for each respondent. This assumes that products are viewed as bundles of attributes [10]. The tradeoff estimates are then employed in clustering respondents in order to identify market segments.

The conjoint measurement approach of determining tradeoffs is also proven to be valuable in answering questions of new product design [8, 12, 17]. The methods of determining tradeoffs depend upon the nature of response obtained and its scale properties. A typical research design involves presentation of a number of product concepts designed according to a (full or fractional) factorial design with respect to product attributes and eliciting a ranked preference response from the respondents. In some studies, ordered categorical response data such as "excellent buy" to "poor buy" has been measured [4]. These responses do not truly tap the intended behavior of the respondents.

One's success of identifying segments tends to increase as one uses data that are closer to actual buying behavior. Since actual behavioral data are impossible to obtain for new product concepts, various surrogates such as intentions, preferences, or attitudes have been proposed and utilized. The approach taken by this research is to take the consumer's intended purchase compared to various new product possibilities. Thus the "new products" may

compete with far different existing products even within the same homogeneous segment of consumers. This would, in part, satisfy Stefflre's [14] concern about the need to clarify the competitive nature of the market.

This research also differs from past approaches in that respondents are asked to choose between their existing favorite and each new product possibility. The dependent variable is essentially a No-Yes (0, 1) dichotomy where the respondent either selects the existing brand or one of the new product combinations.

The utility function to be fitted to the "No-Yes" type data should be one of a threshold type. While these threshold data can be analyzed in a number of ways, the multivariate probit model is quite appealing for two basic reasons. First, it fits a probability function which is a defensible representation of the underlying behavioral process. Second, it enables the No-Yes data to be smoothed so as to derive probability of buying estimates for various product concepts. While this model has been documented in the literature for some time [1, 16], it has only recently been applied in the area of marketing [9]. Also, there has been no reported application of the multivariate probit model to market segmentation or product design.

A significant thrust of the product design research has been one of choosing the "best" or optimal product concept(s) for further investigation (e.g., prototype development by R&D) by a firm. This application is quite appropriate for a consumer packaged goods firm which tends to market one or several brands to a potential market or a durable goods manufacturer concerned with the extended problem of choosing the particular options faced by firms such as automobile manufacturers, appliance manufacturers, manufacturers of stereo-type equipment and camera manufacturers. The question involves determination of how many models of the same basic design (i.e., what options on each) should be made available in the marketplace.

We have so far indicated several interrelated aspects, methodological as well as substantive. Briefly, these are: (1) need to use behavioral response data for market segmentation analysis; (2) suitability of multivariate probit model for such analysis; and (3) need to tackle the problem of determining design choices for an appliance type product. Our objective of this paper is to synthesize these trends in a pilot application. It attempts to utilize the multivariate probit model to determine subjective tradeoffs implied by behavioral intention responses for use in market segmentation as well as design of options for a product. The substantive problem arose in the choice of specific options to be provided for a basic camera.

The remainder of this paper is organized into five sections. The second and next section briefly reviews the theory of multivariate probit model and shows how it can be applied to the determination of tradeoffs among product attributes. The third section describes the research design used in this pilot application and analysis methods. The results are reported in the fourth section. Finally, the potential of this research for marketing decisions is discussed along with a few further research ideas.

I. THEORY OF MULTIVARIATE PROBIT MODEL

The literature on multivariate probit model refers to the choice process of a sample of individuals taking a particular action or not (e.g., for buying a car or not, etc.). The action (or response) is then related to a number of characteristics of the individuals. The ensuing discussion of this model is suitably adapted to the situation of product concept evaluation.

Model: Let X_1, X_2, \dots, X_n denote product attributes used in the design of m product concepts. Let x_{ij} denote the value of the j th attribute for the i th concept, $j=1, 2, \dots, n$; $i=1, 2, \dots, m$. Let y_i denote the behavioral intention responses (yes=1, no=0) toward the i th concept from one respondent. The multivariate probit model postulates that the probability of responding yes to the i th stimulus (or $y_i=1$) is described by a normal process. It assumes that the X variables are summarized into an index, I , which is distributed as a standard normal variable. The particular relationship between the index, I and the X variables is assumed to be linear, i.e.,

$$I = \beta_0 + \beta_1 X_1 \dots + \beta_n X_n \quad (1)$$

Further, for each product concept, the respondent is assumed to have a threshold value of the index, I_i , obtained by substituting x_{ij} for X_j into equation (1). Then the probability, P_i , of obtaining a positive response (yes) to i th stimulus is given by:

$$P_i = \text{Prob} (y_i=1) = \text{Prob} (I < I_i) = \int_{-\infty}^{I_i} \phi(u) \, du \quad (2)$$

where $\phi(u)$ is the probability density function of a unit normal variate.

Estimation: Assuming that the respondent gave statistically independent responses to the m concepts, then the likelihood of getting a configuration of (y_1, y_2, \dots, y_m) from the respondent is given by:

$$L = \prod_{i=1}^m \left[P_i^{y_i} (1-P_i)^{1-y_i} \right] \quad (3)$$

Since each P_i is a function of β s, the likelihood, L , is also a function of β s. The β -parameters are estimated by maximizing the likelihood function. The resulting equations to be solved for maximizing L are:

$$\sum_{i=1}^m \left[\frac{y_i}{P_i} - \frac{1-y_i}{1-P_i} \right] \phi(I_i) = 0; \text{ and}$$

$$\sum_{i=1}^m \left[\frac{y_i}{P_i} - \frac{1-y_i}{1-P_i} \right] \phi(I_i) x_{ij} = 0; j=1, 2, \dots, n. \quad (4)$$

These equations are solved using nonlinear iterative methods [3, 15]. A computer program [5] is available for this purpose. The resulting estimates of β 's have some desirable properties when m is large. However, for the product concept problem this is not necessarily so.

Probability Coefficients: We will call the change in the probability of getting a "Yes" response with respect to change in the value of a product attribute as the "probability coefficient." These measure the tradeoffs of the attributes in the overall evaluation of a product concept for yielding the same probability of "Yes" response.

Using equations (1) and (2), the probability coefficient is obtained as:

$$\frac{\partial P_i}{\partial X_j} = \frac{\partial P_i}{\partial I_i} \cdot \frac{\partial I_i}{\partial X_j} = \phi(I_i) b_j ;$$

where b_j is the estimate of β_j (i.e., solution of the equation system (4)). Thus, the change in probability depends upon b_j and all $b_k x_k$ terms which define the point (I_i) of the unit normal for the proposed new product.

To make the model operational for market segmentation or product design, we need to compute a set of probability coefficients for each respondent to permit inter-respondent comparisons. This requires determination of $\phi(I_i)$ and b_j . Owing to the computational aspects of the probit model, special methods are required for determining $\phi(I_i)$ and normalizing the b s.

Determination of $\phi(I_i)$: The value for $\phi(I_i)$ has been approximated by evaluating $\phi(u)$ at the point where,

$$\int_{-\infty}^{\infty} \phi(u) \, d u = \frac{r}{m}$$

where r = the number of yes responses to all proposed product concepts; and
 m = the total number of proposed product concepts.

Because of the S-shaped cumulative normal function, this $\phi(u)$ adjustment has the effect of suppressing probability response for those very unlikely to buy (r/m near 0) or those very likely to buy any product concept (r/m near 1).

Normalization of b_s : The coefficients hereafter referred to will essentially be "normalized" b coefficients designated as B_j . Individually derived b_j exhibited very large values often reaching as extreme as ± 5 . This is because the algorithm attempts to fit the data to either 1 (interpreted as certainty) or 0 (interpreted as absolute 0). In a sense it seems implausible that a consumer would, with certainty, buy a product that he intends to buy. Similarly, it seems unlikely that he would definitely not buy a product that he intends not to buy.

In the spirit of aggregation it seems reasonable to say that the most favorable product concept that the consumer says he will buy really only have a probability of .98 of being realized. Similarly, the most unfavorable product concept might have a probability of being purchased .02 (as opposed to 0). The correspondence of this on the cumulative normal function specifies that our "normalized" B values must be such that:

$$I_{\max} = 2; \text{ and } I_{\min} = -2.$$

Therefore,

$$B_0 + \sum B_{\text{positive}} = I_{\text{max}} = 2$$

$$B_0 + \sum B_{\text{negative}} = I_{\text{min}} = -2 .$$

Taking the difference, we get:

$$\sum B_{\text{positive}} - \sum B_{\text{negative}} = 4$$

or

$$\sum |B| = 4 .$$

This is accomplished by

$$B_j = \frac{4 b_j}{\sum |b_j|} .$$

B_0 can now be easily determined but this is unnecessary as it has no effect on probability of response to new product changes. The probability coefficient (ΔP_j) denoting the individual's response of buying the product concept for changes in the j th attribute is then $B_j \phi(I_i)$. This procedure is appropriate only when there is some variability in the y responses. If all y s were zero or one, the ΔP s are all zero.

III. RESEARCH DESIGN

Data Collection

Respondents selected for the study were a convenience sample of 45 MBA students enrolled in introductory marketing classes. The topic addressed was essentially one of various alternative forms of a new camera. While this sample is not representative of the entire potential market, it is important to note that 73 percent of the respondents owned cameras. As the results of the data analysis will indicate, among the sample surveyed, there was a large variance in preferences as well as film usage and involvement in photography.

The first part of the survey measured general photography-camera preferences and related behavior. Items included: the camera the subject now owns, the brand intended for the next purchase, annual film usage, media exposure, as well as the importance (1 to 6 scale) of a built-in exposure meter, shutter speed adjustment, built-in electronic flash, focus adjustment, and price. A glossary of terms was included to make sure all respondents understood the meaning of the potential camera features.

The proposed new camera was identified as a new pocket camera manufactured by a well-known Japanese manufacturer (the name was disclosed to subjects) of high quality single lens reflex cameras. We assumed that this manufacturer would be interested in anticipated behavior if the camera were to include or exclude the following features: built-in exposure meter, shutter speed adjustment, built-in electronic flash, and a focus adjustment. Since each feature has two possibilities (feature is included or excluded), a total of 2^4 or 16 possible combinations exist. Each respondent was therefore asked if he would buy each of the 16 hypothetical cameras versus the brand previously indicated as the next intended purchase. The price specified for each of the hypothetical cameras reflected the features included. The base price was \$50, and \$15, \$5, \$10, and \$15 was added to the base price for the features of exposure meter, focus adjustment, shutter speed adjustment, and electronic flash, respectively. Thus the most basic model specified was \$50 (no features), and the full feature model was specified at \$95.

From the description, it is apparent that price was treated as a method to recover various costs associated with different product features. This was designed to keep the measurement simple. An alternative approach might be to treat price as another product feature where various price combinations could be considered with various product features. The treatment of price as

a function of features may lead some readers to conclude that the only reason why some respondents preferred fewer options to many was because of increased price; this is not the case. Several respondents indicated during debriefing that they preferred an uncomplicated camera regardless of price.

The probit model was applied to the individual data with the X variables (relating to the exclusion or inclusion of product features) coded in dummy variable fashion as 0 or 1. More complicated product scenarios are possible in which some product attribute such as price or gas mileage in automobiles would be interally scaled. If non-monotonic relationships between purchase probability and attribute level are anticipated, then dummy variables will parallel the concept of ideal points.

Analysis Methods

The data were analyzed using the multivariate probit model at the individual level. Individuals who responded negatively to all of the 16 concept descriptions could not be used in this analysis. This group was treated as a segment by itself and its profile described. We would have a similar difficulty with individuals who responded positively to all 16 descriptions although there were no respondents of this kind in our sample.

As previously discussed, the estimates of β -coefficients for the four design options were normalized for inter-individual comparison. The normalized coefficients, B_s , were then converted into the probability of a positive response, ΔP_j , (i.e., buying the concept) if the respective option were available. The probability "coefficients" were used in developing clusters using McRae's K-means clustering algorithm [11]. These clusters are then the market segments obtained in the analysis. Their profiles are described.

In addition, we related the estimated changes in probabilities with the explicit measures of importances for the four options. Product moment correlations are computed to summarize this relationship.

IV. RESULTS

Positive Responses: The 45 subjects in our exploratory sample turned out to be quite heterogeneous with respect to number of positive (yes) responses to the 16 concepts. The distribution was as follows:

<u>Number of "yes" Responses</u>	<u>Number of Subjects</u>
0	13
1-2	15
3-4	8
5+	<u>9</u>
	45

Model Fit: The probit model fitted quite well for each of the 32 respondents. Although not statistically appropriate, the statistic for testing the joint significance of the four estimated beta-coefficients was found to be significant at better than 0.05 level for 23 out of 32 cases. The other fits were significant at approximately .10 level.

Clustering: The probability coefficients ΔP_j s were used in the clustering of subjects. Using the minimum trace W criterion, 2, 3, 4, and 5 cluster solutions were obtained. The cluster sizes and the value of the criterion are shown in Table 1. Although the 4 and 5 cluster solutions yielded a larger reduction in the within cluster sum of squares, the sizes of individual clusters are too small. In an attempt to generalize from this small sample, we decided on the 3-cluster solution. These clusters along with the previous "all no" response cluster were then the four market segments for these data.

Segments: We can arbitrarily set the change in probability for each of the design options to be zero for the all no-response group. With this addition, Table 2 shows the average changes in probability of "yes" response for the four market segments. We can observe that the market segment numbered 2 is mildly responsive to each of the four design options. Segment 3 is moderately responsive to all but the electronic flash, to which it responds negatively. The fourth market segment is uniformly positively responsive to all the four design options. To investigate these relationships further, we tabulated the members of the four segments by the number of yes responses. These are shown in Table 3. These data suggest that segmentation of respondents by the simple number of "yes" responses would not be highly revealing for the purposes of product design. The respondents of any "yes" category are distributed among all the three market segments 2, 3, and 4.

Segment Profiles: The profiles of the four segments are shown in Table 4. Despite the small samples, a number of interesting differences can be seen. First, the segment 1 (anti to each of the 16 concepts described in this study) appears to be heavy users of film and is more interested in photography. Also, a larger fraction of them owns a single lens reflex camera--which is of higher quality than the product studied here. Segment 2, which is least responsive to design options, appears to be least interested in photography--they never process or print their films, they use a smaller number of rolls of film per year, and rarely read photography-oriented magazines.

The table also shows a partition of segment 1 into two subsegments, 1A and 1B. Segment 1A intends to buy a Kodak instamatic and 1B intends to buy a single lens reflex camera, if they were to buy a camera in the next six months. The profile of segment 1A is more like the least responsive segment 2, while the segment 1B appears to be most sophisticated in its photography

interests. For example, members of group 1B use the most film per year, consider photography as a form of art, and do their own film and print processing. Thus, although its apparent response to the product concepts is totally negative, it may be viable for different (possibly more expensive single lens reflex) cameras. Even though segment 1 is homogeneous in the sense of being non-responsive to the product concepts, it would be in error to conclude that segment members are homogeneous in other respects. In addition, it is possible that in some other research situations that some members of segment 1 would intend to buy the product under all concept specifications. This subsegment would be a most appropriate group to which we would direct promotional and other marketing efforts.

Responsiveness Versus Importance: The response measures (i.e., changes in probability of buying) are related to the explicit measure of importance for each member of the segments 2, 3, and 4. The distribution of correlations are as follows:

<u>Correlation</u>	<u>Number of Respondents</u>
Less than 0.5	12
0.5 - 0.7	5
0.7 - 0.9	4
0.9 and over	<u>11</u>
	32

It is interesting to note the divergence between these two sets of measures. A further predictive or experimental test is needed to determine which of these measures is a good predictor of future brand choice.

V. DISCUSSION AND CONCLUSIONS

The sample, while convenient for illustrative purposes, is clearly restrictive in terms of the diverse segments which exist in the population's response to quality pocket cameras. The methodology does, however, point out a number of product design/segmentation strategies. Figure 1 shows the segments in the two-dimensional space of centroid probability coefficients for focus and flash.

On the basis of positions of segments, a manufacturer may need to consider only two product forms from the possible $2^2=4$ combinations of focus and flash. Thus the data would suggest that the proposed camera have a focus adjustment with optional flash for \$15; if not an option, then two separate products may be required. With a larger sample, additional hypothetical segments such as D and E may emerge. From a qualitative standpoint, the marketer would probably continue to offer the camera with the focus adjustment when faced with group D. Segment E, however, would suggest that a camera without a focus adjustment might be appropriate.

While these qualitative generalizations are useful, similar conclusions might also be derived from more traditional approaches to market segmentation. Specifically, what did we gain by use of the probit model and the related methodology?

First, we have excluded group 1, which either accepts or refuses all product concepts. Secondly, we now have probabilities that can be translated into economic terms. Consider segments D and E, for example. If we offer a camera without a focus adjustment in addition to the two variations previously described, we will be incurring additional product, inventory, and marketing costs that accrue to a three product as opposed to a two-product situation. These additional costs are designated as C. We will therefore

consider the new product variation only if:

$$N_E \cdot \Delta P_{f,E} \cdot CM_E + N_D \cdot \Delta P_{f,D} \cdot CM_D > C$$

where, N_E = estimated number of consumers in segment E;

N_D = estimated number of consumers in segment D;

$\Delta P_{f,E}$ = change in probability of purchase for segment E
for attribute f (focus);

$\Delta P_{f,D}$ = change in probability of purchase for segment D
for attribute f (focus);

CM_E = unit contribution margin to profit and overhead of each
purchase by segment E; and

CM_D = unit contribution margin to profit and overhead of each
purchase by segment D.

In addition, the manner of eliciting response made it no longer necessary to consider competitors' positionings in product space. This is particularly advantageous in the case where perceptions of competitors' products are not homogeneous among the population. For example, some of the respondents indicated that the purchase of the quality pocket camera is considered as a second camera purchase to complement their current single lens reflex. Others indicated that the new camera was being considered instead of another brand of pocket camera or a more complex single lens reflex.

The methodology explored in this paper is easy to implement. The task demanded of the respondent is considerably simplified: in place of comparing a set of product concepts at one time, he/she is asked to compare each concept against his intended purchase. The survey can be done by telephone. Also, the data are remarkably easy to process prior to the formation of actual market segments.

Because this paper was written with some brevity, it is assumed that readers are aware of the usual analyses relating segments to demographics, psychographics, and media exposure variables. It is important, however, to highlight the potential of this methodology in determining the number and form of product offering(s) a firm might pursue. We have indicated how this might be done for our camera problem.

On the basis of this pilot study, we conclude that the product model, the related methodology, and intention measurements offer great potential in terms of product design for divergent segment preferences. Many of the difficulties associated with traditional product positioning-segmentation research seem to have been overcome. The crucial test, and number one priority for this stream of research, is a comparison between this methodology and other models used to evaluate the feasibility of new product/concept opportunities. This test could either be predictive, in the econometric sense of the word, or designed as a laboratory experiment in prediction. A simulated shopping trip, for example, would provide a measure of actual brand choice.

We have found the concept of changes in probabilities to be much more appealing than importance, benefits sought, and similar terms. The proof, however, lies with the validation test results. In any event, such a test is likely to be interesting as well as conclusive; the latter is indicated by the divergence between simple importances and probability coefficients reported by this research.

Following validation, a number of other research avenues are open to extend the usefulness of the research approach. The introduction of intervally scaled attribute levels or even interactions between the X variables poses no statistical difficulty; both, however, do lead to considerably more

complicated decision models than the one previously discussed. Nevertheless, purchase probability response to one attribute change is probably dependent on the level of other attributes and such phenomena as interactions should be included. Although extensions will be helpful, even in its most basic form, the model should prove useful in practice.

TABLE 1
 DESCRIPTIONS OF FOUR CLUSTER SOLUTIONS

No. of Clusters	Trace (W)	Percent Reduction	Size of Cluster Numbered				
			2	3	4	5	6
2	5.78	29	20	12			
3*	4.83	40	12	12	8		
4	3.76	54	5	19	5	3	
5	3.25	60	4	15	5	3	5

TABLE 2
 AVERAGE CHANGES IN PROBABILITY OF "YES"
 RESPONSE FOR THE FOUR MARKET SEGMENTS

Segment	Average Change in "Yes" Probability for the Design Option			
	$\Delta P_{\text{exposure meter}}$	ΔP_{focus}	$\Delta P_{\text{shutter}}$	ΔP_{flash}
1	.0	.0	.0	.0
2	.084	.050	-.084	.102
3	.330	.367	.258	-.130
4	.133	.513	.317	.237

TABLE 3
MARKET SEGMENTS CLASSIFIED BY
NUMBER OF "YES" RESPONSES

Number of "Yes" Responses	Market Segments			
	1	2	3	4
0	13	0	0	0
1-2	0	9	5	1
3-4	0	2	3	3
5+	0	1	4	4
Total	13	12	12	8

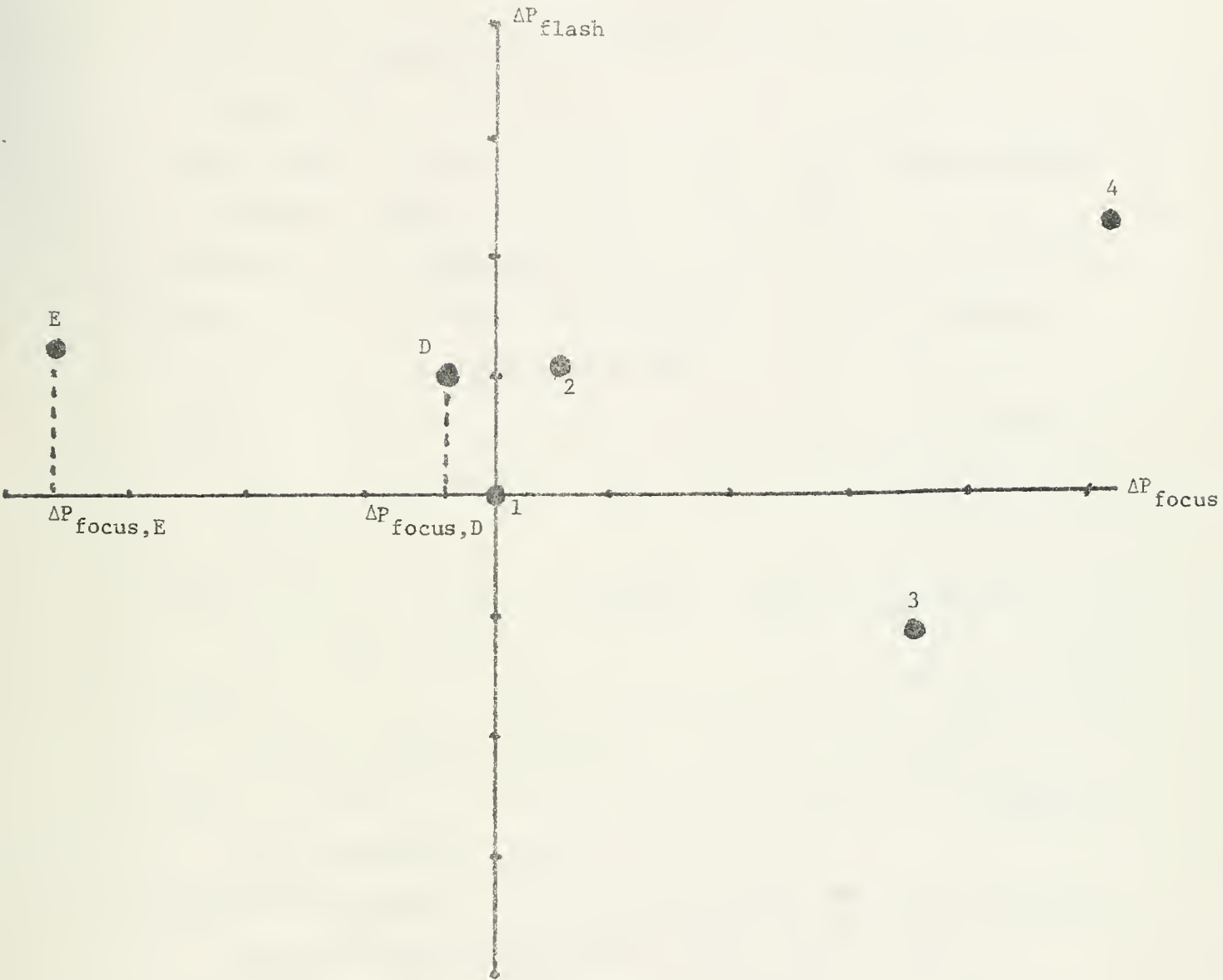
TABLE 4
 PROFILES OF THE FOUR MARKET SEGMENTS

Characteristics	Market Segments						All Responses
	1	1A ^a	1B ^a	2	3	4	
Size of segment	13	6	7	12	12	8	45
Camera ownership (%):							
Any camera	69	67	71	67	92	62	73
Single lens reflex	38	17	57	33	67	25	40
Film usage (rolls/yr.)	14.3	3.5	23.6	4.8	8.	6.1	8.6
% Practicing photography as an art form	31	0	58	25	42	38	33
Readership (issues/yr.)							
Modern Photography	.5	0.	1.0	.2	.8	.9	.6
Popular Photography	.5	0.	.9	.2	1.4	1.5	.8
New Yorker	.8	1.2	.4	2.6	2.8	4.8	2.5
% Doing own film or print processing	15	0	58	0	25	25	20

^aThese two clusters are partitions of cluster 1 (negative response to all 16 concept descriptions) based on intention to buy either a simple camera (cluster 1A) or a single lens camera (cluster 1B).

Figure 1

Two Space Representation of Cluster
Centroids of Probability Coefficients



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