

PRODUCT POSITIONING VIA DETERMINANCY ANALYSIS:

AN INDUSTRIAL MARKETING APPLICATION

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ABSTRACT

The authors propose a straightforward approach to identifying determinant attributes which lends itself to strategic analysis. To operationalize the concept of determinancy, indices are computed for each attribute utilizing t values for mean importance rating and paired t values for the difference in mean brand ratings. This accounts for the real world randomness existing in importance and brand differences and makes the proposed model more realistic. The two t statistics are used as the axes of a chart to produce what we call a Determinancy Space. Based on the attribute importance and difference criteria, competing brands are then positioned in this space to enable the sponsor company to assess its strengths and weaknesses. A case study is described to illustrate a successful application of the approach in an industrial market setting.

Strategic Marketing, product positioning and determinant attribute analysis have become household words in a marketer's lexicon within the last decade. More recently, three outstanding books have appeared in the literature on product management (Urban and Hauser, 1980; Pesselier, 1982; and Wind, 1982), which delve into strategies, theories, and methodologies pertaining to these subjects in sufficient detail to allow practitioners to operationalize some of these ideas. In this paper, we extend some of the ideas on "identification of determinant attributes", as first put forward by Myers and Alpert (1969), and show the strategic implications of our approach.

According to prevailing marketing thought, customers/consumers perceive products as bundles of attributes. These attributes are defined in terms of the benefits customers perceive products as offering. Generally, the product's attributes are not confined to physical characteristics only and may include economic, marketing/service related as well as sociological and psychological benefits over the life cycle of the product. For example, for industrial products, engineering related attributes like durability, reliability and finish may be considered along with marketing and service related attributes like availability of product literature, product seminars, availability of parts and service, etc., together with economic attributes like price, warranty terms, cost of parts and service, etc. On the other hand, for consumer products, such intangibles like image and status may play a vital role in product attitude formation.

An extremely critical problem, therefore, for the marketing manager is to understand how his product is perceived by his customers. In fact, a considerable difference may exist between the marketing manager's perceptions

and those of his customers. Furthermore, because of differing customer needs and expertise, customer perceptions may differ and hence the need for market segmentation.

Expectancy value models (Fishbein, 1967) have been developed to model individuals' attitudes on values for products on the basis of product attributes. In its simplest form, an expectancy value model considers the overall attitude towards an object, or product, to consist of the belief that the object possesses the attribute, weighted by the importance attached to that attribute. Thus:

$$A_o = \sum E_{oi} I_i \text{ where} \quad (1)$$

A_o = the overall attitude towards an object

E_{oi} = the belief that the object possesses attribute i

I_i = the importance an individual places on attribute i

The implication of this model to marketing is that customers will tend to buy those products for whom their overall attitude is the largest, i.e., most preferred.

Product perceptions have also been studied schematically using product maps (Urban and Hauser, 1980, pp. 235-268, and Pesselier, 1982, pp. 273-339).

Employing multivariate statistical techniques like factor analysis, discriminant analysis and multi-dimensional scaling, marketers have successfully shown pictorially, product positions in two and three dimensional spaces. Each dimension of such a space is a composite of several correlated attributes and the points on the map represent the centroids of the product

perceptions, of a given market segment, in terms of the underlying dimensions. Such maps help management understand how customers perceive products in terms of just a few independent dimensions rather than a whole host of highly correlated attributes.

Multiple regression and linear programming (Srinivasan and Schocker, 1973) are quite often used to obtain the direction of increasing preference. The preference or value function is obtained by regressing (or by using linear programming) overall preference against the product's attribute ratings, expressed in terms of the new dimensions. Thus:

$$V = \sum a_i \cdot \text{Dim}_i \quad (2)$$

where the coefficients a_i are obtained through linear regression or linear programming. Relating equation (2) to equation (1), we note the B_{01} corresponds to Dim_1 , the I_1 corresponds to the derived coefficients a_i , and A_0 corresponds to V , the overall preference or value.

Determinant Attribute Analysis - Previous Work

Implicit in both approaches is the assumption that management knows exactly which attributes are used in the value formation process by customers. One of the first significant contributions made in identifying the appropriate set of attributes used by customers was made by Myers and Alpert (1968). In a nutshell, they point out that the attributes must not only be perceived to be important, but they should also be differentiating, i.e., significant differences should be perceived to exist among the competing brands. It is

these product attributes that determine preference.

Myers and Alpert suggested operationalizing determinancy by computing: (1) Mean importance rating, \bar{I} , and (2) Mean perceived brand difference, \bar{BD} , for each attribute across all respondents. They define attribute determinance D as the product of \bar{I} and \bar{BD} . Thus:

$$D = \bar{I} \times \bar{BD}$$

Hansen (1977), in an unpublished paper, criticized the Myers and Alpert approach by pointing out the problem of non-unique solutions and the problem of loss of information through aggregation. The non-unique solution results when an attribute with a high mean importance and a moderate mean perceived difference results in the same determinance score, D , as an attribute with moderate mean importance and a high mean perceived difference. Hansen argued that these two attributes should not be treated the same. The loss of information from aggregation results from gathering the data at an individual level and then reporting the mean scores on importance and brand difference. He rightly indicated that this aggregation procedure could easily mask important differences.

Hansen proposed a modified determinancy model, where respondents are cross-tabulated in a three by three table for each attribute:

Brand Difference of Attribute

		Low	Medium	High
Importance Rating	Low	1	2	3
	Medium	4	5	6
	High	7	8	9

Table 1 - Hansen's Rating Classifications

In his model, the cell scores consisted of the percentage of total respondents who rated the attribute in that cell. An attribute's determinance score was then defined as the percentage of respondents classified in cell 9. Hansen further distinguished attributes as being currently determinant and potentially determinant. Attributes with a high percentage of respondents in cell 9 were termed currently determinant, while those with a high percentage in cell 7 were termed potentially determinant. (Although cells 6 and 8 could also be termed potentially determinant.)

Hansen basically clustered his respondents, attribute-wise, into nine categories and then concentrated on those attributes having high percentages in cells 7 and 9. Though this is an improvement over the Myers and Alpert approach, there is still considerable subjectivity in this process. Depending on how the low, medium, and high categories are defined, entirely different sets of attributes may turn out to be determinant. Another place where subjectivity is used is the process by which the determinant attributes are differentiated from the non-determinant ones. This is done by using an arbitrary percentage cut-off to separate the two sets of attributes. Hansen's

approach does not correct this deficiency also present in the Myers and Alpert approach.

More recently, Arnold, Oum and Tigert (1983) suggested the use of logistic regression to identify determinant attributes. These authors used Alpert's (1971, pp. 184) conceptual development and definition of determinant attributes: "those attributes projected by the product's image which lead to the choice of that product may be called determinant, since they determine preference and purchase" as their starting point and defined attributes to be determinant if the logit regression coefficients were significant. Though this approach has a number of advantages over earlier methods, it may have some potential problems. Statistically, if the attribute ratings are associated, the problem of multicollinearity could increase the standard errors of the logit coefficients significantly, resulting in acceptance of the null hypothesis of a zero coefficient when it is false. This is equivalent to an increase in the probability of the Type II error.

Another potential problem with the methodology, as used, is that it could only be applied with frequently purchased items, since the categorical dependent variable is the last actual occurrence of the choice process. In an industrial setting, where the product life may be several years, such a dependent variable may not be useful. It may, however, be possible to circumvent this problem by asking individuals their choice, assuming they were going to make a purchase in the near future. We admit, the logit approach with its implicit assumption of a latent utility function (see Gensh and Recker, 1979; McFadden, 1980; and Panj and Staelin, 1978) does have appealing properties. However, it does not lend itself to as extensive strategic analyses (to be discussed later) as

our approach does. Moreover, the method we will describe can be explained graphically and thus is quite appealing to managers.

Determinancy Analysis -- A New Approach

Though our approach draws from a number of sources, the roots of our method lie in the Howard/Sheth (1969) model of buyer behavior -- in particular, the concept of an evoked set arising in purchase situations requiring "extensive problem solving". The evoked set is "the set of alternatives that the buyer would actually consider prior to selecting the final brand". Extensive problem solving generally occurs when purchasers are faced with decisions on new, complex, and expensive products. To reduce their risk, the decision makers may spend a significant amount of time gathering information on different brands and reflecting about the relative worth of different product attributes. Expensive industrial products with long product lives often trigger extensive problem solving behavior. In addition to the Howard/Sheth model, our approach also draws to some extent from Martilla and James' (1977) work on "importance-performance analysis". However, we concentrate on the "importance-differentiation" aspects and operationalize the procedure with statistical inferences.

Our hypothesis is that a market for a product, particularly an industrial product, may be segmented by evoked sets since customers having similar needs and similar applications for the product will tend to consider similar sets of brands. The choice set, which is the next step for the customer (see Narayana and Markin, 1975, pp. 1-6, and Kotler, p. 156) is basically a subset of the evoked set. This set is obtained by acquiring more information or by giving

additional thought to the brands in the evoked set. In identifying the determinant attributes, we basically model this extensive problem solving activity where the customer compares brands in his evoked set over the important attributes. If significant differences are perceived between any two evoked brands on an important attribute, the attribute is defined to be determinant. If a brand in the evoked set is completely dominated by other brands, it is dropped from further consideration and becomes part of the "Non-Choice Set".

To carry out the determinancy analysis, we collect data on attribute importance and performance ratings for the evoked brands. (The evoked attribute brands are first identified by asking the customer about the brands he would consider when purchasing the product.) To operationalize our definition of importance and perceived differences, we suggest the use of the t statistic. Thus, we present a probabilistic framework with its underpinnings in inferential statistics to operationalize the concept of determinancy. For example, instead of using the arithmetic means (across respondents) to rank order the attributes by importance and arbitrarily declaring only some of the attributes as important, we suggest using a one way t test.

Defining μ_i as the population mean importance of the i th attribute in a given evoked set (We could have used μ_{ik} , population mean importance for i th attribute in the k th evoked set, but, for notational simplicity, decided to drop the second subscript. Hereafter, the entire discussion is with respect to a specific evoked set with cardinality greater than one.) and μ_0 the average importance computed over all attributes and all respondents, in the same evoked set, we define the i th attribute as important if $H_0: \mu_i \geq \mu_0$ is accepted. Thus, we are declaring an attribute to be important if there is enough evidence in our sample to claim that the mean perception of importance of that attribute

in the population is in the "heavy half". We selected the above hypothesis rather than $H_0: \mu_i \leq \mu_0$, since we considered controlling the probability of declaring an attribute as unimportant when in reality it was important (which is α , the probability of Type I Error) more relevant. This perhaps puts a bias towards including more attributes in the important set, but we felt that taking this conservative approach was preferable to eliminating attributes mistakenly which may be important.

The advantage of the inferential approach over using the arithmetic mean is that it explicitly recognizes that the sample mean importance is just one realization of the random variable \bar{I}_i , the mean importance of the i th attribute. The t statistic, defined for the i th attribute by $t = (\bar{I}_i - \mu_0)/s_{\bar{I}_i}$ is basically the distance in terms of the number of standard errors ($s_{\bar{I}_i}$) that the sample mean of the i th attribute is from μ_0 and is monotonically related (decreasingly) to the probability of \bar{I}_i exceeding \bar{x}_i (one specific realization of \bar{I}_i). Though we can now make probabilistic statements about the importance of an attribute, this approach does have the potential of creating an unappealing situation, where, even though $\bar{I}_i > \bar{I}_j$, $t_{\bar{I}_i} < t_{\bar{I}_j}$. This situation, however, can be avoided, at least for the importance criterion, by judiciously redefining μ_0 . We present the following Lemma to help us do this.

Lemma:

For t_i to be greater than t_j for all pairs of attributes (i,j) for which $\bar{I}_i > \bar{I}_j$, the threshold limit, μ_0 should satisfy:

$$\mu_0 \geq \max_{\substack{i,j \\ j \neq i}} \left\{ \frac{s_{\bar{I}_i} \bar{I}_j - s_{\bar{I}_j} \bar{I}_i}{s_{\bar{I}_i} - s_{\bar{I}_j}} \right\}$$

where, $s_{\bar{I}_i}$ and $s_{\bar{I}_j}$ are the standard errors.

Proof:

For a specific pair of attributes (i,j), if $\bar{I}_i > \bar{I}_j$, we would like to have:

$$t_i > t_j$$

$$\text{or} \quad \frac{\bar{I}_i - \mu_0}{s_{\bar{I}_i}} > \frac{\bar{I}_j - \mu_0}{s_{\bar{I}_j}} \quad (\text{By definition of } t \text{ statistic})$$

$$\text{or} \quad \mu_0 > \frac{s_{\bar{I}_i} \bar{I}_j - s_{\bar{I}_j} \bar{I}_i}{s_{\bar{I}_i} - s_{\bar{I}_j}}$$

Hence, to determine a μ_0 for all pairs (i,j) where $\bar{I}_i > \bar{I}_j$ and $t_i > t_j$, μ_0 must satisfy:

$$\mu_0 > \max_{\substack{i,j \\ j \neq i}} \left\{ \frac{s_{\bar{I}_i} \bar{I}_j - s_{\bar{I}_j} \bar{I}_i}{s_{\bar{I}_i} - s_{\bar{I}_j}} \right\}$$

Thus, if the sample mean importance rating over all attributes for brands in a given evoked set satisfies the above relationship, the t values will be monotonically related to the mean importance values. If the computed grand mean does not satisfy the above relationship, then redefine μ_0 , the threshold limit, as follows:

$$\mu_0 = \max_{\substack{i,j \\ j \neq i}} \left\{ \frac{s_{\bar{I}_i} \bar{I}_j - s_{\bar{I}_j} \bar{I}_i}{s_{\bar{I}_i} - s_{\bar{I}_j}} \right\} + \epsilon$$

where ϵ is some small positive constant.

In a like manner, we propose the t statistic based on paired differences of brand performance ratings to identify the attributes where perceived differences exist.

Denoting the sponsor brand as brand j, let:

X_{ij} = performance rating of brand j on attribute i

X_{ik} = performance rating of brand k on attribute i

$D_{ijk} = X_{ij} - X_{ik}$

$\mu_{ijk} = E[D_{ijk}]$ = population mean of random variable D_{ijk}

d_{ijk} = a specific value of the random variable D_{ijk}

\bar{d}_{ijk} = the sample mean of the d_{ijk}

$s_{\bar{d}_{ijk}}$ = the standard error of $d_{ijk} = \frac{s_{d_{ijk}}}{\sqrt{n}}$, where $s_{d_{ijk}}$ is the standard deviation of the d_{ijk}

and n = number of individuals in the evoked set.

We define the ith attribute as differentiating between brands j and k if we reject $H_0: \mu_{ijk} = 0$.

Note once again because of varying dispersions in the random variables, D_{ijk} , we have the possibility of t_{mjk}^1 being less than t_{njk} even though \bar{d}_{mjk} is greater than \bar{d}_{njk} . This should not, however, be a major concern since we can explain this anomalous situation to a manager. Our explanation should indicate that the t index is related to the probability of $\bar{D}_{.jk}$ exceeding $\bar{d}_{.jk}$ when $\mu_{.jk} = 0$ (where $D_{.jk} = X_{.j} - X_{.k}$ and stands for a rating difference for any attribute). Even

¹Note that the t statistic for importance is represented by a single subscript, i.e., t_i , and the t statistic for difference is represented by a triple subscript, i.e., t_{ijk} .

though \bar{d}_{mjk} is greater than \bar{d}_{njk} , the probability of \bar{d}_{mjk} being greater than \bar{d}_{njk} can be exceeded by the probability of \bar{d}_{njk} being greater than \bar{d}_{mjk} because of the different spreads of the two distributions, as illustrated in Figure 1.

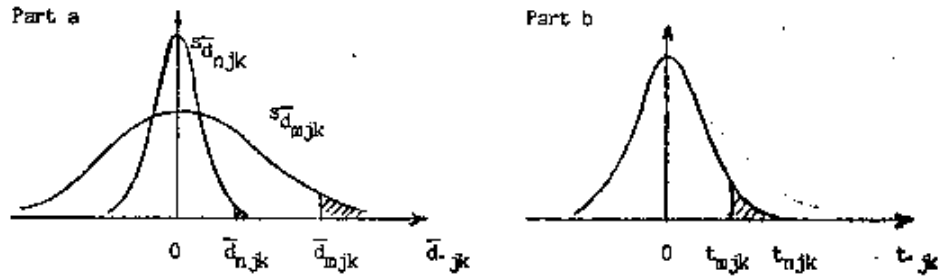


Figure 1: Lack of Monotonicity Between $\bar{d}_{.jk}$ and $t_{.jk}$

Figure 1, Part a, shows a situation where $\bar{d}_{mjk} > \bar{d}_{njk}$, but because:

$$P[\bar{d}_{mjk} > \bar{d}_{njk}] > P[\bar{d}_{njk} > \bar{d}_{mjk}]$$

we have: $t_{mjk} < t_{njk}$ (Part b)

The key idea we should get across is that one should not concentrate on the raw mean differences, $\bar{d}_{.jk}$, but rather on the standardized differences or relative differences measured in terms of the inherent variability in that difference.

Having discussed our approach to identifying important and differentiating attributes, we define, for an evoked set, attribute i to be determinant with respect to brand k if $H_0: \mu_i \geq \mu_0$ is accepted and $H_0: \mu_{ijk} = 0$ is rejected for at least one brand k , $k \neq j$ in the evoked set.

A number of approaches may be employed to perform simultaneous inferences required for establishing determinancy. Some among them are the Tukey method, the Scheffe method, the Bonferroni method (Neter and Wasserman, 1974), and the Roy-Bose method (Morrison, 1976, p. 135). For each of these methods, a t statistic is computed and compared to a critical value. For example, in the Bonferroni method, the critical t value(s) would be $\pm t_{\alpha/2p}$ for the second hypothesis, where p is the number of hypotheses. In this case, p would be two. The Roy-Bose method uses the Hotelling T^2 statistic to compute the critical values and is thus similar to the Scheffe method which uses the F statistic. Morrison (1976, pp. 135-136) gives a table showing the ratio of expected length of 95% Bonferroni to Roy-Bose simultaneous confidence intervals for different sample sizes and number of comparisons. In every case, the Bonferroni confidence interval is shorter. Both Neter and Wasserman (1974, pp. 482) and Green (1978, pp. 223) recommend the Bonferroni procedure when the number of comparisons is small. Generally this procedure will also result in the tightest confidence intervals, which are preferred. Hence in our analysis, we have employed the Bonferroni procedure.

For the Bonferroni intervals, the critical value for t_i is $t_{\alpha/2}(n - 1)$ and for t_{ijk} , they are $\pm t_{\alpha/4}(n - 1)$, where n is the number of customers in the evoked set and the term in parentheses represents the degrees of freedom for the t statistic.

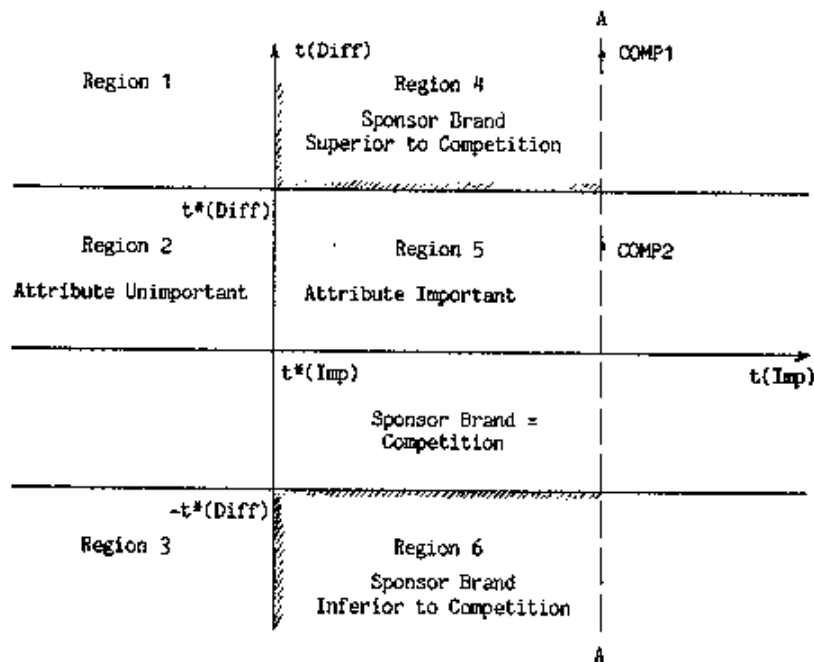
After obtaining the t values (importance and differences) for each attribute for the brands in an evoked set, we are in a position to plot each attribute on a graph which comprises t_i as the X-axis and t_{ijk} as the Y-axis. As proposed earlier, besides operationalizing the identification of determinant

attributes, our approach lends itself to practical strategic ideas for the marketing manager as discussed in the following illustration.

An Illustration of Determinancy Space and Strategic Ideas

The t values for the perceived difference in mean brand ratings and the t values for mean importance rating can be used to define a Determinancy Space. In Figure 2, the X axis represents the t value for mean importance rating and the Y axis represents the t value for the mean difference rating (between the sponsor company's brand and a competitor's brand). The threshold levels are established for both axes, i.e., $t = -1.674$ for importance and $t = \pm 2.005$ for brand rating (corresponding to a Type I Error of 10%). This essentially results in six regions as indicated in Figure 2.

Associated with each attribute is a t value for importance, $t(\text{Imp})$, and one or more t values, $t(\text{Diff})$, for brand differentiation, depending upon the number of brands in an evoked set. For example, if there are three brands in an evoked set, the sponsor company's brand and two competing brands, then there are two t values for brand differentiation. (A paired t value is needed for comparing the sponsor company's brand to each of the two competing brands.) Each competing brand can thus be represented by a point in the determinancy space. For a given attribute and two competing brands, the points will thus lie on a vertical line passing through the $t(\text{Imp})$ value for that attribute. For example, the dotted line A-A in Figure 2 represents an attribute under study. On this line, the positions of two competing brands, COMP1 and COMP2, are depicted with respect to the sponsor brand.



Determinant Regions:

- Region 4 -- Points lying in this region imply that the attribute is important and the sponsor brand is superior to the competing brand.
- Region 6 -- Points lying in this region imply that the attribute is important and the sponsor brand is inferior to the competing brand.

Non-Determinant Regions:

- Region 5 -- Points lying in this region imply that the attribute is important but the sponsor brand and the competing brand are equal.
- Region 2 -- Points lying in this region imply that the attribute is not important and the sponsor brand and the competing brand are equal.
- Region 1 -- Points lying in this region imply that the attribute is not important but the sponsor brand is superior to the competing brand.
- Region 3 -- Points lying in this region imply that the attribute is not important but the sponsor brand is inferior to the competing brand.

Figure 2 - Determinancy Space

Depending on where a competing brand then lies in the determinancy space, appropriate strategies can be developed. The dotted arrows in Figure 3 indicate how we may want to reposition specific attributes in the determinancy space.

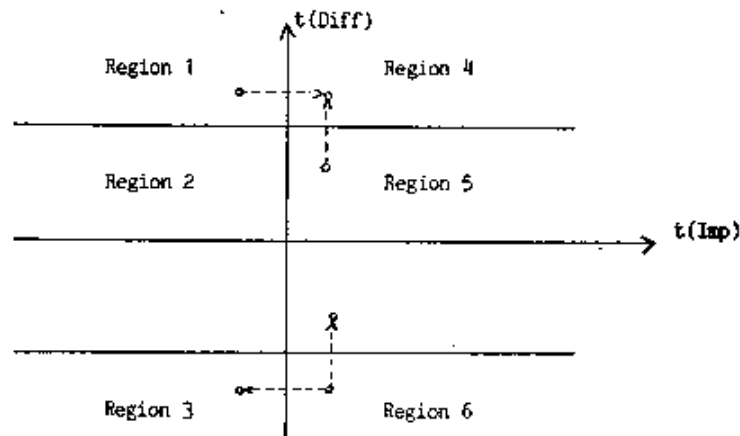


Figure 3 - Repositioning with Respect to Competition in Determinancy Space

Very specific programs, of course, need to be created to accomplish this repositioning. It is here that true creativity is required to change an attribute's importance or perception of a brand's performance on an attribute. For example, location of a competitor's point in Region 6 does not necessarily mean that the sponsor company's brand is inferior to the competition on that attribute. It does indicate, however, that the customers have this perception. The sponsor company may want to have the brands compared independently in a laboratory or have consumers compare their brand and the

competition more objectively. Sylvania TV in its advertisements, for example, claims that in "independent testing", its TV picture was found to be superior to all the major brands and then it proceeds to name these brands. Pepsi carried out a national campaign, the "taste test", where blindfolded individuals were asked to name the cola they preferred the most, in a taste test, and invariably Coca-Cola came out second. Several beer companies have also targeted taste in similar advertisements, with blindfolded customers preferring their brand over some major name brand.

The sponsor company may very well find out that the customer's perceptions are accurate, in which case modifying the design of the product or service so that the sponsor company's brand is made superior to the competition may very well turn out to be an appropriate strategy. A creative communication program would, of course, still be required to change customer perception of the "New, Improved" product.

It should be noted that the analysis is flexible in the sense that a determinancy analysis can be carried out for any market segment. In practice, the market segments may be quite complex. For example, in industrial marketing, the size of the customer firm, the different decision makers within the customer firm, and the different product sizes may all require separate analyses (See Choffray and Lilien, 1980). In each case, however, a particular analysis should be carried out for a common set of evoked brands.

Determinancy Index

In order to operationalize attribute determinancy with respect to determinancy space concepts, we propose a method to compute an attribute Determinancy Index (DI) for the sponsor company with respect to each of the competing brands in the evoked set. Figure 4 represents the possible values that DI should take in the various regions of determinancy space.

As can be seen from Figure 4, DI should be zero on the left of the vertical line (regions 1, 2, and 3) which represents the threshold level of importance $t^*(Imp)$, implying that unimportant attributes cannot be determinant.

Similarly, in Region 5, DI should be zero, implying that even though an attribute may be important, if it is not differentiating, it cannot be determinant. In regions 4 and 6, DI is defined as $A \times B$. However, DI should be positive in region 4 because $t(Diff)$ is positive in this region, implying that the sponsor brand is superior to the competing brand. In region 6, $t(Diff)$ is negative, suggesting that the competing brand is superior to the sponsor brand. DI, in this region should, therefore, also be negative. A formula has been devised (see Shaikh, 1983) to compute values of DI using $t(Imp)$ and $t(Diff)$ for each attribute in the evoked set.

Results of a Case Study

The strategic approach to determinancy analysis outlined in this paper was applied to an industrial product used in a specific application (see Shaikh, 1983, and Hansotia and Shaikh, Forthcoming)². The product line was divided into three size classes and data was collected for two decision-making/influencing

²Pseudonyms are used throughout the discussion of the case study to maintain data confidentiality.

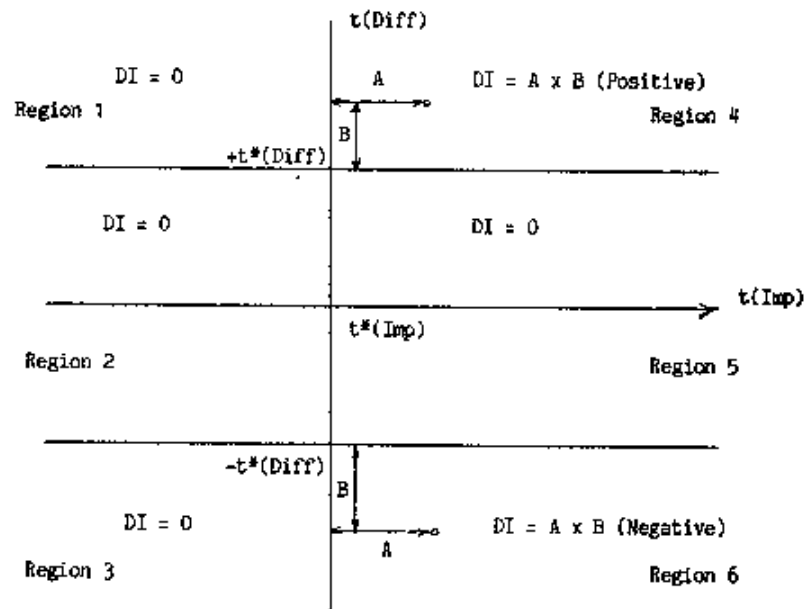


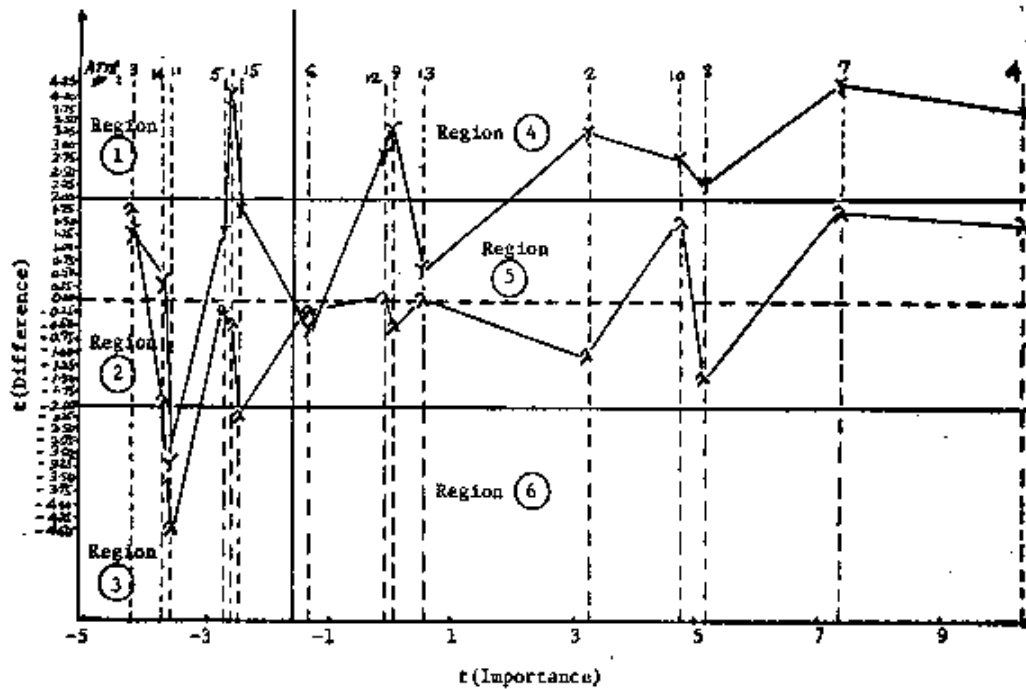
Figure 4 - Determinacy Index Concept

segments. Fifteen attributes were identified. The Determinancy Space concepts were applied to identify determinant attributes in each segment. The sponsor company was able to form short-term and long-term strategies by studying the determinancy space charts for each marketing segment. A number of short-term strategies were promptly implemented to enhance the profitability of its product.

Figure 5 illustrates the determinancy space for one group: small product size, consultants and three brands of a specific evoked set. This illustration is being given for just one group of survey data. Similar analysis was done for other segments as well. Before establishing the determinancy space, we ensured that if $\bar{I}_i > \bar{I}_j$, the corresponding t values, t_i and t_j , also have the same directional relationship, i.e., $t_i > t_j$, for all pairs (i, j) . (A few attributes did not follow the above monotonicity. However, since these attributes were unimportant, μ_0 was set to the grand mean of the standardized ratings, i.e., zero instead of being established through the result of the Lemma discussed earlier.)

An attribute is represented by a dashed vertical line drawn at its t value for importance. The Alpha Company's t difference with respect to each competitor is shown by the greek letter denoting the respective competitor.

All λ points for important attributes lie in Region 5, indicating no significant difference between Alpha and Lambda companies. The chart also indicates that the Alpha company does need to pay attention to certain attributes on which Lambda Company is close to being superior. For example, on Dealer's Reputation, the t value for the difference between Alpha and Lambda companies is -1.48 as opposed to the threshold level ($t = -2.005$). If Lambda



Attribute

- 1 - Dealer Inspection Programs
- *2 - Availability of Technical Literature
- 3 - Annual Operating Cost
- *4 - Reliability
- 5 - Existence of Special Features
- 6 - Noise and Vibration Control
- *7 - Parts and Service Support
- *8 - Dealer's Reputation
- *9 - Help in Installation
- *10 - Manufacturer's Reputation
- 11 - Price
- *12 - Warranty Terms
- 13 - Ease of Maintenance
- 14 - Timely Delivery
- 15 - Supplier Contact

*Determinant Attribute

Figure 5 - Determinancy Space for Small Product Size, Consultants and Alpha, Gamma and Lambda Companies

Company decides to launch its own program against Alpha Company, it would probably attack it on Dealer's Reputation since Alpha Company is more vulnerable on this attribute than other important attributes. One other interesting observation can be made with respect to Supplier Contact ($t_I = -2.46$) on which the Lambda Company has an edge over Alpha Company ($t_D = -2.18$). The Lambda Company may have a lot to gain, with relatively less effort (because t_I is close to the threshold level of -1.674 and t_D is almost significant), by developing a marketing campaign whereby it attempts to change the customers' perception of the importance of Supplier Contact. If this strategy is successful, Lambda Company would have an effective means for competing against Alpha Company.

Price also offers some interesting insights. Even though Price is perceived to be unimportant ($t_I = -3.65$), both Lambda and Gamma companies have a significant edge on Alpha Company. If either or both competitors have this information through their own research, they could use it to their advantage, e.g., increasing prices (assuming the same is true for other decision-making segments). It appears that Alpha Company apparently has a good feel for the market. Knowing that it can get away with a high price, it has chosen to emphasize other services and attributes.

By joining the Y points for all attributes, we can quickly conclude that Alpha Company is enjoying a very comfortable positive perception over Gamma Company on almost all attributes. Alpha Company's strategy with respect to Gamma Company should be to continue to maintain its superiority while paying close attention to such attributes as Dealer Reputation and Manufacturer's Reputation which are on the brink of being non-determinant. If Gamma Company

decides to close the gap between itself and Alpha Company on these attributes, then Alpha Company's comfortable margin will diminish.

Note the sponsor company (Alpha) is perceived to be doing extremely well on the two most important attributes, Reliability and Parts and Service Support. Though the two attributes are not quite determinant with respect to the Lambda Company, the relative difference between them on these two attributes is large. The sponsor company, in an effort to increase its brand's value, decided to piggyback on its brand's strongest attributes by offering an enhanced warranty program. They felt this would not only enhance their rating on warranty terms, but also improve their performance on Manufacturer's and Dealer's Reputation. The latter would be further increased by ensuring the involvement of their dealers in such communication programs like press releases and local advertising.

The sponsor company also needs to carefully scrutinize its program on distribution (and hence availability) of technical literature, particularly with respect to the Lambda Company. If specific desirable engineering features, leading to superior reliability, also exist with respect to the other brands, it needs to spell those out in its technical literature. By increasing the availability of its "new" hard-hitting brochures, it stands to not only improve its image with respect to availability of technical literature, but also to further enhance its brand's reputation with respect to reliability as well as its dealers' reputation (again assuming the dealers play a major role in the distribution of the literature).

The sponsor company's strategies, therefore, should be developed primarily from its base of strength: Reliability and Parts and Service Support. By offering

programs related to these areas, it not only stands to enhance its brand's perception on other attributes, but also to further reinforce its original base. It appears the sponsor company is enjoying a sound halo effect with respect to the Gamma Company. If it is successful in its new programs (and early estimates indicate the new warranty program to be extremely successful; this is because no competitor could offer a similar program at such a low cost because of the sponsor company's outstanding product reliability), it could potentially also enjoy a similar halo effect with respect to the Lambda Company.

Strategic ideas and plans such as those discussed above can be generated by examining the determinancy space and can prove to be very useful in improving the quality of marketing managers' decisions.

Summary

We have presented here a new strategic approach to attribute determinancy analysis to help the marketing manager take stock of his product's position in the marketplace.

Our approach not only identifies which attributes are perceived to be important, by different market segments, but also how a product matches up to the competition on key attributes. Determinancy Perception Maps, such as those presented in the study, can further aid managers in visualizing how their brand competes against other brands and help identify areas of strength and weakness. Such maps should prove to be extremely useful in developing communication programs and other services which could enhance their brand's perceived value. An actual application of the methodology was also discussed using fictitious

names and some comments made on the resulting perception map. All actual strategies developed could not be divulged here because of their proprietary nature. Further analyses such as product positioning and value analysis can also be carried out once the determinant attributes have been identified.

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