PRODUCT DESIGN

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ABSTRACT

Decision-making for the design of successful new products is becoming an increasingly difficult and complex task. The marketing environment is seeing increased competition, more available data, and greater requirements for pertinent marketing information. This thesis assesses the role of analytical consumer-based techniques in simplifying the marketing manager's decision-making process and in producing more effective results. A number of product design procedures (perceptual mapping, preference/choice analysis) reflecting the cognitive structure of the consumer's purchase behavior are reviewed and specific examples of uses of these procedures are evaluated in three different product areas. The thesis concludes that appropriate combinations of the models reviewed, in conjunction with the marketing manager's judgement, can simplify decision-making and produce results that can continue to add significant value to the product design process in years to come.

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PRODUCT DESIGN

I. Background and Overview

II. The Product Design Process and the Role of Models in the Process

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    A. Mapping Procedures
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IV. Specific Product Design Models
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    B. PERCEPTOR
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I. BACKGROUND AND OVERVIEW

Marketing is an interdisciplinary, fast-evolving field which requires complex and rapid decision-making capabilities. It is difficult for the marketing manager to cope with increasing marketing data and increasingly sophisticated information requirements (market response reports vs market status reports) subject to a variety of internal (eg. firm's objectives, goals) and external (eg. competition) environmental constraints. Marketing decision-making is a complex and difficult task and involves understanding and taking into account a number of factors (Kotler and Lilien 1982):

- relationships between consumer responses and marketing inputs
- different activities in the field (eg. product design, testing, introduction)
- competitor's activities
- lagged consumer responses
- market segments and segmented responses
- multiple product strategies (cannibalization)
- interaction of various marketing functions
- multiple organizational goals

Generally, the marketing manager formulates his decisions based on his experience, organizational procedures and standards, data and facts, and analytical methods (models). In the face of rapidly increasing competition (the upsurge of cuisinart competitors, AT&T's information sys-
tem vs IBM's) and the higher rates of new product failures (45-65% for consumer packaged goods; Urban and Hauser 1980), it is becoming increasingly difficult to predict the market's response to a variety of marketing efforts effectively and in detail with the given time and resource constraints of an organization.

With the increasing availability of computing power, the trend has been towards analytical market-based approaches to support the marketing manager's decision-making by providing him with the capability to cope effectively and efficiently with the competitive and rapidly changing marketing field.

These analytical approaches or models simulate a manager's decision-making process by specifying a set of variables and their respective interrelationships in a marketing system or process and by developing a framework for evaluating the facts and data. The marketing models describe the workings of the real marketing system and inherently reduce the complexity involved to simplify the marketing manager's dealings with the system. Additionally, the models simplify and automate the routine procedures in an organization to allow time for creativity, planning and innovation.

This thesis explores the role of models in the design of new products. A number of factors provide the motivation for supporting and improving the decision-making process in this area of marketing. The most critical factor is the risk of producing an unsuccessful product (failure). A second major factor is the cost of designing a new product. Urban and Hauser (1980) estimate investments of $2-6 million in the designing of different products (durables, frequently purchased con-
sumer goods, industrial goods, and services). Their findings show that in the marketing area, product design requires a major commitment of resources with a large portion concentrated in the final testing of the product. For example, product design for consumer durables required an average of 21.3% of the total resources (Urban and Hauser 1980), while industrial product design required a 43% commitment of resources (Mansfield and Rapoport 1975). Testing and introduction for the consumer durables constitute 16.5% and 78.8% of the resources (Urban and Hauser 1980). These results show that emphasis placed on improving decision-making in the early part of the product design methodology could mitigate the costs and risks of introducing a potentially unsuccessful product. The third factor is the time involved in the design of a product. Given the dynamic characteristics of many marketing environments, this factor is often critical in the ultimate introduction of a product. If too much time is spent on the design, the opportunity may be lost (eg. Ford Edsel). On the other hand, if not enough time is spent on the design, key issues may be missed and the product may yet fail.

Kotler and Lilien (1982) state that marketing models:

- provide effectiveness without increased complexity
- provide capability to isolate business areas of potential improvement (increased profits or reduced expenses)
- provide focus on key variables and their impact on product design (eg. mileage in cars).

The success of a new product is ultimately linked to its ability to attract and retain customers (since the number of consumers who will pur-
chase new products will be key input to a firm's goals for profit, market share, etc.).

Consequently, to design a new product attractive to consumers requires a consumer-oriented or proactive approach that emphasizes the satisfaction of consumer needs. This proactive approach is based on the assumption that people seek benefits provided by the products rather than the physical products themselves (Schoeker and Srinivasan 1974). Regardless of the type of good it represents (durables, frequently purchased consumer goods, and industrial goods), a product is seen as the fulfillment or satisfaction of the consumers' physical and psychological needs, and the consumer is essentially buying want satisfaction (eg. Rolls-Royce for 'prestige' in transportation and a bus for 'economy' in transportation).

In the context of this definition, the objective of a product design methodology is to develop a product that satisfies these physical and psychological requirements. The design process and the role of models in this process will be discussed in section II.

A number of managerial and analytical techniques exist to design and position products as physical and psychological entities that fulfill these requirements.

Based on the stages of cognizance in consumer behavior (awareness, perception, preference, choice), these techniques and models provide an understanding of the purchase disposition of the consumer for potential products, to predict market response (as an aggregation of individual responses), and ultimately to evaluate the potential success or failure of a product. The models and their uses and limitations are reviewed in section III. Section IV discusses and compares the model-based proced-
ure designed for use in three product areas: durables, frequently purchased consumer goods, and industrial goods. Each of the three models discussed (LINMAP, PERCEPTOR, DESIGNOR) focus on different aspects or areas of the design process (respectively): idea generation and search for an optimal product vs an overall process that includes market testing vs the elimination of infeasible alternatives. Frequently purchased consumer goods present the least complexity in the design process while industrial goods involving multi-person decision-making processes present the greatest complexity and difficulty. As a result, much of the researched methodology for supporting product design decision-making is in the area of consumer products while little is available for industrial products. The section concludes with implications and directions for these models.

Based on the models, products and design approaches reviewed, the thesis concludes that there is no 'optimal' model for the overall product design process given the specifics of each situation (industrial product, consumer) and the constraints (eg. multiple objectives) of the firm and the environment. The variety of marketing models available provide:

- a good understanding of the consumer's behavior towards purchasing potential new products
- increased accuracy in the prediction of market flexibility in evaluating alternative product strategies
- cost and time savings
- minimization of risk in introducing new products
- clarification and interpretability of options and results (perceptual mapping).
II. PRODUCT DESIGN AND THE ROLE OF MODELS IN THE DESIGN PROCESS

As mentioned in the last section, the objective of a product design methodology is to develop a product that satisfies the physical and psychological requirements of the consumer.

The design process entails the evaluation, refinement, and conversion ideas generated from a market of prespecified products and consumers and the assessment of potential opportunities in this market into a physical and psychological entity. It is composed of a set of iterative functions where the concept of the new product is continuously refined until its conversion into a physical product.

The proactive approach to the design process, as discussed in this thesis assumes a sufficient understanding of consumer decision-making in an existing market environment to enable the prediction of market behavior in different environments. Because an understanding of consumer behavior is critical in this approach to new product development, the design effort is based on a formal model of consumer responses: awareness, perception, preference, and choice (Urban and Hauser, 1980). Marketing models, representing these consumer responses, play a large role in the design process. Most of these models or techniques employ a framework where products are represented abstracting in terms of attributes that would be potentially significant to the consumer in his/her decision-making process. Attributes are the key dimensions of a product that the consumers use when deciding whether or not to purchase a product. The goals, for marketing managers, is to use product design models to identify new product opportunities by combining salient (important) product attributes in some unique way with respect to existing products so
as to yield products that will be attractive to a substantial group of consumers.

Figure 2.1 shows the product design process as an interactive series of tasks between the producer (or the firm) and the consumer. These tasks include: the definition of target markets; the identification of areas of interest or the generation of ideas; the development of a concept, its evaluation, and refinement; and the product fulfillment. Alternative strategies and a marketing program finalize the introduction of a new product. A major technique for identifying markets of competing products is perceptual mapping. This technique is based on Stefflre's theory that an individual will behave towards a new thing in a manner that is similar to the way he behaves towards other things he sees the new thing as being similar to (Silk, 1969). Thus, the technique predicts how consumers will perceive the relative similarity among products, and identifies the key dimensions of the product most important to the consumers. The results of this analysis also identify the products, consumers, and segment markets. These dimensions make up the attribute space that maps consumer perceptions.
Figure 2.1 The Design Process

Steps of an Integrated Consumer Research Program

Schering (1974)
Preference models or techniques are used to predict how consumers will compare new products to existing products and how they will use the key dimensions to evaluate the product's positioning in the product market. Finally, the choice models attempt to predict the consumer's probability of purchasing the product and to control the external factors (e.g. competition) for ensuring a purchase (Urban and Hauser 1980). An aggregation of these individual response models predicts the market potential and indicates the probability of success or failure for a given product.

Preference/choice models have been the most significant methods for predicting market behavior since they are based on how consumers respond to products. These models are useful for isolating consumers with different needs and responses because products intended for the total market may have marginal success if consumers have different perceptions of the product. Markets are thus segmented by identifying the characteristics of the products that consumers prefer and that they will use (benefit segmentation).

The majority of these product design models represent choice on an individual basis. However, not all purchase decisions are made on an individual basis. Often the purchase of a product involves a multiperson decision-making process with peers, 'significant others' or participants within an organization. This characteristic is especially relevant in industrial products (e.g. computers) where the final purchase decision involves a multiperson participation with a variety of constraints and requirements. In this case not only must
the perceptions and preferences of each individual decision-maker in the process be understood, but the interaction and the differentially weighted contributions leading to the final decision must be understood to model the purchase decision process. Though Choffray and Lilien (1979) have devised a decision matrix to depict the role of each participant in the multiperson decision-making process and a decision support system (DESIGNOR, 1979) to evaluate product alternatives subject to profit maximizing objectives, there are few models that represent the overall design process for industrial products (vs. several for durables and frequently purchased consumer goods e.g. PREDICTOR and the marketing manager must still, to a large extent, rely on his own judgement.

The variety of analytical approaches and models offered by market researchers differ in the methods they use to map perceptions of products (similarity vs. importance), to evaluate preferences (probabilistically with considerations for risk and utility vs. deterministically as a function of past preferences), and in the criteria they use to model choice or to predict the purchase decisions of the consumer (profit vs. market share). However, models uniformly assume that market segments or individuals have a common perceptual framework to make it feasible to evaluate a large number of consumers who generate product ideas. Despite this assumption however, individual perceptions are captured in the saliences (or importance weights) used in a large number of preference models.

The models (discussed above and in greater detail in section
III) which support decision-making in the product design process are ultimately supported by consumer measurement techniques. These techniques essentially identify the key attributes and dimensions to be used by the models. In particular, qualitative techniques generate lists of attributes (through interviews, telephone, questionnaires) to ensure that issues relevant to the design process are addressed, while quantitative techniques identify the key attributes from this list to ensure that only the key issues are addressed. These attributes must reflect consumer perceptual dimensions rather than the physical product (Pessemer 1973) and should be 'actionable' (Shocker and Srinivasan 1979) to be meaningful to both the consumer and the firm and to ensure the implementability of the features or attributes desired by the consumer (e.g. the level of sweetness in cereal). Qualitative measurement techniques can be expensive, inaccurate, and irrelevant to the information required in the design process. The techniques should be used with caution and should be specified by the specific information required by the models, the specific managerial questions to be answered, and the corresponding techniques that will provide answers to these questions and issues. Quantitative measurement techniques which provide a means for collecting and quantifying attitudinal data, should be used in a similar fashion. Most behavioral data takes the form of non-metric data and care must be taken against the tendency to treat it as metric data in an effort to produce quantitative output. A number of measurement scales are shown in Figure 2.2. The attitude scales shown are simple questioning methods that seek substantiation of consumers'
(a) Likert

I can get medical service and advice easily any time of the day and night.

<table>
<thead>
<tr>
<th>Strongly Agree</th>
<th>Agree</th>
<th>Neither Agree nor Disagree</th>
<th>Disagree</th>
<th>Strongly Disagree</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>b</td>
<td>c</td>
<td>d</td>
<td>e</td>
</tr>
</tbody>
</table>

(b) Semantic Differential

Gentle to Harsh on
Natural Fabrics Natural Fabrics

(c) Graphical (marked)

Good

Shopping Center Atmosphere

Poor

(d) Graphical (unmarked)

Low Prestige

Reputation

High Prestige

(e) Itemized

Personalness (warm, friendly, personal approach, doctors not assistants, no red tape or bureaucratic hassle).

<table>
<thead>
<tr>
<th>Extremely Poor</th>
<th>Very Poor</th>
<th>Poor</th>
<th>Satisfactory</th>
<th>Good</th>
<th>Very Good</th>
<th>Excellent</th>
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<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
</tbody>
</table>

(f) Pairs

Allocate 100 points between the two auto brands to reflect your preference.

V W Rabbit or Ford Fiesta

Figure 2.2 Different Types of Attribute Scales

attitudes by measuring attributes, similarities between products, tradeoffs between attributes, preferences among products, intent to purchase, propensity to innovate, and demographics.

The accuracy is reliability of the analytical methods used in product design depend not only on the validity of the models used in representing consumer behavior, but also on the techniques used in collecting the data used in the models. In addition, these characteristics (accuracy and reliability) depend on the requirements and constraints of the manager and his ability to understand and feel comfortable with the models and techniques used.
III. PRODUCT DESIGN TECHNIQUES

This section introduces some of the models and techniques used in the product design process. These models, specifically perceptual mapping models and preference/choice models, are presented along several criteria that incorporate their performance and functionality in the design process and their relevance or applicability to the marketing manager's requirements. These include: assumptions, data requirements, model structure, uses, limitations, availability of computer support, and the quality of support provided by the model to the marketing manager.

Market response models can be classified according to whether they model individual behavior directly or whether they model individual behavior and aggregate the individual responses (Lilien 1981). Few deterministic models of consumer behavior exist because of the variability in individual behavior which requires some stochastic component.
A. PERCEPTUAL MAPPING TECHNIQUES

Perceptual mapping is a group of techniques that is widely used for product positioning, for analyzing the market structure, and for overall product design.

Perceptual mapping includes a large family of consumers' perceptions of products in a defined product market. The products are represented (or mapped) by locations in a space of dimensions which distinguish between alternative products relative to the benefits, costs, or other measures of value important to the consumer in making a purchase. Distances between products represent measures of perceived similarity or substitutability between the products (Shocker and Srinavasan 1974).

For example Figure 3.1 shows a perceptual map of pain relievers along the dimensions of "effectiveness" and "gentleness." The dimension "gentleness" gives the perception of "gentle to the stomach" while "effectiveness" is perceived as providing "fast and strong relief" from headaches and other pains. Tylenol is depicted as the most gentle pain reliever on the map while Excedrin is seen as the most effective and least gentle. One could conceive from this map that an opportunity exists for a pain reliever with effectiveness and gentleness.

Perceptual maps such as this provide simple, clear and meaningful methods of representing product positioning especially in comparison to alternative representations of positioning data such as the snake plot in Figure 3.2 which depicts scientists' and managers' perceptions of new communication options.39

Since the perceptual map is a set of dimensions and a "map" of
**Figure 3.1** PERCEPTUAL MAP OF PAIN RELIEVERS*

*Urban and Hauser 1980, p. 187*
Figure 3.2 "Snake Plot" of Scientists' and Managers' Perceptions of New Communications Options
Since the perceptual map is a set of dimensions and a "map" of products along these dimensions, the structure of the models to be used will be better understood if the number of dimensions identified by the measurement techniques of the last section is reduced to a manageable and an interpretable size.

Several different techniques can be used to reduce this set of dimensions and to create perceptual maps of various product markets. The major techniques include attribute-based models like factor analysis and similarity based multi-dimensional scaling techniques. These methods are chosen for review here because of the accuracy, reliability and interpretability of the results they produce and the ease and frequency of their uses (Hauser and Koppelman).

A large number of approaches to model consumer preferences for products are represented by multi-attribute models with parameters that vary for individuals or market segments under different conditions of intended usage. Multi-attribute research is aimed towards understanding the structure of consumer decisions with respect to the products of the firm and the firm's competitors, thus enabling the firm to evaluate and design products for greater consumer satisfaction and profitability (Wilkie and Pessemier 1973).

The basic assumption of the linear compensatory multi-attribute model is that each individual's overall evaluative attitude towards competing products may explain a number of the attributes. That is, an individual associates a particular level of an attribute with each product while the salience or weight of each attribute summarizes the variable importance of the attributes to the individual. However
care must be taken against the incurrence of the halo effect where individuals who favor an alternative tend to rate it high on all alternatives while individuals who dislike the alternative rate it low on all attributes (Beckwith and Lehman 1975). This effect is due to the fact that multi-attribute models are based directly on measured beliefs about alternatives on attributes and consequently raise the issue of bias in the consumer attitudes expressed. To prevent this effect, Beckwith and Lehman recommend:

- explicit measurement of weights
- objective measurement of beliefs about attitudes
- inclusion of only relevant dimensions
- careful interpretation and positioning of dimensions

The two attribute-based methods to be discussed, factor analysis and discriminant analysis attempt to incorporate these factors in their methodologies.


Factor analysis is a class of techniques that reduces data while preserving information in the original set.

Factor analysis requires attribute ratings for data and assumes that these ratings are related to only a few basic dimensions. The objective is to find a number of dimensions that can represent the information in a large set of attribute ratings. (Urban and Hauser 1980). Correlations across products and consumers are examined and the basic dimensions are identified on the basis of these estimates of the correlations or the factor loadings. Data is reduced by eliminating one out of every pair of perfectly correlated ratings. There are two major types of factor analysis. Common Factor Analysis is given by:

\[ y_{ije} = \sum_{k=1}^{z} f_{ek} x_{ijk} + u_{ije} + \epsilon_{ije} \]

while Principal Components Factor Analysis is given by:

\[ y_{ije} = \sum_{k=1}^{A} f_{ek} x_{ijk} + \epsilon_{ije} \]

where

- \( y_{ije} \) = rating of individual \( i \) for product \( j \) on attribute scale \( e \).

- \( f_{ek} \) = factor loading of scale \( e \) and underlying dimension \( k \).

- \( x_{ijk} \) = "factor score", or the position of product \( j \) on underlying dimension \( k \) by individual \( i \).
\( \epsilon_{ij} \) = error term

\( \Delta \) = number of dimensions (two or more)

\( u_{ij \epsilon} \) = unique contribution of individual i's rating of product j on scale \( \epsilon \).

Intuitively, factor analysis searches for a common set of factors that can explain the variations in the consumer ratings of products with respect to the attribute scales (Urban and Hauser 1980). The factor loading explains this variation through correlations of the consumer ratings with the original attribute ratings. Dimensions are named by examining the matrix of correlations among the basic attributes and extracts factor in order of variance magnitudes.

The perceptual map is obtained by plotting the products on positions (\( \bar{x}_{jk} \)) along any dimension by averaging the factor scores across individual consumers (Figure 3.3).

Some of the consumer measures used for the model are given in Figure 3.4a.

Factor analysis works accurately, is inexpensive and easy to use, and has the advantage of providing individual measures that preserve individual idiosyncracies. It encompasses a broad set of data reduction and psychological techniques that can be used to produce perceptual maps.
Figure 3.3  Perceptual Map of Shopping Locations (Koppelman and Hauser, 1979)

![Perceptual Map of Shopping Locations](image)

Figure 3.4  Alternative Consumer Measures to Product Perceptual Maps

MULTIDIMENSIONAL SIMILARITY SCALING

Similarity scaling techniques measure consumers' perceptions from consumer judgements on the relative similarity between pairs of products. There are two approaches to similarity scaling techniques: metric and non-metric. Metric models assume that similarities are measured on an interval scale (which allows statistical manipulations and linear transformation) while non-metric models assume only that the rank order of the similarities is known.

Overall similarity scores for all possible pairs of products are obtained by aggregating similarity judgements of individual consumers in a sample and normalized across products. The larger the score, the greater the similarity. A perceptual map is constructed by "positioning" individual products, as perceived by the consumers, against a space of set dimensions. Distances between products reflect the degree of similarity, and the more similar two products are judged to be, the smaller the distance between them in the perceptual space.

For example, suppose an individual is asked to make preference judgements about automobile models. Figure 3.5 shows a map of the individual's responses where only two characteristics of the cars - "luxuriousness" and "sportiness" - matter in the evaluative judgements of the individual. The consumer's ideal point 1 represents the hypothetical automobile model that possesses the "right" combination of "luxury" and "sportiness." He will prefer products whose combination of attribute levels (luxury and sportiness) are closer to the ideal point than those whose combinations are further away. Thus the
Figure 3.5  Ideal Point Illustration

Stimuli—1968 Car Models
1. Ford Mustang 6
2. Mercury Cougar V8
3. Lincoln Continental V8
4. Ford Thunderbird V8
5. Ford Falcon 6
6. Chrysler Imperial V8
7. Jaguar Sedan
8. AMC Javelin V8
9. Plymouth Barracuda V8
10. Buick Le Sable V8
11. Chevrolet Corvair


Figure 7-1. Illustration of Joint Space of Ideal Points and Stimuli.
consumer will prefer, in this instance, a T-bird to a Cougar.

Multidimensional scaling has been viewed by Krusgal "as a problem of statistical fitting where the objective is to find a configuration that 'best' fits the given similarities and dissimilarities." The coordinates obtained from optimizing the fit are used to plot the perceptual map. The 'goodness-of-fit' is measured by 'stress' (similar to residual sum of squares in regression) such that a minimized stress maximizes the fit. This fit however is constrained by the number of dimensions. Klahr (1969) states that at least eight products are needed for a good two-dimensional perceptual map that provides a good "fit."

Similarity measures are most useful for non-verbal perceptual structures. Additionally, they offer the advantage of collecting data that does not require specification of attributes. However, similarity scaling when used alone, cannot determine psychological dimensions accurately. Also the statistical techniques employing this method are expensive and difficult to use.
Table 3.3 summarizes the three models discussed and Figure 3.6 shows a comparison of perceptual maps obtained from the two techniques. Three major differences were found between attribute-based techniques (factor analysis) and multidimensional similarity scaling:

1. perceptual maps for the attribute-based techniques are derived from directly measured attributes while similarity judgements introduce a similarity construct even though they are made with respect to actual product comparisons. Attributes may be incomplete however if not exhaustively generated.

2. attribute-based techniques assume a common structure among consumers but do not restrict the values of individual measures to a stretching of common measures. This implies that rank orders in similarity scaling cannot be changed (except for reversals).

3. Finally, similarity scaling techniques are limited by the number of products required for producing perceptual maps (at least 8 in the opinion of Klahr, 1969). Attribute-based models such as factor analysis are unrestricted by product, but limited by the number of attributes.

Hauser and Koppelman have found that if attributes have been comprehensively identified, attribute-based models should perform better than multidimensional similarity scaling, with respect to measures of
Figure 3.6
COMPARISON OF PERCEPTUAL MAPS

Factor Analysis
Factor Scores

Non-metric Scaling:
Common Space Positions

STIMULI SET:
- Chicago Loop
- Woodfield
- Edens
- Golf Mill
- Plaza del Lago
- Old Orchard
- Korvette City
### TABLE 3.3

**III. PRODUCT DESIGN TECHNIQUES: MAPPING PROCEDURES**

<table>
<thead>
<tr>
<th>FACTOR ANALYSIS</th>
<th>MULTIDIMENSIONAL SIMILARITY SCALING</th>
</tr>
</thead>
</table>

1) ASSUMPTIONS:
- ratings related to only a few dimensions
- data interval-scaled
- assumes monotone relationship between similarities and distances

2) DATA REQUIREMENTS:
- attribute ratings
- similarity judgements rank-order (metric)
- ordinal measures of dissimilarity (non-metric)

3) MEASUREMENT TYPE:
- eliminate 1 of 2 perfectly correlated ratings to identify basic dimensions
- does not partition data, focuses on complete set of variables
- statistical fitting to determine configuration that best fits given similarities and dissimilarities

4) USE:
- find # of dimensions that can represent information in a large set of attribute ratings
- emphasizes preservation of data
- coordinates obtained from optimizing fit used to plot map

31
TABLE 3.3 continued

4) **LIMITATIONS**
- need complete set of attributes
- used alone, cannot determine psychological dimensions
- produces average perceptions
- good fit limited by number of products required for producing perceptual map (at least 7 - 8)
- restrict individual measures to stretching of common measures
- similarity judgements less direct measures of perception

5) **MODEL STRUCTURE:**
- linear
- deterministic
- individual
- monotone
- individual

6) **COMPUTER SUPPORT:**
- available, inexpensive
- available but complex and costly: PROFIT, INDSCAL
- difficult to use
- expensive
- not as accurate

**Advantages/Disadvantages**
- accurate
- inexpensive
- easy to use
consumer perceptions.

The advantage of perceptual maps derived from multidimensional similarity scaling is that they do not require specification of attributes and are based on measures that complement rather than depend on attribute measures. The disadvantage is that they are difficult to use, more expensive, and not as accurate as factor analysis. If attribute ratings are available, Carroll and Chang's program PROFIT can be used to name the dimensions by estimating the association between the similarity dimensions and the attribute ratings.

Factor analysis was found to be superior to the other two techniques for generating perceptual maps (Hauser and Koppelman 1979). The fact that it performs well indicates that very little information is lost by using reduced factors rather than a full set of attributes.

Of the two discussed, factor analysis offers the most managerially useful structure by identifying unambiguous dimensions. Hauser and Koppelman found that the model may be better on predictability, interpretability, and ease of use. After data collection, the attribute-based techniques are readily available on standard statistical packages at cost and with little requirements for time.

Factor analysis is superior to discriminant analysis and multidimensional similarity scaling for developing consumer perceptions when (Hauser and Koppelman 1979):

- the number of products in an average consumer's evoked set is small,
- consumers perceive products in a category differently,
- attributes representative of the product category have been exhaustively identified by qualitative measurement techniques.
Similarity scaling techniques however require a more difficult consumer task of judging similarities, and require special computer programs at high costs and time requirements. The advantage is that they offer the possibility of identifying new dimensions.
B. PREFERENCE/CHOICE MODELS

As mentioned earlier in this section, both psychological positioning and physical features are part of a good product design. Urban and Hauser (1980) state that while early investigation in most product categories concentrates on the psychological characteristics of the product to find new dimensions, to understand the consumer, and to ensure consumer input to analytical models, later work should shift to physical features to achieve a product that meets the specified psychological positioning. The allocation of time to these two efforts will depend on the particular product. For example, industrial products such as production control instrumentation require more attention towards the physical part of the design process while frequently purchased consumer goods like aspirin or breath-refreshers require greater emphasis in the psychological part of the design. Customer size and frequency of purchase of the product help to determine the allocation of effort toward the physical and psychological design of the product with greater emphasis being placed on the psychological design of a competitive product.

Perceptual maps discussed in the last subsection provide the capability to identify new product opportunities. To decide which of these product opportunities would be optimal, the marketing manager needs to analyze consumer preferences to identify a product attractive to potential consumers. If the consumer's preference process can be modelled, it will provide a better understanding of his/her pur-
chase disposition, predict the purchase potential of a product, and help to design a product that satisfies the consumer's needs and desires.

Preference models undertake two basic approaches (Green and Rao 1972). The internal approach attempts to simultaneously develop a joint space of products and individual consumer points (i.e. combinations of dimension levels that consumers most prefer) from preference data (alone). The external approach uses both similarities and preferences in constructing a joint space of people and products. It requires additional information, but is preferred by marketing researchers because it permits the gathering of salience data as one moves from a perceptual space to an evaluative space, and avoids confounding differences in perception with differences in preference. Carroll and Chang's PREFMAP program uses both metric and non-metric methods in the context of external analysis, and provides both point-point and point-vector representations. INDSCAL, also by Carroll and Chang, offers an alternative approach to scaling individual differences.

There are several forms of preference models that can be used to construct maps of individual products 'positioned' to reflect consumer's perceptions. Of these, the ideal point model provides the greatest interpretability, clarity in conceptualizing and visualizing a set of preferences for a particular product or product market.

Marketing research has traditionally focused on the links in the (product attribute → product preference → product choice) chain. Because of different objectives of firms and measures of success of new
products, marketing research has diverged into either the expectancy-value preference models or the stochastic choice models (Blin, Dodson 1980). Multiattribute research has emphasized the evaluative aspect of choice with preference as the criterion variable while stochastic models have used actual choice as the criterion variable.

A majority of product design approaches model preference decision making behavior due to the case and the reliability of the data collected and the availability of information about decision making. With preference as a criterion variable, an entire preference ranking is obtainable whereas the choice criterion provides only for the decision itself (Shocker and Srinavasan 1979).

This section presents three preference models: preference regression, expectancy-value model, and conjoint analysis; and a choice model: the multinomial logit analysis model. These models are summarized in Table 3.4.
<table>
<thead>
<tr>
<th>PREFERENCE REGRESSION</th>
<th>EXPECTANCY-VALUE</th>
<th>CONJOINT ANALYSIS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1) Assumptions:</strong></td>
<td>• linearity</td>
<td>• independent set of paired comparisons</td>
</tr>
<tr>
<td>• importance of attributes same for all consumers</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>2) Data Requirements:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• rank-order data</td>
<td>• importance weights</td>
<td>• individual total</td>
</tr>
<tr>
<td>• actual product alternatives and concepts</td>
<td>• product perceptions</td>
<td>profile descriptions</td>
</tr>
<tr>
<td>• attribute ratings and preferences</td>
<td>• attribute scales</td>
<td>• ordinal scales</td>
</tr>
<tr>
<td>• attribute importances</td>
<td></td>
<td>• rank order preference</td>
</tr>
<tr>
<td><strong>3) Uses:</strong></td>
<td>• uses direct consumer input</td>
<td>• selects product features for existing and new products</td>
</tr>
<tr>
<td>• reproduces actual observed consumer preferences statistics</td>
<td>• gives early indications</td>
<td>• links features to perception</td>
</tr>
<tr>
<td>• gives core benefit proposition</td>
<td></td>
<td>• links features to preference</td>
</tr>
</tbody>
</table>

38
4) Limitations:
- ignores uncertainty due to external and internal factors
- loses degrees of freedom
- not as accurate as other methods
- not as accurate
- limited to simple consumer choices
- requires more time-consuming consumer task
- utility function shape not clear
- can only analyze a few products because number of features goes up rapidly

5) Model Structure:
- linear and nonlinear
- deterministic
- group
- compositional, linear
- individual
- nonlinear decompositional (additive)
- probabilistic
- individual
- LOGIT, PROBIT

6) Computer Support:
- MONANOVA
PREFERENCE REGRESSION MODEL

Preference regression is a statistical method that attempts to estimate a model that 'best' relates consumer preference to product perception. The linear model denotes the preferences as:

\[ p_{ij} = \sum_{k=1}^{K} w_k x_{ijk} \]

where \( x_{ijk} \) = consumer i's perception of product j along dimension k,

\( w_k \) = importance of dimension k (assumed to be the same for all consumers)

Several algorithms are available for finding weights for the model. For example, MONANOVA (Green and Wind 1973) uses product rankings as the dependent variable and the perception \( x_{ijk} \) as the explanatory variable to calculate the weights. PREFMAP (Carroll and Chang 1967) runs the regression on an individual or aggregate basis. Urban and Hauser (1980) however, argue that the program loses a number of degrees of freedom and is not as accurate as other methods. They add that normal metric regression methods are not naturally inferior to MONANOVA in recovering consumer preferences.
EXPECTANCY-VALUE MODEL

The expectancy-value class of attitude models has received the most attention in marketing literature for modeling consumer preferences among multi-attribute alternatives. Expectancy-value models are based on a compositional or build-up approach where the total utility for a multi-attribute object is found as a weighted sum of the object's perceived attribute level and the associated value ratings as judged explicitly by the respondent (Green and Srinavasan 1974). It is one of the easiest methods for modelling consumer preferences and is given by:

\[ u_{ij} = w_{i1} y_{ij1} + w_{i2} y_{ij2} + \ldots w_{iL} y_{ijL} \]

where \( w_i \) = the importance placed by individual i on attribute.

\( y_{ij} \) = individual i's perception of product j relative to attribute from a set of L attributes.

The model uses consumer specified importance weights and product perceptions for data input. Figure 3.7 shows the preference measurements used in the model to determine the most important aspects of a transportation service to the consumers in a city.

A number of other scales like paired comparison may also be used for input data. However, the wording used for the comparison tests should be carefully composed to avoid the 'halo' effects dis-
We would like to know how important the following transportation characteristics are to you, when you select the means of travel to downtown Evanston. Please be sure to tell us how important they are to you and not how available they are.

<table>
<thead>
<tr>
<th>HOW IMPORTANT IS HAVING A MEANS OF TRANSPORTATION?</th>
<th>Of No Importance</th>
<th>Moderately Important</th>
<th>Important</th>
<th>Very Important</th>
<th>Extremely Important</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Which will always get me places I want to go on time.</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>2. Which will not require me to schedule trips in advance.</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>3. Which will allow me to relax while traveling.</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>4. In which I will not be too hot or too cold during the trip.</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>5. Which will not cause me to worry about being mugged or assaulted.</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
</tbody>
</table>

Figure 3.7. Examples of Preference Measures for Expectancy Values. (This figure represents the first 5 out of 25 scales.)
cussed earlier with multi-attribute models.

The expectancy-value model may be used to predict responses in what if situations (e.g. how much would consumer i's rating of the bus go up if availability were to increase by 50%). Urban and Hauser (1980) have found that this model provides an inexpensive and relatively easy method of analysis in the early stages of product design when the key attributes don't need to be specified, but is not as accurate as some of the other methods discussed. Furthermore, its linearity limits it to cases where consumer choices are simple (e.g. frequently purchased consumer goods) and involves no uncertainty.

The main problem with the expectancy-value model, however, is the redundancy of measurement scales. If two scales are reproduced, they will contribute a double weight to the model. Additionally, since the weights are specified by the consumer, the reliability and validity of their use in a model is questionable without accounting for judgemental error.
CONJOINT ANALYSIS

Conjoint analysis is a set of methods that predicts consumer preferences for multi-attribute options in a wide variety of products. The procedure is based on a decompositional approach where consumers are asked to react to a set of 'total' product profile descriptions. Given the consumer judgements on a prespecified set of alternatives, external analysis is performed to obtain an estimate of the structure of consumer preferences (eg. part worths, importance weights, ideal points). While the objective of the expectancy-value model is to explain predictions, the primary objective of conjoint analysis is to validate these predictions (Green adn Srinivasan). Additionally, since it summarizes ranking information in a total profile, it is used to study the linkage of features to perception and the linkage of features to preference.

Table 3.5 summarizes the steps involved in conjoint analysis and the alternate methods of implementing each of these steps. The goal is to identify the combination of methods that maximizes the predictive validity of the model subject to a given set of constraints. Figure 3.8 and Table 3.6 depict the models of preference available.
<table>
<thead>
<tr>
<th>Step</th>
<th>Alternative methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Selection of a model of preference</td>
<td>Vector model, ideal-point model, part-worth function model, mixed model</td>
</tr>
<tr>
<td>2. Data collection method</td>
<td>Two-factor-at-a-time (trade-off analysis), full-profile (concept evaluation)</td>
</tr>
<tr>
<td>3. Stimulus set construction for the full-profile method</td>
<td>Fractional factorial design, random sampling from multivariate distribution</td>
</tr>
<tr>
<td>4. Stimulus presentation</td>
<td>Verbal description (multiple cue, stimulus card), paragraph description, pictorial or three-dimensional model representation</td>
</tr>
<tr>
<td>5. Measurement scale for the dependent variable</td>
<td>Paired comparisons, rank order, rating scales, constant-sum paired comparisons, category assignment (Carroll, 1969)</td>
</tr>
<tr>
<td>6. Estimation method</td>
<td>MONANOVA, PREFMAP, LINMAP, Johnson's nonmetric tradeoff algorithm, multiple regression, LOGIT, PROBIT</td>
</tr>
</tbody>
</table>
FIGURE 3.8
ALTERNATIVE MODELS OF PREFERENCE

Preference for different levels of attribute p while holding the values for the other attributes constant.
TABLE 3.6 FORMS OF PREFERENCE MODELS

VECTOR MODEL
- a linear compensatory model that denotes preference $s_j$ for the $j^{th}$ product on a set of $t$ chosen attributes ($p = 1, 2, \ldots, t$) as:

$$s_j = \sum_{p=1}^{t} w_p(y_{jp})$$

where $w_p = \text{the individual weights for } t \text{ attributes}$
$y_{jp} = \text{the level of the } p^{th} \text{ attribute for product } j \text{ (here a continuous variable)}$

- geometrically, the preference $s_j$ may be represented as the projection of the product point $y_{jp}$ on the vector $w_p$ in the $t$-dimensional attribute space (Figure 3.).

IDEAL POINT MODEL
- depicts the preference $s_j$ as inversely related to the squared weighted distance $d_j^2$ of the location $y_{jp}$ of the $j^{th}$ product from the individual consumer's ideal point $x_p$ such that a product $j$ will be preferred more it it is closer to the ideal point (with smaller distance $d_j^2$).

- the distance is given by:

$$d_j^2 = \sum_{p=1}^{t} w_p(y_{jp} - x_p)^2$$
is more flexible than the vector model since it breaks down to
the vector model as $x_p \rightarrow +\infty$


PART-WORTH FUNCTION MODEL

- gives preference as a function of the part worth of different
levels of $y_{jp}$ for the $p^{th}$ attribute:

$$s_j = \sum_{p=1}^{t} f_p (y_{jp})$$

- generally, $f_p (y_{jp})$ is estimated only for 3 or 4 selected levels
for $y_{jp}$ with the intermediate points obtained from linear inter-
polation to yield a piecewise linear curve (Figure 3. ).

- breaks down to the ideal point model if $f_p (y_{jp}) = -w_p (y_{jp} - x_p)^2$
and to the vector model if

$$f_p (y_{jp}) = w_p y_{jp}.$$  

The choice of the model depends on the shape of the attributes.
If the attributes are categorical (e.g. high preference for iced and
hot tea and low preference for lukewarm tea), the part-worth function
model is appropriate. In other cases where the highest level is
always optimum (e.g. reliability) or a particular intermediate level
is preferred by an individual (e.g. sweetness in coffee) the vector
model or the ideal model may be appropriate respectively.

The three models may be combined to yield a mixed model where any
one of the models can be transformed into another through dummy variables. The data and the intended usage determine the type of model to be used. For example, if conjoint analysis is to be used to identify features for a product, the part-worth function model is appropriate due to the discrete characteristics of the features.

Generally, the predictions made by the linear compensatory (vector), ideal point, and part-worth function models is quite good. In particular, the linear compensatory model performs well under the conditions of monotone preference-attribute relationships and correlated attributes and attribute measurement errors. Despite its questionable validity and reliability, with respect to the extrapolation of \( y_{jp} \) outside the estimation range, the part-worth function model has been widely accepted due to the greater interpretability and flexibility it provides in comparison to the other models (Green and Srinivasan, 1979).

Using the part-worth model, the conjoint analysis is denoted as:

\[
R_{im} = \sum_{k=1}^{K} \sum_{l=1}^{L} \lambda_{ikl} d_{mkl} + \text{error}
\]

\[
= u_{ik} (\text{feature } k \text{ for product } m) + \text{error}
\]

where

- \( R_{im} \) = individual i's ranking of product m,
- \( \lambda_{ikl} \) = 'utility' level appropriate to represent individual i's valuation of having the \( k \)th attribute at the \( l \)th level,
- \( d_{mkl} \) = \[
\begin{cases} 
1 & \text{if product } m \text{ has feature } k \text{ at level } l, \\
0 & \text{otherwise,}
\end{cases}
\]
- \( u_{ik} \) = utility possessed by product m for the level of feature k.
The utility functions indicate the sensitivity of consumer preferences and perceptions to changes in product features. Using features for existing products, potential product features may also be predicted. For example, Figure 3.9 shows the utility functions for evaluating the features of an airline service.

Parameters in conjoint analysis may be estimated by:
1) methods assuming ordinally-scaled dependent variables (e.g. MONANOVA-Kruskal 1965, PREFMAP-Carroll 1972, LINMAP-Srinivasan and Shocker 1973); 2) methods assuming intervally-scaled dependent variable (i.e. least squares regression); 3) methods relating paired comparison data to a choice probability model (e.g. LOGIT - Green and Carmone 1977, and PROBIT - Rao and Winter 1977). The algorithms differ in their performance criteria or the "poorness of fit" measure and the methods used to minimize this measure. Of the algorithms available, LINMAP is the most appropriate and performs well for the ideal point model. It will be discussed in detail later in the next section.

Conjoint analysis is most appropriately used in the later part of the design process to link product features to the perception and preference for the product. However, the model does not link perceptions to preferences and consequently cannot link features directly to the positioning of the product. The discrete nature of the physical features also makes it difficult to relate the physical design with the psychological
Figure 3.9 Utility Functions for Features of Airline Service to Paris (Green and Wind, 1975)
positioning of the product. Additionally, the model is limited by the number of physical features (per product) which go up rapidly with the number of products considered. Conjoint analysis offers the advantage of measuring individual consumer preferences and incorporating the dynamics of the marketing environment through the nonlinear structure.
MULTINOMIAL LOGIT FUNCTION

Gensch and Recker (1979) hypothesize that an individual decision maker's overall preference or ranking of a choice alternative (product) is a function of the utility that the individual holds for the particular alternative. The multinomial logit choice model, which converts consumer preferences into product purchase estimates, reflects this concept of choice as a function of utility. The model uses data on the intensity of feeling in preference values and translates these values into purchase probabilities. The model is given by (Urban and Hauser 1980):

\[ p_{ij}^T = p_{ij} + e_{ij} \]

where

\[ p_{ij}^T \] = some true choice indicator such as the utility of product \( j \) to individual \( i \),

\[ e_{ij} \] = some error term (random)

and

\[ p_{ij} = \frac{1}{B} \sum_{k=1}^{K} w_k x_{ijk} \]

= the revealed preference measure

where \( w_k \) = the importance of attribute \( k \)

\( x_{ijk} \) = the consumer's evaluation of product \( j \) with respect to attribute \( k \)

\( B \) = an estimated parameter that maximizes the likelihood that a particular observation has occurred.

The consumer will pick the product that maximizes \( p_{ij}^T \) (and hence his
utility). The logit model, which may be expanded to more than two values on the dependent variable, breaks down to the simpler form of probit which is strictly limited to a two-value dependent variable. The model is used in conjunction with preference models to predict market demand as a function of the sensitivity of product preference to design changes. The multinomial logit model takes a realistic approach to modelling consumer behavior by acknowledging and measuring error. It is the best method available for linking preference to choice for estimating demand (Urban and Hauser) although recent work with stochastic models (Blin-Dodson, 1980) has attempted to go even further by linking choice to the attitudinal structure of the consumer.

Gensch and Recker (1979) postulate that the multinomial logit model is superior to the linear approach for a number of reasons:

- it can be developed from a behavioral utility theory framework,
- it implicitly incorporates the bounds on choice,
- it incorporates idiosyncratic individual differences,
- it allows individuals to consider unique attributes per alternative,
- it incorporates the theoretical concepts of marginal utility, threshold and saturation,
- it recognizes the validity of the results by incorporating an error term.
The limitations are:

- it uses only the first preference information rather than the full rank order preference information
- it absorbs some product-specific effects such as product 'inertia' (Urban and Hauser 1980) where a consumer is hesitant to pick a new product vs. an existing line of products
- it requires expensive sampling
- it assumes that the error term is random which implies that the ratio of any two products do not change regardless of what the evoked set us as long as those two products are in the evoked set.

The techniques summarized in this section have attempted to model the consumer's decision process in purchasing a product. Specifically, this involves the modelling of perception, preference and choice to predict the purchase probability or the market potential.

Several of the models discussed link consumer perceptions to preferences, and provide reasonable results in identifying potentially attractive product opportunities. Choice models link preference to choice and incorporate the error (due to external factors) in predicting purchase probabilities. However, there is still need for models that can incorporate the overall process of perception, preference, and choice. This integrated approach to modelling consumer purchase behavior will provide greater accuracy in predicting potential (due to feedback from choice data) and a better understanding of the consumer's overall behavior.
IV. USE OF PRODUCT DESIGN MODELS

A number of procedures and models have been developed to aid in the design of new products. In this section, we look at three models (LINMAP, PERCEPTOR, and DESIGNOR) that are applicable to three different product markets respectively: durables, frequently purchased consumer products, and industrial products. Each model is described and compared in terms of its structure, uses, assumptions, limitations and implications for further study.
LINMAP: MODEL OVERVIEW

Shocker and Srivavasan's (1974) procedure LINMAP presents a consumer-based model that combines the prediction of consumers' purchase disposition for different products in a product market with a search process that identifies optimal new product ideas. The framework used to identify new product opportunities consists of four basic stages depicted in Figure 4.1.

1. A relevant product market is found by identifying products perceived by consumers as having similar or substitutable usages.

2. The products are represented in an attribute space where the dimensions or attributes are required to be 'actionable.' That is, not only should the attributes be relevant to consumer preferences among products and the inter-product spatial distances be consistent with corresponding similarities and differences but they should also specify actions to be taken by the manufacturer in implementing the product as a physical and psychological entity.

3. A model is developed to predict consumer behavior toward new product ideas (i.e., model the process by which each individual in a sample reacts to nonexistent alternatives and chooses among competing products).

4. The model developed is used to implement a location or a set of locations of new products that maximize specified firm objectives.
FIGURE 4.1 LINMAP FRAMEWORK FOR IDENTIFICATION OF NEW PRODUCT IDEAS

IDENTIFY THE RELEVANT MARKET

REPRESENT THE PRODUCTS IN AN ATTRIBUTE SPACE MEANINGFUL TO BOTH USERS AND MANUFACTURERS

PROVIDE A BEHAVIORAL MODEL CONSISTENT WITH USER BUYING DECISIONS

USE THE ABOVE MODEL TO IMPLEMENT A SEARCH FOR THE LOCATION OR SET OF LOCATIONS OF NEW PRODUCTS THAT MAXIMIZE FIRM OBJECTIVES
LINMAP: MODEL DEVELOPMENT

Shocker and Srinavasan assume ideal point and attribute saliences to be idiosyncratic and consequently develop the model in terms of a single user. The inputs to the model, as shown in Figure 4.2 are

1) the known locations or coordinates of n products in the attribute space or

\[ Y_j = \{ y_{jp} \} \]

where \[ y_{jp} \] = the \( i^{th} \) component vector of attribute values or location of product \( j \) on attribute (dimension) \( p \) where \( (p = 1, 2, \ldots t) \) and \( (j = 1, 2, \ldots n) \)

and 2) the pairwise preferences of the user between the \( n \) products represented by the ordered set \[ \Omega = \{ (j, k) \} \], where \( j \) denotes the preferred product on a forced choice from a paired comparison between products \( j \) and \( k \).

The model outputs are estimates of the location of the individual's ideal point as given by:

\[ X = \{ x_p \} \quad \text{the consumer's ideal point (}\text{t-component vector}) \]

\[ W = \{ w_p \} \quad \text{the t-component vector of saliences indicating the relative importance of each attribute to the user} \]

where \( p \in P \) denotes the ideal point of the consumer or his most preferred location. The degree of preference is then indicated by the squared
weighted Euclidean distance between the ideal point and a product \( j \):

\[
s = d_j^2 = \left[ \sum_{p \in P} w_p \left( y_{jp} - x_p \right)^2 \right] \quad \text{for all } j \in J
\]

such that the smaller the value of \( s \) or the closer the product to the ideal point, the more preferred the product will be. The optimum set of salience estimates and the ideal point or \((W, X)\) is found by minimizing the 'poorness of fit' criterion:

\[
\text{minimize } \sum_{(j, k) \in \Omega} z_{jk}
\]

where \( z_{jk} \) = a measure of 'poorness of fit' for the pair \((j, k)\) such that for any pair \((j, k)\) where \( j \) is preferred to product \( k \), the implied ideal point model constraint

\[
s_k \geq s_j \quad \text{for all } (j, k) \in \Omega
\]

is violated as 'minimally as possible.'

An index of fit \( C \) is defined as a monotone transformation of any nonnegative number \( B \) which denotes the optimum value of the objective function above and given by:

\[
C = \frac{B}{1+B}
\]

Because the transformation is strictly monotonically increasing, \( B \) and \( C \) are equivalent objectives in that a solution \((W, X)\) minimizing one
FIGURE 4.2 LINMAP MODEL

\[ \sqrt{s_j} = d_j \left[ \sum_{p=1}^{t} (y_{jp} - x_p)^2 w_p \right]^{1/2} \]

The Euclidean distance between the ideal point and the \( j \)th product is given by:

The ideal point model postulates:

\[ s_j < s_k \quad \text{if product } j \text{ preferred to product } k \]

The objective of LINMAP is then to:

- minimize poorness of fit \( z_{jk} \) for \((j, k)\) or determine
- solution \( W, X \) with \( w_p > 0 \)

\[ \exists s_j < s_k \quad \text{violated minimally} \]
objective will also minimize the other. $C$ is bounded between zero and unity and is analogous to the coefficient of determination, $1 - R^2$, in multiple regression.

For the choice model, Shocker and Srinavasan define

$$\Pi_j = \frac{a}{d_j^b} \quad (a > 0, b > 0)$$

as the measure of an individual's probability of purchasing a product $j$ where $b$ influences the rate at which $\Pi_j$ decays with distance and $a$ is a normalization constant. From the ideal point model, the condition

$$d_j \leq d_k$$

implies that

$$\Pi_j \geq \Pi_k$$

and the probability for an individual choosing product $j$ becomes greater as the distance of the product from the ideal point decreases. For cases where $d_k = 0, \Pi_k = 1$ and $\Pi_j = 0$ is defined for products $j = k$.

Shocker and Srinavasan posit the search criterion $q_i$ as a function of all feasible unknown locations for new products (assuming only one product idea is generated per search):

$$q_i = \frac{\Pi_{ir} + \sum_j x_i \cdot \Pi_{ij}}{\Pi_{ir} + \sum_{i \in \Psi} y_i \cdot \Pi_{ij}}$$

62
where $\Pi_{ir}$ = the measure of consumer i's likelihood of purchasing the new product r.

$\mathcal{X}_i$ = set of firm's existing products in $\psi_i$

Thus, the search criterion is defined as the ratio of the individual's likelihood of choosing the new and existing products of the firm to the likelihood of purchasing all products.

The firm's objective is defined by the total Incremental Revenue given by

$$TIR = \sum_{i=1}^{m} (q_i - h_i) s_i$$

where $s_i$ = measure of the demand for the product by consumer i

$q_i s_i$ = share of consumer i's demand (in $'$s) obtained by the firm's new and existing products (total revenue

$$TR = \sum_{i=1}^{m} q_i s_i$$

$h_i$ = firm's share of the consumer's purchases of existing products

This objective provides a prediction of revenue that takes into consideration potential cannibalization of the firm's existing products.
LINMAP: USES

The procedure described has a number of uses. For example, the objective TIR incorporates cannibalization and the procedure may thus be used to extend the firm's product line. It may be also used to develop a response to new products introduced by the competitor. LINMAP may be used to discourage a competitive product's entry, using a product response that minimizes the competitors profitability.

Additionally, it may be used to identify new products to replace its (dying) existing products by searching for an optimum product in an attribute space that does not contain the firm's existing product. The LINMAP framework can evaluate consequences of marketing decisions as well as additions and can evaluate product entry alternatives in a number of different product markets.
LINMAP: LIMITATIONS

The LINMAP procedure has a number of limitations:

1. In the choice model, \( a \) is implied as

\[
a = 1/\sum_{j \in \psi} (1/d_j)^b
\]

where \( \psi \) is the set of all available products from the restriction

\[
\sum_{j \in \psi} \Pi_j = 1
\]

such that the individual is presumed to choose among all available products.

2. As \( b \to \infty \), the individual is assumed to choose only the brand closest to his ideal.

3. The behavioral framework assumes a static environment; i.e. competitive conditions are assumed to be constant and the consumer is assumed to have knowledge of the attributes.
PERCEPTOR: MODEL OVERVIEW

PERCEPTOR "provides managers with a better understanding of the perception, preference, and purchase structure of their markets, specifies measurement needs, serves as structure to interpret experimental results, and aids managers in channelling their creative efforts to develop successful new product designs" (Urban 1975).

Urban sees the design of frequently purchased consumer products as a process of:

1. creating and designing new product concepts
2. screening new products
3. test marketing
4. national introduction

Based on this view, he formulates the PERCEPTOR model and measurement methodology to aid market managers in the design of these products. The model is structured as a trial and repeat process that produces estimates of long-run market share for the new product and links to physical and psychological product attributes through multidimensional scaling procedures. Ideal and existing products are positioned on the perceptual maps with the position determining the product's design and the distance from the ideal indicating its purchase probability. The trial and repeat submodels may also be used to simulate market tests before introduction.
PERCEPTOR: MODEL DEVELOPMENT

PERCEPTOR is structured around the generation of an estimated long run market share for the new product. This structure provides a good basis for evaluating the potential of the concept, selecting between alternative concepts and refining concepts.

1. **Long-run market share**
   
   \[ m = ts \]
   
   where \( m \) = long run market share
   
   \( t \) = fraction of target group who try the new product, \( 0 \leq t \leq 1.0 \)
   
   \( s \) = share of purchases of new product by those who have tried the product

2. **Long-run trial**

   \[ t = qwv \]
   
   \( q \) = long-run or ultimate probability of trial given awareness and availability
   
   \( w \) = long-run aided awareness of new product
   
   \( v \) = long-run percentage of availability of new product, i.e.
   
   sales volume of store \( x \) percentage of stores carrying product

3. **Market Share** of group of consumers who have used the product is given by:

   \[ s = \frac{p_{21}}{1 + p_{21} - p_{11}} \]
   
   where \( p_{ij} \) = probability of purchase of product \( j \) next time given the
purchase of product i for last time.

\[ i, j = \begin{cases} 
1 \text{ for new products,} \\
2 \text{ for all other products.} 
\end{cases} \]

The equation is a two-state markov process which 1) assumes that the frequency of purchase of the new product is the same as existing product and that 2) the consumer will find the product at the next opportunity. The assumption may be relaxed by multiplying the market share (s) by an index to reflect the relative usage rates of products. Consumers could be segmented on the basis of their usage rates and the overall market share would be the average of each segment weighted by segment size and usage rate.

4. **Trial model: perception and preference map**

\[ x_{by} = \sum_{a=1}^{A} f_{ya} r_{ba} \]

where \( x_{by} \) = coordinates of brand b on dimension y for the perceptual map of those who have not tried the new product but are aware of the concept (b = 1, 2, ... B),

B = new product; y = 1, 2, ... Y

\( I_y \) = coordinates of the one ideal point of dimension y for map of those who have not tried the new product but are aware of the concept

\( f_{ya} \) = factor score coefficient for dimension y and attribute scale a (a = 1, 2, ... A)
r_{ba} = \text{standardized rating of product b on scale a.}

5. Probability of purchase

\[ q = \alpha_0 + \alpha_1 \beta^2 \]

where \( q = \text{probability of trial of new product given awareness and availability} \quad 0 \leq q \leq 1.0 \)

\( \alpha_0, \alpha_1 \) = coefficients to be determined empirically.

\( \beta^2 \) = squared distance from ideal point (individual) to the new product on the map for those who are aware but have not yet used the brand, ie:

\[ \sum_{z=1}^{Z} h_z (x'_{bz} - I'_z)^2 \]

where \( x'_{bz} \) = rotated coordinates of product b on dimension z (z = 1, 2, ... Z)

As the product is positioned closer to the ideal point, its probability of choice increases nonlinearly.

6. Probability of repeat

\[ p_{11} = \alpha_0 + \alpha_1 \beta^2 \]

where \( p_{11} = \text{probability of repeat purchase if product was pur-} \)
chased last; \(0 \leq p_{11} \leq 1.0 \)

\[ \tilde{\alpha}_0, \tilde{\alpha}_1 = \text{coefficients determined empirically} \]

\[ \tilde{\alpha}_p^2 = \text{distance squared from ideal point to new product after use} \]

7. **Sources of new brand share**

\[ K_b = m \left( \left( \frac{e_b}{D_{bb}} \right) / \sum_{B=1}^{B-1} \left( \frac{e_b}{D_{bb}} \right) \right) \]

where \( K_b = \text{loss in market share of existing brand } b \).

\[ m = \text{market share of new product.} \]

\[ e_b = \text{fraction of people who have product } b \text{ in their evoked set.} \]

\[ D_{bb}^2 = \text{distance squared from product } b \text{ to new brand } B \text{ in users map.} \]
PERCEPTOR: USE

Urban describes how the PERCEPTOR model and the supporting empirical analysis may be used:

1) prior maps may be generated using managerial judgements and past data.
2) exploratory and base survey may be conducted to estimate joint space maps of the existing market structure and to search for potential new product concepts.
3) base map coordinates, ideal points and distance parameters \((\alpha_0, \alpha_1)\) may be used to depict trial and repeat maps for positioning new products.
4) the new product position may be identified by specifying the coordinates of the product.
5) after a product position has been determined, test market or simulated market tests may be conducted before the actual introduction of the product.
6) a product may also be repositioned or redesigned after its maturity.

The model was used in a study of Canadian beers. Measurement was conducted to determine the size and composition of the evoked set (Table 4.1), from similarity judgements, paired comparison, preference evaluations, and brand ratings on a set of scales for eight specified products. Using factor analysis on the evoked set to generate dimensions
and product coordinates (factor scores) (table 4.2), the attribute space was divided into two taste and social dimensions. The results were confirmed by non-metric similarity scaling.

Carroll and Chary's PREFMAP procedure was used to generate individual ideal points from constant sum preference data which were aggregated for perceptual maps. The performance is shown in Table 4.3.

The brand coordinates and ideal points were used to estimate the parameters of the trial and repeat function (Table 4.5).

The concept rating and the factor score coefficients obtained from factor analysis of ratings specify the new concept positions on the map. Table 4.6 gives the trial and repeat predictions and observations.

The overall trial/repeat model was tested for some national products and yielded satisfactory results for market share as seen in Table 4.7.

Table 4.8 shows the performance of the overall trial model while Table 4.9 shows the performance of the source of share structure. Both produce good results as indicated by the small variance between actual and predicted shares.

OTHER USES OF PERCEPTOR:

for a personal care product, improved product positioning was achieved by recommendations for two alternative strategies of aligning product claims with performance and improving physical product through R&D with increases in market share of one percent and three percent respectively.
for a medicinal product, a product opportunity was found along a new dimension.

<table>
<thead>
<tr>
<th>Product</th>
<th>Median Evoked Set Size</th>
<th>Total Number of Brands Evoked</th>
<th>Number of Brands Necessary to Account for 80% of Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canadian Beer</td>
<td>7</td>
<td>15</td>
<td>7</td>
</tr>
<tr>
<td>Aerosal Deodorant</td>
<td>3</td>
<td>20</td>
<td>6</td>
</tr>
<tr>
<td>Skin Care Product</td>
<td>5</td>
<td>30</td>
<td>12</td>
</tr>
<tr>
<td>Over the Counter Medicinal Product</td>
<td>3</td>
<td>20</td>
<td>5</td>
</tr>
<tr>
<td>Pain Relief Product</td>
<td>3</td>
<td>18</td>
<td>6</td>
</tr>
<tr>
<td>Antacid</td>
<td>3</td>
<td>35</td>
<td>6</td>
</tr>
<tr>
<td>Shampoo</td>
<td>4</td>
<td>30</td>
<td>20</td>
</tr>
</tbody>
</table>

**Table 4.2**

<table>
<thead>
<tr>
<th>Overall Factor Analysis Dimensions</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative Variance</td>
<td>0.34</td>
<td>0.54</td>
<td>0.57</td>
</tr>
<tr>
<td>Eigen values</td>
<td>5.80</td>
<td>3.40</td>
<td>0.534</td>
</tr>
</tbody>
</table>

### TABLE 4.3
Overall PREFMAP Goodness of Fit

<table>
<thead>
<tr>
<th>Phase</th>
<th>Correlation of Predicted and Observed Average Preference</th>
<th>Average Correlations of Observed and Predicted Preference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(n = 8 brands)</td>
<td>(n = 45 individuals)</td>
</tr>
<tr>
<td>1</td>
<td>0.98</td>
<td>0.87</td>
</tr>
<tr>
<td>2</td>
<td>0.953</td>
<td>0.82</td>
</tr>
<tr>
<td>3</td>
<td>0.952</td>
<td>0.73</td>
</tr>
<tr>
<td>4</td>
<td>0.93</td>
<td>0.66</td>
</tr>
</tbody>
</table>

### TABLE 4.4
Distance Function Fits

<table>
<thead>
<tr>
<th>Product</th>
<th>$R^2$</th>
<th>$a_0$</th>
<th>$a_1$</th>
<th>$t$</th>
<th>df</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beer</td>
<td>0.87</td>
<td>12.5</td>
<td>-13.3</td>
<td>6.9</td>
<td>6</td>
</tr>
<tr>
<td>Skin Care Product</td>
<td>0.68</td>
<td>21.0</td>
<td>-16.9</td>
<td>6.25</td>
<td>11</td>
</tr>
<tr>
<td>Over the Counter Medicinal</td>
<td>0.94</td>
<td>36.3</td>
<td>-15.8</td>
<td>9.63</td>
<td>5</td>
</tr>
<tr>
<td>Pain Relief Product</td>
<td>0.84</td>
<td>28.7</td>
<td>-16.1</td>
<td>5.71</td>
<td>6</td>
</tr>
</tbody>
</table>

### TABLE 4.5
Prediction of New Concept Trial and Repeat

<table>
<thead>
<tr>
<th>Predicted Trial ($p$)</th>
<th>Observed Trial</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concept A</td>
<td>0.26</td>
</tr>
<tr>
<td>Concept B</td>
<td>0.37</td>
</tr>
<tr>
<td>Concept C</td>
<td>0.30</td>
</tr>
<tr>
<td>Concept D</td>
<td>0.45</td>
</tr>
<tr>
<td>Concept E</td>
<td>0.26</td>
</tr>
<tr>
<td>Concept F</td>
<td>0.38</td>
</tr>
<tr>
<td>Concept G</td>
<td>0.39</td>
</tr>
<tr>
<td>Concept H</td>
<td>1.00</td>
</tr>
</tbody>
</table>

### TABLE 4.6
Predicted Repeat ($pu$) Observed Repeat

<table>
<thead>
<tr>
<th>Predicted Repeat ($pu$)</th>
<th>Observed Repeat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concept A</td>
<td>0.41</td>
</tr>
<tr>
<td>Concept B</td>
<td>0.47</td>
</tr>
<tr>
<td>Concept C</td>
<td>0.45</td>
</tr>
<tr>
<td>Concept D</td>
<td>0.74</td>
</tr>
<tr>
<td>Concept E</td>
<td>0.65</td>
</tr>
</tbody>
</table>

Urban, G.L. (1975)
### TABLE 4.7
Reasonableness of Macro Structure

<table>
<thead>
<tr>
<th>New Product</th>
<th>Long-Run Trial (i)</th>
<th>Repeat Probability (pi)</th>
<th>Nonrepeat Probability (pni)</th>
<th>Predicted Share (m)</th>
<th>Actual Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skin Care Product</td>
<td>0.12</td>
<td>0.75</td>
<td>0.20</td>
<td>5.3%</td>
<td>5.9%</td>
</tr>
<tr>
<td>Toilet Soap</td>
<td>0.35</td>
<td>0.13</td>
<td>0.13</td>
<td>4.6%</td>
<td>5.0%</td>
</tr>
<tr>
<td>Over Counter Medicinal</td>
<td>0.32</td>
<td>0.6</td>
<td>0.2</td>
<td>10.6%</td>
<td>10.0%</td>
</tr>
<tr>
<td>New Hand Lotion</td>
<td>0.68</td>
<td>0.55</td>
<td>0.38</td>
<td>29.0%</td>
<td>27.0%</td>
</tr>
<tr>
<td>Shampoo</td>
<td>0.22</td>
<td>0.46</td>
<td>0.12</td>
<td>8.0%*</td>
<td>7.0%</td>
</tr>
<tr>
<td>Specialty Cake Mix</td>
<td>0.20</td>
<td>0.5</td>
<td>0.2</td>
<td>1.1%*</td>
<td>1.3%</td>
</tr>
</tbody>
</table>

* Adjusted for frequency of purchase of new product relative to existing brands.

### TABLE 4.8
Cumulative Trial Structure

<table>
<thead>
<tr>
<th>Intent (g)</th>
<th>Awareness (u) Distribution(s)</th>
<th>Estimated Trial by Awareness (i)</th>
<th>Estimated Trial with Sampling (I')</th>
<th>Observed Trial</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skin Care Product</td>
<td>0.12</td>
<td>0.45</td>
<td>0.8</td>
<td>4.3%</td>
</tr>
<tr>
<td>Cereal</td>
<td>0.54</td>
<td>0.50</td>
<td>0.7</td>
<td>18.9%</td>
</tr>
<tr>
<td>Shampoo</td>
<td>0.37</td>
<td>0.60</td>
<td>0.98</td>
<td>21.8%</td>
</tr>
<tr>
<td>Cake Mix</td>
<td>0.28</td>
<td>0.65</td>
<td>0.80</td>
<td>14.5%</td>
</tr>
<tr>
<td>Toilet Soap</td>
<td>0.33</td>
<td>0.75</td>
<td>0.95</td>
<td>23.5%</td>
</tr>
</tbody>
</table>

* The trial by sampling (I') was estimated by I' = n'u, n = fraction of target group sampled and u = fraction who use sample.

Total trial was I' = I + I'' − I", I" = total trial, I = trial generated by awareness (2), I" = trial generated by sampling. This formulation assumes awareness and sampling to be independent. This is probably reasonable, since sampling is usually random in the target group.

### TABLE 4.9
Source of New Brand Share

<table>
<thead>
<tr>
<th>Brands</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>New</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of Last Purchases</td>
<td>0.409</td>
<td>0.098</td>
<td>0.065</td>
<td>0.016</td>
<td>0.049</td>
<td>0.164</td>
<td>0.049</td>
<td>0.032</td>
<td>0.016</td>
<td>0.098</td>
<td>—</td>
</tr>
<tr>
<td>Observed Share</td>
<td>0.232</td>
<td>0.081</td>
<td>0.032</td>
<td>0.016</td>
<td>0.042</td>
<td>0.094</td>
<td>0.034</td>
<td>0.008</td>
<td>0.019</td>
<td>0.043</td>
<td>0.33</td>
</tr>
<tr>
<td>Predicted Share</td>
<td>0.204</td>
<td>0.082</td>
<td>0.054</td>
<td>0.011</td>
<td>0.042</td>
<td>0.123</td>
<td>0.044</td>
<td>0.027</td>
<td>0.014</td>
<td>0.083</td>
<td>0.33</td>
</tr>
</tbody>
</table>

* Urban, G. L., (1975)
The DESIGNOR model is used for industrial product design decision support. The model is based on the premise that, with respect to purchase decisions, organizations have the tendency to reduce the set of known alternative decisions into a manageable set of feasible products that meet the firm's requirements and satisfy potential buyer needs (Chottray and Lilien 1979). Thus, the model focuses only on the elimination of infeasible alternatives in the organization's buying process (Figure 4.3). Relevant dimensions are determined from the collection of disjoint measurements from a representative sample of firms in a target market. Segment response models denote the relationship between the acceptance rate and the product design characteristics. The total market function is then derived by the aggregation of these segment responses weighted by their relative size (Figure 4.4). The model allows the assessment of product design tradeoffs and provides a tool for product line planning.
Figure 4.3
A Model of Organizational Buying

- Elimination of Unfeasible Alternatives
  - Decision Participants' Evoked Set
  - Acceptable or Feasible Set of Alternatives
  - Individually Preferred Alternatives
  - Organization's Choice

---

Figure 4.4

Development of the Market Acceptance Model

<table>
<thead>
<tr>
<th>Steps</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measurement</td>
<td>Assessment of</td>
</tr>
<tr>
<td></td>
<td>- Specification</td>
</tr>
<tr>
<td></td>
<td>- Dimension relevance</td>
</tr>
<tr>
<td></td>
<td>- Purchase requirements along these dimensions</td>
</tr>
<tr>
<td>Segmentation</td>
<td>Grouping of target</td>
</tr>
<tr>
<td></td>
<td>Customers on the basis of homogeneity of specification dimensions</td>
</tr>
<tr>
<td>Model Formulation</td>
<td>Market acceptance data generation</td>
</tr>
<tr>
<td></td>
<td>Model calibration</td>
</tr>
<tr>
<td>Use</td>
<td>Product Design Optimization</td>
</tr>
<tr>
<td></td>
<td>Sensitivity Analysis</td>
</tr>
</tbody>
</table>

Choffray, J.M. and G.L. Lilien (1979)

78
The product design proposed by Choffray and Lilien employs the *market acceptance model* which is viewed as the elasticities of segment acceptance rates with respect to each partial acceptance rate:

\[
\epsilon[p, p_e] = \frac{dp}{dp_e} \frac{p_e}{p} = \alpha_e
\]

where \(\alpha_e\) = percent change in segment acceptance rate induced by 1% in acceptance along specification dimension \(e\).

Probabilistically, if all \(\alpha\)'s = unity then segment acceptance rate = product of all acceptance rates such that specification dimensions are statistically independent.

However, if all \(\alpha\)'s = unity then \(\alpha\)'s measure the interdependence of company requirements and can be used to assess complementarity and substitutability of design options.

Because of these features, the model structure allows the investigation of complex tradeoffs among design features.
Alternative products are evaluated with respect to the profit criterion given by:

\[ \Pi(y) = MP(y) \left[ d - C(y) \right] \cdot q \]

and the optimal design is a maximization of the potential profits with respect to the design vector \( y \) subject to the firm's development objectives and constraints:

\[ \begin{align*}
    H(x) &= 0 \\
    G(x) &\leq 0
\end{align*} \]

\[ x \in \Omega \]

where

\[ C(y) = \text{unit production cost for manufacturing product design } y_1 \ldots y_n \]

\[ P(y) = \text{fraction of the market that will find product design } y_1 \ldots y_n \text{ acceptable} \]

\[ M = \text{size of the market} \]

\[ d = \text{price/unit} \]

\[ \Pi(y) = \text{potential profit associated with product design } y. \]
\( q = \text{fraction of the market aware of the product and who purchase if the product is acceptable.} \)

The total market acceptance rate \( P(\mathbf{y}) \) as a function of product design, is an aggregation of segment acceptance functions or:

\[
P(\mathbf{y}) = \sum_{s=1}^{S} w_s P_s(\mathbf{y})
\]

where \( w_s = \text{fraction of the market in that segment} \)

and \( P_s(\mathbf{y}) = \text{market acceptance function for segment } S. \)

The total market acceptance rate (Figure 4.5) is used for cost benefit analysis of product line extensions by comparing the profits from a single product design to those resulting from segment specific designs.

The segment acceptance rates relate design characteristics requirements to the partial acceptance rate (fraction of firms that will find it acceptable) where the segments are agglomerate clusters of target users (consumers) grouped on the basis of common specification dimensions.

\[
P(\mathbf{y}) = \alpha_0 \prod_{\varepsilon=1}^{n} (P_{\varepsilon}(\mathbf{y}_{\varepsilon})) ^{\alpha_{\varepsilon}}
\]

where \( P(\mathbf{y}) = \text{segment acceptance rate for design characteristics } \mathbf{y}. \)

\( P_{\varepsilon}(\mathbf{y}_{\varepsilon}) = \text{partial acceptance rate for design characteristics } \mathbf{y}_{\varepsilon}. \)
EXHIBIT 4.5

Empirical Distribution of Company
Requirements along Dimension $\ell$.
\( \alpha_e, \ e = 0, \ldots, n \) = parameters to be estimated.

\[ n = \text{number of specification dimensions for the segment} \]

The partial acceptance rates are determined by the dimensions firms use to specify their product requirements. There are three types of dimensions with corresponding partial acceptance rates.

1. **Boundary specification dimensions** require the satisfaction of either a minimum or a maximum value condition to be satisfied by the product. Beyond this constraint, the product is rejected as infeasible (e.g. warranty required 18 months). The observed partial acceptance rate is:

\[
\min: \ \Pi_e(y_e) = \int_0^{y_e} f_{x_e}(x) \, dx = F_{x_e}(y_e)
\]

\[
\max: \ \Pi_e(y_e) = 1 - F_{x_e}(y_e)
\]

where \( e \) corresponds to minimum or the maximum requirement for the design characteristic \( y_e \). In most applications, due to the small size of potential customers:

\[ P_e(y_e) = \Pi_e(y_e) \]

2. **Range specification dimension** requires that products fall within a given range or target by the firm (e.g. production tolerance range). The observed partial acceptance rate is given by:
\[ \Pi(y_e) = \text{Prob}\left( x_e < y_e < x_e + r_e \right) \]
\[ = \int_{0}^{\infty} \int_{y_e - x_e}^{\infty} f_{x_e e}(x_e, r_e) \, dx_e \, dr_e \]
\[ = \int_{0}^{\infty} f_{x_e e}(x_e) \left( 1 - F_{r_e e}(y_e - x_e) \right) \, dx_e \]

(if \( x_e, r_e \) are independent)

where \( x_e \) = design dimension
\( x_e \) = lower range limit \( \left( f_{x_e e}, F_{x_e e} \right) \)
\( r_e \) = range length \( \left( f_{r_e e}, F_{r_e e} \right) \)

3. **Discrete specification dimension** requires that to be feasible a product must incorporate the specific features (e.g. automatic sort in copier). i.e. if \( x_e \) is a discrete dimension, \( y_e = 0 \) or 1 and

\[ \Pi(y_e) = \text{empirical proportion of the population that requires } y_e \text{ if } y_e = 1 \]
DESIGNOR: USE

DESIGNOR has been used for a study of a piece of capital equipment with three major design dimensions: warranty period, horsepower rating, and price/horsepower.

The acceptability function is given by:

\[ P(h, w, p) = \alpha_0 [P_H(h)]^{\alpha_1} [P_W(w)]^{\alpha_2} [P_D(d)]^{\alpha_3} \]

where

- \( P_H(h) \) = partial market acceptance rate for horsepower rating.
- \( P_W(w) \) = partial market acceptance rate for warranty period \( w \), and
- \( P_D(d) \) = partial market acceptance rate for price \( d \).

Partial acceptance rates and the market acceptance rates were calculated using regression. Horsepower was found to be a range specification dimension. Figure 4.6 shows the design tradeoffs between warranty and horsepower with increased sensitivity of the market to changes in warranty length at low prices/hp.

The optimal design shown in Figure 4.7 was found by a search for a maximum profit design. Using the results from a sensitivity analysis where profit was found to be more sensitive to an increase in price than a decrease in price and conversely for horsepower, a two-product profit maximizing strategy was formed for two different market segments.
Figure 4.6
Sample Tradeoff Curves
between Warranty Period and Price
FIGURE 4.7
Product Optimization Contours

Optimal Design:
Price = $11.98/hp
HP = 548
Warranty = 5-2/3 years

Horsepower = 600 (HP)
**Exhibit 4.8**

Product Design: A Comparison of Strategies

<table>
<thead>
<tr>
<th>Strategy 1</th>
<th>Strategy 2</th>
</tr>
</thead>
</table>
| Horsepower: 548       | \[
| Price/hp: 11.98       | 11.88                 |
| Warranty: 5.66        | 5.66                  |
| Profit: $2.61MM       | $3.84MM               |

\[
\begin{align*}
\{ HP_1 & 537 \\
HP_2 & 964
\end{align*}
\]

A cost benefit analysis of this product line extension strategy can be assessed on the basis of profit differentials. For example, the two-product strategy will be optimum as long as costs $\leq$ $1.23MM/year otherwise the one-product strategy will be better.

**Limitations:** Note that Designer looks at Market Potential rather than market sales. It can be used prior to other procedures.
COMPARISON

Relevance to the Design Process

1. Of the three models presented, only PERCEPTOR focuses on the entire design process. LINMAP concentrates on the identification of new product ideas while DESIGNOR focuses only on the elimination of infeasible product alternatives in the industrial design process (i.e., market potential).

Model

2. Both LINMAP and PERCEPTOR use an attribute space to map the positions of products and indicate preference in proportion to the measure of the distance of the product from an individual's ideal point. The difference is that Shocker and Srinivasan require the attributes in LINMAP to be "actionable" or relevant to both the consumer and the firm. DESIGNOR, on the other hand, uses the physical product specifications and incorporates this concept of actionability through the product requirement dimensions in the partial acceptance rates that ultimately influence the design criterion. A product that does not meet the firm's constraints and the consumer's interests does not enter the criterion.

3. Two of the methods discussed are based on similarity data. LINMAP and PERCEPTOR both use the similarity data to plot the products on the perceptual map while PERCEPTOR segments the group by the similarity of product dimensions. DESIGNOR
models the industrial adoption process as being strongly dependent on derived demand such that purchase specifications are a major step in the purchasing process. Consumer buyer behavior for frequently purchased products and durables however, is dependent on the availability of the product, the perception, the preference, and ultimately the choice. Product specifications are not crucial - rather it is the perceptions and preferences that account for the brand switching type of behavior. Hence, the similarity measures are extensively used.

4. Only PERCEPTOR uses the evoked set of products and consequently the market defined is relevant to the choice decisions.

Consumer Behavior

5. DESIGNOR assumes that the buying process for firms is multiperson in nature and is a sequential process of elimination of infeasible alternatives subject to the firm's constraints. PERCEPTOR and LINMAP however, model the consumer behavior for buying frequently purchased goods and durables respectively as a maximization of individual preferences for a combination or set of attributes.

6. The search criteria for an optimal new product is different for all three models. DESIGNOR uses a profit-maximizing criterion while LINMAP uses revenues and PERCEPTOR uses market shares with trial and repeat probabilities.
7. Compared to PERCEPTOR, an important advantage of LINMAP is that the attribute salience estimates can be constrained to be non-negative to assure that distances in the attribute space will also be non-negative. Desired constraints may also be placed on the relative magnitudes of the attribute saliences and the signs and magnitudes of the ideal point estimates to incorporate prior information and to ensure better interpretability.

8. LINMAP enforces no real preconditions on the ideal point and as a result a natural ideal point (more (less) is preferred to less (more)) is possible. This is not possible with PERCEPTOR which uses PREFMAP to derive its perceptual map.

9. Additionally, the sum-of-absolute-errors as the poorness-of-fit measure in LINMAP as opposed to the sum-of-squared errors in PERCEPTOR tends to produce more robust estimates.

10. Both LINMAP and PERCEPTOR assume homogeneity in perception to locate optimal products. In contrast, DESIGNOR assumes homogeneity in preference by grouping segments with similar specified dimensions to evaluate infeasible alternatives.

11. A limitation in LINMAP is that it employs a behavioral framework that assumes a static environment where competitive conditions are constant and the consumer's knowledge of the attributes is as good as the knowledge of existing
brands. PERCEPTOR may mitigate this effect by starting the design with an evoked set of products where the consumer's knowledge is greater than for the whole set of products. The limitation is that due to the small size of the evoked sets, appropriate methods like factor analysis have to be used to produce valid perceptual maps.

12. An advantage of PERCEPTOR is that it links perception and preference to choice behavior which allow tests of internal validity. Neither LINMAP nor DESIGNOR, both of which focus on the idea generation stage of the design process, offer this option. The only test is their application to real products and cases.

13. DESIGNOR assumes that organizations evaluate products on a non-compensating scheme (recall the compensatory model discussed in the last section) which is nonlinear and absent of saliences. Both LINMAP and PERCEPTOR however employ a compensatory scheme as the rationale for consumer buying behavior; that is, an individual gives greater importance or weight to an attribute or set of attributes he most prefers.

14. PERCEPTOR only handles two products ('us' and 'them') vs a larger range in LINMAP and DESIGNOR.

**CONCLUSION and Future Implications**

The three models discussed have been chosen for their applications to a variety of product-makets: durables, frequently purchased
consumer products, and industrial products. Figure 4.8 presents a succinct table comparing the three models. It is clear to see that these models are different in their approach to the design process and in the products they address for design purposes. Industrial buying behavior as demonstrated by Choffray and Lilien in DESIG Nor is considerably different from the individual consumer behavior. Decisions are based at a multi-person level using physical product specifications and firm objectives and constraints rather than at an individual level using both the physical and psychological parts of the product or the attributes and individual perceptions and preferences for the attributes that best satisfy idiosyncratic needs and desires. In this respect, LINMAP and PERCEPTOR are not applicable to industrial products.

LINMAP is at this point the best available procedure that incorporates the ideal point model and generates perceptual maps (Shocker and Srinavasan 1973). If the perception and preference model in this procedure can be linked to a choice model as in PERCEPTOR, the product design derived will have greater accuracy and 'follow-through' in the process. Similarly, DESIG Nor may be extended to evaluating choice based on criteria other than the firm's profits.

Combined with managerial judgement, these product design models offer reduced time and costs, greater flexibility in evaluating alternatives, and a better understanding of consumer/customer behavior to enable a proactive design approach that promotes greater success in the introduction of new products.
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V. CRITIQUE, EVALUATION, CONCLUSION, AND DIRECTIONS FOR FUTURE WORK

The current marketing environment is a complex field where the available data and management information requirements are constantly increasing in magnitude and sophistication, and the constraints imposed by time, costs, and competition are making it more difficult and risky to design successful products. The product design process can be improved or made more effective by using analytical methods to support managerial judgement.

This thesis has explored the role of analytical market-based methods in supporting and simplifying the decision-making process for a marketing manager. In particular, the models reviewed follow a proactive or consumer-based approach that considerably reduces the uncertainty (risk) in a product design by identifying the physical and psychological needs and requirements of the consumer in the early stages of the design process when substantial investments in time, money and effort have not been made. The new product, designed by following this approach, fulfills the physical and psychological requirements with the objective of maximizing potential customers (product attraction).

A number of product design models reflecting consumer behavior towards a product (awareness, perception, preference, and choice) were reviewed and evaluated with respect to assumptions, uses, and limitations. Finally, specific models applied in three different product areas (durables, frequently-purchased consumer goods, and
industrial products) were compared and evaluated with respect to their methodologies and effectiveness in identifying optimal new product opportunities.

Perceptual product maps (spaces), ideal point models, and distance-related modes of preference provide easily interpretable geometric representations that will help the marketing managers to understand the visualize the marketing environment more clearly and to implement creative strategies from the alternatives (scenarios) provided. Furthermore, these models can improve the firm's information system by exposing pertinent factors from within the firm (e.g. effects of effects of declining sales) and from the environment (e.g. effects of competitors' actions) to effectively evaluate strategies for a new product.

It should be kept in mind, however, that these models aid in the decision-making process and consequently are not stand-alone methods for designing products. A number of models and methods should be used simultaneously in conjunction with managerial judgement to substantiate results and to provide greater accuracy in predictions and estimations. The 'best' model in product design is thus a mix of qualitative and quantitative techniques balanced with managerial judgement. This mix of techniques is optimized when the identified product opportunity meets the marketing manager's objectives and constraints and the marketing manager understands, accepts, and feels comfortable with the results. The performance of this mix of techniques and methods depends not only on the limitations of the particular models and techniques, but also on the extent of effort
on the part of the manager and the firm.

The currently available product design models are constrained by a number of limitations. A majority of the models assume a single firm objective. Yet, an organization often pursues several goals with approximately equal weights simultaneously. A product opportunity optimized by a single goal may not be optimum for all of the goals. This characteristic presently exists in the design of industrial products where multiperson decision-making criteria have to be incorporated in the design of a product. Research advances in this product area may perhaps be analogous and applicable to the design of durables and frequently purchased consumer goods.

Marketing research in the application of stochastic models to consumer buying behavior has yet to make significant contributions to the product design process. The models discussed in section III indicate that these stochastic models account for the uncertainty and the dynamic characteristics in the marketing environment better than deterministic models. The risks or uncertainties caused by variable changes in consumer behavior (e.g. natural foods), in environmental constraints (e.g. better fuel economy cars), and firm objectives (e.g. diversification) need to be incorporated in these models to represent the marketing system more closely to the real system and to consequently predict more accurate results in market responses.

Other implications for future research include:

- Link perception, preference and choice in a model to find predict market behavior more accurately (from the feedback provided by the choice variable) to enable the marketing manager to do a better job of coordinating his marketing program
o investigate product usage situations with multiple simultaneous benefits (e.g. general purpose household cleaner vs. specialized cleaner for windows) to better understand and predict the buying process in this area where definition of product market boundaries appear to be critical.

Marketing research has a long way to go before producing results that can be directly applied to the marketing environment (with minimized managerial judgement). Despite the enormous contributions in the area, consumer behavior at present is not sufficiently understood to allow the modelling of idiosyncrasies, randomness, and external influences (peers and environment) in the purchase behavior. This lack in understanding consumer behavior also accounts for the difficulty in obtaining accurate and pertinent consumer response measurements. To account for this variability in the marketing environment and in consumer behavior, models need to be more adaptive (to external factors) in structure and need to account for feedback variables (from the market and the manager) that will allow continuous adjustments for modelling error. These models should be complex enough to produce optimal results and comprehensible to the marketing manager's creative input.
Bibliography


