# CHAPTER III

RESEARCH METHODOLOGY

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OBJECTIVES OF THE PRESENT STUDY:

The objectives of the present study for all the Brands under study are as under:

- To identify the factors which have led to brand failure of the brands under study?
- To assess the underlying perceptions developed by consumers in emerging markets regarding as to why brands fail.
- To compare the brand failures vis-à-vis ideal brand concept in terms of consumer acceptance/importance using perceptual maps.
- To formulate an optimal strategy to avoid brand mistakes and escape brand failures.

HYPOTHESIS OF THE STUDY:

In both the product categories the following hypothesis has been laid down as Null Form:

- H0 (I) There is no significant linear co-relation between the different attributes of brand failures.
- H0 (II) There is a significant difference between the perception of the companies and customers regarding the brand line extension products.

SCOPE:

A pilot survey was conducted by the researcher to spot out the scope of present study. This pilot survey was mainly done to check out Brand Extension failures in emerging markets. This survey helped the researcher to enlist various product categories and brands to be studied. Pilot survey also served the purpose to pre-test the questionnaire and the feedback of the respondents was well taken and helped researcher to select two product categories for study. This pilot survey was basically divided into two phases:

Phase I:

This Phase was primarily undertaken to identify and select the product categories and Brand line extensions to be studied. Hence this phase of pilot survey had three stages:
STAGE 1: Identification of product categories:

In this stage the researcher approached various retailers and wholesalers of the Fast Moving consumer goods (FMCG) in different regions from Srinagar city for informal interview to identify product categories. And the researcher concluded that Emerging Indian market has witnessed failures varying from low magnitude to very high magnitude like:

- Pepsi cafechino,
- Ready to eat pizza from Amul.
- Dulux paints Seven Day Fragrance.
- Ponds toothpaste.
- Black Cherry Vanilla Coke.
- Diet Black cherry Vanilla Coke.
- Virgin Cola, Virgin Vodka, Virgin jeans.
- GPI Ms.Cigrattes.
- Kellogg’ Cereal Mates.

STAGE II: Selection of product categories:

After identification of the products the consumers were asked to rank these in order of their magnitude as failures. The total number of consumer interviewed was about 100. the products which were ranked highest belonged to:

- a) Cold drinks and
- b) Ready to eat Foods.

STAGE III: Selection of brands:

Further three brands from cold drinks and two brands from ready to eat foods were selected for the study. The researcher has selected following products for analysis based on the feedback from the consumers, retailers and wholesalers:

- Pepsi Café chino
- Black Cherry Vanilla Coke
Phase II:

The second phase of pilot survey was concerned with questionnaire development and its pretesting prerequisite to designing a questionnaire is to determine what is exactly required to be measured to achieve the objectives of the study. The objective of adding the question 1 & 2 was to measure the awareness about the brands and its failure. The next objective was to find out the importance of the attributes selected of the product categories and as such question 3, 4, 5, 6, & 7 were incorporated to measure the magnitude of importance for brand line extensions. However, the attributes incorporated were not exhaustive; hence question 8 was added to measure any additional factor responsible for brand line extension failures. To know brand loyalty of respondents’, question 9 was added. And to measure brand sensitivity question 10 was incorporated. The role of question 11 was to measure any other strong factor or change in Brand line extensions as perceived by consumers.

PRE-TESTING THE QUESTIONNAIRE:

After drafting the questionnaire for cold drinks and ready to eat product categories it was pretested with more than 100 retailers, wholesalers and customers, this initial survey data provided sufficient inputs to design a more structured questionnaire with all the relevant factors responsible for brand failures. Thus, the questionnaire designed was used for data collection from the respondents (questionnaire is given in Appendix).

SAMPLING DESIGN:

Two studies were taken as basis for this study:

- Brand Equity special on India’s most trusted Brands-rankings overall population, by demographics and by regions, published in the brand equity edition of the economic Times dated 18th July, 2001 and,
- Asian Development bank report on giving and fund raises in India.
It was further decided to concentrate on Socio-Economic Categories (SEC) A,B and C that is on the upper three classes of society based on education and occupation. This categorization into A,B and C was done on the basis of research conducted by Market Research Society India (MRSI) which has developed a Socio–Economic classification for understanding the expenditure behavior of Indians. It has developed a Socio-economic classification system for households and individuals which club all the people who are likely to behave similarly. These include:

- SEC A1 and A2 collectively called SEC–A
- SEC B1 and B2 collectively called SEC–B
- SEC –C
- SEC –E1 and E2 collectively called SEC –E

There are in all eight Socio-Economic groups, A1 donates the upper most and E2 stands for the lowest Socio-Economic class of people in India. This survey was confined to SEC A,B and C in urban India only with a view to focusing on the prime target audience for most consumer branded products. According to Brand Equity (18th July, 2001), it is felt that a rural consumer is asked to rate various brands, His ratings would be driven mainly by familiarity or popularity, and again in Brand Equity (18th July, 2001) it has been suggested that awareness and usage amongst SEC D and SEC E households is restricted to a small number of brands, hence these two classes are also considered inappropriate to assess the brand failures. The next crucial step was to determine within these three Socio-Economic categories. The idea was to interview all possible consumers who use the brands. Thus the consumers were divided as:

i) CHIEF WAGE EARNERS: They are the ones who contribute maximum to the household income.

ii) HOUSEWIVES: With the growth in education standards of women they participate more in decision making in the households.

iii) YOUNG ADULTS: this is the category of consumers which is very expressive as far as their choices are concerned.
These categories of consumers were also supported by literature review and also the same categories of consumers were surveyed by the Brand Equity for survey on Brands (18<sup>th</sup> July).

The survey was conducted across four cities of North India, the cities chosen were based on the survey of Brand Equity on Brands (18<sup>th</sup>, July, 2001):

- Delhi-Metro City of India.
- Ludhiana-Class I City of India ,
- Jammu-Class II City of India and
- Srinagar–Class II City of India

The Average monthly income For SEC-A,SEC,B and SEC-C(AC Nielson) is as :

<table>
<thead>
<tr>
<th>SEC CATEGORY</th>
<th>AVERAGE MONTHLY HOUSE HOLD INCOME</th>
</tr>
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<tbody>
<tr>
<td>SEC A</td>
<td>40000</td>
</tr>
<tr>
<td>SEC B</td>
<td>25000</td>
</tr>
<tr>
<td>SEC C</td>
<td>12000</td>
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*Table 1: Average Income*

**SAMPLE SIZE:**

The total sample size of this survey was 1450. This sample size was divided as :

<table>
<thead>
<tr>
<th>CITY</th>
<th>SAMPLE%</th>
<th>SAMPLE SIZE</th>
</tr>
</thead>
<tbody>
<tr>
<td>DELHI</td>
<td>30</td>
<td>435</td>
</tr>
<tr>
<td>LUDHIANA</td>
<td>20</td>
<td>290</td>
</tr>
<tr>
<td>JAMMU</td>
<td>20</td>
<td>290</td>
</tr>
<tr>
<td>SRINAGAR</td>
<td>30</td>
<td>435</td>
</tr>
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</table>

*Table 2: Sample size*
SAMPLING METHOD:
A stratified random sampling method was used for this study. Field interviews were conducted in the four cities. Each city was divided into four different regions—north, south, east and west. The total sample was distributed among each region of the four selected cities.

STATISTICAL TECHNIQUES USED
Over the years several different techniques have been used to assist marketers with their brand strategies. To effectively position (or reposition) a brand, the company must know how this brand is perceived in relationship to other brands in the product category. The primary techniques are Factor Analysis, Discriminant Analysis, Multi-attribute Compositional Models and Multidimensional Scaling. Each has advantages and disadvantages (Green and Rao 1972; Hauser and Kopleman 1979).

Discriminant analysis is one of the techniques used for product positioning analysis (Johnson 1970; Pesseinier 1977). As in factor analysis, the input data are usually a matrix of subjects’ ratings of objects on a variety of attributes. Discriminant analysis determines the consumers’ perceptual dimensions on the basis of which attributes best differentiate the brands. However, these dimensions, which are defined by examining discriminant coefficients, are not easily or intuitively interpretable into managerial actions (Huber and Holbrook 1979), realize that the dimensions provided by discriminant analysis accentuate the difference between the brands and are also a function of the attributes asked. Consequently, as in factor analysis the dimensions furnished by discriminate analysis are not necessarily reflective of consumer perceptions of the objects’ characteristics, but only consumer perceptions of the objects on the attributes asked.

In the last decade Multi-attribute Compositional Models have become popular with marketers who wish to construct more preferred products (Green, Carroll, and Goldberg 1981; Green and DeSarbo 1978; Green and Srinivasan 1978; Hauser and Shugan 1980; Wilkie and Pessemier 1973). One widely used compositional model is conjoint measurement. This technique is used to determine which combination of a limited number
of attributes is most preferred by consumers. The technique is helpful in uncovering both new product concepts and key words to be included in the product’s advertisement copy. The drawback of using most of the Multiattribute Compositional Models is that, although they can provide insight about consumer preference, they cannot provide any information about product positioning in relation to product dimensions. That is, the relative degree of similarity between different bundles of concepts, in terms of product dimensions, is not provided. Attempts have been made recently to model the links from physical features to perceptions to preference. Hauser and Simmie (1981) extended Lancaster’s work (1966, 1971) to include a physical feature to perception link. Their model assumes that consumers have stochastically rational behavior and that if brand Y is perceived to have 25% more of a psychological feature (based on physical ingredients) than brand X, the consumer has a high probability of preferring brand Y on the psychological dimension because it delivers more value. TRINODAL, in contrast does not explicitly request consumer evaluations of product attributes, but rather infers them from preferences and misclassification data. DeSarbo and Ro (1983) are also exploring the physical feature/perception/preference process, but by means of a constrained unfolding procedure. Their objective is primarily the segmentation of consumers, whereas TRINODAL seeks to evaluate consistency of advertisements and brand images.

Conjoint analysis is the most common approach in terms of Multiattribute Compositional Models. For taxonomy of conjoint methods, refer to Carroll and Green (1995). Green and Krieger (1989) conclude that conjoint analysis provides practical advantages over multidimensional scaling in terms of measurement and data collection for evaluating brand positioning. These authors suggest that the combination of conjoint for analytical purposes and multidimensional scaling for display purposes offers an attractive combination for researchers.

Multidimensional scaling is another technique frequently applied to product positioning problems (Green, Wind, and Claycamp 1975; Green Wind, and Jain 1972; Moinpour, McCullough, and MacLachlan 1976). Unlike the previous attribute-based techniques, where the resulting dimensions depend on the attributes set, multidimensional scaling
produces dimensions based on consumer judgments or preferences of the actual brands. These resulting dimensions are postulated to be the basic effective dimensions upon which consumers evaluate the brands of a product class.

A variety of different Multidimensional Scaling algorithms are available. The most commonly employed algorithms use either similarity or preference data. The multidimensional algorithms that use similarity data construct geometrically spaced models such that the more similar objects, or brands, are placed closed together. Preference data algorithms, such as PREFMAP-2, produce joint space maps of both consumer ideal points and objects (Carroll 1972; Chang and Carroll 1971). These joint space maps are constructed so that consumer ideal points and objects are placed in a common spatial configuration. For nonmetric maps of this type, the objects and ideal points are positioned so that the objects’ relative proximity to an individual’s ideal point best preserves the rank order preferences of that individual. Unfortunately, the dimensions of the multidimensional scaling maps are often difficult to interpret. Also, when used to analyze where one should reposition a product, the dimensions provided are only those which already exist with prevailing brands. Thus some new dimension, or product concept, which a consumer might use to differentiate a brand, is only revealed in a multi-dimensional scaling map sometime after the new concept has been introduced in the marketplace.

Several articles discuss and demonstrate the use of factor analysis for product positioning (Hauser and Urban 1977; Hauser and Wisniewski 1979; Huber and Holbrook 1979). Usually the input data consist of a three-dimensional matrix of subjects’ ratings of objects on a variety of attributes. The advantages of factor analysis are that both subjective and objective attributes can be used and that the dimensions of the product space are relatively easily determined from factor loadings. Of the several limitations of using factor analysis for measuring consumer perceptions, perhaps the greatest is that the dimensions obtained are actually a function of the data collected. For instance, in principal component analysis, the first principal component will be composed of the attribute which are highly correlated and explain the most variance. Consequently, if one attribute, with high variance across brands, is asked repeatedly several related forms this attribute will be output as a major
factor or dimension. (For example, a fuel efficiency factor can be generated if subjects are asked to rate cars on miles per gallon, acceleration, power, economy of running car, etc.) Thus factors are more a function of the attributes asked than of product characteristics consumers hold to be important.

Huber and Holbrook (1979) compare and contrast factor analysis and discriminant analysis with the conclusions. According to this analysis, discriminant analysis is more likely to yield objective dimensions while factor analysis is more likely to yield effective dimensions. These findings lead to the conclusion about the best use for each method. Hauser and Koppelman (1979) conclude that attribute-based techniques such as factor analysis and discriminant analysis provide better measures of consumer perceptions that similarity technique such as multidimensional scaling if the set of attributes is reasonably complete. In addition, Hauser and Koppelman (1979) show that factor analysis is typically better than discriminant analysis. In our table, we provide a description of the “best use” for each method, recognizing that no one approach is best in all circumstances. Each method has strengths and/limitations that make it more or less appropriate in specific decision making situations.

Keon (1983) also describes four primary methods for evaluating a brand’s current or potential positioning. The methods are: Multidimensional Scaling, Factor Analysis, Discriminant Analysis, and Multiattribute Compositional Models.

The effectiveness of any positioning strategy will depend on how consumers perceive competing organizations. Since we have already seen that many methods exist for the production of perceptual maps but as suggested by (Hauser and Koppleman 1979) that factor analysis performs better than any other technique with respect to both predictive ability and interpretability. Accordingly, factor analysis was identified as the main analytic technique to be used in the development of perceptual maps.

A) FACTOR ANALYSIS:

Characteristics:
Factor analysis is not a single statistical method. Unlike the t test or ANNOVA, it is not a test of differences between groups of subjects. Rather, factor analysis represents a complex array of structure analyzing procedures used to identify the interrelationships among large set of observed variables and then, through data reduction, to group a smaller set of these variables into dimensions or factors that have common characteristics (Nunnally & Bernstein, 1994).

A factor is a linear combination or cluster of related observed variables that represents a specific underlying dimension of a construct, which is distinct from other factors included in the solution (Tabachnick & Fidell, 2001).

**Correlation Matrix:**

The correlation matrix is both square and symmetric. It is square matrix because it has as many rows as columns. It is symmetric because the principal diagonal of R is composed of 1’s and the values below this diagonal are equal to those above the diagonal except that the numbers are transposed. The numbers in row 1 are similar to column 1. This is because the correlation between the row and column items is the same (e.g. C1 with C2 and C2 with C1). It is common, therefore, to avoid redundancy by presenting only the lower left or upper right triangle of the matrix. When both triangles are presented the matrix is called a full matrix.

A correlation matrix summarizes the interrelationships among a set of variable or, as in our case, a set of items in a scale. The most common form of correlation matrix used in factor analysis is a matrix consisting of Pearson product moment correlations (also called Pearson r or r_{xy}). A correlation matrix that is an identity matrix is not a welcome sight in factor analysis because its presence would imply that there are no interrelationships among the items. The presence of an identity matrix is tested for in Barlett’s test of Sphericity (Bartlett, 1950).

A value of 0 for a determinant indicates that there is at least one linear dependency in the matrix. That means that one or more columns (or rows) in the matrix can be obtained by linear transformations of other columns (or rows) or combinations of columns (or rows).
The correlation matrix and significance table provides us with a beginning sense of which items might cluster in future factor analyses. It is also important to examine not only the $p$ values but also the absolute size of the correlations because large sample sizes can contribute to small correlations being highly significant. This is a particular concern in factor analysis because we are usually dealing with large samples.

**Tests of Matrices:**

During the exploratory phase of factor analysis, it is important to determine sufficient numbers of significant correlations among the items are not significant; it will not be possible to obtain a parsimonious set of factors that represent the numerous items in the proposed scale. Rather, there could be as many factors as there are items. There are several tests that can be undertaken to ascertain whether it would be judicious to proceed with factor analysis. These tests include Bartlett’s test of Sphericity and the Kaiser- Meyer-Olkin test.

**Bartlett’s test of Sphericity**

Bartlett’s test of Sphericity (Bartlett, 1950) test the null hypothesis that the correlation matrix is an identity matrix (i.e., that there is no relationship among the items). The null hypothesis states that there are all 1’s on the diagonal of the matrix and 0’s on the off-diagonal. Larger values or Bartlett’s test indicate greater likelihood that the correlation matrix is not an identity matrix and that null hypothesis will be rejected.

In Bartlett’s test of Sphericity the Degrees of Freedom, df, represent the number correlations above or below the principal diagonal of the correlation matrix. The Bartlett’s test involves the determinant of the correlation matrix. If the value of this determinant is negative logarithm of 0’s or negative numbers.

The Bartlett’s test is influenced by the sample size, N, with large sample sizes resulting in larger values of Bartlett’s test. Gorsuch (1993, p. 150) points out that with only 20 subjects and 10 items, all that is needed is an interterm average correlations of 36 for Bartlett’s test to be significant, for even the most trivial correlations, that the correlation matrix is not an indicate, for even the most trivial correlations, that the correlation matrix. Pedhaszur and
Schmelkin (1991) suggest, therefore, that Bartlett’s test be used only as a minimum standard for assessing the quality of the correlation matrix. That is, when Bartlett’s test is not found to be significant (i.e., the resulting value is too small to reject the null hypothesis), the matrix should not be factor analyzed.

**Kaiser- Meyer- Olkin Test (KMO):**

A second indicator of the strength of the relationship among items is the partial correlation coefficient. These partial correlations represent the correlations between each pair of items after removing the linear effects of all other items. The Kaiser-Meyer-Olkin test (KMO) is a measure of sampling adequacy that compares the magnitudes of the calculated correlation coefficients to the partial correlation coefficients.

**Evaluating the size of the KMO:**

When evaluating the size of the overall KMO, Kaiser (1974,) suggests using the following criteria for these values:

- Above. 90 is ‘marvelous’
- In the .80 is “meritorious”
- In the. 70s is just “middling”
- Less than. 60 ‘medicore,’ “miserable,” or “unacceptable”

In Addition to the overall KMO, a measure of sampling adequacy (MSA) can also be computer for each individual item using only the simple and partial correlation coefficients involving the particular item under consideration.

The MSA for an individual item indicates how strongly that item is correlated with other items in the Matrix. The same interpretation for standards of excellence outlined above for the KMO (Kaiser, 1974) is applied to the individual MSAs. It is ideal to have individual MSAs that are greater than 70.

**Anti- Image Correlation:**
The results of these analyses are given as a single KMO value and in the form of an anti-image correlation matrix (AIC). The AIC reports the MSAs for each individual item on the diagonal. The negatives of the partial correlations between pairs of items having first controlled for the effects of all other items) are presented on the off-diagonal. If the correlation matrix is factorable, the MSA values on the diagonal of the AIC should be large and the values negatives of the partial correlations should be small (Hair, Anderson, Tatham, & Black, 1995; Tabachnick & Fidel, 2001).

Variance in Factor Analysis Models:

Variance condensation refers to the process by which the variance shared among a set of items of variables is compressed into

a) One or more factors reflecting the variance that the items share in common
b) Possible unique factors that represent the variance that items do not share with one another (Nunnally & Bernstein, 1994).

This process is based on a multivariate linear model in which the sources of variance in scores on set of items to be analyzed are broken down into three uncorrelated components: common variable, specific variance, and error variance (Kline, 1994).
**Principal Component Analysis (PCA):**

Principal component analysis (PCA) was developed by Pearson (1901) and adopted for factor analysis by Hotelling (1933) (Harmam, 1976). A goal for the user of PCA is to summarize the interrelationships among a set of original variable in terms of a smaller set of orthogonal (i.e., uncorrelated) principal compounds that are linear combinations of the original variables (Goddard & Kirby, 1976). All three of the variance components (common, specific, and error variance) play an important role in the identification of the principal components.

Principal components analysis (PCA) is a straight forward, easily understood, and commonly used extraction technique in factor analysis. Its goal is to arrive at a succinct set of uncorrelated components that extract variance in descending order and that can empirically, parsimoniously, and effectively summarize the data set. PCA is especially useful when the researcher wants to summarize the relationships among a large number of variables with a smaller number of components (Tabachnick & Fidell, 2001).

**Estimating the Initial Communalities:**

PCA assumes that there is an variance to be analyzed as the number of observed variables and that all of the variance in an item can be explained by the extracted factors. PCA’s initial estimate of the communality (i.e., the variance that the items and factors share in common) therefore is 1.00. These are the values that are placed initially on the diagonal of the correlation matrix when it is analyzed by PCA. In essence, there is no change in the correlation matrix.

**Eigen Values:**

Eigen values are direct indices of how much of the total item variance is accounted for by a particular component (Hair, Anderson, Tatham, & Black, 1995). The larger the Eigen value, the more the variance in the items is explained by that component.
Scree Plot:

A third method for determining the number of factors against their Eigen values in descending order of magnitude to indentify distinct breaks in the slope of the plot. This method, called the Scree Plot, was first offered by Cattell (1966) as a way to identify distinct breaks between the steep slope of the larger Eigen values and the trailing off the smaller ones. Cattle referred to this gradual trailing off as the Scree because it is akin to the rubble that ends up at the foot of a mountain. To determine where the break occurs, a straight line is drawn with a ruler through the lower values of the plotted Eigen values. The point where the factors curve above the straight line drawn through the smaller Eigen values identifies the number of factors (Cattell & Jaspars, 1967; Gorsuch, 1983).

Importance of Rotating Factors in Geometric Space:

Factor rotation involves turning the reference axes of the factors about their origin in order to achieve a simpler and theoretically more meaningful factor solution that is produced by the unrotated factor solution. To achieve this, the positions of the items are fixed in geometric space while the factor axes rotated through specified angles.

The Varimax Rotation:

Varimax (Kaiser, 1958, 1959) is the default option in both SPSS for Windows and SAS and is the most commonly used orthogonal rotation. Among some writers (e.g., Nunnally & Bernstein, 1994) it is the definitive orthogonal solution. The goal of Varimax is to simplify the columns of the unrotated factor-loading matrix. To accomplish this goal, varimax maximizes the variances of the loadings within the factors while also maximizing differences between the high and low loadings on a particular factor (hence the name Varimax). In essence, higher loading on a factor are made higher and lower loading are made lower (Tabachnick & Fidel, 2001).

The main advantage of Varimax solution is that it is easily interpreted and provides relatively clear information about which items correlate most strongly with a given factor. Varimax provides us, therefore, with a good picture of our ability to reach a simple structure. Factor scores generated for each individual are also more interpretable because
the explained variances among the factors do not overlap and are therefore independent of each other.

**PERCEPTUAL MAPPING:**

To position an offering, the firm designs and develops it in such a way members of the target segment both perceive it to distinct and value it more than competitive offerings. Three common ways to positioning are following.

- Our product is unique (“The only product or service in the market that has a particular attribute” as in Polaroid is the only one capable of making instant photos).
- Our product is different (“More twice the [feature] than competitors” as in Listerine kills more germs than competing brands).
- Our product is similar (“Same functionality as [competitor] at lower price” as in Meisterbrau tastes like Budweiser at a fraction of its price).

To position products in increasingly crowded markets managers must understand the dimensions along which target customers perceive products in a category and low those customers views the firm’s offer relative to the competitive offers. In order words, the managers have to first understand the competitive structure of their markets as perceived by their customers, they have to understand how their customers (current or potentially) view their brand. Which brands do those customers perceive to be their closest competitors. What product and company attributes seem to be most responsible for these perceived differences.

Once managers have answers to these questions, they can assess how well or poorly their offerings are positioned in markets. They can then identify the critical elements of a marketing plan that differentiate their offerings from those of competitive offerings. They should try to find out what they have to do get their target customer segments to perceive their offering as different. Based on customer perceptions, which target segments are most attractive and how should they position their new products with respect in their existing
products. Which product name is most closely associated with attributes their segment perceives to be desirable.

There are many intuitive approaches that managers use to develop an understanding of the competitive structure of their markets. The perceptual mapping methods provide formal mechanisms to depict the competitive structure of markets in a manner that facilitates differentiating and positioning decisions.

A perceptual map is a spatial representation in which competing alternatives are plotted in a Euclidean space. The map has the following characteristics:

1. The pair wise distances between product alternatives directly indicate the “perceived similarities” between any pair of products, that is, how close or far apart the products are in the minds of customers.
2. A vector on the map (shown by a line segment with an arrow) indicates both magnitude and direction in the Euclidean space. Vectors are usually used to geometrically denote attributes of the perceptual maps.
3. The axes of the map are a special set of vectors suggesting the underlying dimensions that best characterize how customers differentiate between alternatives. Most frequently, orthogonal axes (straight lines at right angles) are used to represent the dimensions of the map, although nonorthogonal axes can also be used. In either case the axes can be rigidly rotated to aid interpretation. For example, in a two-dimensional map the horizontal and vertical axes are often used to characterize the two dimensions of the map. However, the axes can be rotated so that the southwest to northwest becomes one axis, and southeast to northwest becomes the other axis.

Perceptual maps facilities decision making by enabling managers to summarize and visualize key elements of the market structure for their products. By summarizing a large amount of information, such maps help managers to think strategically about product positioning.

In addition to summarization, maps offer managers a pictorial view of the competitive structure of their markets, helping, them to sharpen their thinking about how their market
works. People are better at processing visual how their customers perceive the structure of a market, a data-derived map provides finer details. The details in a perceptual map are especially helpful to those making decisions in new contexts, such as when the firm is developing a positioning strategy for a new product. Other options, such as bar charts and snake plots are also available to pictorially summarize customer perceptions. However, plots of this type are difficult to interpret if they include more than three or four alternatives. In addition, snake plots suggest that managers pay equal attention to all attributes, thereby implicitly assigning the same weight to each attribute.

**Applications of perceptual maps:**

The value of a perceptual map stems from the notion that perception is reality; that is, customers perceptions, in part, determine customer behavior. A primary use of perceptual mapping is to provide insights into the market structure for a defined set of competing alternatives. Because any location on a map results from the combined effects of number of beliefs and perceptions, the map suggests which attributes of a product the firm should modify to effect a desired change in the position of the product. By making assumptions about how changes in the physical characteristics of a product influence customer perceptions, managers can tentatively predict the sales or market shares that would be associated with alternative positions on a map. Green (1975) urges caution here, pointing out that the primary use of perceptual maps should be providing diagnostic insights, rather than making specific predictions about sales.

**Perceptual Mapping Techniques:**

Psychometricians first developed perceptual mapping techniques to map psychological measurements of how people perceive things that vary on multiple dimensions. Marketers have adapted these Multidimensional Scaling (MDS) methods to represent customer perceptions and preferences for a set of entities (brands, geometric shapes, department stores, presidential candidates, etc.) on a map in Euclidean space.

Customer behavior is influenced by both perceptions and preferences. Two products may be perceived to be different, although physically they may essentially be the same. For
example, Toyota Corolla and Chevy Prizm are physically nearly identical cars with different names. However, customers perceived the Corolla to be superior to the Prizm. In other cases customers may not be able to perceive any differences even when the products are different. For example, in blind taste tests most customers cannot identify different brands of beer or cola. Customers are also unable to identify different brands of wine even when their prices differ by several hundred percent (experts, however, can distinguish different wines).

MDS methods vary depending on the nature of input data (e.g., similarities data, perceptions data, or preference data) and how these data are manipulated to derive the map. The three major approaches are:

1. Perceptual maps from attribute-based data,
2. Perceptual maps from similarity-based data, and
3. Joint-space maps that include both customer perceptions and their preferences.

We in our study have included the perceptual maps from Attribute based data. Cooper (1983) and Green, Carmone, and Smith (1989) have described this method in detail.

**Attribute-based methods**

Managers can use attribute-based methods to derive perceptual maps from data consisting of customer evaluations of products (more generally, competing alternatives) along pre-specified dimensions. There are four major steps to this method.

**Step 1:** Identify the set of products and the attributes on which those products will be evaluated. The attributes one chooses to include in the analysis depend on the objectives of the study. For strategic positioning studies one should select a broad set of competing alternatives and attributes. For example, the alternatives can be product class (e.g., mutual funds, bonds, and stocks in the financial services industry) or product forms (e.g., subcompact, compact and intermediate in the automobile industry). For tactical positioning studies the alternatives can be close competitive offerings (e.g., different brands of shampoo, or different fragrances in
shampoo, such as floral and herbal) and the attributes can be more operational in nature (e.g., colour and miles per gallon.) The alternatives you choose should vary along all the chosen attributes. Kotler (1991) has summarized a number of generic attributes that can provide useful starting point in selecting attributes for the study.

**Step 2:** Obtain perceptions data. The data for perceptual mapping typically come from questionnaires administered to a sample of customers in defined target segments. You should first organize the data into a matrix representing customer perceptions of each alternative on each of the prespecified attributes. Customers can either rank or rate all alternatives on one attribute at a time, or customers can rank or rate one alternative at a time along all the attributes. For example, airlines differ along many perceptual attributes, such as convenience, punctuality, overall service, and comfort.

A key assumption in perceptual mapping is that all customers whose data are used in the study share roughly the same perceptions about the alternatives. Therefore it is important that you obtain data from a homogeneous sample of customers.

**Step 3:** Select a perceptual mapping method. In positioning studies it is not unusual to obtain customer evaluations on 10 or more attributes relevant to the set of alternatives under consideration. However, it is unlikely that all these attributes extract unique information about the perceptions that customers have about these alternatives. It is more likely that subsets of attributes tap the same underlying construct (also referred to as factor, axis, or dimension). Thus perceived overall service and comfort might both be attributes that tap the more fundamental dimension of perceived quality.

Perceptual mapping techniques offer a systematic method for extracting information about the underlying construct (s) from a data matrix consisting of customer perceptions on observable attributes. While there are several methods for doing this with attribute-based data, **Hauser and Koppelman (1979)** recommend factor analysis.
In summary, attribute-based methods provide a powerful set of tools for perceptual mapping. They are particularly useful when the product alternatives are differentiated along tangible attributes that are well understood and evaluated by customers. Compared with similarity-based methods, attribute-based methods identify the underlying dimensions more clearly. A further advantage is that you can develop the maps even when the respondents evaluate only a few alternatives.

**CONSTRAINTS OF THE STUDY:**

The study suffers from the following constraints:

1. The brands under study have operations in other countries also and are being sold in those countries as well. But the researcher due to lack of funds could not interview consumes / customers in these countries.

2. Another limitation of this study is that people in India are wary of revealing income or matters related to income, thus it is possible that some respondents have reported wrong income. The income revealed by them did not match their living standard. Researcher could not get out of the assumed pattern of chief wage earners (CWE) Housewives and young adults.

3. Some times the respondents did not fill the questionnaire immediately when they were told about the study and the brands under study. They sent their completed questionnaires through mail. It is possible they would have lost the idea about the study when they actually sat for filling up of the questionnaire.

4. Researcher feels a bias may have been created in favoring the companies and brands under study and not using other brands/companies.

5. Researcher has not included the Rural population and the Lower socio economic classes of the urban Indian population as the available secondary information showed that penetration of branded products is negligible. This might act as a handicap of this study as the ground realities might be different.

6. Perceptual mapping provides only a partial explanation of consumers perceptions, based on attributes and alternatives included in the study.
REFERENCES:

- Chang, J.J. and J.D. Carroll (1971), “How to use PREFMAP and PREMAP 2-Programs which Relate Preference Date to Multidimensional Scaling Solution,” Bel Telephone Laboratories, Murray Hill, NJ.


• Green, Paul E., Y. Wind and A. K. Jain (1972), “A Note on Measurement of Social-Psychological Belief Systems,” Journal of Marketing Research, 9 (May), 204-08.


http://www.adb.org/documents/books/Investing In Ourselves/IND.


