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Modeling of Customer Preferences on Product Features and Comparing the Competitors' Performances

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ABSTRACT Understanding of consumers' perception about various product features helps companies to identify their own strengths and weaknesses. This article aims at finding the relative brand position of a company along with the nature of preference as perceived by the customers towards its major competitors. Information obtained through a feedback survey was subjected to analysis using multivariate statistical techniques. Feature-based preferences by the customers to evaluating companies' performances in the retail footwear market are reported here.

KEYWORDS cluster analysis, competitors, footwear attributes, preference mapping, preference score, principal component analysis

1. INTRODUCTION

In matters of product quality offered by several companies, there exists a strong link among consumer perception, their satisfaction level and retention for the company. Aysar and William (1997) showed that the orientation towards both quality and competitiveness for a company improves its performance in the areas of business growth and customer satisfaction. With better understanding of consumers' perception about product quality and service, a company can identify its relative strengths and weakness and chart a path for future progress and improvement. The renowned quality management experts (Deming, 1992; Juran & Gryna, 1990; Feigenbaum, 1986), emphasize that all activities within a company should be directed towards higher customer satisfaction. Due to the increase in the number of competitors, consumer perception and the respective preferences can change rapidly over time. The top management of the companies in India has recognized the urgency of transforming their organizations to consumer-focused organizations.

Reliable and valued information from the supply chain is, therefore, the prime concern in today's retail business for delivering the right products or services to end-users. Many retail operations are trying to establish their

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quality through integrated retail chains and reviewing the performance from the perspective of end point customers by adopting on-line and/or off-line surveys. With the increase in volume and complexity of retail business, the need for further improvement has become steeper and faster too. Sustenance of the supplier-customer relationship on a continuous basis requires monitoring and feedback of parameters affecting customer satisfaction.

The literature on understanding customer perceptions and developing consumer preference models is reviewed here. Thompson et al. (2004), conducted a study to identify and define sensory characteristics of commercial chocolate milks and to link the differences to consumer preferences through the application of internal and external preference mapping. In the work of Petrick (2003), the satisfaction, perceived value and quality models were utilized to assess cruise passengers' behavioural intentions. Iglesias (2004), through a retail banking sector study, established a strong effect of preconceptions about the service category on the perceptions of quality during service. In another study, for assessing customer reactions, Homburg et al. (2005) showed that repurchase intentions of customers are influenced by the magnitude of the price increase and the perceived fairness of the motive for the price increase. Implementation of a CRM (customer relationship management) model based on a customer satisfaction survey has been immensely successful for profitable customer segmentation (Jang and Sang, 2005; Roh et al., 2005). A recent study by Das and Gauri (2006) demonstrates the importance for a footwear company to know its consumers' perceptions about the product features and service it provides.

In India, after liberalization and globalization took place a few years back, the concept of manufacturing began to be slowly transformed into a service operation for retail businesses. Moreover, the companies began to face a tough challenge to retain their market share due to increase in number of competitors venturing into the vast Indian market. This situation has stimulated consumer expectations to change rapidly over time. The first author of this article has observed rapid switching of the customers' preferences in footwear business through repeat retail surveys. In this article, an attempt has been taken to identify the relative brand position of a reputable Indian footwear company (referred to as Parent-com) in relation to its three major footwear competitors (referred to as *C*-1, *C*-2, *C*-3, respectively) and also to identify consumer preferences based on footwear features and service provided by the retail outlets. The competing brands must be analytically identified for better planning of policies and actions for the company Parent-Com in order to meet consumer choice and communication in terms of footwear features leading to business growth over time. Principal component analysis is used here to find the linear combinations of the footwear attributes for determining relationship with the companies. The cluster analysis technique is used to form groups of interviewed customers based on the preferences given with respect to the footwear attributes. Preference mapping is used, based on the principal components of attributes found and the groups of the customers formed, to identify the preference of customers towards Parent-com and its prevailing competitors in the market.

The article is organized as follows. The article contains a brief discussion on principal component analysis, cluster analysis and preference mapping technique in *Section* 2. The profile of the database considered for this work is explained in *Section* 3. Implementations and results are provided in the *Section* 4. *Section* 5 discusses about the interpretation of the results obtained. The conclusions of the study are drawn *Section* 6. Finally, the article highlights some future work in *Section* 7.

2. MATERIALS AND METHODS

2.1. Principal Component Analysis

The method of principal components is primarily a data analytic technique that obtains linear transformations of a group of correlated variables such that certain optimal conditions are achieved. The most important of these conditions is that the transformed variables are uncorrelated (Jackson, 1991; Johnson and Wichern, 1996).

Here principal component analysis has been applied to find the linear combinations of the attributes such that the different attributes (*Style, Price, Quality*, and *Service*) vis-à-vis different companies (*Parent-com*, *C*-1, *C*-2, and *C*-3) can be plotted to find out the relations between different companies and attributes. See *Section* 4.3 for details.

2.2. Cluster Analysis

Cluster analysis is a technique for grouping individuals or objects so that objects in the same cluster are more like each other than they are like objects in other clusters (Johnson, 1967; Everitt, 1980).

Here the main objective is to partition the dataset on the basis of similarity into different clusters. Using these, it would be able to reduce the number of observations in such a way that all the observations having approximately the same preference regarding different companies are under the same cluster. The general perceptions of segmented (or, clustered) customers about different companies are found out using this methodology. See *Section* 4.4 for details.

2.3. Preference Mapping

Preference mapping is the two dimensional representation of preference data. It is a commonly used tool in understanding the qualitative attributes (features) of product that drives consumer preferences (Schlich, 1995; McEwan, 1996). The most common practice is to add preference data in the form of *point vector* models, which is called the preference map. This mapping is potentially very powerful since it allows the preference data to be linked to objective data. The preference score for each object (response) for a given judge (respondent - individual or group), whose value is between 0 (minimum) and 1 (maximum), is calculated from the prediction of the model for the judge. The more the product is preferred, the higher the score. This technique has been implemented in a number of studies with a variety of products; however, no such application exists for an essential and fashionable commodity like footwear.

In this study, the objective of using preference mapping is to visualize the preference of groups of customers towards different companies on the basis of footwear attributes. See *Section* 4.5 for details.

3. PROFILE OF THE DATABASE

Since, for any opinion survey, personal interviews always help to improve relationships with customers, it was decided to collect the consumer's feedback on the choice of product (footwear) features like *Style*, *Price*, and *Quality* along with *Service level* in the retail outlets in ordered dichotomous scale through personal interviews. The target group of customers has been specified as people living in the eastern part of India, specifically in Kolkata city, to maintain the cost of survey within an acceptable level. The information were collected from the individuals having some familiarity with the *Parent-com's* product. The scales for each product attribute are decided as follows.

1. perception about *Style* [Good, not good]
2. perception about *Price* [Expensive, not expensive]
3. perception about *Quality* [Satisfactory, not satisfactory]
4. perception about *Service level* [Strong, weak]

Altogether four footwear companies, C-1, C-2, C-3, and Parent-com are considered in the survey. Out of the responses from 501 consumers, only 247 complete observations were found and subjected to analysis.

4. IMPLEMENTATION AND RESULTS

4.1. Score Calculation

Each footwear attribute has two levels, low (0) and high (1), with high (1) being the target level as described in Table 1.

Accordingly, the customers' choices are converted into '0' or '1'. From the responses of 247 customers, Table 2 is constructed where the cell values represent the total number of customers reaching the target value.

TABLE 1 **Target for Footwear Features**

Attributes	Target (1)
Style	Good
Price	Not expensive
Quality	Satisfactory
Service	Strong

TABLE 2 **Count on Customers Reaching *Target***

	Parent-com	*C-1*	*C-2*	*C-3*
Style	111	87	140	99
Price	227	70	238	183
Quality	117	194	128	77
Service	142	161	129	96

TABLE 3 Proportion of Customers Reaching *Target*

	Style	*Price*	*Quality*	*Service*
Parent-com	0.449	0.919	0.474	0.575
C-1	0.352	0.283	0.785	0.652
C-2	0.567	0.964	0.518	0.522
C-3	0.401	0.741	0.312	0.389

Next, the proportion of customers (p_{ij}) reaching targets are estimated, where $p_{ij}=$ (number of customers reaching the target)/(Total number of customers), $i = Style,\ Price,\ Quality$ and $Service$; $j = Parent\text{-}com$, C-1, C-2, and C-3. Clearly $0 \leq p_{ij} \leq 1$. $p_{ij}=1$ implies that for ith attribute, jth company reaches its target and $p_{ij}=0$ implies that for ith attribute, jth company is far from the target. In real-life environment, however, $p_{ij}=1$ (or, 0) may not be feasible for all i for a particular company.

It may be said that j'th company is most preferred for ith attribute if $p_{ij'} \geq p_{ij}\ \forall j \neq j'$. Similarly, i'th attribute is most preferred for jth company if $p_{i'j} \geq p_{ij}\ \forall i \neq i'$. So it is expected that if jth company reaches its target, then $p_{ij} \to 1\ \forall i$.

In Table 3, proportion of customers reaching the target value is calculated. For example, $p_{11}=$ proportion of customers choosing style for C-1 as 'Good' $=(87/247)=0.352$. The remaining proportions, thus computed, are as follows.

From the estimated values of p_{ij} some idea about the customers' preference towards a company for a given attribute can be obtained.

4.2. Principal Component Analysis

While applying principal component analysis on the covariance matrix, using data from Table 3, three principal components (F1, F2, F3) are found of which the first component explains about 82.8% of the total variability whereas the second one is accounted for 15.6% and the rest of the variability is explained by third principal component. See Table 4 for details. Since, the fourth eigen value is zero, it indicates singularity of the covariance matrix. So there is a linear relationship between the attributes.

TABLE 4 Proportion of Trace

	F1	F2	F3
Eigen value	0.129	0.024	0.002
Variability (%)	82.82	15.60	1.58
Cumulative %	82.82	98.42	100

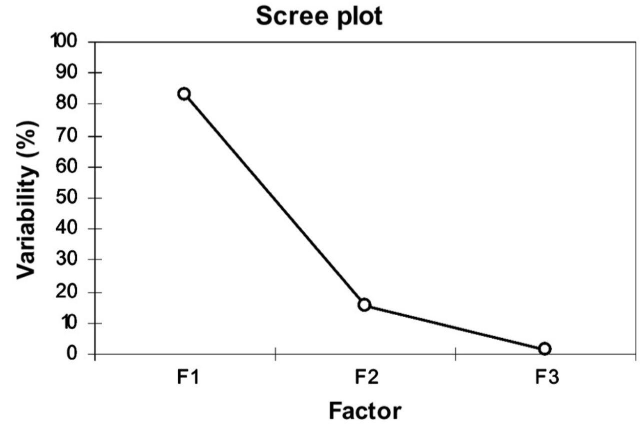

FIGURE 1 SCREE plot.

From the SCREE plot (see Figure 1) and also from the proportion of trace explained (see Table 4) it is decided that first two principal components are sufficient to explain the total variability. The correlation biplot is now drawn to see the relationship among the footwear attributes (see Figure 2). The rules of association in the plot are as follows:

If the two vectors make an angle which is less than 45°, then they are positively correlated. If the angle between the two vectors is within 45° and 135° then the vectors are said to be uncorrelated. If the angle

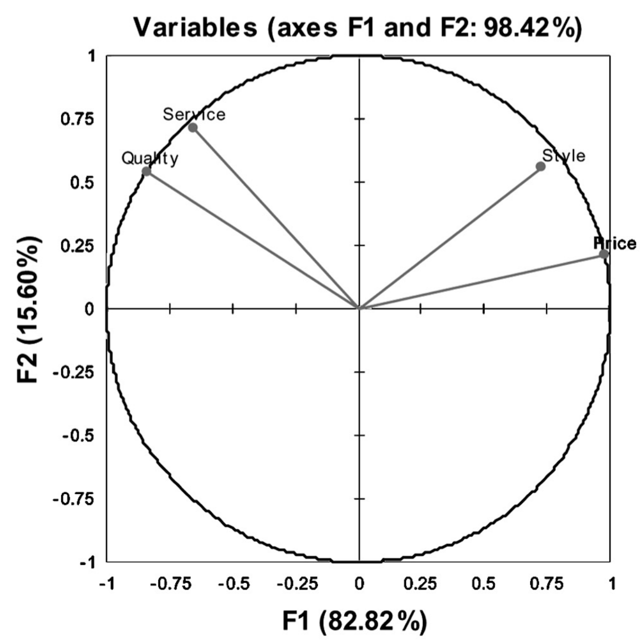

FIGURE 2 Principal component correlation biplot (F1–F2).

TABLE 5 **Matrix U and Matrix X**

	Eigen vectors (U)			Proportion with deviation from average (X)			
	F1	F2	F3	*Parent-com*	*C*-1	*C*-2	*C*-3
Style	0.187	0.327	0.736	0.01	−0.09	0.12	−0.04
Price	0.845	0.417	−0.190	0.19	−0.44	0.24	0.01
Quality	−0.459	0.682	0.216	−0.05	0.26	0.00	−0.21
Service	−0.200	0.504	−0.612	0.04	0.12	−0.01	−0.15

between the two vectors is more than 135° then the vectors are said to be negatively correlated.

Using these definitions, we conclude from Figure 2 that *Style* and *Price* are correlated, *Style* and *Service* are uncorrelated, and that *Style* and *Quality* are also uncorrelated. *Price* and *Quality* are negatively correlated. *Price* and *Service* are also negatively correlated. So it may be said that as the *Quality* reaches its target value, *Price* deviates from the target, in other words, as *Quality* becomes satisfactory *Price* reaches to expensive.

Next, to compute the factor score (or, Z-score) for the four companies, two matrices **U** and **X** are considered. Matrix **U** consists of eigen vectors for different factors. Matrix **X** is constructed, using Table 3, by subtracting the overall average value of each attribute from the individual proportion of customers reaching the target. The results are shown in Table 5. $\mathbf{U}'\mathbf{X}$ provides the matrix for Z-Scores (see Table 6).

The corresponding plot on the factor space is shown in Figure 3.

It is observed from Figure 2 that F1 is dominated by *Price* and *Quality*; F2 is dominated by *Service* and *Quality*. From Figure 3, it is observed that with respect to F1, *Parent-com*, *C*-2 and *C*-3 form a group whereas *C*-1 is alone. Similarly, with respect to F2, *Parent-com*, *C*-2 and *C*-1 form a group, where *C*-3 is alone. Combining F1 and F2, *Parent-com* and *C*-2 form a group, where *C*-1 and *C*-3 are of separate nature.

TABLE 6 **Z-Scores**

	F1	F2	F3
Parent-com	0.178	0.070	−0.067
C-1	−0.536	0.024	0.003
C-2	0.228	0.131	0.053
C-3	0.130	−0.225	0.011

The footwear attributes are imposed now on the same factor space. In the three-dimensional figure (see Figure 4), the actual positions (directions) of four attributes and four companies can be visualized.

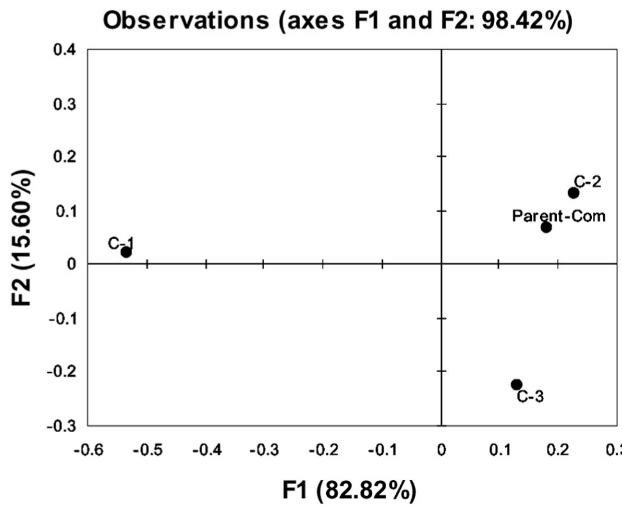

FIGURE 3 **Plotting of different companies on factor space.**

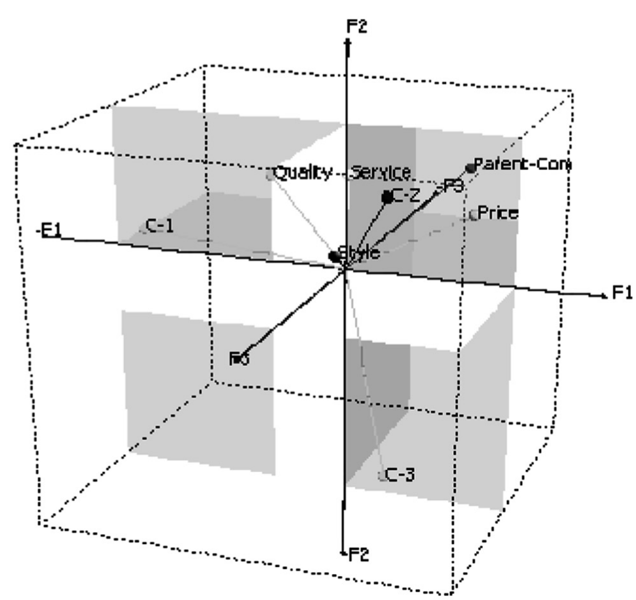

FIGURE 4 **3D-plot of four companies on factor space.**

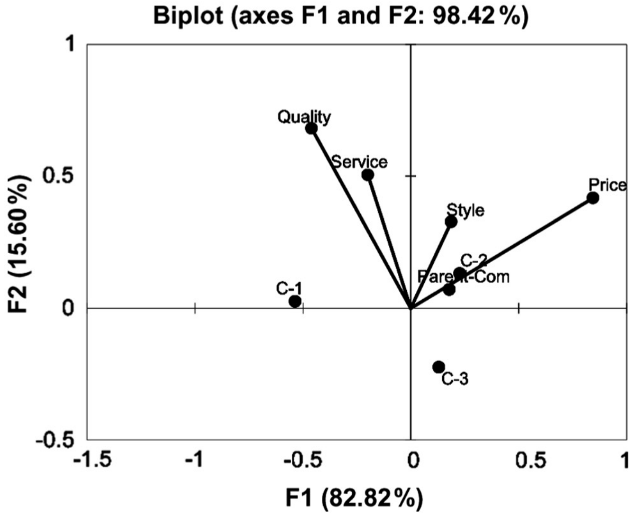

FIGURE 5 Principal component biplot (F1–F2).

Taking projection of F3 axis on F1 axis, F2 on F1, and F1 on F2 respectively, Figure 5 is generated.

From Figure 5 it is observed that with respect to *Price* and *Style*, *Parent-com*, *C*-2 and *C*-3 are in a better position in terms of reaching its target whereas the company *C*-1 is not in a good position with respect to *Style* and *Price*. If *Quality* is considered, then *C*-1 is the best as the vector of *Quality* is towards *C*-1. When the attribute *Service* is considered all the companies except *C*-3 are in a good position.

4.3. Weighted Responses and Cluster Analysis

The weighted responses and their frequencies using the raw data for different combinations of attribute are now computed for each of the four companies. The weights, as perceived by the footwear company management, based on the socio-economic conditions of the customers under study, are 0.2 for *Style*, 0.3 for *Price*, 0.4 for *Quality* and 0.1 for *Service* respectively. The total weight for four attributes, thus, becomes 1. A sample computation of weighted response corresponding to each of 247 respondents' preferences on four attributes of a company's (*Parent-com*, for example) footwear is shown in Table 7.

Note that the minimum and maximum values of weighted response for an individual with respect to a company are 0 (in case of not meeting the *target*, as defined in Table 1) and 1 (meeting the *target*). Other values of weighted responses may occur due to different combinations of four attributes. For example, a weighted response of 0.5 can occur due to (*Quality* + *Service*) or (*Style* + *Price*). Accordingly, the reason for inclination towards attributes by the customers can be explained (see Section 4.3). Similar calculations hold for other three companies. The composite response, thus calculated, for the four companies are shown in Table 8. The information in Table 8 is used for cluster analysis.

Since, the respondents are spread over the eastern part of India covering a large geographical area, it is decided to group them into homogeneous groups on the basis of their responses (see Table 8) in order to make the results of preference mapping easier to interpret. For this purpose agglomerative hierarchical clustering is chosen. This method begins with every customer as his/her own cluster and successively merges clusters/customers until all subjects, who show a common response pattern, are contained in a single cluster. Euclidian distance is chosen as a measure of dissimilarity and Ward's method is used for clustering (Ward, 1963).

TABLE 7 Calculation of Weighted Response

	Parent-Com				
Customer no.	*Style* (0.2)	*Price* (0.3)	*Quality* (0.4)	*Service* (0.1)	Weighted response
1	1	0	1	1	0.7 ($= 1 \times 0.2 + 0 \times 0.3 + 1 \times 0.4 + 1 \times 0.1$)
2	0	0	1	1	0.5
3	0	0	1	1	0.5
4	0	0	1	1	0.5
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
247	1	0	0	1	0.3

TABLE 8 Weighted Response for All Companies

Customer no.	*Parent-Com*	*C*-1	*C*-2	*C*-3
1	0.7	0.5	0.7	0.7
2	0.5	0.1	0.5	0.2
3	0.5	0.7	0.5	1
4	0.5	0.7	0.7	0.5
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
247	0.3	0.5	0.9	0

The dotted line in Figure 6 is the automatic truncation line, leading to three groups. Table 9 represents centroid distances. The last column in Table 9 shows the number of customers falling in each group. Several possibilities of group separation for all the four companies may arise. For example, considering Parent-com, groups are well separated. Group-1 is dominated by *Style*, Group-2 is dominated either by *Quality* and *Service* or by *Style* and *Price* and Group-3 mostly by *Quality*. Similarly, for the company *C-3*, Group-1 is dominated by *Style*, Group-2 is dominated mostly by *Quality* and Group-3 by *Service*. For *C-1*, Group-1 and Group-3 can be separated from Group-2 either by *Quality* or by *Price* and *Service*. Group-2 for *C-1* is mostly dominated by *Quality* and *Style*. For *C-2*, Group-2 and Group-3 can be explained either by *Quality* and *Service* or by *Style* and *Price*. Group-1 for C-2 is mostly dominated by *Style*. All these possibilities of group separation are explored through preference mapping (see Section 4.4).

4.4. Preference Mapping

For preference mapping, a linear model is fitted first for each group on the *Z*-Score of principal

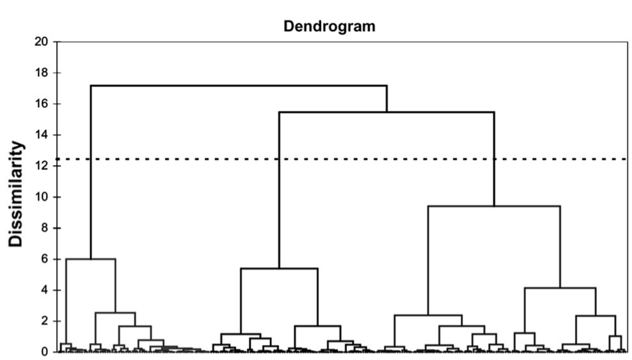

FIGURE 6 Dendogram for grouping of customers.

TABLE 9 Centroid Distances

Group	*Parent-com*	*C*-1	*C*-2	*C*-3	# Customers
1	0.185	0.457	0.609	0.228	109
2	0.539	0.562	0.495	0.753	66
3	0.760	0.432	0.486	0.122	72

component analysis (see Table 6), considering group centroids as response variables. The estimated regression coefficients (including intercept) and R^2 values are given in Table 10. The significance of principal components (*regressor variables*) is self-explanatory based on the R^2 values found.

It shows by analyzing Table 10 that the only significant model with good prediction across all three groups is the model containing F2 and F3 with R^2 values above .95. Therefore the computations for the predicted values given in Table 11 are done using the model with F2 and F3. From the models developed, considering the model containing F2 and F3, a sample calculation for the predicted value is shown next

$$\begin{aligned}&\text{Predicted value of } C\text{-1 for Group-1}\\&\quad = 0.370 + (0.719) * (0.024) + (3.219) * (0.003)\\&\quad = 0.397\end{aligned}$$

All other predicted values are calculated, using the model with F2 and F3, for each company and produced in Table 11.

The predicted values are then standardized for each group using the following transformation.

$$\textit{Transfomed Value} = \frac{\textit{Actual Value} - \textit{Minimum Value}}{\textit{Maximum Value} - \textit{Minimum Value}}$$

These transformed values are called *preference scores*, which are given in Table 12 for F2–F3 combination of principal components. High preference score means more preferable company for that group of customers. Preference score equal to '1' means *most preferred* and preference score equal to '0' means *least preferred*.

Now, for better visualization of preference for the three groups of customers towards the four companies, the three-dimensional figure (*see* Figure 7) is drawn to see the actual positions (directions) of groups of customers and the companies. The preference map, corresponding to the significant model developed

TABLE 10 Regression Coefficients and R^2

	Intercept	F1	F2	F3	R^2 (F1 & F2)	R^2 (F1 & F3)	R^2 (F2 & F3)
Group-1	0.370	−0.112	0.719	3.219	0.357	0.684	0.959
Group-2	0.588	0.014	−0.729	−0.003	1.000	0.002	0.998
Group-3	0.450	0.079	1.364	−3.008	0.674	0.338	0.988

TABLE 11 Estimated Values of the Four Companies for Four Groups

Company	Group-1	Group-2	Group-3
Parent-Com	0.205	0.537	0.747
C-1	0.397	0.570	0.474
C-2	0.635	0.492	0.469
C-3	0.244	0.752	0.110

TABLE 12 Preference Scores

	Principal component: (F2–F3)		
	Group-1	Group-2	Group-3
Parent-Com	0.000	0.172	1.000
C-1	0.446	0.300	0.571
C-2	1.000	0.000	0.562
C-3	0.086	1.000	0.000

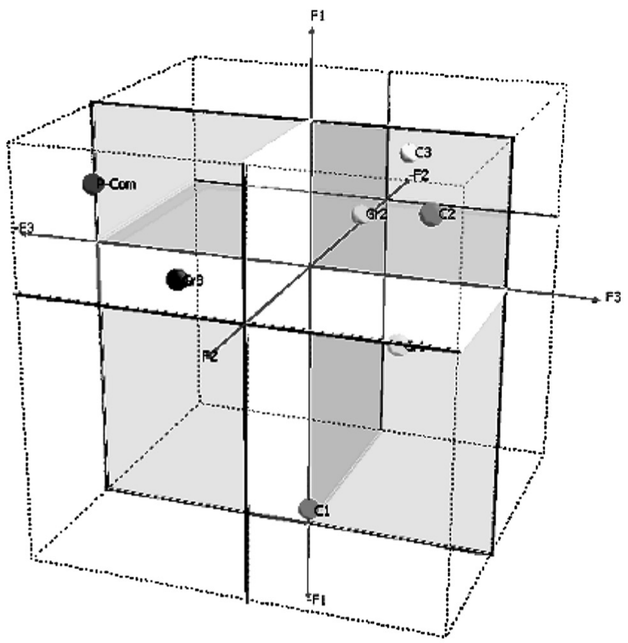

FIGURE 7 3D-Plot for customers (group) perception vs. companies.

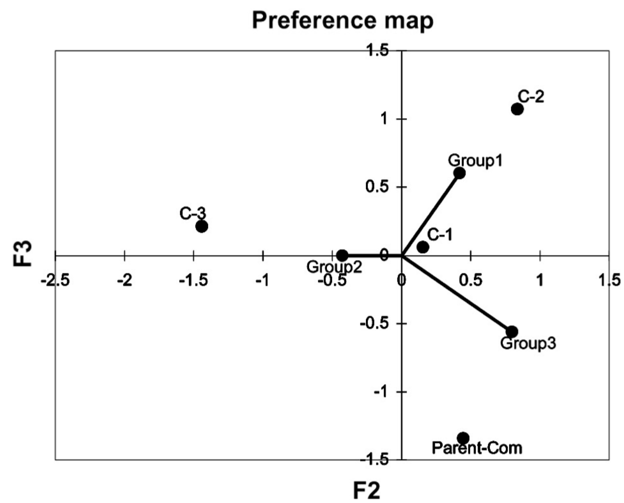

FIGURE 8 Preference map of customer perception (F2-F3).

containing F2 and F3, is next developed by taking projection of F1 axis on F2 and F3 axes (*see* Figure 8).

From the preference map (see Figures 7 and 8) and also from preference scores (see Table 12) it is observed that *Parent-com* is preferred by Group-3. *C*-3 is preferred by Group-2 customers whereas *C*-1 and *C*-2 are by Group-1 customers.

5. DISCUSSION

The objectives of this work are twofold, namely, to find out how different companies are preferred by customers and also on the basis of footwear attributes. Initially, the relationship between four companies and four footwear attributes are studied thoroughly. As observed from the PCA, the first principal component reflects the effect of *Price* and *Quality* (see Table 5) and explains about 83% of the total variability. On the other hand, the second principal component is the effect of *Quality* and *Service* (see Table 5), explaining approximately 15% of the total variability. The third principal component is characterized by *Style* and *Service* and explains the remaining variability. A positive correlation between (*Price, Style*) and (*Quality, Service*) is observed (see

Figure 2). The negative correlation between *Price* and *Quality* reveals that as *Quality* of footwear goes high, *Price* becomes more and more expensive. The performance of three footwear companies, namely, *Parent-com*, *C*-2, and *C*-3 is good to meet the *target* with respect to *Price* and *Style* (see Figure 5). The performance of the company *C*-1 is the best in terms of *Quality*. Considering the attribute *Service*, all the companies except *C*-3 are in a good position.

Using cluster analysis, three distinct groups of customers are observed based on their views with respect to footwear attributes. From the centroid distances it is possible to explore the possibilities of inclination towards different companies of the respective groups on the basis of footwear attributes. Now, it is observed using preference map that Group-1 customers prefer C-1 and *C-2*, Group-2 prefer C-3 and Group-3 prefer *Parent-com*.

So, combining groups of customers and the footwear attributes as explained by the principal components F1, F2 and F3 (ref. Table-10), it is observed that the customers of Group-1 prefer the three footwear attributes *Quality, Style* and *Service*. In general, Group-1 customers are ready to pay for satisfactory *Quality* and *Stylish* footwear. *C*-1 (*Quality* and *Service*) and *C*-2 (*Style and Service*) may be the preferred companies to Group-1 customers. The vector direction of Group-2 is aligned with F2, but its direction is just the opposite to that of *Price* and *Quality*. It appears that the customers of Group-2 do not prefer footwear with superior quality and low price, which is not a realistic situation. Further, since the Group-2 customers are in the direction of *C*-3, it comes out with the fact that the customers of Group-2 do not have the right idea of footwear attributes of *C*-3. The customers belonging to Group-3 have preference towards *Parent-Com* on the basis of *Style*, *Price* and *Service*. Since, *Style* is the most important variable for Group-3 customers, it may be said that the customers of Group-3 are eager to have *Stylish* footwear without bothering about *Quality*.

6. CONCLUSIONS

In this study, preference mapping is used to identify how the customers prefer the *Parent-com* along with the competitors prevailing in the market. Initially, principal component analysis is used to determine the factors, a linear combination of attributes. So, different factors can be explained in terms of different attributes viz., *Style*, *Price*, *Quality* and *Service*. The first principal component is characterized by *Price* and *Quality*, second principal component is characterized by *Quality* and *Service* whereas third principal component is characterized by *Style* and *Service*. *Parent-com* and *C*-2 both are in good position with respect to *Style* and *Price*, whereas *C*-1 is in good position with respect to *Quality*. However, there is no evidence for preferring *C*-3 with respect to any attribute. Then the interviewed customers are segmented into three groups using cluster analysis on the basis of their preferences. On the basis of these three groups and different principal components, the perception of different groups about different companies is obtained. The customers with respect to *Style, Price* and *Service* prefer *Parent-com* and *C*-2, whereas *C*-1 is mostly preferred because of *Quality*. Though some customers (group-2) prefer *C*-3, but no attribute is found significant for the preference of *C*-3. *Parent-Com* and *C*-2 are accepted to almost all the customers (group-1 and group-2) and they are in a good situation with respect to *Style, Price* and *Service*. Further, *Parent*-com and *C*-2 are the competitors of each other regarding all the attributes considered.

FUTURE SCOPE

This study can be extended for product positioning in the market and also for new product launching. There may be need to carry out some experimental design, use conjoint analysis and then be able to take decision about significant (dominant) attributes to be incorporated into the new product for a successful launching in the market. Estimation of market share from the designed data can also be worked out.

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