AN EMPIRICAL STUDY ON IDENTIFICATION OF CONSUMER PREFERENCES IN FOOTWEAR MARKET THROUGH APPLICATION OF FACTOR, CLUSTER AND CONJOINT ANALYSIS

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ABSTRACT

This study tried to explain the affect of twenty-one important product attributes on consumer behaviour in footwear market. All the indicators used in the study came out as strong factors with very high factor loadings, the highest remains the appearance or look of the merchandise and lowest packaging . Six, very strong and relevant factors or components were extracted from the exploratory factor analysis namely Intrinsic and Extrinsic Attributes, Reliability, Convenience, Health Consciousness, Fashion Consciousness and Aesthetics and Technology and appearance.

From six components (extracted from factor analysis), the indicators with highest factor scores from each component were chosen for cluster analysis. Three distinct and differentiating clusters or segments were formed namely Status Conscious, Impulsive & Casual and Value for Money on basis of those six variables. All the six variables came out to be very significantly different among the clusters and helped in segmenting the customers. The study also attempted to understand the utility value and preferences of the customers in terms of product categories. For which three product categories each having two levels or option of footwear product matrix were selected. Utility of all the eight product option was calculated through conjoint analysis according to the preferences of the customers. To understand the probability of preferences of the customers according to the options four simulation cases were formed in conjoint analysis.

Keywords: *Consumer Behaviour, Buying Factors, Footwear Market.*

INTRODUCTION

India is the second largest global producer of footwear after China, accounting for 13% of global footwear production of 16 billion pairs. India produces 2065 million pairs of different categories of footwear (leather footwear - 909 million pairs, leather shoe uppers - 100 million pairs and non-leather footwear - 1056 million pairs). India exports about 115 million pairs. Thus, nearly 95% of its production goes to meet its own domestic demand.

Domestic footwear market is estimated to be over Rs15,000 crore in value terms and has grown at the rate of 8.8% over the last couple of years. Men's footwear accounts for almost half of the total market, with women's shoes constituting 40%, and kids' footwear the remaining. The domestic market is substantially price driven, with branded footwear constituting less than 42% of the total market size.

Consumer behaviour involves the psychological processes that consumers go through in recognising their needs, finding ways to solve these needs, making purchase decisions (e.g., whether to purchase a product and, if so, which brand and where), interpret information, make plans, and implement these plans (Hafstorm, Jung, & Young, 1992).

According to Azizi & Makkizadeh, 2012 separating markets precisely and applying marketing programs proportional to the known sections is one of the most important success tools in competitive

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markets and for the marketers it is very important to develop a deeper understanding of the impact of different factors on consumer buying behaviour.

Canabal, 2002 concluded that the rapid transition of India to a market economy has increased the choices of products and services available to consumers, thus increasing their confusion and need for consumer education. (Walsh, et al., 2001) concluded in their study that decision making styles are important to marketing because they determine consumer behaviour, are relatively stable over time and thus are relevant for market segmentation.

LITERATURE REVIEW:

Saha, Dey, & Bhattacharyya, 2010 found that the factors to be considered by shoe manufacturers and marketers are quality, durability, right pricing, after sale service, and convenient location of the retail shops. Consumers prefer the buy the shoes from exclusive shoe outlets rather than through supermarkets or department stores. Male and female are found to have similar opinion regarding the importance of these factors. They are only found to differ in case of product warranty, store is conveniently located, TV advertising and lucky draws.

Thongchai & Nuntana, 2013 in their study concluded "Well Trained and Experienced Salesforce", "Product Quality and Functions", "Attractive Store and Product Presentation", "Price and Perceived Value", "Health and Comfort", and "Fashion and Trends" as the most important factors which affect the footwear buying.

Goel & Dewan, 2011 in their study identified availability and variety, ambience, service, price, advertisement, prestige and quality as the most important factors which influences consumer preferences of shopping at organised retail stores.

Due to the increase of number of new players in the market product differentiation in this competitive market is gaining its importance which has been defined as a product offering is perceived by the consumer to differ from its competition on any physical or nonphysical product characteristic (Dickson, 1987).

Market segmentation and target marketing explains how the customer wants to identify product attributes and their relative importance in the targeted segment and is instrumental in the creation of superior customer value by segmenting a market and identifying appropriate target segments along with finding out the relevant product attributes that appeal most to these segments (Lonial, Menezes, & Zaim, 2000).

Marketers should know the consumer preferences and their values and can develop the necessary marketing strategies to increase customer satisfaction, loyalty and retention, thus strengthening their competitive position. It is impossible today to remain cost competitive and offer every feature desired by customers (Pullman & Moore, 2002)

Cachon, Terwiesch, & Xu, Fall 2005 mentioned three versions of the retail assortment problem: a traditional, no-search, version that does not explicitly consider consumer search and two versions that implement two different consumer search models. Analysis suggests the retailer's decision to add a product to an assortment should not only consider the direct costs and revenues of the product, but also anticipate the indirect benefit an extended assortment has in preventing consumer search.

There is a growing need to evaluate the drivers of shopping behaviour in the Indian context (Banerjee & Sinha, 2002). The knowledge of consumer shopping behaviour is an essential input to the development of an effective marketing strategy, which is required for the effectiveness, and success of any business. The study of Howell WR, 1987 further suggested that consumers are using shopping strategies rather than brand strategies in solving many consumption problems.

RESEARCH OBJECTIVES

The primary objective is to study the consumer preferences in the footwear market in India. The study tried to extract important factors related to product attributes which affects the consumer buying styles. It also tried to segment the footwear market into some distinct and differentiating clusters according to preferences of the customers towards certain important product attributes. Lastly, this study also attempted to study the preferences of the customers based on utility value of various options among the various popular categories of footwear products.

RESEARCH METHODOLOGY

The research design of the study is partly exploratory and partly descriptive in nature. The objective of exploratory research is to explore or search through a problem or situation to provide insight and understanding (Malhotra & Birks, 2006). The major objective of Exploratory Research is to identify and define the problem and scope by helping to arrive at the best research design, method of data collection and sample, which is characterized by highly flexible, unstructured and at times informal research methods (Easwaran & Singh, 2010). In the study, the researcher tried to use both primary and secondary data. Primary Data is originated by the researcher for the specific purpose of addressing the problem at hand (Malhotra & Birks, 2006). Thus primary data are the raw data, which is needed to be further, processed and secondary data are the published data.

As a data collecting tool, the researchers have used, structured non-disguised questionnaire with both open and close ended questions. A Questionnaire is called a scheduled interview form or measuring instrument including formalized set of questions for obtaining information from respondents (Malhotra & Birks, 2006). Non-disguised approach is a direct approach in which purpose of the project is disclosed to the respondents or is otherwise obvious to them from the questions asked. The reason for asking structured questions is to improve the consistency of the wording used in doing the study at different places which increases the reliability of the study by ensuring that every respondent is asked the same question (Nargundkar, 2004) and the survey instrument was used to collect data through personal interviews.

Likert Scales were formed in form of 21 statements on 21 different product attributes and the respondents were asked about their agreement and disagreement with the statements. All the attributes were scanned from the market through pilot survey, which were kept specific to the footwear market. On the basis of number of components extracted from exploratory factor analysis, the indicators with highest factor scores from each component were chosen for conduction cluster analysis.

To understand the product option preferences by the customers, conjoint analysis was executed, for which three product attributes each having two levels or options on footwear product matrix namely type of shoes, type of material and price range with two levels of Category (Formal and Casual), Type of materials (Leather and Non-Leather) and Price (Below Rs.1500/- and Above Rs. 1500/-) were selected for the study.

In the research study, we have implemented Probability Sampling Technique (Nargundkar, 2004), where each sampling unit has a known probability of being included in the sample. Systematic sampling technique has been used in the study, where the sample frame is the list of loyal customers in the footwear stores in Kolkata and Delhi. The Sample size was calculated to 150. Statistical Inferences were drawn from the primary data collected by applying statistical tool like SPSS 19 and statistical analysis like Exploratory Factor Analysis, Cluster Analysis and Conjoint Analysis.

FINDINGS AND ANALYSIS

Factor Analysis

Factor analysis attempts to identify underlying variables, or factors, that explain the pattern of correlations within a set of observed variables. Factor analysis is often used in data reduction to identify a small number of factors that explain most of the variance observed in a much larger number of manifest variables. Factor analysis can also be used to generate hypotheses regarding causal mechanisms or to screen variables for subsequent analysis (for example, to identify co linearity prior to performing a linear regression analysis)

A Likert Scale was formed of 21 statements on 21 different product attributes and the respondents were asked about their agreement and disagreement with the statements. All the attributes were scanned from the market through pilot survey, which were kept specific to the footwear market. The attributes are as follows:

Quality, Price, Brand , Comfort, Fit, Odourless, Nice colours, Beautiful packaging, Appearance, Design, Advanced Technology, Country of origin, Durability, Variety, Warranty, Reparability, Light Weight, Environment friendly Material, Availability, Maintenance and Fashionable

CONSIDERATIONS IN FACTOR ANALYSIS:

In the study a sample size of 100 respondents were taken but it needed to be tested whether it is adequate or not for the study, which was checked through using of Kaiser-Meyer-Olkin Measure of Sampling Adequacy and Barlett's Test of Sphericity as shown in the Table 1. Any value of More than 0.5 shows that the sample size is adequate. KMO Value >0.5 -0.7 Shows Mediocre Sample Size, Value > 0.7 shows Good Sample and Value > 0.8 shows Great Sample size. As the value KMO is 0.750 in this study, it shows that the sample adequacy is Good.

Table1: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.750
Bartlett's Test of Sphericity	Approx. Chi-Square	1161.903
	Df	210
	Sig.	.000

Correlation Matrix shows the simple correlations, r, between all possible pairs of variables included in the analysis. The Pearson correlation coefficient between all the variables chosen for the study and the matrix has been used to study the pattern of relationship. After the evaluation, it was concluded that there was no problem of singularity or high correlation in data as none of the correlation coefficients were greater than 0.8. To sum up all variables in the study correlate fairly well either negatively or positively and none of the correlation coefficients is particularly large; therefore there is no need to consider eliminating any variable at this stage.

To study the reliability of the data collected, reliability test was done on the data collected on twenty-one Likert Statements. Cronbach's alpha determines the internal consistency or average correlation of items in a survey instrument to gauge its reliability (Cronbach, 1951). In the study a very high Cronbach Alpha Value was deduced (the more it tends to 1 the better it is) ie .822 (see Table 2) which proves that the data is highly reliable. It was tested on all the twenty-one statements or indicators selected for the study.

Table 2: Reliability Statistics

Cronbach's Alpha	N of Items
.822	21

Table 3 list the Eigen values associated with each linear component (factor) before extraction, after extraction and after rotation. First few factors explain relatively large amounts of variance whereas subsequent factors explain only small amount of variance. In the study the first 6 components with Eigen values more than 1 are extracted which defines 71.554% of variance, which can be treated as quite high.

Table 3: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.042	28.770	28.770	6.042	28.770	28.770	4.665	22.212	22.212
2	2.809	13.377	42.147	2.809	13.377	42.147	3.312	15.771	37.983
3	2.104	10.018	52.165	2.104	10.018	52.165	2.093	9.965	47.947
4	1.609	7.661	59.826	1.609	7.661	59.826	1.769	8.425	56.372
5	1.386	6.600	66.425	1.386	6.600	66.425	1.761	8.385	64.757
6	1.077	5.129	71.554	1.077	5.129	71.554	1.427	6.797	71.554

7	.979	4.662	76.216						
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19	.133	.634	98.973						
20	.128	.610	99.583						
21	.088	.417	100.000						

Extraction Method: Principal Component Analysis.

Within each factor (to the extent possible), the items are sorted from the one with the highest factor weight or loading for that factor to the one with the lowest loading on that first factor. Loadings resulting from an orthogonal rotation are correlation coefficients of each item with the factor, so they range from -1.0 through 0 to + 1.0. A negative loading just means that the question needs to be interpreted in the opposite direction from the way it is written for that factor, but here no negative loading was extracted. Usually, factor loadings lower than .30 are considered low, which is why we suppressed loadings less than .30. On the other hand, loadings of .40 or greater are typically considered high. This is just a guideline, however, and one could set the criterion for "high" loadings as low as .30 or as high as .50. Setting the criterion lower than .30 or higher than .50 would be very unusual. All the indicators used in the study came out as strong factors with very high factor loadings, (see Annexure: Communalities Table) the highest remains the appearance or look of the merchandise (0.869) and lowest packaging (0.474).

Table 4 shows us the factor score for each variable across the components. We went across each row, and selected the factor that each variable loaded most strongly on. We tried to examine the content of the items that have high loadings from each factor to see if they fit together conceptually and can be named. Based on these factor loadings, we think the factors represent the following 6 Components:

Table 4: Rotated Component Matrix

	Components					
	1	2	3	4	5	6
Price	.832	.058	.226	.028	.004	.036
Quality	.880	.180	.126	.008	.010	.051
Design	.785	.114	.067	-.137	.069	.061
Fit	.843	.172	.069	-.024	-.057	.201
Comfort	.825	.066	-.030	-.037	-.179	.251
Variety	.622	.503	.238	-.103	-.099	-.073
Durability	.197	.820	.234	.159	.079	-.062
Warranty	.116	.794	.378	-.037	.131	-.137
Availability	.218	.213	.869	-.088	.001	-.007
Maintenance	.154	.130	.845	-.028	.064	.248
Reparability	.138	.778	.240	.093	.157	-.002
Environment friendly material	.148	.636	-.239	.189	.135	.495

COO	.056	.682	-.307	-.236	.152	.151
Appearance	.212	.107	.168	.111	-.052	.856
Beautiful packaging	.030	.286	-.016	-.071	.621	-.032
Nice colours	-.030	-.007	-.068	.473	.655	.257
Odourless	-.052	.062	-.179	.839	.041	.136
Fashionable	-.007	.143	.095	-.121	.832	.038
Lightweight	-.029	.015	.073	.790	-.085	.052
Brand	.765	-.057	-.017	.097	.262	-.240
Advanced Technology	.000	.124	-.056	-.086	-.177	.784

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 8 iterations.

Using the Rotated Component matrix following 6 factors were extracted:

Component 1 – Intrinsic and Extrinsic Attributes		
Indicator	*Factor Loading*	*Explanation*
Price	.832	Factors like price, quality, design, fit, comfort, variety and brand name forms the intrinsic and extrinsic attributes of a footwear product. Most of the factors plays a very important role in this component because of their high factor scores. These factor influences the buying decision of the customers.
Quality	.880	
Design	.785	
Fit	.843	
Comfort	.825	
Variety	.622	
Brand	.765	
Component 2-Reliability		
Indicator	*Factor Loading*	*Explanation*
Durability	.820	Durability, warranty, reparability, environment friendly material and country of origin contributes very strongly to this component. So reliability of the footwear products is one of the important factor which influences the customer's choice set.
Warranty	.794	
Reparability	.778	
Environment friendly Material	.636	
Country of origin	.682	
Component 3- Convenience		
Indicator	*Factor Loading*	*Explanation*
Availability	.869	Customers search for convenience and accessibility in their shopping options and product choice. At the same time they prefer easy maintenance products or rather hassle free product experience.
Maintenance	.845	
Component 4- Health Consciousness		
Indicator	*Factor Loading*	*Explanation*
Odourless	.839	These customers want odourfree and lightweight products. They dislike products which are heavier and have typical odour in products. So they are health conscious customers.
Lightweight	.790	

Component 5- Fashion Consciousness and Aesthetics		
Indicator	*Factor Loading*	*Explanation*
Beautiful Packaging	.621	These customers prefer beautiful packaging of the products, prefer nice colours and are very fashionable. They are quite fashion conscious and specific in their colour preferences.
Nice colours	.655	
Fashionable	.832	
Component 6- Technology and appearance		
Indicator	*Factor Loading*	*Explanation*
Appearance	.856	The appearance and look of the products play a very important rule in influencing the customers. These customers are influenced by advance technology and innovativeness in the products.
Advance Technology	.784	

CLUSTER ANALYSIS

It is a data reduction tool that creates subgroups that are more manageable than individual datum. Cluster analysis (CA) is an exploratory data analysis tool for organizing observed data (e.g. people, things, events, brands, companies) into meaningful taxonomies, groups, or clusters, based on combinations of factors, which maximizes the similarity of cases within each cluster while maximizing the dissimilarity between groups that are initially unknown (Banerjee & Agarwal, 2013).

Using cluster analysis, a customer 'type' can represent a homogeneous market segment. Identifying their particular needs in that market allows products to be designed with greater precision and direct appeal within the segment. Targeting specific segments is cheaper and more accurate than broad-scale marketing. Customers respond better to segment marketing which addresses their specific needs, leading to increased market share and customer retention.

Cluster analysis, like factor analysis, makes no distinction between dependent and independent variables. The entire set of interdependent relationships is examined. Whereas factor analysis reduces the number of variables by grouping them into a smaller set of factors, cluster analysis reduces the number of observations or cases by grouping them into a smaller set of clusters.

From the 6 factors or components extracted from exploratory factor analysis as shown above, the indicators with highest factor scores from each component were chosen for cluster analysis ie 6 variables with highest factor loading from all 6 components were chosen for Cluster Analysis namely Quality, Durability, Availability, Odourless, Fashionable and Appearance.

TECHNIQUE ADAPTED

As we don't know the number of groups or clusters that will emerge in our sample and because we want an optimum solution, a two-stage sequence of analysis occurs as follows:

1. A hierarchical cluster analysis using Ward's method applying squared Euclidean Distance as the distance or similarity measure was carried out. This helped to determine the optimum number of clusters we should work with.
2. In the next stage the hierarchical cluster analysis was rerun with the selected number of clusters, which enabled us to allocate every case in our sample to a particular cluster.

HIERARCHICAL CLUSTER ANALYSIS

This is the major statistical method for finding relatively homogeneous clusters of cases based on measured characteristics. It starts with each case as a separate cluster, i.e. there are as many clusters as cases, and then combines the clusters sequentially, reducing the number of clusters at each step until only one cluster is left. The clustering method uses the dissimilarities or distances between objects when forming the clusters. The SPSS programme calculates 'distances' between data points in terms of the specified variables.

WARD'S METHOD

This method is distinct from other methods because it uses an analysis of variance approach to evaluate the distances between clusters. In general, this method is very efficient. Cluster membership is assessed by calculating the total sum of squared deviations from the mean of a cluster. The criterion for fusion is that it should produce the smallest possible increase in the error sum of squares.

The results start with an agglomeration schedule which provides a solution for every possible number of clusters from 1 to 100 (the number of our cases). The column to focus on is the central one which has the heading 'coefficients'. Reading from the bottom upwards, it shows the agglomeration coefficient for one cluster to another.

Table 5: Agglomeration Schedule

Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	90	100	.000	0	0	10
2	89	99	.000	0	0	11
3	66	98	.000	0	0	34
4	82	97	.000	0	0	18
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93	3	42	57.338	80	0	94
94	3	7	70.276	93	88	96
95	4	5	92.415	92	87	97
96	1	3	136.188	91	94	98
97	2	4	180.420	89	95	98
98	1	2	277.176	96	97	99
99	1	9	427.450	98	90	0

If we rewrite the coefficients as in the below mentioned Table 6 (as it is not provided on SPSS) it is easier to see the changes in the coefficients as the number of clusters increase. The final column, headed 'Change', enables us to determine the optimum number of clusters. In this case it is 3 clusters as succeeding clustering add very much less to distinguishing between cases. A clear demarcation point seems to be there after 3rd Row.

Table 6: Reformed agglomeration table

No. of clusters	Agglomeration Last Step	Coefficients this step	Change
2	740.280	584.779	155.5
3	584.779	497.830	86.9
4	497.830	432.242	65.6
5	432.242	374.225	58.0

K-MEANS CLUSTERING

This method of clustering is very different from the hierarchical clustering and Ward method, which had been applied previously when there is no prior knowledge of how many clusters there may be or what they are characterized by. K-means clustering is used when you already have hypotheses concerning the number of clusters in your cases or variables. This is the type of research question that can be addressed by the k-means clustering algorithm. In our study we have used both the hierarchical and the k-means techniques successively. The former (Ward's method) is used to get some sense of the possible number of clusters and the way they merge as seen from the dendrogram. As from Table 6 we have deduced 3 Clusters. Then the clustering is rerun with only a chosen optimum number in which to place all the cases through k means clustering. One of the biggest problems with cluster analysis is identifying the optimum number of clusters. As the fusion process continues, increasingly dissimilar clusters must be fused.

Table 7: Final Cluster Centers

	Cluster		
	1	2	3
Quality	5	3	4
Durability	3	1	4
Availability	4	1	3
Appearance	5	1	4
Odourless	2.70	2.60	3.53
Fashionable	3.26	3.00	4.25

It is at this point that clear distinguishing characteristics of the clusters are visible and the Cluster 3 is the most attractive cluster as the market size is the highest (See Table 8). Cluster 1 has 23%, Cluster 2 has 5% and Cluster 3 has 72% of sample size.

Table 8: Number of Cases in each Cluster

Cluster	1	23.000
	2	5.000
	3	72.000
Valid	100.000	
Missing	.000	

The ANOVA Table indicates which variables contribute the most to our cluster solution. Variables with large mean square errors and lowest F statistics provide the least help in differentiating between clusters. In the study no variables have this symptom and so it can be concluded that all the variables are very significantly different among the clusters and helps in segmenting the respondents.

Table 9: ANOVA

	Cluster		Error			
	Mean Square	df	Mean Square	df	f	Sig.
Quality	9.227	2	.561	97	16.436	.000
Durability	43.376	2	.666	97	65.092	.000
Availability	20.066	2	.867	97	23.141	.000
Appearance	26.891	2	.779	97	34.537	.000
Odourless	7.288	2	1.278	97	5.700	.005
Fashionable	10.953	2	1.051	97	10.422	.000

Table 10: Distances between Final Cluster Centers

Cluster	1	2	3
1		5.245	2.144
2	5.245		5.960
3	2.144	5.960	

The differences between Final Cluster Centres Table, shows the Euclidean distances between the final cluster centres. Greater distances between clusters mean there are greater dissimilarities. So Cluster 2 & 3 has the highest dissimilarity followed by Cluster 1 & 2 and Cluster 1& 3 are the most similar one. The dissimilar cluster groups have been ranked as per the Table 11:

Table 11: Cluster Groups and Distances

Rank	Cluster	Distance
1	Cluster 2 & 3	5.960
2	Cluster 1 & 2	5.245
3	Cluster 1 & 3	2.144

When cluster memberships are significantly different they can be used as a new grouping variable in other analyses. The significant differences between variables for the clusters suggest the ways in which the clusters differ or on which they are based, the more the difference the more the uniqueness in the segment. This helps the marketers if they want to enter into multiple similar segments with their product lines or can target the next segment in their growth strategy. It is never advisable to cater to multiple dissimilar segments. Cluster 2 (see Table 10) is quite different and distinct from any other cluster. These differentiations do not indicate any positive or negatives aspects of a cluster, it depends on subjective evaluation of the marketers.

Table 12, which explains the market characteristics of the four different clusters, is formed from Table 7.

Cluster Name	Cluster Variables					
	Quality	**Durability**	**Availability**	**Appearance**	**Odourless**	**Fashion**
Cluster 1 **Status Conscious**	Highly Quality Conscious	Durability is neither significant nor insignificant factor.	Availability of their preferred merchandise is important.	Appearance or look of the merchandise is one of the most important factor.	Odourless Merchandise is moderately less influencing factor.	Fashionable and trendy merchandise is an important factor.
Cluster 2 **Impulsive and Casual**	Quality is neither significant nor an insignificant factor.	Durability is the least important factor.	Availability of preferred merchandise is the least important factor.	Appearance or look of the merchandise is one of the least important factor.	Odourless Merchandise is moderately less influencing factor	Fashionable and trendy merchandise is neither significant nor an insignificant factor.
Cluster 3 **Value for Money**	Quality consciousness is on the higher side.	Durability is an important factor.	Availability of preferred merchandise is neither significant nor an insignificant factor.	Appearance or look of the merchandise is an important factor.	Odourless Merchandise is relatively an influencing factor	Fashionable and trendy merchandise is a very important factor

CONJOINT ANALYSIS

Conjoint analysis attempts to determine the relative importance consumers attach to salient attributes and the utilities they attach to the levels of attributes. This information is derived from consumers' evaluations of brands or from brand profiles composed of these attributes and their levels. The respondents are presented with stimuli that consist of combinations of attribute levels. They are asked to evaluate these stimuli in terms of their desirability. Conjoint procedures attempt to assign values to the levels of each attribute so that the resulting values or utilities attached to the stimuli match, as closely as possible, the input evaluations provided by the respondents. The underlying assumption is that any set of stimuli are evaluated as a bundle of attributes.

CONDUCTING CONJOINT ANALYSIS:

Formulating the problem involves identifying the salient attributes and their levels. These attributes and levels are used for constructing the stimuli, used in a conjoint evaluation task.

In the Conjoint analysis we have used the full-profile (also known as full-concept) approach, where respondents rank, order, or score a set of profiles, or cards, according to preference. Each profile describes a complete product or service and consists of a different combination of factor levels for all factors (attributes) of interest.

An Orthogonal Array

The full-profile approach uses fractional factorial design, which presents a suitable fraction of all possible combinations of the factor levels. The resulting set, called an orthogonal array, is designed to capture the main effects for each factor level. Interactions between levels of one factor with levels of another factor are assumed to be negligible. It is also used to generate factor-level combinations, known as holdout cases, which are rated by the subjects but are not used to build the preference model and simulations, which is the ability to predict preference for product profiles that weren't rated by the subjects . In this study no holdout cases were used but four simulation cases were used to predict the preference of first four product profiles which were listed separately following the experimental profiles in the Orthogonal Plan. Simulation cases were not rated by the subjects but represent product profiles of interest to the researchers. The Conjoint procedure uses the analysis of the experimental data to make predictions about the relative preference for each of the simulation profiles. But for our study, as the combination of product attributes are limited the holdout cases are nil and have used only regular plan cases.

The Experimental Stimuli

Each set of factor levels in an orthogonal design represents a different version of the product under study and is presented to the respondents in the form of an individual product profile. This helps the respondent to focus on only the one product currently under evaluation. The stimuli is been standardized by making sure that the profiles are all similar in physical appearance except for the different combinations of features.

The aim of the present study is to understand the influence of three product attributes each having two levels or option of footwear product matrix namely type of shoes, type of material and price range. Two levels of Category (Formal and Casual), Type of materials (Leather and Non-Leather) and Price (Below Rs.1500/- and Above Rs. 1500/-) are selected. Thus an orthogonal array is generated- that comprises of eight profiles; this orthogonal array was presented to respondents. To reduce the complexity in collection of data we kept the options limited. The respondents ranked the profiles on the basis of their preferences. The product attributes were selected on the basis of broader merchandise categories stored by most of the footwear retailers in the organised sector, which was distinctly retrieved from the pilot survey.

Table 13: Orthogonal Design

	Card ID	1	2	3	Preference from 1 to 8
1	1	Formal	Leather	Less than 1500	
2	2	Formal	Leather	More than 1500	
3	3	Formal	Non Leather	Less than 1500	
4	4	Formal	Non Leather	More than 1500	
5	5	Casual	Non Leather	Less than 1500	
6	6	Casual	Leather	More than 1500	
7	7	Casual	Non Leather	More than 1500	
8	8	Casual	Leather	Less than 1500	

Table 14, displays the variables used in our study, with their variable labels, values and relation to ranks. The Discrete model indicates that the factor levels are categorical and that no assumption is made about the relationship between the factor and the scores or ranks. The Linear model indicates an expected linear relationship between the factor and the scores or ranks

Table 14: Factor Name, Factor Label, Value & Label & Model Description

Factor Name	Factor Label	Value	Label	Relation to Ranks or Scores
Type of Shoe	Category	1,2	Formal, Casual	Discrete
Material Used	Material	1,2	Leather, Non Leather	Discrete
Price Range	Price	1,3	Less than 1500, More than 1500	Linear

We then run the Conjoint Syntax in SPSS for Conjoint Analysis to get the utility of each variable and subsequently we ran simulation also. Table 15 shows the utility (part-worth) scores and their standard errors for each factor level. Higher utility values indicate greater preference. Since the utilities are all expressed in a common unit, they can be added together to give the total utility of any combination.

Table 15: Utilities

		Utility Estimate	Std. Error
CATEGORY	FORMAL	.006	.148
	CASUAL	-.006	.148
MATERIAL	LEATHER	.169	.148
	NON LEATHER	-.169	.148
PRICE	LESS THAN 1500	-.138	.295
	MORE THAN 1500	-.275	.591
(Constant)	4.706	.467	

The total utility for the eight profiles were calculated as:
The Total Utility for 8 profiles are given as:
Total Utility for Profile 1:
Utility (Formal) + Utility (Leather) + Utility (Less than 1500) + Constant = 4.743
Total Utility for Profile 2:
Utility (Formal) + Utility (Leather) + Utility (More than 1500) + Constant = 4.606
Total Utility for Profile 3:
Utility (Formal) + Utility (Non Leather) + Utility (Less than 1500) + Constant = 4.405
Total Utility for Profile 4:
Utility (Formal) + Utility (Non Leather) + Utility (More than 1500) + Constant = 4.268
Total Utility for Profile 5:
Utility (Casual) + Utility (Non Leather) + Utility (Less than 1500) + Constant = 4.393
Total Utility for Profile 6:
Utility (Casual) + Utility (Leather) + Utility (More than 1500) + Constant = 4.594
Total Utility for Profile 7:
Utility (Casual) + Utility (Non Leather) + Utility (More than 1500) + Constant = 4.256
Total Utility for Profile 8:
Utility (Casual) + Utility (Leather) + Utility (Less than 1500) + Constant = 4.731

As per the value of the total utility score of each profile utility has been sequenced as Profile 1, Profile 8, Profile 2, Profile 6, Profile 3, Profile 5, Profile 4 and Profile 7.

Table 16: Importance Values

Importance	Values
CATEGORY	34.764
MATERIAL	28.228
PRICE	37.008
Averaged Importance Score	

The range of the utility values (highest to lowest) for each factor provides a measure of how important the factor was to overall preference. Factors with greater utility ranges play a more significant role than those with smaller ranges. The results show that price range has the most influence on overall preference followed by categories of shoes and material turned up as the least significant differentiating factor. The results in Table 16 shows that in terms of importance of attributes material plays the least important role in determining overall preference with 28.29%, Price plays the most significant role with 37.008% and category plays a moderate significant role with 34.76%.

Table 17: Coefficients

	B Coefficient
	Estimate
PRICE	-.138

Coefficients: The regression equation is given as: Y= bX ; Y= -.138X

Y is the dependent variable ie Utility of any preference, and X is the independent variable (price). Table 17 shows the linear regression coefficients for those factors specified as Linear. The more the price reduces the more the utility of the combination increases.

Table 18: Correlations

	Value	Sig.
Pearson's R	.914	.041
Kendall's tau	.923	.024

a. Correlations between observed and estimated preferences

Table 18 displays two statistics, Pearson's R and Kendall's tau, which provide measures of the correlation between the observed and estimated preferences. We observe a significant correlation between the observed and estimated preferences.

Conjoint Analysis results should be assessed for accuracy, reliability and validity. The objective is to ascertain how consistently the model predicts the set of preference evaluations under different situations (Tripathi & Siddiqui, 2010). Results derived in this study from the Conjoint Analysis are reliable and valid as while evaluating the goodness of fit of the estimated conjoint model, we found out that value of Kendall's tau is 0.923, value of Pearson's R is 0.914. Both these values are reasonably high and these results are significant at 5 percent level of significance. The values for Pearson's R and Kendall's tau are clearly above 0.9, which indicates a very strong correlation and thus a very high concurrent validity (Klein, Nihalani, & Krishnan, 2010).

Table 19:Preference Scores of Simulations

Card Number	ID	Score
1	9	4.744
2	10	4.406
3	11	4.594
4	12	4.256

Table 20: Preference Probabilities of Simulations

Card Number	ID	Maximum Utility	Bradley-Terry-Luce	Logit
1	9	23.8%	26.4%	26.0%
2	10	16.3%	24.5%	22.4%
3	11	30.0%	25.5%	29.4%
4	12	30.0%	23.6%	22.2%

a. Including tied simulations
b. 40 out of 40 subjects are used in the Bradley-Terry-Luce and Logit methods because these subjects have all nonnegative scores.

One of the most important application of conjoint analysis is the ability to predict preference for product profiles that weren't rated by the subjects separately in a group as stated earlier. These are referred to as simulation cases. 4 simulation cases are entered now in the file -

9. *Formal, Leather, Less Than 1500*
10. *Formal, Non Leather, Less Than 1500*
11. *Casual, Leather, More Than 1500*
12. *Casual, Non Leather, More Than 1500*

Table 20 gives the predicted probabilities of choosing each of the simulation cases as the most preferred one, under three different probability-of-choice models. The maximum utility model determines the probability as the number of respondents predicted to choose the profile divided by the total number of respondents. For each respondent, the predicted choice is simply the profile with the largest total utility. As per this method ID 11 & 12 will be preferred equally in the first choice, then ID 9 followed by ID 10. The BTL (Bradley-Terry-Luce) model determines the probability as the ratio of a profile's utility to that for all simulation profiles, averaged across all respondents. According to this method ID 9 will lead the preference followed by ID11 and ID 10 and ID12 will be the least preferred. The logit model is similar to BTL but uses the natural log of the utilities instead of the utilities. As per this method the sequence of preference will be ID11, ID9, ID10 and ID12. The probabilistic models like BTL and Logit, captures more information from each respondent and yields more stable share estimates. The standard errors for share predictions from logit or Bradley-Terry-Luce simulations are always smaller than under the Maximum Utility (MU) Model. MU Model requires large sample size also to stabilize share-of-choice estimates relative to probabilistic simulation models (Orme, 2010). So it is always suggestible to take the preferences according to BTL and Logit Model.

CONCLUSION

A Likert Scale was formed of 21 statements on 21 different product attributes and the respondents were asked about their agreement and disagreement with the statements. All the attributes were scanned from the market through pilot survey, which were kept specific to the footwear market. The attributes are as follows: Quality, Price, Brand , Comfort, Fit, Odourless, Nice colours, Beautiful packaging, Appearance, Design, Advanced Technology, Country of origin, Durability, Variety, Warranty, Reparability, Light Weight, Environment friendly Material, Availability, Maintenance and Fashionable. All the indicators used in the study came out as strong factors with very high factor loadings, the highest remains the appearance or look of the merchandise and lowest packaging . Six, very strong and relevant factors or components were extracted from the exploratory factor analysis namely Intrinsic and Extrinsic Attributes, Reliability, Convenience, Health Consciousness, Fashion Consciousness and Aesthetics and Technology and appearance.

From the 6 factors or components extracted from exploratory factor analysis as shown above, the indicators with highest factor scores from each component were chosen for cluster analysis ie 6 variables with highest factor loading from all 6 components were chosen for Cluster Analysis namely Quality, Durability, Availability, Odourless, Fashionable and Appearance to find suitable segments. Three distinct and differentiating clusters or segments were formed namely Status Conscious, Impulsive & Casual and Value for Money. All the six variables are very significantly different among the clusters and helped in segmenting the customers.

The study also attempted to understand the utility value and preferences of the customers in terms of product categories. For which three product categories each having two levels or option of footwear product matrix namely type of shoes, type of material and price range, two levels of Category (Formal and Casual), Type of materials (Leather and Non-Leather) and Price (Below Rs.1500/- and Above Rs. 1500/-) were selected. Utility of all the eight product option was calculated through conjoint analysis according to the preferences of the customers. Leather formal shoes priced below Rs. 1500 were concluded having highest utility, Non Leather Casualwear priced more than 1500 have the lowest utility value to the customers. To understand the probability of preferences of the customers according to the options four simulation cases were formed in conjoint analysis where it was found out that Leather Formalwear priced less than 1500 and Leather Casualwear priced more than 1500 have the highest probability to be preferred by the customers in different segment. Hence this study's attempt to explain the consumer behaviourism in footwear market, may be concluded as considerably successful.

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ANNEXURE

Communalities

	Initial	Extraction
Price	1.000	.750
Quality	1.000	.826
Design	1.000	.661
Fit	1.000	.790
Comfort	1.000	.781
Durability	1.000	.745
Variety	1.000	.808
Warranty	1.000	.821
Availability	1.000	.856
Maintenance	1.000	.832
Reparability	1.000	.715
Environment friendly material	1.000	.786
COO	1.000	.664
Appearance	1.000	.869
Beautiful packaging	1.000	.474
Nice colours	1.000	.723
Odourless	1.000	.762
Fashionable	1.000	.751
Lightweight	1.000	.644
Brand	1.000	.720

Extraction Method: Principal Component Analysis.