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An Analytical Study of the psychographic factors responsible for segmentation for FMCG in Haryana

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ABSTACT

Segmentation is the need of modern marketing because to serve the entire market is no more profitable. The very first step of market segmentation is to identify which variables are most first step of market segmentation is to identify which variables are most important to segment or to group the customers into homogeneous groups. Usually more than one variable is used to give the description of market segments. The most common variables used are demographic, geographic, psychographic, and behaviuoral. In case of personal care products in the present study psychographic variables are taken in to consideration. The human behavior is dominated by the internal psycho of the individual and the way it treat with the society. The main psychographic variables as values, social interest, and attitude are broadly taken into consideration. Factor analysis is used to get the factors affecting the purchase of personal care products.

Keywords: Psychographic variables, personal care, factor analysis, segmentation

INTRODUCTION

The human behavior is dominated by the internal psycho of the individual and the way it treat with the society. Values, social interest, attitude are broadly taken into consideration.Demographic segmentation is perhaps the most commonly used and most easy or natural segmentation to assess. It has been widely described in the literature that demographic characteristics is an important factor to determine fruit intake (Turrell et. al, 2002). But demographic variables are losing their importance because of the cultural and social changes. Demographic are no more good for segmentation (Yenkelovich, 1968). However, they are useful only when they are correlated with the relevant objective function, such as purchase behavior or brand preference (Matsuno, 1998). The present study is related with the purchase behavior influenced psychographic variables.

Mainly psychographic segmentation is based on attitude, lifestyle, value and interest. Lifestyle segmentation has been used for several marketing and advertising purposes (Wells and Tigers, 1977). The most widely used measures of lifestyle segmentation are Rotech's value survey, List of Values (LOV), Values and life Style (VALS2), and Activities, Interest, and Opinions (AIO).In the present study twenty five psychographic variables are used to segment the consumers. To reduce the data set or to make feasible study explanatory factor analysis was used. By which six meaningful psychographic factors were found.

One of the most common scales was used in the study that is Likert scale. It was developed by RensisLikert in 1932. The Likert scale can be four-point, five-point, six-point, and so on. The even-numbered scale usually forces a respondent to choose while the odd-numbered scale provides an option for indecision or neutrality. The five point scale was used in the study as 1=strongly disagree, 2=disagree, 3=not sure, 4=agree, and 5=strongly agree.

OBJECTIVE

The main objective of this study is to find out the major psychographic factors responsible for market segmentation for FMCG in Indian market.

RESEARCH METHODOLOGY

Data collection: Primary data is collected within the region of Haryana with the help of questionnaire.
Sample size and Sampling Design: 400 respondents are selected with multistage random sampling design.

RESULT AND DISCUSSION

Before segmenting the market for personal care product the factor analysis was done to reduce the data set and to get the variables affecting the purchase behavior of consumers. An explanatory factor analysis was applied on twenty five psychographic variables.
For doing factor analysis to check the problem of multi-collinearity the correlation coefficient of each and every variable was calculated. Correlation coefficients were not excessively large and each variable was reasonably correlated with other. Therefore none of the variable was drop out however principal component analysis was used for factor that is why there is no problem of multi collinearity.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.828
Bartlett's Test of Sphericity	Approx. Chi-Square	6680.173
	Df	300
	Sig.	.000

Kaiser (1974) recommends a bare minimum of 0.5 and that values between 0.5 and 0.7 are mediocre, values between 0.7 and 0.8 are good, values between 0.8 and 0.9 are great and values above 0.9 are superb (Hutcheson &Sofroniou, 1999). Here in the present study the value is 0.828, which falls into the range of being great, so we should be confident that the sample size is adequate for factor analysis. Barlett's measure tests the null hypothesis that the original correlation matrix is an identity matrix. For factor analysis to work there should be some relationship between variables because if correlation matrix were an identity matrix then all correlation coefficients would be zero. Therefore Bartlett's measure tests that whether there is significant difference relationship or not. Therefore a significant Bartlett's test tells that null correlation matrix is not an identity matrix. For the present study data, Bartlett's test is highly significant ($p < .001$), and therefore factor analysis is appropriate.

Through total variance explained method it is decided that which variable is to retain or which is to discard on the basis of the variance explained by the factors. This method lists the eigenvalues associated with each linear factor before extraction, after extraction and after rotation. Before extraction 25 linear components were identified. The eigenvalue associated with each factor represent the variance explained by the component. It is clear from this method that the first few factors explain relatively large amount of variance. First factor explain 15.693% of variance, whereas subsequent factors explain small amounts of variance. SPSS then extracts all factors with eigenvalues greater than 1, which leaves us with four factors. The eigenvalues associated with these factors are again displayed (and the percentage of variance explained) in the columns labeled**Extraction Sums of Squared Loadings**. The values in this part of the table are the same as the values before extraction, except that the values for the discarded factors are ignored (hence, the table is blank after the fourth factor). In the final part of the table (**labeledRotation Sums of Squared Loadings)**, the eigenvalues

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	3.923	15.693	15.693	3.923	15.693	15.693	3.860	15.439	15.439
2	2.986	11.943	27.636	2.986	11.943	27.636	2.767	11.067	26.505
3	2.903	11.612	39.248	2.903	11.612	39.248	2.758	11.032	37.538
4	2.783	11.134	50.382	2.783	11.134	50.382	2.623	10.490	48.028
5	2.293	9.173	59.555	2.293	9.173	59.555	2.591	10.364	58.392
6	2.270	9.079	68.634	2.270	9.079	68.634	2.560	10.242	68.634
7	.993	3.971	72.604						
8	.940	3.761	76.365						
9	.705	2.821	79.186						
10	.625	2.501	81.687						
11	.598	2.392	84.079						
12	.569	2.278	86.357						
13	.494	1.976	88.333						

14	.465	1.859	90.192						
15	.429	1.717	91.909						
16	.391	1.563	93.472						
17	.390	1.558	95.031						
18	.330	1.318	96.349						
19	.228	.912	97.261						
20	.199	.797	98.057						
21	.181	.723	98.780						
22	.164	.655	99.435						
23	.075	.301	99.736						
24	.040	.159	99.894						
25	.026	.106	100.000						

Extraction Method: Principal Component Analysis.

of the factors after rotation are displayed. Rotation has the effect of optimizing the factor structure and one consequence for these data is that the relative importance of the six factors is equalized. Before rotation, factor 1 accounted for considerably more variance than the remaining five.

Communalities

	Initial	Extraction
s1	1.000	.708
s2	1.000	.680
s3	1.000	.646
s4	1.000	.857
s5	1.000	.659
s6	1.000	.873
s7	1.000	.879
s8	1.000	.543
s9	1.000	.505
s10	1.000	.719
s11	1.000	.693
s12	1.000	.740
s13	1.000	.685
s14	1.000	.834
s15	1.000	.828
s16	1.000	.459
s17	1.000	.393
s18	1.000	.370
s19	1.000	.770
s20	1.000	.570
s21	1.000	.657
s22	1.000	.868
s23	1.000	.698
s24	1.000	.746
s25	1.000	.779

Extraction Method: Principal Component Analysis.

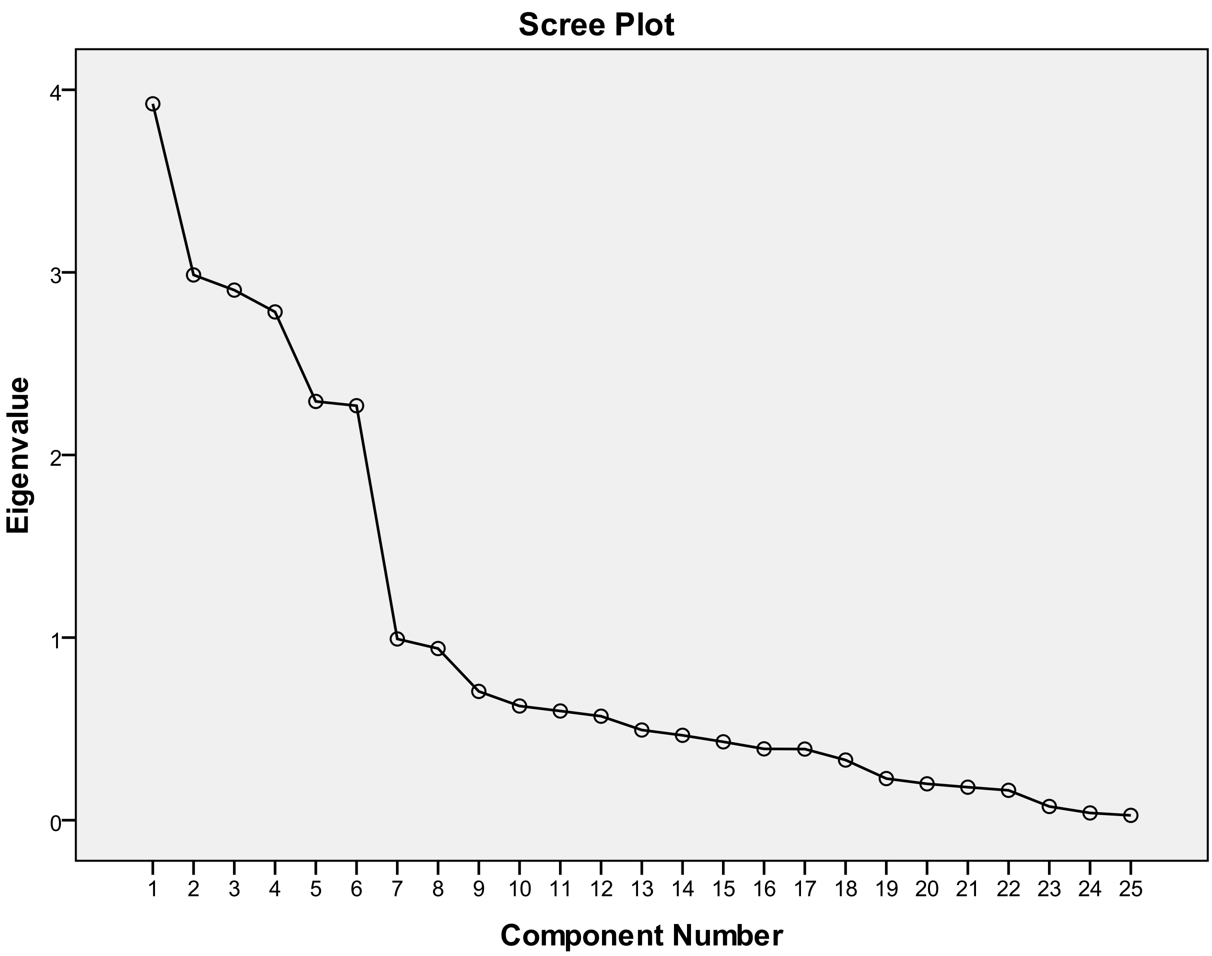
The above table of communality show the common variance associated with the variables. The communalities in the column labeled**extraction** reflect the common variance. It means 70.8% variance is common associated with the first variable. The amount of variance in each variable that can be explained by retained factors is represented by communalities after extraction.**ComponentMatrix**[a]

	Component					
	1	2	3	4	5	6
s24	.839					
s12	.836					

s23	.807					
s13	.800					
s20	.742					
s9	.697					
s19		.718				
s25		.718				
s22		-.566		.430		.512
s7		-.559		.456		.498
s18		.551				
s16		.550				
s17		.503				
s1			.635	-.474		
s21			.590	-.445		
s2			.553	-.502		
s10			.552	-.518		
s14			.549	.464	-.504	
s8			.411			
s4			.535		-.576	
s15			.494	.430	-.564	
s6		-.515		.487		.522
s11				.413		-.467
s5						-.462
s3			.411			-.431

Extraction Method: Principal Component Analysis.
a. 6 components extracted.

The above table shows the component matrix before extraction and describes the loadings of every variable onto each factor. Most variables load highly onto the first factor.



The scree plot shown above is difficult to interpret because it begins to tail off after six factors .

The table below shows the rotated component matrix which contains the same information as the component matrix but for this matrix the factors are clearly interpreted. If comparison is done between this and before rotation matrix variable and most variable loaded highly onto first factor and the remaining factors did not get a look. This matrix shows that which variable is highly loaded on which factor.

Rotated Component Matrix[a]

	Component					
	1	2	3	4	5	6
s24	.854					
s12	.852					
s23	.821					
s13	.809					
s20	.752					
s9	.698					
s10		.844				
s1		.833				
s2		.821				
s21		.806				
s25			.880			
s19			.875			
s16			.664			
s17			.623			
s18			.587			
s7				.933		
s6				.931		
s22				.928		
s4					.924	
s15					.908	
s14					.905	
s11						.830
s5						.807
s3						.801
s8						.732

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

The table of transformation matrix provides the information about the degree to which factors were rotated to obtain the final solution. If no rotation were necessary this matrix would be identity matrix. If orthogonal rotation were completely appropriate then a symmetrical matrix will appear.

Component Transformation Matrix

Component		1	2	3	4	5	6
Dimension	1	.977	-.025	.081	.108	-.026	.159
	2	-.003	-.163	.807	-.539	.179	-.024
	3	-.030	.688	-.037	-.105	.540	.470
	4	-.138	-.584	.113	.476	.447	.448
	5	-.158	.248	.419	.319	-.644	.471
	6	.010	.310	.391	.599	.248	-.575

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

CONCLUSION

Here in the present study a principal component analysis was conducted on 25 variables or statements with orthogonal rotation or varimax. The Kaiser- Meyer-Olkin measure verified the sampling adequacy for the analysis, KMO = 0.828 (great according to field, 2009) and all KMO values for individual items were > 0.7, which is above the acceptable limit of 0.5. Bartlett's test of sphericity χ^2 (300) = 6680.173, $p < 0.001$, indicated that correlations between items were sufficiently large for principal component analysis. An initial analysis was run to obtain the eigenvalues for each factor. The factor analysis retained only six components in the final result and the table below shows the factor loadings after rotation. The items that grouped same factor indicate that factor 1 represent the personal values, factor 2 work values, 3 social interests, 4 general attitude for life, 5 prudent and factor 6 is of brand conspicuous. It means that these are the factor responsible for segmentation of FMCG market in India.

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