European Journal of Business and Management www.iiste.org
ISSN 2222-1905 (Paper) ISSN 2222-2839 (Online)
Vol.6, No.14, 2014

A Study of Psychographic Variables Proposed for Segmentation for Personal Care Products through Factor Analysis

Dr. (Mrs.) Kiran Mor
Professor, Humanities & Social Sciences, NIT Kurukshetra

Sulekha
Research Scholar Humanities & Social Sciences, NIT Kurukshetra

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
in 1964, in "New criteria for market segmentation" Daniel Yankelovich asserted that traditional demographic traits such as age, gender, education and income are no longer enough to serve as the bases for market segmentation. Nowadays non-demographic traits such as value, taste and preferences are more likely to influence customers' purchase than the demographics. Nowadays, market segmentation strategy has become the most needed strategy of marketing because it is not possible or profitable to serve the whole market with a single product.
Market segmentation tends to divide the market according to some specified bases in such a way that each segment or part of market has a specific requirement and need a specific marketing mix. A marketing mix can then be devised to reach the segment identified economically and efficiently. Consumers are different in their demographics, geographic and psychographic aspects. These can be the possible bases of market segmentation. But due to more intensive competition and more demanding consumers, the basis of market segmentation is increasingly complex. The main purpose of 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 factors are found.
OBJECTIVE
The main objective of this study is to find out the psychographic factors for segmenting the market for personal care products.
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.
Questionnaire:
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 get the key factor for segmentation in the personal care market.
Analytical Tools:
Exploratory factor analysis is used for the purpose of the present study.
RESULTS AND DISCUSSION
For personal care product the factor analysis is 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. In order to apply factor analysis the problem of multi-collinearity is to be checked and correlation coefficient of each and every variable is calculated. Correlation coefficients are not excessively large and each

variable is reasonably correlated with other. Therefore none of the variable is drop out however principal component analysis is used for factor that is why there is no problem of multi collinearity.

Table 1.1: 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.

	Table 1.2 : 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						
dimension0	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.									

The above table shows that which variable is to retain or which is to discard on the basis of the variance explained by the factors. The above table 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 the table 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 (**labeled Rotation Sums of Squared Loadings)**, the eigenvalues 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.

Table 1.3 : 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.

European Journal of Business and Management
ISSN 2222-1905 (Paper) ISSN 2222-2839 (Online)
Vol.6, No.14, 2014

Table 1.4 : Component Matrix[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.

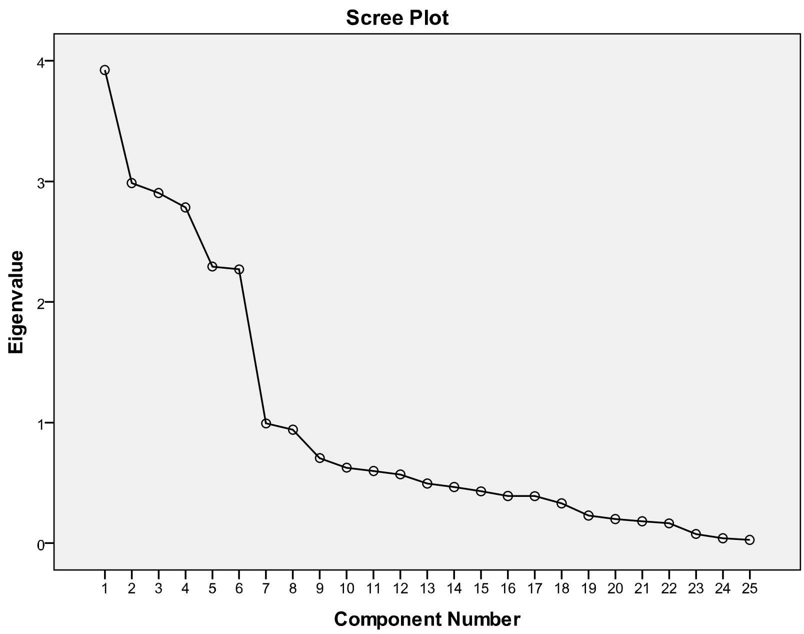

Figure 1.1: Scree Plot

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.

Table 1.5 : 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.

Table 1.6 : Component Transformation Matrix

Component		1	2	3	4	5	6
	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.

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.

Table 1.7: Summary of Exploratory Factor Analysis results for the questionnaire having 25 items related to the consumer psychographic

Items	Personal values	Work values	Social interest	General attitude for life	Prudent	Brand conspicuous
I feel secure because of current economic situation.		0.844				
I respect authority.		0.833				
I will consider product value when I buy it.						0.801
I spend a constant amount of money every month.					0.924	
I usually buy well-known brands.						0.807
I like a routine life.				0.931		
I do not like to take risks.				0.933		
I will think things over before I buy a product.						0.732
I am emotional.	0.69					
I can usually achieve my goals.		0.821				
I like to buy something that can express my status						0.830
I often care about others.	0.852					
I have a lot of friends.	o.809					
I like to go for shopping.					0.905	
I usually go for cinema.					0.908	
I always ready for debates on public issues.			0.664			
I keep my eye on current affairs.			0.623			
I am influenced by social media.			0.587			
I am interested in national events.			0.875			
I always care for my family health in every sense.	0.752					
My work emotion will not affect my family.		0.806				
I look life as a challenge.				0.928		
I love to talk with friends.	0.821					
I like to help others.	0.854					
I usually participate in social activities.			0.880			
Eigenvalues	**3.92**	**2.99**	**2.90**	**2.78**	**2.29**	**2.27**
% of variance	**15.69**	**11.94**	**11.61**	**11.13**	**9.17**	**9.07**
Croanbach α (Reliability)	**0.887**	**0.847**	**0.783**	**0.927**	**0.908**	**0.807**

CONCLUSION

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 is clear from the analysis that these six factors are explaining the unique feature of the different psychographic profiles of consumer searching for personal care products. It is suggested to the marketers that they should use such factors to make their products more close to the consumers.

REFERENCES

Yu Xia (2011), "Competitive strategies and market segmentation for suppliers with substitutable products", *European Journal of Operational Research,* Vol.210, Pages: 194-203.

Frank M. Bass, Douglas J. Tigert and Ronald T Lonsdale (1968), "Market segmentation: Group versus Individual behavior", *Journal of marketing research,* Vol.5, No.3, Pages: 264-270.

Kevin Kuan-Shun Chiu, Ru-Jen Lin, Maxwell K. Hsu and Shih-Chih Chen (2011), "Symbolic and functional brand effects for market segmentation", *Australian Journal of Business and Management Research,* Vol.1, No.6, Pages: 75-86.

KC Behura and JK Panda (2012), "Rural Marketing of FMCG Companies in India", *VSRD International Journal of Business & Management Research,* Vol. 2, No.2, Pages: 66-74.

Valters Kaze, Roberts Skapars(2011), "Paradigm shift in consumer segmentation to gain competitive advantages in post-crisis FMCG markets: lifestyle or social values?", *Journal of economics and management,* Vol.16, Pages:1266-1273.

Ian Wilson and Maria Mukhina (2012), "Market segmentation in Russian subsidiaries of FMCG MNEs Practitioner and academic perspectives", *Marketing Intelligence & Planning,* Vol. 30, No. 1, pages: 53-68

D.M. Sezhiyan(2010), "Assessing the Stability of Market Segment – A fuzzy Clustering Approach, *IIMS Journal of Management Science,* Vol. 1, No. 2, Pages:129-137.

Anupam Jain and Meenakshi Sharma (2012), "Brand Awareness and Customer Preferences for FMCG Products in Rural Market: An Empirical Study on the Rural Market of Garhwal Region", *VSRD International Journal of Business and Management,* Vol. 2, No. 8, Pages: 434-443.

Amandeep singh (2010), "market segmentation in FMCG: time to drive new basis for market segmentation", *International Journal of Research in Commerce and Management*, Vol.1, no. 8. Pages: 140-145.

Dolnicar S, Freitag R. and Randle M.(2005), "To Segment or Not to Segment? An Investigation of Segmentation Strategy Success Under Varying Market Conditions", *Australasian Marketing Journal*, Vol. 13, No. 1, Pages: 20-35.