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A Factor Analysis of Consumer's Buying Behavior of Sanitary Pads

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Abstract

The purpose of this research is to investigate into what factors influence the buying behaviour of consumers of sanitary pads in Takoradi Polytechnic. Consumer behaviour has been changed dramatically in the past decade. In today's world of growing competition where there are numerous brands selling the same products, consumers is having an abundant number of choices and many other factors influence their buying behaviour. In order to accomplish this objective of the study, a sample of five hundred (500) consumers were sampled from both female (staff and student) of the Polytechnic community. A ten item questionnaire that employs a five-point differential scale ranging from 'strongly disagree' to 'strongly agree' was administered to the respondent. Among other things, the study result reveal that there are four dimensional factors informing the purchasing behaviour of consumers of sanitary pads, which accounted for 65.3% of variance in the original variables. Using factor analysis via principal component factoring with resulting data analysis done in SPSS (16), the dimensions adduced to be influencing buying behaviour of sanitary pads were: Health features (factor 1), Product features (factor 2), and Social influence (factor 3) and Economic factors(factor 4). This study is useful to the marketers as they can create various marketing programme that they believe will be of interest to the consumers. It can also boost their marketing strategy and also help other people who are working in other industries or in any private sector organization.

Keywords: Consumer Buying Behaviour, Sanitary pads, Factor analysis, Principal Component Factoring.

1. Introduction

Consumers are individuals and households that buy the firms product for personal consumption (Kotler, 2001). It often used to describe two different kinds of consuming entities; the personal consumer and the organizational consumer. The activities, these consumers under take when obtaining, consuming and disposing of product and service is known as consumer behavior .Consumer behavior involves studying how people buy, what they buy, when they buy and why they buy. When a consumer wanted to make the purchase decision, they pass through recognition, search information, evaluation and purchase feedback (Blackwell, Minirad and Engel, 2006). At last the consumer will choose a product or brand to consume from various choices in the market. However, these factors affecting the buying behavior of consumers vary due to diverse environmental factors and individual determinants. Consumer buying behavior is influenced by two major factors; these factors are individual and environmental. The major categories of individual factors affecting consumer behavior are demographics, consumer knowledge, and perception, learning motivation, personality, beliefs and life styles. The second category of factors is environmental factors which include items outside of the individual that affect the consumers' decision making process. These factors include cultural, social class, reference group, family and household. The above factors are the major determinants behind the decision of consumers to opt for a given good or service. (Blackwell, Minirad and Engel, 2006).

2. Review of Methods

Factor analysis is a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors. Factor analysis (including common factor analysis and principal component analysis) is used to examine the interdependence among variables and to explain the underlying common dimensions (factors) that are responsible for the correlations among the variables. The procedure allows one to condense the information in a large set of variables into a smaller set of variables by identifying variables that are influenced by the same underlying dimensions. We can therefore look upon the underlying dimensions or factors, which are of primary interest but directly unobservable, as the new set of variables. Factor analysis facilitates the transformation from the original observable variables to the new variables (factors) with as little loss of information as possible (Everitt and Dunn, 2001; Johnson and Wichern, 1992; Sharma, 1996).

Given the latent factors $F' = (F_1, F_2, ..., F_m)$ and the observable (indicator) variables

$X' = (X_1, X_2, ... X_p)$, where $m \ll p$, the data model, in matrix notation, is given by

$$(X-\mu)_{p\times 1} = L_{P\times m}F_{m\times 1} + \varepsilon_{p\times 1} \quad \ldots\ldots\ldots(1)$$

Where $L_{p\times m}$ is a $p\times m$ matrix of coefficients lij, i = 1, 2… p; j= 1, 2.., m.

The lijs are referred to as the factor loadings. The entities $\varepsilon' = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_p)$ are thought of as specific error terms or factors associated with $X_1, X_2, ..., X_P$ respectively. The mean corrected vector $(X-\mu)_{p\times 1}$, where $\mu = E[X] = (\mu_1, \mu_2, ..., \mu_P)'$ is taken to be the response variable (Johnson and Wichern 1992). For an orthogonal factor model, the analysis of the data is done under the assumption that,

$$E[F] = O_{(m\times 1)} \qquad E[\varepsilon] = O_{(p\times 1)} \qquad COV(F) = I_{(m\times m)}$$

$$COV(\varepsilon_i, \varepsilon_j) = 0 \qquad COV(F_i, \varepsilon_j) = 0$$

Where O is a matrix of zeros. It follows from the assumptions that:

- The factors are independent,
- The specific error terms are independent
- The factors and specific error terms are independent.

However, as mentioned above, the observable variables $X_1, X_2, ..., X_P$ are correlated because they are influenced by some common underlying dimensions (factors). The correlation among the indicator variables facilitates the identification of the common latent factors as the indicator variables that are influenced by the same factor tend to 'load' highly on (have a high correlation coefficient with) that common factor and also amongst themselves (Everitt and Dunn 2001; Johnson and Wichern, 1992; Sharma, 1996).

In the orthogonal model, the coefficients (pattern loadings) $lij, i = 1,2,..., p; j = 1,2,..., m$ are the same as the simple correlations (structure loadings) between the indicator variables X_i and the factors F_j, and the variance (communality) that Xi shares with F_j is given by l^2ij (Sharma, 1996). Thus the total communality of an indicator variable Xi with all the m common factors is given by

$$l^2{}_{i1} + l^2{}_{i2} +,..., l^2{}_{im}.$$

2.1 *Principal Component Factoring*

Factor analysis can be done using several techniques. One of such popular techniques is principal component factoring (PCF), which uses Principal Component Analysis (PCA) to extract the dimensions (factors) influencing the observed variables, by analyzing the correlation amongst them. In principal component analysis, new uncorrelated variables are formed which are a linear combination of the original (observable) variables, and the number of new variables is equal to the old variables. However, the new variables are formed such that the first principal component accounts for the highest variance in the data, the second accounts the highest remaining variance in the data, the third principal component accounts for the remaining variance not accounted for by the first and second components, and so on. (Everitt and Dunn 2001; Johnson and Wichern, 1992; Sharma, 1996).

Given the observed variables $X_1, X_2,..., X_p$ and the coefficients (weights) $wij, i = 1,2,..., p. j = 1,2,..., p.$, the principal component $C_1, C_{2,} ..., C_p$ are given by

$$\left.\begin{array}{l} C_1 = w_{11}X_1 + w_{12}X_2 + \cdots + w_{1p}X_p \\ C_2 = w_{21}X_1 + w_{22}X_2 + \cdots + w_{2p}X_p \\ \quad \vdots \qquad \vdots \qquad \vdots \qquad \vdots \\ C_p = w_{p1}X_1 + w_{p2}X_2 + \cdots + w_{pp}X_p \end{array}\right\} \qquad \ldots\ldots\ldots\ldots\ldots(2)$$

To place a limit on the variance of the $C_{is}, i = 1,2,..., p$ and to guarantee that the new axes representing the C_{is} are uncorrelated, the weights $wij, i = 1,2,..., p, j = 1,2,..., p.$ are estimated subject to the conditions given by Equations 1 and 2 respectively (Everitt and Dunn 2001; Johnson and Wichern, 1992; Sharma, 1996).

And $w_i' \bullet w_i = 1$ $\qquad \ldots\ldots\ldots(3)$

$$w_i' \bullet w_j = 0 \quad \textit{for all} \quad i \neq j \qquad \ldots\ldots\ldots (4)$$

Where $w_i' = (w_{i1}, w_{i2}, \ldots, w_{ip})$

Given the mean μ_1 and the standard deviation σ_{ii} of the variable X_i, the transformed variables

$Z_i, i = 1,2,\dots, p$, given by

$$Z_i = \frac{X_i - \mu_i}{\sigma_{ii}} \qquad \cdots\cdots\cdots(5)$$

This could be used to form the principal components (Johnson and Wichern, 1992). Expressed in matrix notation, the vector of standardized variables could be written as

$$Z = \left(V^{1/2}\right)^{-1}(X - \mu)$$

Where $\mu' = \left(\mu^1, \mu^2, \dots, \mu_p\right)$ and $V^{1/2}$ is the standard deviation matrix given by

$$V^{1/2} = \begin{bmatrix} \sigma_{11} & 0 & \cdots & 0 \\ 0 & \sigma_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{pp} \end{bmatrix}$$

$$E[Z_i] = 0, \quad Var[Z_i] = 1, \; i = 1, \cdots, p \; and \; \operatorname{cov}(Z) = \left(V^{1/2}\right)^{-1} \Sigma \left(V^{1/2}\right)^{-1} = \rho$$

Where the variance-covariance matrix $\sum$ and the correlation matrix ρ of X are given by

$$\Sigma = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 & \cdots & \sigma_{1p}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 & \cdots & \sigma_{2p}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{p1}^2 & \sigma_{p2}^2 & \cdots & \sigma_{pp}^2 \end{bmatrix}$$

$$\rho = \begin{bmatrix} \frac{\sigma_{11}^2}{\sigma_{11}\sigma_{11}} & \frac{\sigma_{12}^2}{\sigma_{11}\sigma_{22}} & \cdots & \frac{\sigma_{1p}^2}{\sigma_{11}\sigma_{pp}} \\ \frac{\sigma_{12}^2}{\sigma_{11}\sigma_{22}} & \frac{\sigma_{22}^2}{\sigma_{22}\sigma_{22}} & \cdots & \frac{\sigma_{2p}^2}{\sigma_{22}\sigma_{pp}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\sigma_{1p}^2}{\sigma_{11}\sigma_{pp}} & \frac{\sigma_{2p}^2}{\sigma_{22}\sigma_{pp}} & \cdots & \frac{\sigma_{pp}^2}{\sigma_{pp}\sigma_{pp}} \end{bmatrix}$$

and $\rho_{ij} = \dfrac{\sum_{k=1}^{n}(x_{ki} - \mu_i)(x_{kj} - \mu_j)}{n}$, $i \neq j$ is the covariance between variables x_i and x_j , each of which has n observations. The p principal components $C' = \left[C_1, C_2, \cdots, C_p\right]$ are then given by

$$C = A'Z$$

Where $A = \left[\ell_1, \ell_2, \cdots \ell_p\right]$ and the ℓ_i s, $i = 1, 2, \cdots, p$ are the eigenvectors of ρ are such that

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq o, \; \ell_i' \cdot \ell_i = 1 \text{and} \; \ell_i' \cdot \ell_j = 0.$$

And $Var(C_i) = \ell'_i \rho \ell_i = \lambda_i \; \sum_{i=1}^{p} Var(C_i) = \sum_{i=1}^{p} Var(Z_i) = \rho$

Thus the proportion of the variance in the data that is accounted for by the C_i is given by λ_j / ρ.

The correlations between a given PC, C_i and a given standardized variable Z_j referred to as the loading of variable Z_j on C_i, is given by $Corr(C_i, Z_j) = \ell_{ij} \cdot \lambda_j^{(1/2)}$.

The loading reflects the degree to which each Z_j influences each C_i given the effect of the other variables $Z_k, j \neq k$ (Hair et al., 2006; Johnson and Wichern, 1992; Sharma, 1996). In Principal Component Factoring the initial communalities of the indicator variables are one.

3. Results

Table 1: Correlation Matrix

Variables		V1	V2	V3	V4	V5	V6	V7	V8	V9
	V1		.							
	V2	.019								
	V3	-.067	.492							
	V4	.290	.144	.038						
	V5	.049	.312	.345	.050					
	V6	.323	.291	.170	.287	.079				
	V7	.198	.255	.328	.123	.107	.401			
	V8	.150	.202	.179	.175	.020	.290	.362		
	V9	.142	.063	.050	.315	.064	.157	.132	.315	
	V10	.169	-.030	-.134	.301	-.080	.222	.169	.281	.368

Source: Results from analysis of data, 2016

Table 1 shows the correlation between the variables. It shows a moderately high correlation between V3 and V2 (0.492), V7 and V6 (0.401) and a very low correlation between V1 and V2 (0.019).

Table 2 : KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.724
Bartlett's Test of Sphericity	Approx. Chi-Square	871.871
	df	45
	Sig.	.000

Source: Results from analysis of data, 2016

Table 2 shows that the adequacy of the sample as measured by KMO is 0.7(0.724). The sampling is adequate and sufficient if KMO value is larger than 0.5 (Field, 2000). According to Pallant (2013), the value of KMO should be 0.6 and above, Kaiser (1974) recommends a bare minimum of 0.5 and a value between 0.7 and 0.8 are good (Hutchen and Sofroniou, 1999). The KMO of 0.7 for this study is greater than the threshold of 0.5 (Kaiser, 1974). The strength of relationship measured by Bartlett test of sphericity p value of 0.000 suggest the sample size is adequate and that ,at least some of the variables are inter-correlated and therefore the data is suitable for factor analysis and also it checks the null hypothesis that the original correlation matrix is an identity matrix (Pallant,2013;Field,2000).

Table 3: Communalities

	Initial	Extraction
V1	1.000	.725
V2	1.000	.605
V3	1.000	.698
V4	1.000	.613
V5	1.000	.645
V6	1.000	.633
V7	1.000	.668
V8	1.000	.633
V9	1.000	.703
V10	1.000	.603

Source: Results from analysis of data, 2016

The communality is the proportion of common variance within a variable. Therefore before extraction, all of the variance associated with a variable assumed to be common variance. Principal Component Factoring work on the assumption that all the variance associated with a variable is supposed to be 1(one) before factor extraction. Thus the communality matrix gives information about how much of the variance in each item is explained. From table 3 all ten variables remained in the final factor solution and all the final communalities are at least 60% of the initial communalities of each variable were account

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Table 4 :Total Variance Explained

Factors	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	2.705	27.052	27.052	2.705	27.052	27.052	1.784
2	1.791	17.913	44.965	1.791	17.913	44.965	1.922
3	1.028	10.280	55.245	1.028	10.280	55.245	1.617
4	1.003	10.031	65.277	1.003	10.031	65.277	1.853
5	.744	7.440	72.717				
6	.646	6.460	79.177				
7	.590	5.899	85.076				
8	.550	5.501	90.576				
9	.512	5.122	95.699				
10	.430	4.301	100.000				

Source: Results from analysis of data, 2016

As shown in table 4, total variance of 65.3% is achieved for four factors. The first factor eigenvalue is equal to 2.705 and explains 27.1% of the variance in the original data. The second factor eigenvalue is 1.791 and explains 17.9% of the variance, the third factor eigenvalue is 1.028 and explains10.3% of the variance and the fourth factor eigenvalue is 1.003 which explains 10.0% of the variance. The first four factors explain 65.3% of the variance in the data more than the minimum 60% (Hair *et al* 2006); therefore, by eigenvalue criteria these four factors have been retained.

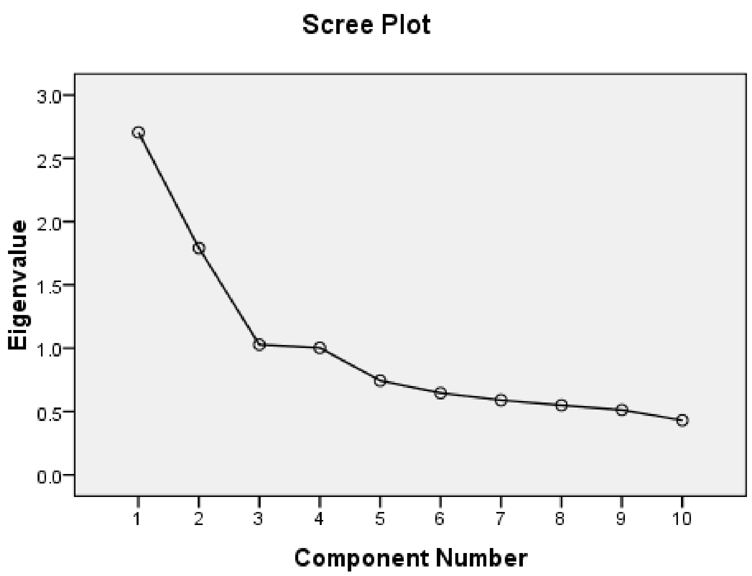

Figure 1: plot of eigenvalues against factor number.

Source: Results from analysis of data, 2016

To supplement the eigenvalue criteria as mentioned in table 4, a scree plot graph of the eigenvalues against all the factors (Catell, 1966) was obtained as shown in figure 1. The plot also shows that five factors should be retained as the plot curve begins to flatten between the 4^{th} and 5^{th} factors suggesting a fifth factor. However, the fifth factor has eigenvalue less than 1 as seen in table 4. Hence four factors have been retained.

Table 5: Rotated Component Matrix

	Component			
	1	2	3	4
V5	.771			
V3	.743			
V2	.714			
V7		.779		
V8		.664		
V9			.829	
V10			.695	
V1				.840
V6				
V4				

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

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V9			.829	
V10			.695	
V1				.840
V6				
V4				

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

Source: Results from analysis of data,2016

Table 5 shows the extracted factors and the loadings of the various variables on the factors. A Varimax rotation method was used so that each variable load on only one factor. This is an orthogonal method which ensures that the factors are uncorrelated. Tabachnick and Fidell (2000), stated variables with factor loadings of 0.4 and above should be considered. However, a higher value of 0.5 was chosen in this study to ensure that only variables of practical significance are included in the final solution. After performing the Varimax Rotation Method with Kaiser Normalization, Factor 1 comprised of three items with factor loadings ranging from 0.71 to 0.77, the items are V5, V3 and V2. Factor 2 comprised of two items with factor loadings ranging from0.66 to 0.78, the items are V7 and V8. Factor 3 comprised of two items with factor loadings ranging from 0.69 to 0.83, the items are V9 and V10. Factor 4 comprised of one item with factor loading 0.84 and has item V1. Four new factors were successfully constructed using factor analysis and assigned as the factors influencing the consumer' buying behaviour.

Table 6: Naming of factors with factor loadings and the percentage of variance.

NAME	Factor Loading	Percentage of variance
FACTOR ONE: HEALTH FEATURES		
V5= I use it because it has higher absorption capacity.	**.771**	
V3= I use it because I feel comfortable in it.	**.743**	**27.1**
V2= I use it because it does not give any side effect.	**.714**	
FACTOR TWO: PRODUCT FEATURE		
V7= I use it because of its fragrance.	**.779**	**17.9**
V8= I use it because its packaging is attractive.	**.664**	
FACTOR THREE: SOCIAL INFLUENCE		
V9=I use it because of family tradition.	**.829**	**10.3**
V10= I use it because I like their advert.	**.695**	
FACTOR FOUR: ECONOMIC FACTOR		
V1= I use it because it is less expensive.	**.840**	**10.0**

Source: Results from analysis of data, 2016

Table 6 shows the names of the new factors with factor loadings and percentage of variance explained. The first factor (health features) shows the highest percentage of variance explained (27.1%). The second factor (product features) explains 17.9% of the variance, the third factor (social influence) explains10.3% of the variance and the fourth factor (economic factor) explains 10.0% of the variance

Table 7: variables with their codes

Variables (items)
V1= I use it because it is less expensive.
V2= I use it because it does not give any side effect
V3= I use it because I feel comfortable in it.
V4= I use it because my doctor prescribed it for me
V5= I use it because it has higher absorption capacity
V6= I use it because of its quantity in the pack.
V7= I use it because of its fragrance.
V8= I use it because its packaging is attractive
V9= I use it because of family tradition
V10= I use it because like their advert

4. Conclusion

This study conducted a Principal Component Factoring with an orthogonal rotation (Varimax). The ten items related to consumer buying behaviour were reduced to four factors using a combination of three criteria to decide on the number of factors to retain for interpretation. The total variance of 65.3% is achieved for four factors. It can be seen that consumer's buying behaviour is driven by a number of factors like; price, quality, family and friends recommendations, features, advertisements and packaging. In the light of this research findings, the consumers buying behavior on sanitary pads appears to be influenced by: Health features of the pad; consumers consider health issues when buying a brand of pad, that is in order to avoid any discomfort and boost their self confidence. They also prefer to use a brand that feels comfortable, does not give any side effects and has higher absorption capacity. This is the first factor realized from the study. Product features; it was deduced in the study that consumers purchase a particular brand of sanitary pad based on the attractiveness of the packaging and fragrance in the pad. Social influence; the third factor consider selecting a brand based on family tradition and advertisement influence. The last factor considered before buying a brand is economic factor. Consumers prefer to use a brand that is economically convenient.

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