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FACTORS AFFECTING SHOPPING BEHAVIOR OF ASIAN WOMEN CONSUMERS

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ABSTRACT

The objective of this paper was to assess the structure underlying the attitude statements relating to shopping behavior of Asian women consumers. It is tempting to undertake an analysis that would address factors that explain women purchase intentions. Data were collected from 1500 respondents, in particular married women. By using explanatory factor analysis, we found 5 factors related to women shopping behavior namely loyalty program, brand loyalty, introduction to new products, price and product quality.

Keywords: factor analysis, shopping behavior, consumers

1. INTRODUCTION

Consumers are nowadays having varieties of products to buy. Trade liberalization in the developing countries has enabled the existence of many types of goods in the market. Given such alternative products, customers have to make various shopping decision. For example, they have to make choice of which product and from which supplier to buy. The fundamental question in this regard is that what are the factors that drive the shopping behavior of customers? This paper aims to identify the factors affecting shopping behavior of customers. In particular, it aims to assess the structure underlying the attitude statements related to shopping behavior and to examine whether or not the constructs extracted from attitude statements are related to social-demographic variables. Both common factor and principal component analyses are used as analytical tools to achieve these objectives.

Many scholars have researched to better understand why customers select particular goods for their purchasing (Gupta, Su and Walter 2004; Inman, Shankar and Ferraro 2004; Schoenbachler and Gordon 2002).

Wolfinbarger et al., (2001) pointed out the important question what motivates consumers to shop. As such, they acknowledged that consumers shop differently depending on whether their motivations are primarily experiential or goal-oriented.

2. LITERATURE REVIEW

The marketing literature reached the causal relationships between quality, satisfaction, perceived value, and repurchase/loyalty intentions (Cronin et al. 2000). Perceived value and satisfaction have both been found to be predictors of repurchase or loyalty intentions

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(Bolton and Drew 1991; Dabholkar et al. 2000). Figure 1 shows the relationships between quality, value, satisfaction and loyalty constructs in the consumers' evaluation process.

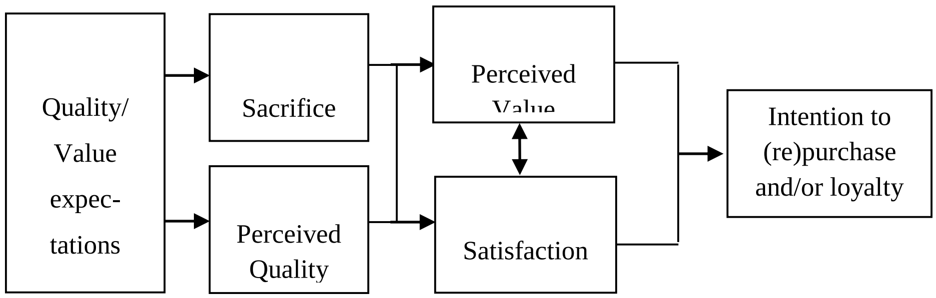

Figure 1: Relationships between quality, value, satisfaction and loyalty

Marketing researchers have attempted to measure quality and value perceptions, satisfaction and loyalty in shopping behaviors. To better understand the underlying factors that determine the purchase intentions, this study analyze the women shopping behaviors with regarding purchasing.

As pointed out above, this part reviews the existing literature on the underlying methods for carrying out of the factors analysis. In particular, this part addresses the following issues: factors extraction method, factor retention criteria, and factor rotation methods.

The method is used to reduce attribute space from a larger number of variables to a smaller number of factors. There are several different types of factor analysis. However, the most common used methods are principal components analysis (PCA) and principal axis factoring (common factor analysis (CFA)). In general, both methods identify dimensions (latent variables) in the data. In relation to the variance to be represented in the factors, CFA represents the common variance of variables, excluding unique variance; and it is a correlation-focused approach seeking to reproduce the inter-correlation among the variables. On the other hand, PCA reflects both common and unique variance of the variables and it is a variance-focused approach seeking to reproduce both the total variable variance with all components and to reproduce the correlations (Hair, et al, 2006).

Factor retention refers to a number of factors to be retained. Several criteria exist on the decision of number of factors (components) to retain. Eigenvalues greater than one, the Screen test, parallel analysis, a priori theory, and proportion of variance, among others, are the criteria than can be used to decide on the number of factors to retain. However, the methods result to different number of factors to be retained (Fabrigar et al 1999). In addition to that, it is argued that no technique seems to be highly accurate compared to others with regards to number of factors to be retained. In this case it advisable to use the combination of techniques (Ford, et al, 1986, Fabrigar, et al 1999). In the next sections, we describe three techniques that have been used in this paper: Latent root criteria, scree test criteria, and percentage of variance criteria.

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In this criterion all factors having Eigenvalues greater than 1 will be retained (Hair et al, 2006). However, the shortcoming with the technique is that it does not consistently give accurate number of factors (i.e. it tends to overestimate or underestimate the true number of factors). For this reason, Zwick and Velicer, (1986) argue that the method should probably not to be used alone as criterion to retain number of factors. This means that, it should be used in combination with other methods.

Another commonly used method for determining the number of factors to be retained is scree test by Cattell (1966). In this test, the components are plotted on the X-axis and the corresponding Eigen values on the Y-axis. The plotted line has a negative slope, and components before one starting the elbow are retained and the components after the one starting the elbow (Hayton, et al, 2004) are dropped. Although this rule is used, it suffers from some criticism of being subjectivity and ambiguity. The reason for the criticism it that the curve has multiple elbows or is a smooth curve and that the researcher may be tempted to set the cut-off at the number of factors desired by his or her research agenda. The evidence shows that when compared with latent root criterion, the screen test results in a at least one and sometimes two or three more factor to be retained than does the latent root criterion (Hair, et al, 2006).

This approach is based on retaining number of factors that gives a high proportion of variance accounted for or that gives the most interpretable solution. The purpose is to ensure practical significance for derived factors by making sure that they explain at least a specified amount of variance (Hair, et al, 2006). Although no absolute threshold has been adopted for all application, some researchers in natural sciences extract factors that account at least 95% of the variance. In social sciences, it is common to extract factors that account for 60% of the total variance (Hair, et al, 2006).

Factor rotation is usually performed to make the factor matrix more understandable and to interpret factors easily. There are two factor-rotation methods that are used: orthogonal and oblique factor rotation (Hair et, al 2006). Orthogonal factor rotation allows the factors to be extracted so that their axes are maintained at 90 degrees. Each factor is independent of all other factors that is factors are not correlated. The correlation between the factors is determined to be zero. In relation to this study we used combination of these methods described above in retaining the number of factors.

3. METHODOLOGY

The data for this study were collected from a large sample of consumers (1500 respondents), in particular married women. Through an online survey, twenty-one (21) attitude statements relating to shopping behavior, and five social demographic variables were obtained.

To assess the structure of the underlying attitude statements relating to shopping behaviour of customers, we performed both PCA and CFA. The number of factors to be retained for both methods was determined using a combination of three criteria: scree

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test criterion, latent criterion (or Eigenvalues rule), and percentage of variance criterion. In relation to factor rotation methods we used both the oblique rotation and orthogonal VARIMAX rotation for comparability of the underlying structure. Moreover, we used t-test to determine whether or not the constructs are related to the socio –demographic variables.

In this part the paper analyses attitude statements regarding purchasing behavior of customers. It also analyses the constructs to see whether or not relate to social demographic variables. We started our analysis by assessing the appropriateness of using factor analysis for this type of data, and then we proceed to discuss the output from factor analysis. The last part in this section, presents t-test results for examining the relationship between the factors and socio-demographic variables.

In order to use factor analysis, Hair et al, (2006) argue that the following conditions should be fulfilled: variables should be metric, sample size should be at least 50, but for better results a sample size of 100 is recommended, the study should comprise at least five times as many observations as the number of variables to be analyzed, and the more acceptable sample size should have a 10:1 ratio. In addition to that, the sample should be homogenous, and variables should be inter-correlated to produce representative factors; a statistical test for presence of correlations among the variables should be significant at 0.05-level (i.e. Bartlett test of sphericity). Measure of sampling adequacy should be at least 0.5 for overall and for each variable.

4. RESULTS AND DISCUSSION

Relating our data with the above conditions, we found that all variables are metric and constitute a homogenous set of attitudes from female consumers. In this case, we concluded our data to be appropriate for factor analysis. The sample size in this study is 71:1 (i.e. 1500 and 21); ratio of observations to variables, which is above acceptable limits (10:1). This is adequate for calculation of correlations between variables presented in table 1.

Table 1 below shows correlation matrix between variables. From this correlation matrix we found that that most of the correlations are significant at 0.01-level. This result provides us an adequate basis for proceeding with empirical examination of adequacy of factor analysis on both an overall test and test for each variable.

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Table 1: Correlation Matrix

	Correlation among variables*																				
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1.	1.000	**.263**	**.422**	**-.139**	**.534**	**.252**	**.539**	**-.317**	**.342**	**.072**	**-.170**	.019	-.016	**-.167**	**.494**	**.162**	.055	**.354**	**.100**	.054	**.139**
2.		1.000	**.193**	**-.239**	**.284**	**.337**	**.303**	**-.215**	**.102**	-.017	.012	.020	-.003	-.019	**.262**	**.104**	**-.073**	**.099**	**.076**	.014	**.097**
3.			1.000	.015	**.482**	**.192**	**.381**	**-.172**	**.366**	**.100**	**-.166**	**.082**	**.073**	**-.180**	**.395**	**.135**	**.084**	**.366**	**.127**	.037	**.132**
4.				1.000	**-.124**	**-.165**	**-.189**	**.320**	-.037	.051	**.098**	.059	**.096**	**.094**	**-.161**	.024	**.099**	**-.060**	.020	**.061**	.036
5.					1.000	**.283**	**.547**	**-.278**	**.400**	**.067**	**-.255**	.056	.056	**-.263**	**.518**	**.168**	**.096**	**.454**	**.127**	.032	**.153**
6.						1.000	**.345**	**-.220**	**.114**	**-.063**	.039	-.050	-.004	-.007	**.265**	**.108**	.001	**.132**	**.064**	-.011	**.083**
7.							1.000	**-.333**	**.300**	**.091**	**-.132**	.051	**.069**	**-.164**	**.585**	**.211**	**.100**	**.338**	**.168**	**.075**	**.166**
8.								1.000	**-.231**	.053	**.254**	.042	**.100**	**.224**	**-.284**	-.022	**.074**	**-.263**	-.034	**.064**	-.012
9.									1.000	**.080**	**-.373**	.042	-.003	**-.409**	**.322**	**.103**	.045	**.514**	**.086**	**-.066**	**.072**
10.										1.000	**.134**	.507	**.434**	.048	**.123**	**.439**	**.424**	**.140**	**.603**	**.497**	**.511**
11.											1.000	.158	**.195**	**.741**	**-.130**	**.131**	**.089**	**-.372**	**.086**	**.198**	**.128**
12.												1.000	**.448**	**.063**	**.082**	**.386**	**.311**	**.076**	**.489**	**.370**	**.402**
13.													1.000	**.149**	**.120**	**.417**	**.462**	.057	**.409**	**.370**	**.457**
14.														1.000	**-.146**	**.085**	**.066**	**-.391**	.020	**.151**	**.085**
15.															1.000	**.268**	**.145**	**.378**	**.160**	**.089**	**.234**
16																1.000	**.469**	**.184**	**.554**	**.472**	**.596**
17.																	1.000	**.182**	**.432**	**.406**	**.471**
18.																		1.000	**.195**	.030	**.164**
19.																			1.000	**.572**	**.629**
20.																				1.000	**.660**
21.																					1.000

Note: Bolded values are significant at the $p < 0.01$: *The variables' names are listed in the appendix 1

We run anti-image correlation matrix to determine unexplained correlation when the effects of other variables are taken into account (see table 2). If the partial correlations are high (indicating no underlying factors), then factor analysis is inappropriate. In relation to our data, we found that partial correlation values range from 0.001 to 0.651, which is within the acceptable threshold of 0.70.

Table 2: Anti-Image Correlation and Measures of Sampling Adequacy

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	**.913**																				
2	-.050	**.849**																			
3	-.140	-.049	**.917**																		
4	.005	.155	-.121	**.757**																	
5	-.191	-.093	-.195	.004	**.916**																
6	-.012	-.197	-.033	.049	-.074	**.848**															
7	-.213	-.056	-.043	.051	-.191	-.138	**.893**														
8	.100	.044	-.018	-.233	-.011	.077	.099	**.885**													
9	-.075	.012	-.123	-.047	-.066	-.004	-.007	.030	**.900**												
10	-.038	.041	-.018	.029	.029	.101	-.001	-.039	-.057	**.904**											
11	.015	-.054	.008	-.022	.067	-.117	-.032	-.106	.059	-.073	**.715**										
12	.017	-.021	-.028	-.010	-.026	.072	.027	.016	-.022	-.216	-.094	**.895**									
13	.091	.001	-.026	-.031	-.027	.004	-.023	-.041	.005	-.098	-.037	-.219	**.903**								
14	-.039	.000	-.007	-.021	.023	.017	.032	.004	.142	.043	-.651	.058	-.041	**.715**							
15	-.131	-.036	-.091	.062	-.136	-.016	-.300	.046	-.039	-.010	-.005	.011	-.042	-.017	**.909**						
16	-.028	-.035	.029	-.013	.009	-.035	-.027	-.008	-.040	-.011	-.033	-.071	-.073	-.034	-.097	**.930**					
17	.009	.120	.012	-.035	-.019	-.006	-.014	-.057	.037	-.099	.021	.028	-.229	-.028	-.015	-.176	**.907**				
18	-.036	.038	-.082	-.015	-.142	-.006	.001	.076	-.271	-.027	.097	.015	.019	.100	-.085	-.028	-.120	**.906**			
19	.044	-.034	-.015	.005	.017	-.055	-.056	.045	.012	-.280	.019	-.174	.001	.026	.066	-.175	-.044	-.073	**.899**		
20	-.041	.022	.009	-.008	.002	.049	-.021	-.020	.093	-.122	-.039	-.011	.019	-.014	.037	-.046	-.061	.046	-.181	**.883**	
21	-.015	-.053	.003	-.017	-.019	-.039	.047	.013	-.026	-.051	.012	-.001	-.126	-.023	-.086	-.221	-.091	-.017	-.209	-.400	**.884**

Note: Measures of Sampling Adequacy (MSA) are on the diagonal (bolded values)
KMO Overall Measure of sampling Adequacy is 0.880, significance at 0.000

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Finally we examined the measure of sampling adequacy (MSA), which looks not only at the correlations, but also at their patterns between variables. In this case, we found that the overall MSA value falls within acceptable range (above 0.50) with a value of 0.88. Moreover, the results indicate that MSA values for each variable ranges from 0.715 to 0.930. These results meet also the requirements for factor analysis. As such, we continued with factor analysis without deleting any variable at this stage.

In the first analysis, we use principal component analysis to assess dimensionality of 21 attitude statements towards shopping behavior. The first output is presented in Table 3 below. In this analysis, latent root criterion (i.e. components with eigenvalues greater than 1) suggests that four factors should be retained. Retentions of four factors represent 57.3% of the variance of the 21 variables. However, scree test criterion (see figure 1 below) suggests that 5 factors should be retained. This represents 61.2% of the total variance. Since the number of factors retained by using scree test criteria represents larger proportion of variance than those in eigenvalues criteria, we concluded that scree test is suitable for this analysis and therefore we retain five factors for further analysis.

When common factor analysis (CFA) was used, we found that almost the same results as in component analysis (see table 3). For example, as in PCA, while latent criterion suggests retention of four factors, scree test allows the retention of five factors. The major difference between PCA and CFA is that, CAF considers only the common variance associated with a set of variables, in the final common factor model (see table 3, the last three columns). For example eigenvalues for the 4th factor is now below the threshold of 1. Therefore, for comparability purposes between the two methods, we retained five factors for further analysis.

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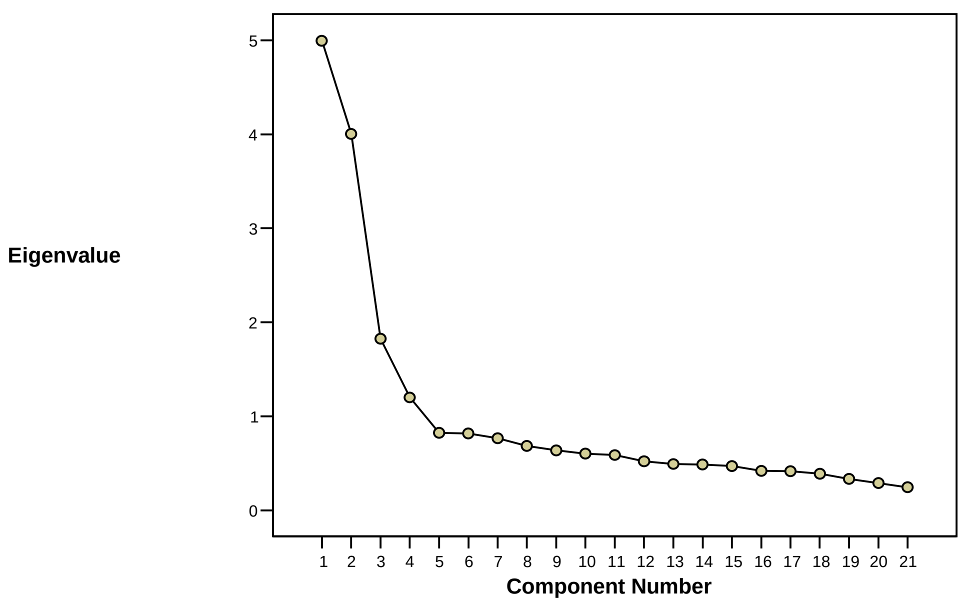
Table 3: Results for extraction of component/factors

Factors	Initial Eigen-values			Extraction Sums of Squared Loadings by **PCA**			Extraction Sums of Squared Loadings by **CFA**		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4,994	23,780	23,780	4,994	23,780	23,780	4,499	21,422	21,422
2	4,003	19,064	42,844	4,003	19,064	42,844	3,517	16,750	38,172
3	1,824	8,686	51,530	1,824	8,686	51,530	1,356	6,457	44,629
4	1,200	5,716	57,245	1,200	5,716	57,245	,603	2,870	47,499
5	,823	3,918	61,163						
6	,817	3,889	65,053						
7	,766	3,650	68,702						
8	,684	3,257	71,959						
9	,638	3,039	74,998						
10	,602	2,864	77,862						
11	,588	2,799	80,661						
12	,521	2,479	83,140						
13	,493	2,345	85,485						
14	,486	2,315	87,800						
15	,471	2,243	90,043						
16	,420	1,998	92,041						
17	,415	1,977	94,018						
18	,390	1,856	95,874						
19	,334	1,588	97,462						
20	,289	1,376	98,838						
21	,244	1,162	100,000						

Figure 2: Scree Plot



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With five factors to be analyzed, we now turn to the interpretation of these factors. Table 4 presents the un-rotated component factor matrix and communalities. Communalities explain how well each variable is explained by five components extracted. Examining factor-loading patterns we can see that the first factor has large number of high loadings (high loading is defined as greater than 0.40, (Hair, et al, 2006)), followed by factor two having four high loadings. Factor three has only three high loadings, while factor four and five have only 1 high loading each.

In order to be able to interpret these factors, we rotated the factor matrix to redistribute the variance from the earlier factors and the later factors. However, before we rotate the components, we examined the communalities to see whether any variables have to be deleted by having low communalities. Higher community values indicate that a large amount of variance in a variable has been extracted by the factor solution, while low communalities show that a substantial portion of the variable's variance is not accounted for by the factors. It is argued that, although, there is no statistical guideline for lower or higher communalities, but 0.50 is used as threshold (Hair, et al, 2006). In this case, a variable with communalities below 0.50 will be less in common with other variables and it can be deleted (Hair, et al, 2006). Looking to communalities (in table 4, last column), we found two variables (variable 12, and variable 13) with communalities below 0.50. Therefore, we delete these two variables in a rotated solution because they have less in common with other variables.

Table 4: Un-rotated Component Matrix

	Component					
Variables	1	2	3	4	5	**Comm**
Having a customer card makes me feel special as a customer of that store.	.668	.464	-.002	-.113	.025	.675
I buy most of my groceries at a store of which I have a loyalty card.	.653	.451	-.095	-.202	.117	.693
I prefer loyalty programs over every-day-low prices	.646	.384	.035	-.045	-.010	.568
I feel attached to the brands and products that I buy.	.623	-.351	.203	.147	-.252	.637
I consider myself to be a brand-loyal consumer.	.600	-.409	.281	.092	-.188	.651
I try to stick with the same brands.	.599	-.477	.072	.206	-.017	.634
Because of the customer card, I pay more attention to special offers.	.556	.492	-.171	-.098	.006	.589
I'm very careful with respect to trying innovative products.	.546	-.389	-.344	.059	.007	.571
When I'm used a particular brand, I do not like to buy another brand.	.545	-.445	.188	.177	-.217	.608
I buy less at specialty stores (e.g. butcher, backery) because I have a loyalty card of a supermarket.	.505	.428	-.161	.080	-.186	.505
I prefer to purchase food products that are similar in taste.	.504	-.346	-.006	.410	.110	.554
If a supermarket does not have a loyalty card, I may miss special promotions.	.460	.457	-.112	-.079	.162	**.466***
I like to be a member of loyalty programs.	.506	.554	.008	-.138	-.039	.583
Having a loyalty card will affect my purchase behavior.	.457	.502	-.038	.080	.015	**.469***
I often switch brands when there are promotions.	-.290	.461	-.131	.441	.234	.563
I rarely try new products.	.437	-.453	-.354	.117	.137	.554
I frequently try out new brands.	-.183	.533	.609	.257	-.181	.787
I'm often buy new products as one of the first in my group of friends.	-.113	.575	.603	.245	-.077	.773
I do not pay attention to prices when I buy groceries.	.295	-.273	.499	-.029	.397	.569
I often try to safe money to buy cheaper products which are perhaps somewhat of less quality.	-.103	.287	-.303	.672	.228	.688
For food products, quality is more important than price.	.298	-.262	.499	-.188	.516	.708

***Communalities values which are below 0.50**

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We rotated factor matrix by using both orthogonal (VARIMAX) and Oblique rotations. The results from orthogonal rotation are presented in table 5. From the table 5, we can see that factor loadings for each variable are maximized on one factor and all of the loadings are above 0.50, meaning that more than one-half of the variance is accounted for by the loading on a single factor.

Moreover, oblique rotation reveals the same results as those obtained in orthogonal rotation. By examining the variables loading on each factor, we found that the interpretation is exactly the same as in VARIMAX rotation. However, there is an one exception, factor one in oblique rotation solution, is factor two in varimax rotation, and factor one in varimax rotation, is factor two is oblique rotation. However, the variables loaded on each factor in both methods are the same.

We used rotated factor matrix in naming the factors. Hair, et al, (2006) suggest that, naming of factor is based on loading with cutoff point of 0.50 on each variable. Meaning that variable with loading below 0.50 may not be included

Table 5: VARIMAX Rotated Component Matrix*

	Component				
Variables	**1**	**2**	**3**	**4**	**5**
Having a customer card makes me feel special as a customer of that store.	**.833**				
I buy most of my groceries at a store of which I have a loyalty card.	**.830**				
I like to be a member of loyalty programs.	**.786**				
Because of the customer card, I pay more attention to special offers.	**.751**				
I prefer loyalty programs over every-day-low prices	**.739**				
I buy less at specialty stores (e.g. butcher, bakery) because I have a loyalty card of a supermarket.	**.660**				
When I'm used a particular brand, I do not like to buy another brand.		**.759**			
I feel attached to the brands and products that I buy.		**.748**			
I consider myself to be a brand-loyal consumer.		**.735**			
I try to stick with the same brands.		**.730**			
I prefer to purchase food products that are similar in taste.		**.665**			
I frequently try out new brands.			**.878**		
I'm often buy new products as one of the first in my group of friends.			**.853**		
I rarely try new products.			**-.581**		
I'm very careful with respect to trying innovative products.			**-.559**		
For food products, quality is more important than price.				**.771**	
I do not pay attention to prices when I buy groceries.				**.763**	
I often try to save money to buy cheaper products which are perhaps somewhat of less quality.					**.830**
I often switch brands when there are promotions.					**.645**

*variables with communality values less than 0.40 were deleted, before rotating the factors

In relation to common factor analysis, the results are slightly different with the results from component analysis, although there are some similarities. However, the primary differences between the common factor analysis and PCA, is that, in CFA there are lower loadings, caused by lower communalities of the variables. With lower loadings in CFA, it makes very difficult to retain five factors for interpretation, as only four factors managed to capture enough loadings. Factor five has very low loadings (below the threshold of

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0.50), which makes very difficult to interpret; therefore we decide to rotate factor solution again, extracting only four factors (see table 6). However, in interpretation of factors, we base only on component rotation matrix with five factors.

Table 6: Varimax Rotated Factor Matrix

Variables	Factor 1	2	3	4	Communality
I buy most of my groceries at a store of which I have a loyalty card.	**,792**				,644
Having a customer card makes me feel special as a customer of that store.	**,788**				,516
Because of the customer card, I pay more attention to special offers.	**,713**				,645
I like to be a member of loyalty programs.	**,712**				,520
I prefer loyalty programs over every-day-low prices	**,680**				,506
I buy less at specialty stores (eg butcher, backery) because I have a loyalty card of a supermarket.	**,599**				,393
Having a loyalty card will affect my purchase behavior.	**,597**				,392
If a supermarket does not have a loyalty card, I may miss special promotions.	**,590**				,354
I try to stick with the same brands.		**,720**			,581
I consider myself to be a brand-loyal consumer.		**,660**			,562
When I'm used a particular brand, I do not like to buy another brand.		**,651**			,486
I feel attached to the brands and products that I buy.		**,651**			,509
I prefer to purchase food products that are similar in taste.		**,612**			,397
I'm very careful with respect to trying innovative products.		**,508**			,472
I rarely try new products.		**,486**	**-,428**		,421
I'm often buy new products as one of the first in my group of friends.			**,821**		,728
I frequently try out new brands.			**,810**		,695
I often try to safe money to buy cheaper products which are perhaps somewhat of less quality.				**-,521**	,284
I often switch brands when there are promotions.				**-,453**	,332
For food products, quality is more important than price.				**,431**	,280
I do not pay attention to prices when I buy groceries.				**,360**	,258

The first factor accounted for 23.8% of the variation in the data, and it is loaded with six variables which are related to having a customer card and being a member of loyalty programs. In light of this, we label this factor as loyalty program. The second factor explains 19.1% of the total variation, and it is loaded with five variables which are related to being attached to particular brands, and not willing to switch to other brands. Thus, we name the second factor as brand loyalty. Factor three is named as “new products”, and accounted for 8.7% of the variance. The four items in this factor were all related to attitude towards the introduction of new products in relation to shopping behavior. The fourth factor is loaded with two variables, which are related to price increase and price promotions. Therefore we name this factor as price. The last factor also explained 3.9% of the total variance, and having variables which are related to attitude towards product quality. In this light we label this factor as product quality.

The factors extracted from the variables in this study are consistent with variables studied in other researches. In relation to loyalty programs, it is argued that loyalty programs are

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used in stimulating product usage, retaining and creating repeat purchase behavior among customers (Magi, 2003; Latham, and Locke, 1991). Brand loyalty has also been explained to influence shopping behavior of customers (Chaudhuri and Holbrook, 2001). Regarding product quality, it is argued that, this variable is an important influence of consumer behavior (Parasuramna, et al, 1996; Bilkey and Nes, 1982). Price has been also studied as variable influencing shopping behavior of customers (Ingene, 1984). It has been argued that consumers may engage in price comparisons to minimize purchase price.

In examining the relationship between five factors (extracted by using component analysis) with socio-demographic variables we use t-test to test if there are differences between groups in relation to shopping behavior. The results are presented in the table 7 and 8.

When viewing two groups of social class variable (high class and middle class), we find that measures for loyalty program and brand loyalty have significant differences between the two groups, while the measures for new product, price and quality have no significant difference between the two social class groups. In relation to region districts (Amsterdam, Rotterdam, Utrecht vs. North region), we found that loyalty program, brand loyalty, and quality have significant differences between the two regions. On the other hand, measures for new product and price have no significant differences.

Table 7: Mean differences between groups of consumers based on two variables

	Mean Scores for Social Class		T-Test results		Mean Scores for Regions		T-Test Results	
Measure	High Class (A)	MiddlClass (C)	t-value	p-value	Amsterdam	North	t-value	p-value
Loyalty Program	-,178	,047	-1,974	,049	,108	-,185	2,780	,006
Brand Loyalty	-,113	,159	-2,428	,015	-,077	,154	-2,269	,024
New Product	-,036	-,016	-,177	,860	-,076	,052	-1,304	,193
Price	-,010	-,025	,133	,895	-,094	-,088	-,055	,956
Quality	-,019	-,042	,200	,841	-,004	-,201	1,933	,054

Apart from that, we also found that there are significant differences between the two groups (housewife in with no kids and housewife with kids) in relation to attitude toward brand loyalty and attitude towards new products. The results also show that, there is a significant difference between the two groups of number of inhabitants (below 20,000 and above 100,000 people) in city in relation to attitude toward loyalty programs. However, there is no significant difference regarding the two groups, in relation to brand loyalty, introduction of new products, price, and product quality.

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Table 8: Mean differences between groups of consumers based on two variables

	Mean Scores for family life cycle		T-Test results		Mean Score for No. of inhabitants		T-Test Results	
Measure	H/wife, no kids	H/wife, with kids	t-value	p-value	1 – 20,000	Above 100,000	t-value	p-value
Loyalty Program	-,207	-,040	-1,493	,136	**-,095**	**,077**	**-2,462**	**,014**
Brand Loyalty	-,319	-,119	-1,723	,085	-,016	-,049	,463	,644
New Product	**,679**	**,148**	**4,435**	**,000**	-,044	-,015	-,397	,692
Price	,139	,121	,146	,884	,038	-,041	1,096	,274
Quality	-,044	-,131	,731	,465	-,045	,015	-,814	,416

5. CONCLUSION

The objective of this paper was to assess the structure underlying the attitudes statements relating to shopping behavior of customers, and to find out if extracted factors were related to socio-demographic variables. On the basis of Bartlett test (p= 0.000, and KMO measure (0.88), we conclude that there is underlying factors which allowed to use factor analysis in the data. By using PCA, with combination of latent root criterion, scree test and percentage of variance explained, we extracted five factors. We label these factors as loyalty program, brand loyalty, introduction to new products, price and product quality.

The relationship between the extracted constructs and demographic variables show that: (1) the measures for loyalty program and brand loyalty have significant differences between the two groups of social class. However, the measures for new product, price and quality have no significant difference between the two social class groups. In relation to the nations we found that loyalty program, brand loyalty, and quality have significant differences between the two regions. On the other hand, measures for new product and price have no significant differences.

In addition, we found that there are significant differences between the two groups (housewife in with no kids and housewife with kids) in relation to attitude toward brand loyalty and attitude towards new products. Similarly, the results show that, there is a significant difference between the two groups of number of inhabitants (below 20,000 and above 100,000 people) in city in relation to attitude toward loyalty programs, but there is no significant difference between the two groups, in relation to brand loyalty, introduction of new products, price, and product quality.

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