DOI: 10.18843/ijcms/v9i2/04
DOI URL: http://dx.doi.org/10.18843/ijcms/v9i2/04

Buying Insurance Online: Are we there yet?

Dr. V. Uma Maheswari,

Assistant Professor and Head,
Department of MBA, Guru Nanak College Chennai, Velachery,
Chennai, India

Dr. Uma Chandrasekaran,

Associate Professor,
Department of Management Studies,
School of Management, Pondicherry University (A Central University),
Pondicherry, India

ABSTRACT

The study has been undertaken with the objective of identifying the factors that influences the online channel adoption intent of the customers for the financial products and to zero in on the segment that is interested in the online channel by combining the identified factors with the demographic and behavioural variables of the customers. New variables had been introduced for the study along with using the variables from existing literature. Exploratory factor analysis had been carried out and 9 factors had been identified. Perceived benefits and Perceived usefulness had emerged as the most influential factor followed by system quality and informational quality. Segmentation had been done based on the identified factors.

Keywords*: Online Channel, Financial Products, Behavioral Intention, Customer Behaviour, Factor Analysis. Cluster analysis, Insurance, TAM, and Segmentation.*

Introduction:

E-finance seems to be the most promising part of e-commerce as financial services are information sensitive and often requires no physical delivery (Sato & Hawkins, 2001). E-finance is successful with simple time-sensitive products like broking and catching up slow with products like e-insurance (Sato et al.2001). This could be due to the infrequent contacts between the customer and the service provider (Allen, Mc Andrews, & Strahan, 2002). E-finance not only offers a huge opportunity for industrial and the most advanced emerging markets but also for the countries with underdeveloped financial system (Claessens, Glaessnerm, & D Klingebiel, 2000).

Insurance companies in India are actively using the digital platform not only for promoting their product offering but also to provide better pre and post-sales service to existing customers and to resolve the queries of potential customers. One such initiative is that the majority of the insurance companies have opened their pages on social and professional networking sites like LinkedIn, Facebook, Twitter, YouTube, Blog and Google+. They share product information, resolve doubts, and get feedback from customers. The insurance companies are also actively urging customers to visit their company websites in order have better pricing and product information and product choice. HDFC Life has aggressively promoted its online term plan Click2Protect and came out with television advertisement campaigns supported by other media such as print, Out Of Home advertising, Direct To Home, digital and social media. Eventually the company has insured over 1.6 lakh lives during a period of over two years (Press Release HDFC Life). ICICI Prudential Life launched a digital campaign for its online term plan ICICI Pru iCare. The company went only for the digital media as it is an online plan which can be bought online without any offline verifications and it is targeted at customers who are active on the Internet. According to the brand, approximately 2.2 lakh views have been generated for the videos and edits. Bharti AXA General Insurance came out with a digital campaign promoted on Facebook, YouTube and Twitter as a support to the television campaign on creating awareness of the importance of a critical illness health insurance policy. The company's website visits have doubled due to the digital campaign.

Although the Life Insurance Corporation of India that holds a market share of 70% gets 95.99% of their individual new business premium from individual agents for the financial year 2013-14 (IRDA Annual Report, 2013-14), the company emphasizes its digital presence in all its communications to the target audience with appeals to visit their website for better product information and to start using the customer portal for payment of premium, transparent claim settlement process and so on. One cannot deny the fact that online channel is here to stay and this study aims at exploring the factors influencing the online channel adoption among the customers and to identify the most viable segment for e-finance by clubbing the demographic and behavioral variables like age, gender, number of hours available for access, number of hours spent online, number of years of internet usage with behavioural intention towards online channel.

Literature Review:

The adoption of the technology depends on the users' attitude and intentions conditioned by the perceived usefulness and perceived ease of use of the technology (David et al. 1989). TAM 2 added that the Social influence processes and cognitive instrumental processes significantly influence user acceptance. (Venkatesh & Davis, 2000). Unified Theoretical Model found performance expectancy to be a direct determinant of user acceptance and usage behavior and variables like age, gender, experience and voluntariness are also found to influence intention to use (Venkatesh & Bala, 2008). TAM3 suggests that the effect of perceived ease of use on perceived usefulness will be moderated by experience; and the determinants of perceived ease of use will not have any significant effects on perceived usefulness. (Venkatesh & Bala, 2008). The Technology Readiness Index (TRI) measures an individual's technology readiness based on positive factors of optimism and innovativeness and negative factors of discomfort and insecurity (Parasuraman, 2000). Updated D&M IS Success Model measures the intention to use online channel in terms of satisfaction with service quality, system quality and information quality (DeLone & McLean, 2003).Technology Readiness and Acceptance Model (TRAM) postulates that TR is a causal antecedent of perceived usefulness and perceived ease of use and the effect of TR is primarily through PEOU (Lin, Shih, & Sher, 2007). It has been found that perceived behavioural control (PBC), self-efficacy, and availability were more critical in determining continuance of intention for the socio-economically disadvantaged customers (Hsieh et al. 2008) and perceived access barriers influences the customer attitudes and beliefs about Internet use and technology in general (Porter and Donthu 2006). Socio-economic variables decide the customer access to computerised banking and the customers' perceived innovation characteristics decides the possibility of customer adopting computer banking (Lee, Lee, & Eastwood, 2003). Variables like awareness and benefits of the online channel (Laforet & Li, 2005), trust, security, perceived risks (Lall Mahamood, 2007), (Luo, Li, Zhang, & J Shim, 2010), (Mukherjee & Nath, 2003), (Floh & Treiblmaier, 2006), (Khare, Dixit, Chaudhary, Kochhar, & Mishra, 2012), (Dixit & Dr. Datta, 2010), (Sharma, 2011), website qualities (Kesharwani & Bisht, 2012), (Pikkarainen, Pikkarainen, Karjaluoto, & Pahnila, 2004) web skills, product involvement, online purchasing experience (McKechnie, Winklhofer, & Ennew, 2006), (Koufaris, 2002), Perceived Behavioural Control, Perceived difficulty in using computers (Tan, 2000), (Mattila, Karjaluoto, & Pento, 2003) have been found to influence the online channel adoption for various types of financial services.

For this study, variables like System Quality (SQ) and Information Quality (IQ) (DeLone & McLean, 2003), Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Davis, Bagozzi, & Warshaw, 1989) have been taken from existing literature. Variables measuring customer efficacy as defined for this study are perceived benefits PB, Perceived Access Barriers PAB, Perceived Safety PS and Usage Intensity of the Internet UI. Perceived Benefits are measured in terms of the degree to which consumers believe buying of financial products online would result in value addition (right product and price) and cost reduction (Search cost, Psychological cost, Time cost). Perceived Access Barriers are measured in terms of Internet connectivity, having to share a computer with other users and time available to use the computer. Perceived Safety is measured as the degree to which consumers express trust and feel that online transactions are safe. Usage Intensity is measured in terms of frequency with which the consumers use the internet for downloading, social networking, blogging, information search, comparison of brands, purchase and so on.

Methodology:

Non- probability convenience sampling method was used. Primary data was collected during the period June 2013 – May 2014 by administering an online questionnaire to 392 respondents age 25 years and above, employed/self employed and who have bought at least 1 financial product online and have at least 1 insurance product bought online or offline. The questionnaire had three parts. Part I the respondents' profile, Part II their Internet usage pattern and Part III the respondents' opinion/rating using 5-point Likert scale on using the online channel for buying financial products. The questionnaire had 41 items of which 20 items were drawn from existing literature and 21 items were constructed for the study. New variables included for the study were Perceived Safety, Usage Intensity, Perceived Benefits and Perceived Access Barriers.

Identification of Latent Variables:

An exploratory factor analysis was carried out as it helps to explore the main dimensions to develop a model from a relatively large set of latent constructs represented by a set of items (Henson & Roberts, 2006),(Thompson, 2004). Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (Kaiser, 1970) and Bartlett's Test of Sphericity (Bartlett, 1950) was done to assess the suitability of the data for factor analysis. (Kaiser, 1970) recommends a minimum of 0.5 KMO statistics, 0.6 are considered as mediocre, 0.7 as middling, 0.8 as meritorious and 0.9 as marvelous. For the study on agents the KMO statistic falls above 0.8 which is considered to be meritorious and thus the sample size is adequate for factor analysis (Table 1)
Bartlett's test of sphericity tests the hypothesis that the correlation matrix is an identify matrix; i.e. all diagonal elements are 1 and all off-diagonal elements are 0, implying that all of the variables are uncorrelated. The Sig. value for this analysis implies that the null hypothesis should be rejected and thus it is concluded that there are correlations in the data set that are appropriate for factor analysis. This analysis meets this requirement **(Table 1)**.

Method of factor extraction and determining the number of factors to be retained:
The oblique rotation methods, such as direct oblimin, promax, orthoblique, and procrustes, account for relationships, or correlations, between factors (Beavers, et al., 2013). (Browne, 2001) stated that the oblique rotation method is more appropriate in most "practical situations" (p. 114) because correlated factors more accurately represent reality and oblique rotation produces a simpler factor pattern. Oblique methods produce superior results with correlated factors and oblique and orthogonal methods result in nearly identical factor loading solutions when constructs are uncorrelated. Most social science studies involve correlated factors (Schmitt, 2011). The present study on customers uses Maximum Likelihood Method for factor extraction and oblique promax of oblique rotation is chosen for factor rotation. The eigenvalues and scree test are used to determine how many factors to retain. According to Kaiser's criterion, factors that are above the eigenvalue of 1 (Kaiser 1960) should be retained. Thus the factors with eigenvalues >1 are retained and the 9 factors account for 69.799% of variability **(Table 2)**. Based on the screen test (Cattell, 1978) which consists of eigenvalues and factors, the point of inflexion should be determined by drawing the horizontal line and a vertical line starting from each end of the curve. The break point (Point of inflexion) in the data occurs at the 10th factor and the curve turns flat and thus 9 factors are chosen for analysis **(Figure 1)**.

Communalities and factor structure:

Communalities measure the extent to which an item correlates with other items of the data set. Communalities above 0.4 are considered to be good as the items with communality below 0.4 will have difficulty in loading to a single factor. The communalities for the items of the study on customers online channel adoption intent have all fallen above 0.4 **(Table 3)** and indicates the items are correlated with other items of the study.
The pattern matrix **(Table 4)** shows the factor loading of the items under each factor. Factor loadings satisfy the cut off level suggested by Stevens (1992) using a cut-off of 0.4, irrespective of sample size, for interpretative purposes. The pattern matrix also signifies convergent and discriminant validity which is evident by the high loadings within factors and no cross-loadings between factors. Discriminant Validity can also be checked by examining the factor correlation matrix. Correlations between factors have not exceeded 0.7 **(Table 5)** and thus factors are distinct and uncorrelated.

Customers' Present Online Purchasing behaviour and Future Purchasing Intent across Different Product Categories:

It is evident that 75-85% of the respondents purchase train, airline and movie tickets online and use Internet banking, 45-60% of the customers would like to use the online channel for Books and CDs/DVDs, 35-40% of the customers prefer to use the online channel for Life Insurance, Motor Insurance, Health Insurance, Mutual Fund and computer accessories, 15-30% of the customers intend to use the online channel for cosmetics, home appliances, clothes furniture, jewellery and fast food. Thus the online channel usage intent is very high for Internet banking and ticket booking followed by buying books and CDs/DVDs online. The intent to use the online channel for insurance and mutual funds is moderate while it is the least preferred mode for cosmetics, home appliances, clothes furniture, jewellery and fast food. **(Table 6)**

Cluster Analysis:

Two Step Cluster is an algorithm primarily designed to analyze large datasets. The algorithm groups the observations in clusters, using the approach criterion. Two Step uses both continuous and categorical attributes and it can automatically determine the optimal number of clusters.
The categorical variables included are

- gender
- age of the customers classified as 25-35 years and above 35 years
- time spent online for personal work by the customers - less than 2 hours a day and 2 hours and more per day

- computer and Internet access time available for customers - less than 2 hours a day and 2 hours and more per day
- age of first access to Internet for the customer - less than 30 years and 30 years and more
- Internet usage period - less than 6 years and 6 years and more
- Intent to buy insurance online classified as - no intent to buy insurance online and intent to buy insurance online.

The continuous variable used is Behavioural Intention and the continuous variables used in the evaluation fields are SQ, IQ, PB, PAB, PEOU, PU, UI and PS. The Log-likelihood option for distance measure is chosen and Schwarz's Bayesian Criterion BIC is chosen to determine the number of clusters automatically.

From the Figure 2, it is inferred that there are totally 4 clusters; the size of the largest cluster is 32.1% and the smallest is 15.6% and the ratio of largest to smallest cluster is 2.07. The strongest predictor of the clusters is age of first access to Internet followed by age of the respondent. The model summary is provided in Table 3. **(Figure 2)**

Cluster 1: Cluster 1 comprises of customers who are female (50.8%), 36 years and above (100%), have less than 2 hours of access time to Internet (59.5%), spend less than 2 hours of time online per day (85.7%), do not have the intent to buy insurance online (73%), have been using the Internet for 6 years and more (62.7%), had their first access to Internet at 30 years and above (97.6%). This cluster has the least score on Behavioural Intention (7.59) towards buying financial products online, System Quality (15.86), Information Quality (18.37), Perceived Benefits (16.33), usage intensity (23.19), Perceived Safety (8.08) and the second next lowest rating for Perceived Usefulness (15.99), Perceived Ease of Use (16.03) and the second next highest Perceived Access Barriers (10.6) compared to other 3 clusters.

Cluster 2: Cluster 2 comprises of customers who are female (58.3%), aged between 25 and 35 years (72.8%), have less than 2 hours of access time to Internet (100%), spend less than 2 hours of time online per day (100%), do not have the intent to buy insurance online (68%), have been using the Internet for 6 years and more (77.7%), had their first access to Internet at less than 30 years (100%). This cluster has the second least score on Behavioural Intention (9.16) towards buying financial products online, System Quality (17.37), Information Quality (19.40), Perceived Benefits (17.27), usage intensity (23.19), Perceived Safety (8.63) and lowest rating for Perceived Usefulness (15.81), Perceived Ease of Use (15.17) and highest Perceived Access Barriers (11.5) compared to other 3 clusters.

Cluster 3: Cluster 3 comprises of customers who are male (68.5%), aged between 25 and 35 years (97.1%), have more than 2 hours of access time to Internet (93.1%), spend 2 hours and more of time online per day (71.6%), have the intent to buy insurance online (69.8%), have been using the Internet for 6 years and more (61.8%), had their first access to Internet at less than 30 years (100%). This cluster has highest score on Behavioural Intention (11.03) towards buying financial products online, System Quality (19.26), Information Quality (24.15), usage intensity (31.25) Perceived Safety (11.40) and the second highest in Perceived Benefits (18.43), Perceived Usefulness (16.72), Perceived Ease of Use (16.46) and second lowest Perceived Access Barriers (10.13).

Cluster 4: Cluster 4 comprises of customers who are male (100%), aged 36 years and above (100%), have more than 2 hours of access time to Internet (75.4%), spend 2 hours and more of time online per day (55.7%), have the intent to buy insurance online (82%), have been using the Internet for 6 years and more (100%), had their first access to Internet at less than 30 years (100%). This cluster has the second highest score on Behavioural Intention (10.39) towards buying financial products online, System Quality (18.44), Information Quality (23.28), usage intensity (31.16) Perceived Safety (10.18) and the highest score on Perceived Benefits (19.59), Perceived Usefulness (18..82), Perceived Ease of Use (18.13) and lowest Perceived Access Barriers (9.74).(**Table 8)**

Discussion:

From the above analysis it is been found that all the latent variables have very good convergent validity, discriminant validity and composite reliability. The factor Perceived Benefits accounts for about 29.6% of the total variance explained followed by perceived usefulness for 11.3% (Table 2) . This clearly indicates that online channel adoption intent of customers for financial products primarily depend on the customers' perception of how useful the channel is in terms reducing the cost and increasing the value. Perceived Usefulness and Perceived Benefits are highly interrelated and will influence one another very strongly. System quality and Information Quality of the online channel account for nearly 6% variability individually stating the importance of usability of the channel itself.

There are two segments, who score low on BI for online buying of financial products and do not want to buy insurance online, comprise of female customers, who have less than 2 hours of access time online, who spend less than 2 hours online and who have been using the Internet more than 6 years. From this it can be concluded that female customers as well as customers who have access time and spending time of less than 2 hours have low BI for buying financial products online. Age and Age of first access to the Internet do not discriminate the respondents with respect to intention to use the online channel for buying insurance for this segment.

Again there are two segments that want to buy insurance online and have high BI for buying financial products online. The common profiles of these segments are male, who have 2 hours of access time and spending time online, who have been using the Internet for 6 years and more, and had their first-time access to the Internet below 30 years of age. But these two segments comprise of customers both in the age of 25 and 35 years as well as 36 and above in which the latter's BI for buying financial products online is comparatively more than the former. The above result goes in line with (Hsieh, Rai, & Keil, 2008), (Porter & Donthu, 2006) who have reported that the Internet digital divide, based on socio-economic status like income, education gender and access to technology based on money and affordability, socio-economic variables affects the usage of technology. It is also in conformity with the research results of BCG CCCI Digital influence study 2013 that also reveals that those who have been using the Internet for more than 2 years tend to use the Internet extensively for various search and purchase activities.

Thus it can be concluded that the segments that are very attractive to the marketer for selling financial products online are male customers, irrespective of age group, who spend 2 hours and more of time online per day, have been using the Internet for 6 years and more, and have more than 2 hours of access time to the Internet.

References:

Allen, F., Mc Andrews, J., & Strahan, P. (2002). E-Finance: An Introduction. *Journal of Financial Services Research, 22*(1), 5-27.

Bartlett, M. (1950). Tests of significance in factor analysis. *British Journal of Psychology, 3*(2), 77-85.

Beavers, A. S., Lounsbury, J. W., Richards, J. K., Huck, S. W., Skolits, G. J., & Esquivel, S. L. (2013). Practical considerations for using exploratory factor analysis in educational research. *Practical Assessment, Research & Evaluation*, *18*(6), 1-13. Retrieved from http://www.pareonline.net/pdf/v18n6.pdf

Browne, M. W. (2001). An overview of analytic rotation in exploratory factor analysis. *Multivariate Behavioral Research*, *36*(1), 111-150. doi:10.1207/S15327906MBR3601_05

Cattell, R. B. (1978). *Use of Factor Analysis in Behavioral and Life Sciences.* New York: Plenum.

Claessens, S., Glaessnerm, T., & D Klingebiel. (2000). E-finance in emerging markets: is leapfrogging possible? *Financial Sector Discussion*.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science, 35*, 982-1003.

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems, 19*(4), 9-30.

Dixit, N., & Dr. Datta, S. (2010). Acceptance of E-banking among Adult Customers: An Empirical Investigation in India. *Journal of Internet Banking and Commerce, 15*(2).

Floh, A., & Treiblmaier, H. (2006). What keeps the e-banking customer loyal? A multigroup analysis of the moderating role of consumer characteristics on e-loyalty in the financial service industry. *Journal of Electronic Commerce Research, 7*(2), 97-110.

Henson, R., & Roberts, J. (2006). Use of Exploratory Factor Analysis in Published Research:Common Errors and Some Comment on Improved Practice. *Educational and Psychological Measurement, 66*(3).

Hsieh, J. J., Rai, A., & Keil, M. (2008). Understanding Digital Inequality: Comparing Continued Use Behavioral Models of the Socio-Economically Advantaged and Disadvantaged. *MIS Quarterly, 32*(1), 97-126.

IRDA Annual Report. (2013-14). Retrieved from https://www.irda.gov.in/ADMINCMS/cms/frmGeneral_NoYearList.aspx?DF=AR&mid=11.1

Kaiser, H. (1970). A Second-Generation Little Jiffy. *Psychometrika*, *35*(4), 401-15.

Kesharwani, A., & Bisht, S. S. (2012). The impact of trust and perceived risk on internet banking adoption in India: An extension of technology acceptance model. *International Journal of Bank Marketing, 30*(4), 303–322.

Khare, A., Dixit, S., Chaudhary, R., Kochhar, P., & Mishra, S. (2012). Customer behavior toward online insurance services in India. *Journal of Database Marketing & Customer Strategy Management, 19*, 120–133.

Koufaris, M. (2002). Applying the Technology Acceptance Model and Flow Theory to Online Consumer Behavior. *Information Systems Research*, *13*(2), 205–223.

Laforet, S., & Li, X. (2005). Consumers' attitudes towards online and mobile banking in China. *International Journal of Bank Marketing, 23*(5), 362 – 380.

Lall Mahamood, M. (2007). An Examination of Individual's Perceived Security and Privacy of the Internet in Malaysia and the Influence of This on Their Intention to Use E-Commerce: Using An Extension of the Technology Acceptance Model. *Journal of Internet Banking and Commerce, 12*(3).

Lee, E., Lee, J., & Eastwood, D. (2003). A two-step estimation of customer adoption of technology based service innovations. *The Journal of Customer Affairs, 37*(2), 256-282.

Lin, C.-H., Shih, H.-Y., & Sher, P. J. (2007). Integrating technology readiness into technology acceptance: The TRAM model. *Psychology & Marketing, 24*, 641-657. doi:10.1002/mar.20177

Luo, X., Li, H., Zhang, J., & J Shim, J. (2010). Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services. *Decision Support Systems, 49*, 222–234.

Mattila, M., Karjaluoto, H., & Pento, T. (2003). Internet banking adoption Among mature customers: Early majority or laggards? *Journal of Services Marketing Research, 17*(5), 514-528.

McKechnie, S., Winklhofer, H., & Ennew, C. (2006). Applying the technology acceptance model to the online retailing of financial services. *International Journal of Retail & Distribution Management, 34*(4), 388 -410.

Mukherjee, A., & Nath, P. (2003). A model of trust in online relationship banking. *International Journal of Bank Marketing, 21*(1), 5-15.

Parasuraman, A. (2000). Technology Readiness Index (TRI): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies. *Journal of Service Research, 2*(4), 307-320.

Pikkarainen, T., Pikkarainen, K., Karjaluoto, H., & Pahnila, S. (2004). Consumer acceptance of online banking: an extension of the technology acceptance model. *Internet Research, 14*(3), 224-235.

Porter, C., & Donthu, N. (2006). Using the technology acceptance model to explain how attitudes determine Internet usage: The role of perceived access barriers and demographics. *Journal of Business Research, 59*(6), 999–1007.

Sato, S., & Hawkins, J. (2001). Electronic finance: an overview of the issues, A chapter in Electronic finance: a new perspective and challenges. *Bank for International Settlements, 7*, 1-12.

Schmitt, T. A. (2011). Current methodological considerations in exploratory and confirmatory factor analysis. *Journal of Psychoeducational Assessment, 29*(4), 304-321. doi:10.1177/0734282911406653

Sharma, A. (2011). Mobile Banking Technology Adoption and Challenges. *International Journal of Multidisciplinary Research, 1*(6), 147-157.

Tan, M. (2000). Factors Influencing the Adoption of Internet Banking. *Journal of Association for the Information Systems, 1*(5).

Thompson, B. (2004). *Exploratory and confirmatory factor analysis: understanding concepts and applications.* Washington, DC: American Psychological Association.

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. *Decision Sciences, 39*(2), 273-315.

Venkatesh, V., & Davis, F. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science, 46*, 186-204.

Table 1: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.834
Bartlett's Test of Sphericity	Approx. Chi-Square	10332.131
	Df	496
	Sig.	.000

Table 2: Total Variance Explained Extraction Method: Maximum Likelihood

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	11.234	35.106	35.106	9.465	29.577	29.577	7.388
2	3.506	10.955	46.061	3.602	11.255	40.832	6.396
3	2.302	7.193	53.254	2.039	6.372	47.204	8.171
4	1.926	6.020	59.274	2.039	6.373	53.577	5.225

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
5	1.602	5.006	64.280	1.517	4.740	58.316	5.391
6	1.355	4.234	68.514	1.000	3.124	61.441	6.795
7	1.100	3.437	71.951	1.045	3.265	64.706	5.699
8	1.034	3.231	75.183	.819	2.561	67.266	3.874
9	1.010	3.155	78.338	.811	2.533	69.799	2.844
10	.771	2.410	80.747				
11	.694	2.169	82.916				
12	.589	1.841	84.757				
13	.524	1.637	86.394				
14	.489	1.528	87.922				
15	.469	1.466	89.388				
16	.402	1.256	90.644				
17	.352	1.099	91.743				
18	.329	1.028	92.771				
19	.300	.936	93.707				
20	.283	.883	94.590				
21	.254	.795	95.385				
22	.231	.723	96.108				
23	.192	.601	96.709				
24	.185	.579	97.288				
25	.164	.513	97.801				
26	.146	.456	98.257				
27	.129	.403	98.660				
28	.120	.375	99.034				
29	.095	.297	99.331				
30	.092	.286	99.617				
31	.068	.213	99.831				
32	.054	.169	100.000				

Table 3: Communalities

	Initial	Extraction
UI3	.703	.845
UI6	.709`	.413
UI7	.710	.408
UI8	.621	.620
SQ2	.736	.793
SQ3	.602	.568
SQ4	.658	.589
SQ5	.683	.562
IQ1	.730	.618
IQ2	.717	.656
IQ3	.745	.765
IQ4	.794	.794

	Initial	Extraction
PS1	.743	.840
PS2	.697	.744
PS3	.580	.506
PB1	.756	.733
PB2	.753	.721
PB3	.759	.729
PB5	.724	.673
PU1	.744	.658
PU2	.774	.725
PU3	.799	.813
PU4	.845	.869
PEOU2	.735	.658
PEOU3	.828	.814
PEOU4	.814	.851
BI1	.838	.782
BI2	.899	.981
BI3	.877	.835
PAB1	.661	.626
PAB2	.653	.723
PAB3	.583	.423
Extraction Method: Maximum Likelihood.		

Table 4: Pattern Matrix[A]

	Factor								
	1	2	3	4	5	6	7	8	9
PB2	.855								
PB3	.821								
PB1	.817								
PB5	.552								
PU3		.907							
PU4		.883							
PU2		.699							
PU1		.523							
IQ3			.872						
IQ4			.871						
IQ2			.722						
IQ1			.647						
SQ2				.842					
SQ4				.681					
SQ3				.593					
SQ5				.436					
PEOU4					.847				
PEOU3					.777				
PEOU2					.612				
BI2						.932			
BI3						.796			
BI1						.733			
UI3							.928		
UI8							.702		

UI7							.578		
UI6							.404		
PS1								.830	
PS2								.817	
PS3								.587	
PAB2									.871
PAB1									.702
PAB3									.573

Extraction Method: Maximum Likelihood Rotation
Method: Promax with Kaiser Normalization. a. Rotation converged in 8 iterations.

Table 5: Factor Correlation Matrix

Factor	1	2	3	4	5	6	7	8	9
1	1.000	.466	.637	.403	.333	.617	.386	.271	.038
2	.466	1.000	.510	.262	.504	.319	.400	.119	-.387
3	.637	.510	1.000	.543	.452	.526	.494	.322	-.076
4	.403	.262	.543	1.000	.256	.374	.393	.237	-.124
5	.333	.504	.452	.256	1.000	.332	.350	.265	-.237
6	.617	.319	.526	.374	.332	1.000	.448	.481	.117
7	.386	.400	.494	.393	.350	.448	1.000	.329	-.295
8	.271	.119	.322	.237	.265	.481	.329	1.000	-.002
9	.038	-.387	-.076	-.124	-.237	.117	-.295	-.002	1.000

Extraction Method: Maximum Likelihood.
Rotation Method: Promax with Kaiser Normalization.

Table 6: Customers' Present OE Purchasing Behaviour and Future Purchasing Intent across Different Product Categories

	Have purchased online but prefer to buy offline in Future		Have never purchased online and prefer to continue with offline in future		Have never purchased online and prefer to try online in future		Have Purchased online and prefer to continue with online in future	
	Freq.	**%**	**Freq.**	**%**	**Freq.**	**%**	**Freq.**	**%**
Fast food	43	11	271	69.1	42	10.7	36	9.2
Cosmetics	37	9.4	271	69.1	53	13.5	31	7.9
Books	34	8.7	137	34.9	102	26.0	119	30.4
CD/DVDS	18	4.6	197	50.3	105	26.8	72	18.4
Furniture	30	7.7	285	72.7	53	13.5	24	6.1
Clothes	45	11.5	228	58.2	88	22.4	31	7.9
Life Insurance	11	2.8	232	59.2	89	22.7	60	15.3
Motor Insurance	19	4.8	223	56.9	79	20.2	71	18.1
Health Insurance	12	3.1	242	61.7	94	24.0	44	11.2
HomeApp-liances	44	11.2	244	62.2	76	19.4	28	7.1

	Have purchased online but prefer to buy offline in Future		Have never purchased online and prefer to continue with offline in future		Have never purchased online and prefer to try online in future		Have Purchased online and prefer to continue with online in future	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Train tickets	19	4.8	39	9.9	32	8.2	302	77.0
Movie Tickets	22	5.6	55	14.0	41	10.5	274	69.9
Airline Tickets	7	1.8	74	18.9	40	10.2	271	69.1
Computer accessories	24	6.1	206	52.6	57	14.5	105	26.8
Jewellery	31	7.9	303	77.3	34	8.7	24	6.1
Internet Banking	**15**	**3.8**	**82**	**20.9**	**45**	**11.5**	**250**	**63.8**
Mutual Funds	**15**	**3.8**	**217**	**55.4**	**76**	**19.4**	**84**	**21.4**

Table 7: Intention to Buy Online in Future for Different Categories of Products

	Intend to buy offline		Intent to buy online	
	Frequency	%	Frequency	%
Fast food	314	80.1	78	19.9
Cosmetics	308	78.5	84	21.4
Books	171	43.6	221	56.4
CD/DVDS	215	54.9	177	45.1
Furniture	315	80.4	77	19.6
Clothes	273	69.7	119	30.3
Life Insurance	243	62	149	38
Motor Insurance	242	61.7	150	38.3
Health Insurance	254	64.8	138	35.2
Home Appliances	288	73.4	104	26.6
Train tickets	58	14.7	334	85.3
Movie Tickets	77	19.6	315	80.4
Airline tickets	81	20.7	311	79.3
Computer accessories	230	58.7	162	41.3
Jewellery	334	85.2	58	14.8
Internet Banking	97	24.7	295	75.3
Mutual Funds	232	59.2	160	40.8

Table 8: Cluster Comparison

Clusters

Input (Predictor) Importance

1.0 0.8 0.6 0.4 0.2 0.0

Cluster	1	2	3	4
Label				
Description				
Size	32.1% (126)	26.3% (103)	26.0% (102)	15.6% (61)
Inputs	Gender Female (50.8%)	Gender Female (58.3%)	Gender Male (68.6%)	Gender Male (100.0%)
	Age of the respondents 36 and above (100.0%)	Age of the respondents 25-35 (72.8%)	Age of the respondents 25-35 (97.1%)	Age of the respondents 36 and above (100.0%)
	Access time to internet less than 2 hours (59.5%)	Access time to internet less than 2 hours (100.0%)	Access time to internet More than two hours (93.1%)	Access time to internet More than two hours (75.4%)
	Time spent online per day less than 2 hours (85.7%)	Time spent online per day less than 2 hours (100.0%)	Time spent online per day More than two hours (71.6%)	Time spent online per day More than two hours (55.7%)
	Intent to buy insurance online Not intended to transact online for insurance (73.0%)	Intent to buy insurance online Not intended to transact online for insurance (68.0%)	Intent to buy insurance online Intended to transact online for insurance products (59.8%)	Intent to buy insurance online Intended to transact online for insurance products (82.0%)
	Internet Usage Period 6 years and more (62.7%)	Internet Usage Period 6 years and more (77.7%)	Internet Usage Period 6 years and more (61.8%)	Internet Usage Period 6 years and more (100.0%)
	Age of access More than 30 years (97.6%)	Age of access less than 30 years (100.0%)	Age of access less than 30 years (100.0%)	Age of access less than 30 years (100.0%)
	BI 7.59	BI 9.16	BI 11.03	BI 10.39
Evaluation Fields	SQ 15.86	SQ 17.37	SQ 19.26	SQ 18.44
	IQ 18.37	IQ 19.40	IQ 24.15	IQ 23.28
	PB 16.33	PB 17.27	PB 18.43	PB 19.59
	PU 15.99	PU 15.81	PU 16.72	PU 18.82
	PEOU 16.03	PEOU 15.17	PEOU 16.46	PEOU 18.13
	PAB 10.60	PAB 11.50	PAB 10.13	PAB 9.74
	UI 23.19	UI 28.19	UI 31.25	UI 31.16
	PS 8.08	PS 8.63	PS 11.40	PS 10.18

Figure 1: Scree Plot

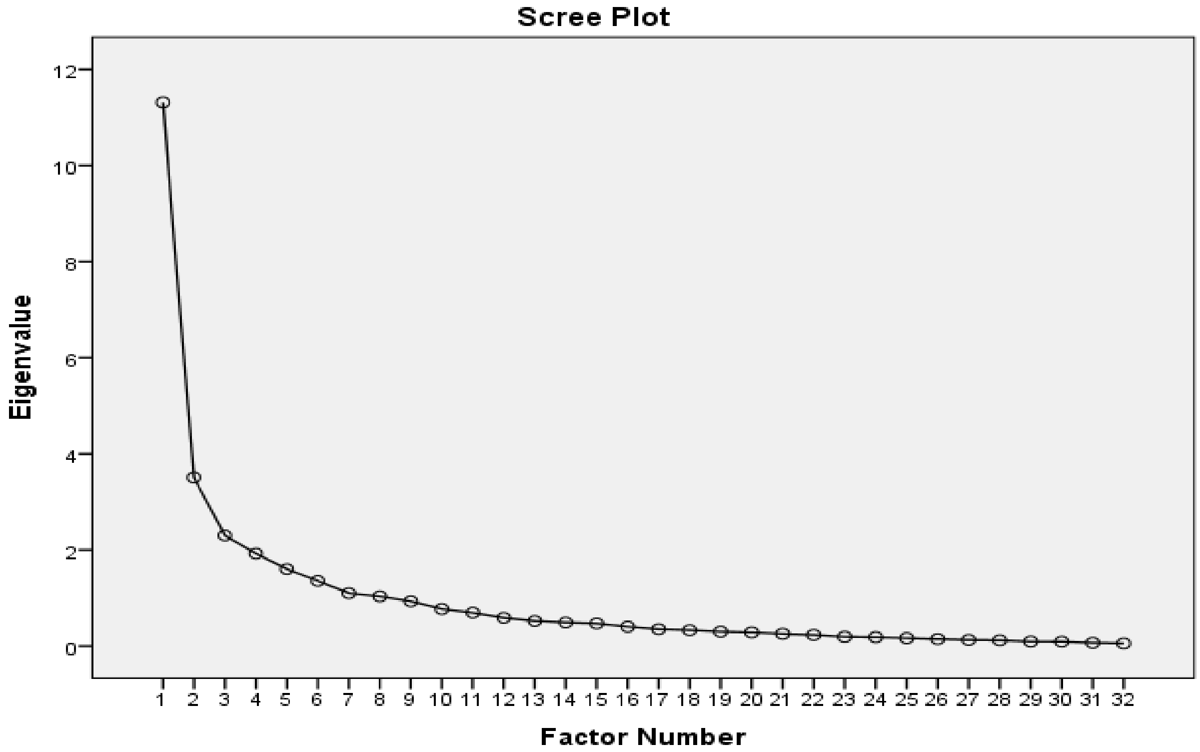
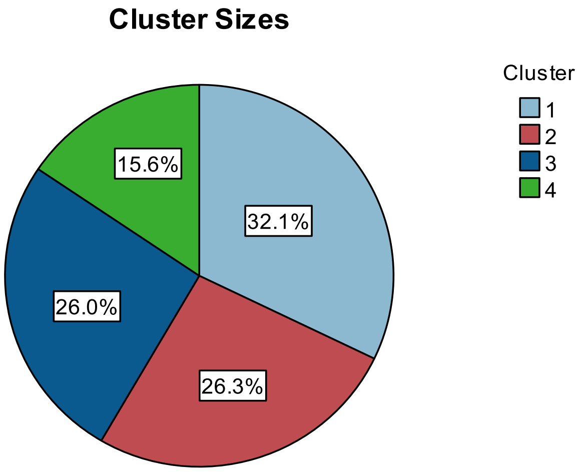


FIGURE 2 CLUSTER SIZES



Size of Smallest Cluster	61 (15.6%)
Size of Largest Cluster	126 (32.1%)
Ratio of Sizes: Largest Cluster to Smallest Cluster	2.07

******