A Study on Purchase Intention of Internet Consumers using Fuzzy ART(Adaptive Resonance Theory)

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Abstract

The purpose of this paper is to analyze the purchase intention of consumers in the online bookstore. AIO(Activities, Interests and Opinions), a method of measuring consumers' lifestyle, and Factor Analysis are performed to understand consumers' propensity and to find out the main factors which effect purchase intention. After Factor Analysis, factor scores for each consumer are obtained. To divide consumers into several meaningful groups, the factor scores are used as an input data of Fuzzy ART(Adaptive Resonance Theory). Finally, the characteristics and differences among each group are compared by Frequency Analysis. The experiment showed that each group has a different purchase intention. Consequently, marketing strategy can be applied to the online bookstores through this study.

1. Introduction

Due to the wide spread of internet services and the rapid growth of people who purchase goods via internet, the industrial structure and marketing field have been rapidly changed[1]. Table 1 shows the total transaction value of goods and services in Korea.

Table 1 Total Transaction Value of Goods and Services

(Unit: billion won, %)

Classification	2005		2006		From the previous year	
		Composition		Composition	Change	Change rate
Total	10,675.6	100.0	13,459.6	100.0	2,784.0	26.1
B2C	7,920.7	74.2	9,131.5	67.8	1,210.8	15.3
B2B	462.5	4.3	502.1	3.7	39.6	8.6
Others	2,292.3	21.5	3,826.0	28.4	1,533.6	66.9

In Table 1, the total sales of goods and services in Cyber Shopping Malls recorded 13,459.6 billion won in 2006, a rise of 2,784.0 billion won or 26.1 percent from 2005[2]. It showed a great rate increase especially in business to consumer (B2C) transaction. Thus, many companies are making efforts to keep good relationship with customers on the internet. It is important for companies to analyze and understand online consumers' characteristics and needs for effective CRM (Customer Relationship Management) and distinctive marketing strategy; Consequently e-CRM, an online relationship marketing approach, has become essential for the successful e-Business[3]. Based on the above, this study aims to propose a distinctive marketing strategy for consumers using online bookstores by analyzing the important factors which influence purchase intention and splitting consumers into several groups that had similar lifestyle and personality. The procedure of this study is shown in Fig. 1.

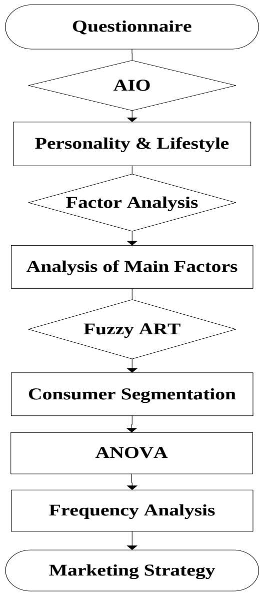

Fig. 1 Research Procedure

2. Methodology

2.1 Data Collection

Self-administered questionnaires using a 5-point Likert scale were distributed to 400 high school and college students in Seoul in February 2007. To improve this reliability, pilot survey had been conducted by 20 students who usually purchase books via online bookstores. From the pilot survey, questions which are not suitable or difficult to understand were modified. Except 38 questionnaires that were not responded properly, a total of 362 questionnaires were analyzed by SPSS 12.0.

2.2 Personality and Lifestyle

The consumers' behavior is differently presented according to their personality, lifestyle and surroundings. In other words, lifestyle and personality can affect the consumers' behavior. These lifestyle and personality are mostly influenced by parents, friends, culture and social life. AIO(Activities, Interests and Opinions), VALS(Value and Life-Style Survey) and LOV(List of Value) are typical methods to understand people's lifestyle. VALS was developed by mail survey of Americans which was conducted at SRI(Standard Research Institute) international in 1980. It divides the American lifestyle into nine types. LOV divided people in terms of nine lists of value which are associated with personal daily life. One previous study proved that LOV is more useful than VALS in predicting consumers' purchase intention[4]. But it is not proper to apply both methods in Korea because these were investigated and developed in the USA. In addition, all measurement lists are fixed. On the other hand, AIO can not only measure consumers' behavior by dividing a region of Activity, Interest and Opinion but change the items of list according to the purpose of research. Thus, the questionnaire was developed considering the life style dimension proposed by Joseph T. Plummer[5]. Table 2 shows the life style dimensions of AIO.

Table 2 Life Style Dimensions

Activities	Interests	Opinions	Demographics
Work	Family	Themselves	Age
Hobbies	Home	Social	Education
Social events	Job	Politics	Income
Vacation	Community	Business	Occupation
Entertainment	Recreation	Economics	Family size
Club membership	Fashion	Education	Dwelling
Community	Food	Products	Geography
Shopping	Media	Future	City size
Sports	Achievements	Culture	Stage in life cycle

2.3 Factor Analysis

(1) Validity and Reliability Analysis

Factor Analysis is done by reducing many variables into several factors which consist of similar variables. Before this, it should be judged whether the sample data is suitable for Factor Analysis. Kaiser-Meyer-Olkin(KMO) of sampling adequacy and Bartlett's test of sphericity are used to verify the sample data. KMO represents the fitness value of sample. As indicated in Table 3, the KMO value is greater than 0.7 which means the data set is suitable for Factor Analysis[6]. Bartlett verifies that whether correlation matrix between variables is an identity matrix. The significant probability, 0.000 in Table 3 indicates that the null hypothesis, correlation matrix is an identity matrix, is rejected. Consequently, both tests confirm that the data are suitable for Factor Analysis.

Table 3 KMO measure and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.765
Bartlett's Test of Sphericity	Approx Chi-Square	2427.293
	df	190
	Sig	0.000

Cronbach's α for internal consistency reliability is used to verify the measurement items. Cronbach's α has the value between 0 and 1. The α value greater than 0.7 indicates high reliability, the value between 0.7 and 0.35 means acceptable reliability, and the value lower than 0.35 means the reliability should be rejected[7]. Table 4 shows that the all Cronbach's α values for each item are greater than 0.75.

Table 4 Reliability Analysis

Item Statistics	Alpha if Item deleted	Total Alpha
Q1	0.783	0.805
Q2	0.789	
Q3	0.778	
Q4	0.782	
Q5	0.793	
Q6	0.790	
Q7	0.793	
Q8	0.789	
Q9	0.798	
Q10	0.787	
Q11	0.796	
Q12	0.795	
Q13	0.807	
Q14	0.792	
Q15	0.802	
Q16	0.801	
Q17	0.792	
Q18	0.792	
Q19	0.785	
Q20	0.799	

(2) PCA(Principle Component Analysis)

All data were submitted to a principle component analysis with a varimax rotation. Seven factors which are greater than 1, an eigenvalue, emerged. Table 5 shows the result of principle component analysis. These seven factors accounted for 70.275% of the variance. Communality is the coefficient described by the variable of the extracted factor. If this coefficient is smaller than 0.4, the variable is excluded. Factor loading is the coefficient representing the correlation between each variable and factor. Generally, it is judged that the coefficient greater than ± 0.3 has a reasonable significance and the coefficient greater than ± 0.5 has a high significance.

Table 5 Principle Component Analysis

Factors and Items	Communality	Factor Loading	Eigenvalue	Cumulative percent of variance(%)
(Factor 1)			4.614	23.069
1-1. I compare book prices on the website	0.833	0.603		
1-2. I check on discount coupon when using online bookstores	0.717	0.788		
1-3. I use online bookstores to save money	0.804	0.769		
1-4. Online bookstores is convenient to use	0.745	0.823		
(Factor 2)			2.779	36.964
2-1. I ordinarily recommend a book to people	0.566	0.525		
2-2. I usually purchase books in the bestseller lists	0.801	0.797		
2-3. I am interested in books written by the famous writer	0.658	0.646		
2-4 I usually purchase books that other people recommend	0.484	0.653		
(Factor 3)			1.826	46.096
3-1. Online bookstores should offer more information about the books	0.651	0.665		
3-2. Online bookstores should extend the discount services	0.695	0.784		
3-3. Online bookstores should reduce the delivery time	0.777	0.856		
(Factor 4)			1.453	53.359
4-1. Online bookstores should offer more multimedia services such as image contents	0.742	0.559		
4-2. I use online bookstores to save time	0.799	0.781		
4-3. I regularly visit the online bookstores	0.715	0.720		
(Factor 5)			1.291	59.815
5-1. I usually get information about books through online bookstores	0.764	0.718		
5-2. I like using online bookstores because I can compare many books	0.741	0.757		
(Factor 6)			1.061	65.121
6-1. I like talking with people about books	0.695	0.556		
6-2. I usually make a list of books for purchase in advance	0.613	0.757		
(Factor 7)			1.031	70.275
7-1. I check on comment left by other readers before purchasing books	0.737	0.801		
7-2. I am interested in the monthly and yearly ranking of selling books.	0.518	0.379		

2.4 Cluster Analysis

Cluster analysis is to classify a set of data into the several meaningful groups. There are various clustering algorithms that are widely used. K-means is one of the clustering algorithms, and it has been used widely because of its easiness of application. But the major drawback of K-means clustering is that it often falls in local optima and the result largely depends on the initial cluster centers[8]. Thus, in this paper, Fuzzy ART is used for consumer segmentation. The advantage of using Fuzzy ART is that repetition of all data is not necessary when a new data is put. As shown in Table 6, after factor analysis, the factor scores for each respondent are obtained. To use these scores as input data for Fuzzy ART which scores range from 0 and 1, Normalization is performed by the equation (1). χ_i' represents the normalized data for each χ_i which is an original data. The minimum factor score is -3.36602 and the maximum factor score is 3.76331. Table 7 shows the normalized data.

$$\chi_i' = \frac{\chi_i + |Min|}{Max + |Min|} \tag{1}$$

Table 6 Factor Scores for Each Respondent toward Seven Factors

Factors / Respondents(n=362)	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
1	2.14822	0.83218	0.27347	-0.04347	-0.70847	1.07935	0.81202
2	0.76422	-0.03462	-1.34829	0.43873	-0.50707	-1.37558	0.34570
3	-0.41430	0.16632	1.07863	-1.44846	-1.77233	-1.60233	0.93476
4	1.66826	-1.44523	-0.85072	-0.59840	0.18553	0.67183	0.80669
5	-0.59466	-0.88626	-0.82729	-0.49790	2.99541	-0.62220	-0.03287
6	-1.36356	1.42057	-1.12385	1.38528	0.59468	0.42771	0.89657
7	-0.93813	-1.65381	0.65066	0.17596	-1.56161	2.40772	-0.59114
8	0.29203	-0.01714	0.68356	0.56861	0.18186	0.52596	-0.19551
9	0.41057	0.14387	-1.42779	1.99533	1.38000	0.71280	-0.20268
…	…	…	…	…	…	…	…
362	1.18970	-0.89860	0.05095	0.56862	0.56840	-0.24107	-0.57794

Table 7 Normalization for Fuzzy ART

Factors / Respondents(n=362)	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
1	0.77346	0.58886	0.51050	0.46604	0.37276	0.62353	0.58604
2	0.57933	0.46728	0.28302	0.53368	0.40101	0.27919	0.52063
3	0.41402	0.49547	0.62343	0.26897	0.22354	0.24739	0.60325
4	0.70614	0.26942	0.35281	0.38820	0.49816	0.56637	0.58529
5	0.38873	0.34783	0.35610	0.40230	0.89229	0.38486	0.46753
6	0.28088	0.67139	0.31450	0.66644	0.55555	0.53213	0.59789
7	0.34055	0.24016	0.56340	0.49682	0.25310	0.80986	0.38922
8	0.51310	0.46973	0.56802	0.55189	0.49765	0.54591	0.44471
9	0.52973	0.49232	0.27187	0.75201	0.66570	0.57212	0.44371
…	…	…	…	…	…	…	…
362	0.63901	0.34609	0.47928	0.55189	0.55186	0.43832	0.39107

3. ART(Adaptive Resonance Theory)

3.1 Overview

The human brain has the ability to learn and memorize a large number of new concepts in a manner that does not necessarily cause existing ones to be forgotten. In order to design a truly intelligent pattern recognition machine, compatible with the human brain, it would be highly desirable to impart this ability to recognition models. For most pattern recognition paradigms, however, after a model has successfully learned to recognize all of the objects, no further modification of parameters is allowed. If at some future time some objects are subtracted, or new ones are added, a fully trained model must be modified to learn a new pattern, at which time, the previously learned objects are forgotten. The ability of a neural network to adapt and learn a new pattern well at any stage of operation is termed as plasticity, while the ability to remain stable in response to irrelevant inputs is called as stability. The existing pattern recognition models have the burden of making a learning system to be stable against irrelevant inputs, but plasticity novel inputs, at the same time. ART is designed to solve the stability-plasticity burden. As such, ART provides a mechanism by which the network can learn new patterns without forgetting old knowledge. The incorporation of a vigilance test allows ART architecture to resolve the stability-plasticity burden. New patterns from the environment can create additional classification categories, but they cannot cause an existing memory to be changed unless they are similar to existing categories[9]. ART was introduced as a theory of human cognitive information processing. This theory has led to an evolving series of neural network models for unsupervised and supervised category learning. These models, including ART1, ART2, ARTMAP, Fuzzy ART, and Fuzzy ARTMAP, are capable of learning stable recognition categories in response to arbitrary input sequences[10]. ART1 can stably learn to categorize binary inputs and ART2 can learn to categorize analog patterns presented in an arbitrary order. ARTMAP can rapidly self organize stable categorical mappings between m-dimensional input vectors and n-dimensional output vectors. Fuzzy ART, which incorporate computations from fuzzy set theory into the ART1 neural network, is capable of fast stable learning of recognition categories in response to arbitrary sequences of either analog or binary input patterns[11][12]. Fuzzy ARTMAP, the combination of ARTMAP with Fuzzy ART, can rapidly learn stable categorical mappings between analog input and output vectors.

3.2 Fuzzy ART

Using one of the unsupervised ART networks rather than the simpler competitive learning system, important stability properties of the network can be exploited[13]. Indeed, unlike competitive learning, when new patterns are produced by the monitored process, ART networks can continue to learn and incorporate new information. ART1 and Fuzzy ART are examples of unsupervised ART methods, which are capable of learning in both off-line and on-line training modes. Dissimilarities among input patterns are only considered in their measurement space for clustering. After clustering this space, each of their clusters is given by a weight vector. ART1 only tolerates binary numbers within an input vector. Fuzzy ART can process any real number, scaled to the continuous range between 0 and 1. The differences between ART1 and Fuzzy ART reflect the modifications needed to accommodate patterns with continuous-valued components. Fuzzy ART is the most recent adaptive resonance framework that provides a unified architecture for both binary and continuous value inputs. Fuzzy ART operations reduce to ART1 as a special case. The generalization of learning both analog and binary input patterns is achieved by replacing the appearance of the logical AND intersection operator ($\cap$) in ART1 by the MIN operator ($\wedge$) of fuzzy set theory. By incorporation from fuzzy set theory into ART1, Fuzzy ART does not require a binary representation of input patterns to be clustered. An additional desirable property of Fuzzy ART is that, due to the simple nature of its architecture, responses of the neural network to input patterns are easily explained, in contrast to other models, where in general, it is more difficult to explain why an input pattern produces a specific output[14]. Because of its algorithmic simplicity, and of the several properties that facilitate the implementation of the neural network, Fuzzy ART neural network has been exploited in this paper for consumer segmentation. A Fuzzy ART model consists of three fields such as input layer F_0, comparison layer F_1 and output layer F_2. Each field has M, 2M, and N nodes, respectively. In the layers F_1 and F_2, two kinds of weights such as bottom-up weights and top-down weights are connected each other. **a**, an input vector is preprocessed by so-called complement coding in the layer F_0. Layer F_1 compares the similarity between the input vector and top-down weight vector and layer F_2 chooses the node with the maximum competitive signal of bottom-up weights when an input vector is presented. Fig. 2 shows the general architecture of the Fuzzy ART network.

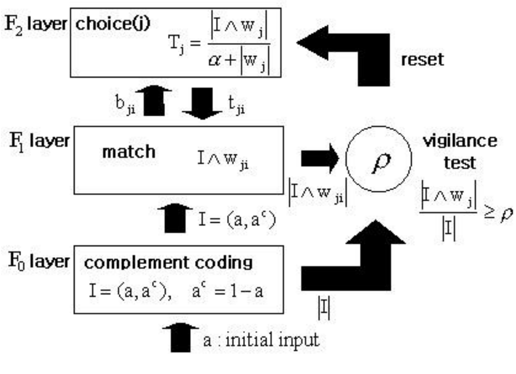

Fig. 2 Architecture of Fuzzy ART

In Fig. 2, representative vector W_J of Fuzzy ART contains both the top-down weights and bottom-up weights. When the winning node, J of F_2 layer is chosen, its top-down and bottom-up weights are updated in the same manner. Here, since both weights have same values, either weight can be considered to be representative pattern. Hence, fast learning is possible by updating only one of both weights.

$$t_J^{(new)} = \beta(I \wedge t_J^{(old)}) + (1-\beta)t_J^{(old)} \tag{2}$$

$$b_J^{(new)} = \beta(I \wedge b_J^{(old)}) + (1-\beta)b_J^{(old)} \tag{3}$$

Where, β is learning rate parameter, I is input vector, and t_J and b_J is top-down and bottom-up weight vectors associated with node J, respectively. However, Fuzzy ART inherently yields problems according to the range of learning parameter β. In the fast learning $\beta = 1$, prototype can be fast stable owing to update rule based on the fuzzy AND operator ($\wedge$) between input vector and weight vector. The proposed algorithm is based on that fast learning is applied to the committed node, whereas slow learning is applied to the uncommitted node.

4. ANOVA(Analysis of Variance)

Five groups are clustered using ART and ANOVA(Analysis of Variance) is performed to evaluate the discrimination among the five groups. Table 8 and Table 9 shows the differences between K-means(K=5) and Fuzzy ART. In the case of using Fuzzy ART, each group was significantly different on all factors(P<0.01) in Table 9. But in the case of K-means, each group was sigficantly different on factor 1, factor 2, factor 3, factor 4, and factor 6 in Table 8. Thus, it can not be explained that factor 5 and factor 7 differently affect each group. Consequently, using Fuzzy ART for consumer segmentation showed higher performance than using K-means in this study.

Table 8 ANOVA(Analysis of Variance) for K-means

Factors \ Groups	Group 1 (65)	Group 2 (15)	Group 3 (91)	Group 4 (93)	Group 5 (98)	F	Sig.
Factor 1	-0.48180	-0.34839	0.57087	-0.74052	0.53795	40.491	0.000^{***}
Factor 2	-0.85739	2.22996	-0.00981	0.16545	0.12243	48.058	0.000^{***}
Factor 3	0.08217	0.13690	-0.61989	-0.25479	0.76022	7.315	0.000^{***}
Factor 4	1.01528	1.23371	0.27791	-0.87905	-0.28665	18.490	0.000^{***}
Factor 5	0.31527	-0.21980	-0.38683	0.42240	-0.21894	2.582	0.044
Factor 6	-0.38145	-1.36017	0.69813	0.18265	-0.39518	7.225	0.000^{***}
Factor 7	-0.32669	-0.67184	-0.12843	-0.12035	0.55183	2.806	0.031

*** P<0.01

Table 9 ANOVA(Analysis of Variance) for Fuzzy ART

Factors \ Groups	Group 1 (47)	Group 2 (58)	Group 3 (47)	Group 4 (134)	Group 5 (76)	F	Sig.
Factor 1	0.78096	0.35821	0.34592	0.26250	0.40871	41.206	0.000^{***}
Factor 2	0.42859	0.24760	0.68322	0.37366	0.60215	56.027	0.000^{***}
Factor 3	0.41635	0.45165	0.30704	0.69450	0.21715	8.890	0.000^{***}
Factor 4	0.44597	0.80702	0.47866	0.33552	0.31573	12.798	0.000^{***}
Factor 5	0.31030	0.72428	0.41377	0.45768	0.65438	48.947	0.000^{***}
Factor 6	0.36902	0.40300	0.47289	0.72851	0.45646	5.583	0.001^{***}
Factor 7	0.43181	0.48856	0.77357	0.39425	0.28101	4.290	0.003^{***}

*** P<0.01

5. Frequency Analysis

After cluster analysis, the characteristics and differences among each group are compared by frequency analysis as shown in Table 10.

Table 10 Frequency Analysis

	Group 1 (47)	Group 2 (58)	Group 3 (47)	Group 4 (134)	Group 5 (76)
Gender	Male(30) Female(17)	Male(35) Female(23)	Male(19) Female(28)	Male(56) Female(78)	Male(45) Female(31)
Age	Teens (62%) Twenties (38%)	Teens (31%) Twenties (60%) Thirties (9%)	Teens (65%) Twenties (35%)	Teens (39%) Twenties (55%) Thirties (6%)	Teens (43%) Twenties (52%) Thirties (5%)
The frequency of purchase	Below 2 (73%) 3~5 (27%)	Below 2 (49%) 3~5 (24%) 6~9 (27%)	Below 2 (50%) 3~5 (29%) 6~9(13%) 10 Above (8%)	Below 2 (37%) 3~5(19%) 6~9(27%) 10 Above (17%)	Below 2 (35%) 3~5 (41%) 6~9 (24%)
Interests	Literature & Fiction (26%) Foreign Language (21%) Textbook & Technical (16%)	Textbook & Technical (35%) Self-help book (25%) Business & Management (13%)	Literature & Fiction (29%) Textbook & Technical (18%) Self-help book (14%)	Literature & Fiction (35%) Foreign Language (24%) Self-help book (17%)	Foreign Language (27%) Textbook & Technical (20%) Business & Management (11%)

6. Conclusion

In Table 9, group 1 has a great score on factor 1 which means factor 1 strongly affects the purchase intention of this group. This can be called as an economical group. Thus, the service which can provide proper discount coupons for their interesting fields such as literature, fiction and foreign language is required. Group 2 has a great score on factor 4 and factor 5. This group usually uses online bookstores to get information and to compare books. Providing image contents about books and mailing information about their interesting fields, such as technical books and self-help books, is required for this group. Group 3 has a great factor score on factor 2 and factor 7. This group is strongly affected by other people's opinion and advertisement. The service which can provide comments left by other readers in their interesting fields such as literature, fiction and technical books is required for this group. In addition, it is also necessary for online bookstores to give them information about the famous writer and the recommendation lists. Group 4 has a great factor score on factor 3 and factor 6. This group also wants to get more information about books and discount services. As the consumers of group 4 tend to make a list of books for purchase in advance, quick delivery service or informing them of exact delivery time would satisfy their needs. Group 5 has a great factor score on factor 2 and factor 5 and this group is also strongly affected by advertisement and information. The consumers of this group are mainly interested in foreign language and technical books. Thus, the service which can provide advertisement and information about the books written by the famous writer is required. In this study, consumers' characteristics and lifestyle are considered to understand and analyze the important factors which influence purchase intention of the consumers using online bookstores. Seven factors were extracted and the factor scores for each respondent were obtained by factor analysis. To evaluate the effect between the seven factors and respondents, five groups were classified using the factor scores as an input data of Fuzzy ART. Finally, through the ANOVA analysis, it is identified that using Fuzzy ART for consumer segmentation is more effective than using K-means method. But as the respondents of this study are mostly students who experienced in using online bookstores, the result would appear differently according to the consumers' age and experiences.

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