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SEGMENTATION OF ONLINE SHOPPERS BY MEANS OF AN INTEGRATED DATA MINING APPROACH: A CASE STUDY

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Abstract

Recent findings indicate that online shopping is increasing significantly all over the world. Segmentation of online shoppers is an important issue of online firms. This paper handles this issue related to internet-related lifestyle descriptors which are effective in determining segments by an integrated data mining approach. The integrated data mining approach which is used in this study consists of self-organizing map (Kohonen) neural network and association rule mining method which are integrated to identify segments of online shoppers. Similar to the international trends, online shopping has become one of the most noticeable yields of internet in Turkey and the research is conducted in a highly industrialized region. For this multi-dimensional analysis, a visual and a robust data mining software Clementine 8.1 is used for the integrated segmentation task in data mining.

Keywords: *Segmentation, Online Shopping, Data Mining, Kohonen, Association Rules.*

Özet:*. Son zamanlarda elde edilen bulgular, internetten yapılan alışveriş hacminin tüm dünyada arttığını göstermektedir. İnternetten alışveriş yapan tüketicilerin bölümlendirilmesi de doğal olarak söz konusu işletmelerin etkin bir şekilde çözmesi gereken önemli bir sorundur. Bu çalışmada, internetten alışveriş yapan tüketicilerin internet ile ilişkili yaşam biçimlerine göre bölümlendirilmesi problemi bütünleşik bir veri madenciliği yaklaşımı ile incelenmektedir. Araştırmada kullanılan bütünleşik veri madenciliği yaklaşımı, Kohonen sinir ağı ve birliktelik kuralı madenciliği yöntemlerini içermektedir. Bu* *iki yöntemin bütünleşik halde kullanımı ile internetten alışveriş yapan tüketicilerin çeşitli pazar bölümlerine ayrılması amaçlanmıştır. Uluslararası eğilimlere benzer olarak, Türkiye'de de alışveriş internetin en önemli kullanım alanlarından biri olmuştur ve araştırma sanayileşmenin oldukça yüksek olduğu bir bölgede yürütülmüştür. Araştırmada kullanılan çok boyutlu analiz için, Clementine 8.1 adlı bir veri madenciliği yazılımı kullanılmıştır.*

Anahtar Kelimeler: *Bölümlendirme, İnternet Üzerinden Alışveriş, Veri Madenciliği, Kohonen, Birliktelik Kuralları.*

1. Introduction

The use of the internet as a shopping and purchasing medium is significantly expanding all over the world. Thus, the internet has become an important channel in international marketing and a "new" market has been created (Limayem al., 2000: 421-422; Yu, 2006: 380; March, 2004: 297; Kwan et al. 2005: 189-190). This "new" online market has offered new opportunities to consumers. For instance, the internet lets online shoppers to gather every kind of information and to compare products in little time. In addition, it is also thought to have disadvantages such as security issues, privacy issues and etc. (Lokken et al. 2003: 127). In other words, online shoppers have different attitudes, perceptions and behaviours than non-online shoppers. This fact makes the issue of online market segmentation and the determination of segmentation variables very crucial (Tsai and Chiu, 2004: 265; Allred et al. 2006: 310-311). As it is known, efficient segmentation helps companies to understand their customers better. Therefore, tailored marketing strategies can be developed for customers to increase both satisfaction and expected profits (Hung and Tsai, 2006; Lin et al. 2004: 601-603; Limayem et al., 2000: 422; Song et al. 2001: 157). In other words, succesful segmentation allows marketing managers to efficiently target their marketing efforts (Hui and Wan, 2006). Recently, several demographic and socio-economic online segmentation attempts were made, but there is still little attention paid to segmentation based on internet-related lifestyle which is considered to be an important descriptor (Allred et al. 2006: 311; Brengman et al. 2005: 79; Lee and Park, 2005: 146; Hsieh, 2004: 625). In addition, segmentation method also affects the efficiency of segmentation results. Traditional statistical tools such as discriminant analysis, logistic regression, multiple regression, factor analysis, K-means and etc. have been widely applied for segmentation and other tasks in marketing discipline. But these methods have deficiency in extracting previously unknown patterns and ultimately comprehensible information. Data mining approach which provides easy and clear results, overcomes this deficiency. Data mining uses a broad family of computational methods such as statistical analysis, decision trees, neural networks, rule induction and graphic visualization, and can find implicit and potentially useful information (Hand, 2003: 12-13; Iglesia et al. 2006: 899). In spite of this, most of the existing literature focuses on segmentation of online shoppers with the help of traditional statistical methods.

The aim of this paper is to identify segments of online shoppers based on their internet-related lifestyle characteristics. An integrated data mining approach which includes a self-organizing map neural network and an association rule mining is used in the study. First, a self-organizing map neural network is implemented to find clusters based on natural associations, and then Apriori association rule algorithm is applied to each cluster to find sub-segments based on internet-related lifestyle characteristics of respondents. The results obtained in this paper lead to a better understanding of this online market from a internet-related lifestyle perspective and help online companies develop more effective marketing strategies.

2. Literature Review

2.1. Self-organizing Map Neural Networks

A typical artificial neural network consists of a number of simple processing elements called neurons. Each neuron is connected to other neurons by means of directed communication links, each with an associated weight. The weights represent information being used by the net to solve a problem. Artificial neural networks are usually modelled into one input layer, one or several hidden layers and one output layer (Bloom, 2004: 724-725). The learning algorithms of artificial neural networks can be divided into two categories which are supervised and unsupervised algorithms. In supervised learning, the network has its output compared with a known answer, and receives feedback about any errors. Inputs and outputs are both necessary for training the network in supervised artificial neural networks while an unsupervised artificial neural network requires only the inputs (Kuo et al. 2002: 1477).

Kohonen’s self-organizing map neural network, a variation of neural computing networks, is a non-parametric approach that makes no assumptions about the underlying population distribution and is independent of prior information (Kiang et al. 2006: 37). In other words, a self-organizing map is a subtype of artificial neural networks which performs clustering using an unsupervised learning algorithm. Thus, only input variables are required (Kuo et al. 2002: 1477; Kuo et al. 2006: 314).

2.2. Association Rule Mining

Similar to clustering, inducing association rules is another basic task of data mining that can be defined as one process of extracting relationships in huge databases (Angiulli et al. 2004: 217-218). Unlike traditional rule induction that examines one variable at a time, association rules evaluate a combination of variables at a time; therefore, better represent correlated features (Wang et al. 2005: 58-59). An association rule can be represented with if-then statements (Ghosh and Nath, 2004: 124; Lai and Yang, 2000: 4):

If <some conditions are satisfied> then <predict some values of other attribute(s)>

The conditions after the "if" and "then" parts are termed as antecedent and consequent, respectively. This relationship can be represented as antecedent ⇒ consequent (A⇒B) and each such relationship that holds between the attributes of records in a database fulfilling some criteria is termed as an association rule (Tsai and Chen, 2004: 685-686).

An association rule has two parameters which are support and confidence. These parameters include information about the accuracy of the rule. Support is simply the number of transactions that include all items in the antecedent and consequent parts of the rule. In other words, support indicates the frequency of a pattern. Confidence can be defined as the the ratio of the number of transactions that include all items in the consequent as well as the antecedent (namely, the support) to the number of transactions that include all items in the antecedent. It denotes the strength of an association (Sung et al. 2003: 1449-1450; Bounsaythip and Rinta-Runsala, 2001: 23-24).

2.3. Segmentation of Online Shoppers

The relevant literature includes studies which investigate the factors affecting online shopping (LIMAYEM et al., 2000), compare online and non-online shoppers (Lokken et al. 2003), examine the shopping and buying behavior of younger and older online shoppers (Sorce et al., 2005) and identify the role of gender and educational level on the attitudes of Internet users (Hui and Wan, 2006). There are also papers which aim to profile internet buyers in different countries (Lynch and Beck, 2001) and to model how socio-demographic variables, attitudes and beliefs towards internet shopping affect both the adoption decision and usage of the online shopping channel (Soopramanien and

Robertson, 2007). There are also other market segmentation studies which include the use of self-organizing map neural network (Kiang et al., 2004; Hsieh, 2004; Hung and Tsai, 2006), linear and non-linear methods (Bloom, 2004),

As seen, the existing literature includes various studies of online shopper segmentation with different approaches and methods but, gives little attention to segmentation studies based on internet-related lifestyles (Allred et al., 2006; Muthitacharoen et al., 2006; Brengman et al., 2005; Rohm and Swaminathan, 2004). Besides, most of these studies includes the use of traditional statistical methods and provides little insight to the use of data mining methods for the segmentation of online shoppers (Song et al., 2001; Lee et al., 2004; Chang et al., 2007; Vellido et al., 1999). Therefore, the issue of segmentation based on internet-related lifestyles with the help of a data mining approach has been studied here to fill in a gap in the literature.

3. Research

3.1. Population and Sampling Size

The online shoppers' population used in this study is sampled such to have an occupation and have had once bought a product via internet. Ten different occupational groups are defined for the research. These occupational groups are defined as businessman, academician, medical doctor and dentist, teacher, engineer, lawyer, accountant/financial advisor, tradesman, research assistant and economist. The raw data are acquired by a questionnaire. Random sampling is chosen as the sampling method. 205 questionnaire forms have been returned out of 1300 distributed. The questionnaire contains 7 demographic items (gender, marital status, age and etc.), 9 internet usage and internet behaviour items (internet usage, the most important reason for using internet, online shopping frequency, hours being online per day and etc.) and 38 internet-related online shopping lifestyle items (Allred et al., 2006; Brengman et al., 2005). Special attention is devoted to the issue of construct equivalence and translation equivalence concerning the internet-related lifestyle scale of Smith and Swinyard, and such problems are minimized. Lifestyle characteristics of the respondents are measured by a five-point Likert scale where the answers 1, 2, 3, 4 and 5 refer to "I strongly disagree", "I disagree", "I have no idea", "I agree" and "I strongly agree" respectively. Socio-demographic and internet usage characteristics of the respondents are given in Table 1 below.

Table 1 Socio-Demographic and Internet Usage Characteristics of Online Shoppers (n=205)

Variable	Frequency	%	Variable	Frequency	%
Gender			**Monthly Income**		
Male	124	60.5	Less than 1000 TRY	109	53.2
Female	81	39.5	1000-3000 TRY	38	18.5
Age			3001-5000 TRY	20	9.8
20-29	110	53.7	Over 5000	38	18.5
30-39	51	24.9	**Internet Usage**		
40-49	32	15.6	Less Than 1 Year	7	3.4
50-59	12	5.9	1-3 Years	29	14.1
60 years and older	0	0.0	4-5 Years	0	0.0
Education			More Than 5 Years	169	82.5
Primary School	4	2.0	**Internet Usage Location**		
Middle School	0	0.0	Home	34	16.6
High School	16	7.8	Work	160	78.0
B. Sc.	97	47.3	Other	11	5.4
M.Sc.	59	28.8	**The Most Important Reason Of Internet Usage**		
Ph.D.	29	14.1	Shopping	46	22.4
Marital Status			Fun	11	5.4
Married	96	46.8	Information	22	10.7
Single	109	53.2	Business	114	55.6
Widowed	0	0.0	E-mail	12	5.9
Number of Household			**Hours Online Per Day**		
1	62	30.2	Less Than 1 Hour	36	17.6
2	44	21.5	1-3 Hours	99	48.3
3-4	67	32.7	More Than 3 Hours	70	34.1
5 and more	32	15.6	**Internet Issues That Are Faced Mostly**		
Occupation			Security	81	39.5
Businessman	28	13.7	High Cost	7	3.4
Academician	16	7.8	Low Speed	117	57.1
Doctor&Dentist	13	6.3	**Shopping Frequency Per Year**		
Teacher	12	5.9	Less Than 3 Times	74	36.1

Engineer	20	9.8	3-5 Times	99	48.3
Lawyer	5	2.4	6-12 Times	32	15.6
Accountant & Financial Adviser	8	3.9	**Spending Amount Per Year**		
Tradesman	8	3.9	Less Than 250 TRY	23	11.2
Research Assistant	54	26.3	250-499 TRY	113	55.1
Economist	41	20.0	500-1000 TRY	38	18.5
			More Than 1000 TRY	31	15.1
Products That The Respondents Buy Mostly			**Products That The Respondents Buy Mostly**		
Software	21	10.2	Tickets For Theatre, Opera, Concert, Cinema	38	18.5
Book/Magazine	80	39.0	Electronics	5	2.4
CD, DVD, Cassette etc.	10	4.9	Finance Products	14	6.8
Tourism Products	22	10.7	Health/Personal Care Products	1	0.5
Travel Products	14	6.8			

Note: Number of cases under frequency excludes missing observations.

3.2 Steps of the Model

Clementine 8.1 which is used here for the segmentation model, works with data streams. Every operation on the stream is exploited by the nodes that are connected to each other with arrows. A basic stream consists of a source node, a field/record node and an output node. The segmentation model can be seen in Figure 1.

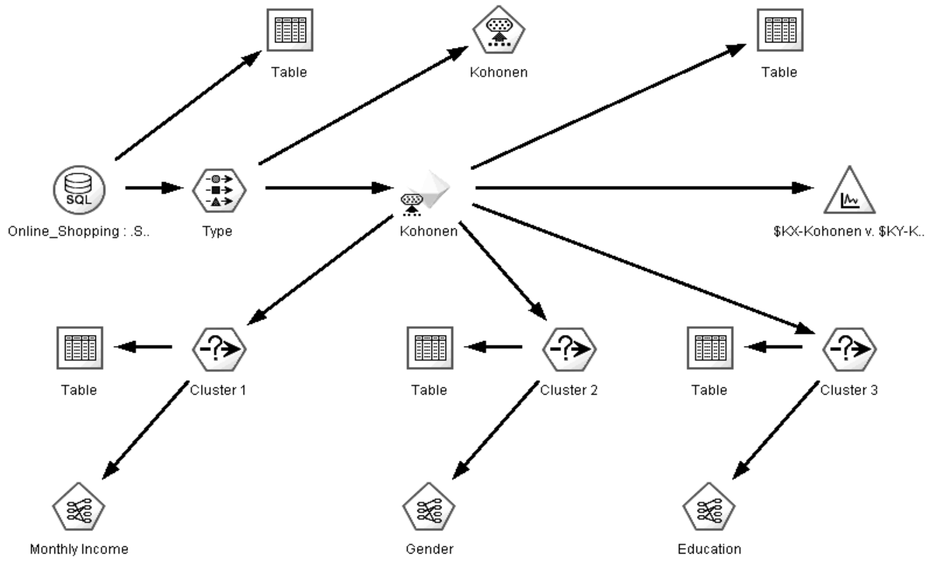

Figure 1 The Segmentation Model

As it is seen from Figure 1, the model starts from a “database” node and goes on with “type” node which is used to specify the field types. After specifying the field types, a “Kohonen” modelling node is added to “type” node. Then “Kohonen” node is executed for all the items. Eight clusters are found with the help of “Kohonen” node. The most important three clusters and their attributes are shown in Table 2.

In order to obtain segments based on internet-related lifestyle characteristics from these clusters, “select” nodes are applied to the records of each cluster. “Apriori” modelling nodes are connected to the “select” nodes.

Table 2 Results of Kohonen Modelling

Most Important Attributes	**Cluster 1 (X = 0, Y = 0)**	**Cluster 2 (X =0, Y =2)**	**Cluster 3 (X = 3, Y = 2)**
Age	20-29 30-39 40-49	20-29	30-39 40-49
Most Important Reason	Shopping	Business	Business E-Mail
Education	Bachelor of Science Master of Science Doctor of Philosophy	Master of Science	High School Bachelor of Science
Gender	Male Female	Male Female	Male
Hours Online Per Day	1-2 Hours	More Than 3 Hours	Less Than 1 Hour 1-2 Hours
Internet Usage	More Than 5 Years	More Than 5 Years	1-3 Years
Marital Status	Married Single	Married Single	Married Single
Monthly Income*	1,000-3,000 TRY 3,001-5,000 TRY	Less Than 1,000 TRY	More Than 5,000 TRY
Number of Household	1 2	1 2	More Than 4
Occupational Group	Engineer Lawyer	Research Assistant	Businessperson
	Count 45 (22%)	**Count 54 (26%)**	**Count 26 (12%)**

In each “Apriori” modelling node, the statements measuring internet-related lifestyle characteristics of the respondents are specified as antecedents and other items (i.e. demographics and internet behaviour) as consequents. After the execution of each “Apriori” modelling node, various association rules are extracted. Association rules that have the largest support and confidence parameter values from each cluster are listed in Table 3.

Table 3 Sample Association Rules

Consequent	Antecedents*
Monthly Income = 1000-3000 TRY *Rule 1* *From cluster 1*	I think internet shopping would avoid the hassle of local shopping= "5" & I enjoy buying things on the internet="4" & I find the internet ordering process hard to understand and use="1" & I think internet shopping offers better selection than local stores="5" & I often go to the internet for product reviews or recommendations="5"
Gender = Female *Rule 2* *From cluster 2*	I would shop on the internet more if the prices were lower="4" & I dislike the idea of shipping charges when buying on the internet="5" & I worry about my credit card number being stolen on the internet="5" & I like to go shopping with my friends="5" & I like the help and friendliness I can get at local stores="5"
Education = High School *Rule 3* *From cluster 3*	I dislike the idea of shipping charges when buying on the internet "5" & I would like not having to leave home when shopping="4" & I worry about my credit card number being stolen on the internet="5" & Buying things on the internet scares me="4" & I find the internet ordering process is hard to understand and use="5"

(*) 1="I strongly disagree", 2="I disagree", 3="I have no idea", 4="I agree", 5="I strongly agree"

Rule accuracy is the most important measure of rule quality and it is also called precision in information retrieval (Flach and Lavrac, 2003). An association rule has three parameters (i.e. support, confidence and lift) which give information about the accuracy of the rule. Support, confidence and lift parameter values calculated for this study are given in Table 4.

Table 4 Analysis Accuracy

Association Rules	Support (%)	Confidence (%)	Lift
Rule 1	21.7	100.0	1.769
Rule 2	17.4	100.0	1.769
Rule 3	15.9	90.0	1.668

3.3 Discussion

As shown in Table 3, for the extracted association rule in the first cluster where the consequent is “monthly income”, the segment within “1000-3000 TRY” monthly income range strongly favour online shopping. This segment can be called “online shopping lovers”. They really like online shopping because their most important reason to use internet is shopping as seen from Table 2. They think that online shopping offers better selection than local stores. They don’t like the hassle of local shopping and they have higher computer literacy and they are better educated. There is another segment consisting of female respondents that belongs to the second cluster. Lifestyle characteristics of this segment is slightly different from the first segment. These respondents think that shipping charges, high prices and security issues are the main drawbacks of online shopping. They mention that they would shop on the internet more if the prices were lower, but they also think that social interaction with other people is absolutely important. This segment can be named as “social online shoppers”. The last association rule in Table 3 is associated with male businesspersons having “high school” education and lack of trust for online shopping security. They find the internet ordering process hard to understand and use. This segment is wealthier than other segments. These respondents can be called “suspicious online shoppers” as they hold the most negative opinion on online shopping.

The findings of this research include similarities with the results of the study that belongs to Brengman et al. (2003) and Allred et al. (2006). The results of this paper also show that better-educated respondents seem to be less concerned with security issues and males are more concerned with security issues as seen in Table 2 and Table 3. In addition, social online shopper segment consists of female respondents. Similar results were found in the paper that belongs to Hui and Wan (2006). According to Lokken et al. (2003), there are persistent concerns about the security of online shopping which is valid for the "suspicious shoppers" segment found here.

4. Conclusions

The aim of this study was to to identify segments of online shoppers based on their internet-related lifestyle characteristics. The segmentation task was accomplished with the help of an integrated data mining approach which includes a self-organizing map neural network and association rule mining in order to support the online shopping management. As data mining results obtained here indicate, three distinct segments associated with monthly income, gender and education can be identified based on internet-related lifestyle characteristics.

Although most of the previous online shopper segmentation studies in the literature are based on demographic and socio-economic descriptors, they have not provided results which sufficiently support the marketing strategies of online companies. As such in the literature, little attention has been given to an important descriptor that is the internet-related lifestyle characteristics of online shoppers. Therefore, the issue of market segmentation in the marketing systems of online firms has been studied here to fill in a gap in the literature. Not only the main findings of this study can be used to support marketing strategies from a internet-related lifestyle perspective, but also this integrated data mining approach can be used for the solution of various other marketing decision problems.

5. Limitations and Recommendations

Like many other researches, the present research has some limitations. First, the research setting is limited to online shoppers in a specific geographical region. Consequently, the samples of this study may not be representative for broader populations of Turkey. Secondly, the profiles of these segments may change through time. This implies that these kinds of researches should be updated. Various data mining methods may have different disadvantages, so various integrated data mining approaches could be used to increase the accuracy of data mining results.

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