Tarım Ekonomisi Dergisi
Turkish Journal of Agricultural Economics
ISSN 1303-0183
http://journal.tarekoder.org

Determination of Factors Affecting The Consumption of Private Label Food Products by Using Artificial Neural Networks and Logistic Regression Model: Case of İzmir Province*

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*"The manuscript is part of a PhD thesis which is completed in the Department of Agricultural Economics of Ege University".
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Geliş Tarihi: 03.11.2017
Kabul Tarihi: 30.11.2017

Tarım Ekonomisi Dergisi
Cilt:23 Sayı:2 Sayfa:311-322

DOI 10.24181/tarekoder.369498

Abstract

In this study, it was aimed to determine the factors affecting the consumption of the market brand food products for consumers living in İzmir with the help of a model, as well as to apply and compare two alternative methods used in model estimation. The primary data that constitute the main material of the study were obtained as a result of the survey conducted with 650 consumers living in the central provinces of İzmir. The dependent variable in the model is "Consumers do not consume or consume private label food products". In the study, twenty-five independent variables were examined under seven main topics that could influence consumers towards private label food product consumption. Seven main topics: market shopping behaviors, important elements in food shopping, package and price tags reading habits, food shopping characteristics, social characteristics, guest hospitality frequency and demographics. Since the dependent variable is a dichotomous variable, logistic regression and artificial neural network methods, as its alternative, are used. According to the results of both methods, while the most effective variable in consumption of private label food products by consumers participating in the research was income variable, the shopping frequency, and behavioral factors during shopping were observed as other effective variables. When the application results of two alternative methods used in the study are assessed; the predictive power (77.23%) of the model obtained using artificial neural network method is higher than the model obtained by logistic regression method (76.15%).
Key words: Private Label, Logistic Regression, Artificial Neural Network, Consumer Behavior

Yapay Sinir Ağı ve Lojistik Regresyon Modeli Kullanılarak Market Markalı Gıda Ürünleri Tüketimini Etkileyen Faktörlerin Belirlenmesi: İzmir İli Örneği
Özet

Bu çalışmada, İzmir İli'nde yaşayan tüketiciler için market markalı gıda ürünü tüketimini etkileyen faktörleri bir model yardımı ile belirlemenin yanında model tahmininde kullanılan alternatif iki yöntemin uygulaması ve karşılaştırılması amaçlanmıştır. Çalışmanın ana materyalini oluşturan birincil veriler, İzmir İli merkez ilçelerde yaşayan 650 tüketici ile yapılan anket çalışması sonucunda elde edilmiştir. Çalışmada tüketicilerin market markalı gıda ürünü tüketimlerini etkileyebileceği düşünülen; market alışverişi davranışları, gıda alışverişinde önem verilen unsurlar, ambalaj ve fiyat okuma alışkanlığı, gıda alışverişi özellikleri, sosyal özellikler, konuk ağırlama sıklığı ve demografik özellikler olmak üzere yedi ana başlık altında yirmi beş bağımsız değişken incelenmiştir. Modeldeki bağımlı değişken, "tüketicilerin market markalı gıda ürünü tüketmesi ya da tüketmemesidir". Bağımlı değişkenin iki sınıflı bir değişken olması nedeni ile çalışmada lojistik regresyon ve onun alternatifi olan yapay sinir ağları yöntemleri kullanılmıştır. Her iki yöntemin de sonuçlarına göre, araştırmaya katılan tüketicilerin market markalı gıda ürünlerini tüketmesinde en etkili değişken gelir değişkeni olur iken, alışveriş sıklığı, alışveriş sırasındaki davranış faktörleri etkili diğer değişkenler olarak gözlenmiştir. Çalışmada kullanılan alternatif iki yöntemin uygulama sonuçları değerlendirildiğinde, yapay sinir ağı yöntemi kullanılarak elde edilen modelin tahmin etme gücü (%77.23) lojistik regresyon yöntemi ile elde edilen modelden (%76.15) daha yüksektir.
Anahtar kelimeler: Market Markası, Lojistik Regresyon, Yapay Sinir Ağları, Tüketici Davranışları

1.INTRODUCTION

The quality and the cost of products are the most essential common requirements for today's consumers. Most people prefer to purchase low cost and high-quality products, particularly because of the increasing hardships in the current economic conditions. This customer preference was able to bring the private label brands into the food retail industry. Private label products are goods produced by a particular retailer or procured externally by retailers and sold using the name of their own label or store brand (Baltas, 1997).

Current food retailers, like most national brand manufacturers, must understand the consumers, determine their product requirements and desires, notice the alterations in their requirements and provide a variety of advantages to customers that create a distinctive enhancement on their products as opposed to other brands (Orel, 2004).

The consumer behavior towards private brand products which are rapidly developing in Turkey in parallel with the increase in customer demand during the financial crisis in 2001, which were already very popular in USA and Europe for many years, very important for the marketing targets of private brand producers and retail markets.

Although private label brands have been dealt with in the world for the first time in 1965 when Frank and his colleagues examined the purchasing behavior of households, researchers have begun to show more interest in the subject in the 90's. Richardson et al. (1996) aimed to categorize household members' propensity for private label brands; and came to a conclusion that the income and risk perception of the household members caused a negative effect on the preferences for store brands, while the household size had a favorable effect. Baltas (1997) analyzed the tendency of British consumers to buy private label brands, using logistic regression analysis, under four main categories and three independent variables; market habits, reasons for buying private label, the relationship between private label and consumer diagrams, and customer appraisal for each category evaluated. The model outcome was 0.81 rate of correct classification.

Consumer research is one of the most difficult types of research. In recent years, modeling studies on consumers have been frequently analyzed using logistic regression and similar statistical methods. Artificial neural networks, that are regarded as alternatives to statistical methods, are limited in their modeling efforts. Kumar et al. (1995) assessment outcomes of their experimental research using an artificial neural network and the logistic regression analyses resulted in qualitative data. According to the authors; If logistic regression interpretability, outcome methods, statistical tests and extrapolative attributes are applicable; plain artificial neural network, correct classification, mixed interference and interpolative attributes can also be applied. Agrawal and Schorling (1996) experimented on comparing the logistic regression on a retailer's three highest selling goods with the artificial neural network's estimative probability. West et al. (1997) examined the customer inclination towards store characteristics and quality using the artificial neural network, the logistic regression and the discriminant analyses. Gan et al. (2005) attempted to analyze the banking preferences of clients by using a logistic model with a multi-layered, feed forward artificial neural network analysis and other possible neural network methods and compared the estimative probability of these methods.

In Turkey; though there have been many different studies conducted on consumer attitudes towards store branding, shopping habits and store brand choices (Kurtuluş et al., 2001, Aydın, 2003, Orel, 2004, Akpınar, 2004, Albayrak and Dölekoğlu, 2006, Akın and Yoldaş, 2010), and even some of these studies were concentrated in İzmir (Savaşçı 2002, Yurtgüder 2004, Fettahlıoğlu 2008); A study showing the factors that affect the consumption of private label food products in İzmir has never been seen until now. The results of this study are expected to hold a particular significance for local retail traders and small manufacturing businesses as it is examining the customer behavior towards food products in particular and the results could perhaps give them a chance to determine the improvements they could make in the market. It is also expected that this study, which includes a comparative analysis of methods used for the analysis of data and application of artificial neural networks, will make a significant contribution to the current literature.

2. MATERIALS and METHODS

The main material of this study was obtained from the original qualitative data collected from the survey that implemented face-to-face interviews with consumers who reside in the central district of Izmir.

2.1. Data Collection

Every household in central İzmir is considered to be the population in the study if one individual is considered to be the frequent grocery shopper in each family. The total sample size was computed by estimating the population proportion (Newbold, 1995):

$$n = \frac{Np(1-p)}{(N-1)\sigma_p^2 + p(1-p)} \qquad (1)$$

N is the number of total households living in central İzmir (N=806.406). By this formula, the minimum sample size for the grocery shopping consumers in central İzmir was found as about 384 with a 95% confidence interval and a 5% margin of error. However, because the artificial neural network analysis requires a large number of samples during the modeling phase, the sampling size, initially aimed to be 650, was able to reach its intended amount. The surveys were gathered during the last few months of 2010 by face-to-face interviews, given by the consumers who had just completed their grocery shopping.

2.2. Methods

In order to determine the factors affecting the consumption of the private label food product, two alternative methods were used: logistic regression and artificial neural networks methods.

Logistic regression, one of the regression analyses that define the relationship between an answer variable and one or more explanatory variables; is often one of the most frequently used methods when the outcome variable is divided into two or more possible values.

The P_i probability rate in this logistic model, or in short known as 'logit', is shown as,

$$P_i = \exp(\sum_{k=0}^{p} \beta_k x_{ik}) \Big/ (1 + \exp(\sum_{k=0}^{p} \beta_k x_{ik})) \qquad (2)$$

and it is referred to as the logistic function. Since the dependent variable has a binary variable in this model, the error term has a distribution with mean zero and variance equal to P(1-P). The error term with these parameters has a binomial distribution and the analysis relies on this theoretical basis. The assumptions on the logistic model are briefly described as (Tatlıdil, 1992):

1. $Y_1, Y_2, \ldots, Y_n$ values are statistically independent,
2. Independent variables (x_k) are independent of one another,
3. Y_i (0,1) i=1,2,3, . . ., n
4. $P(Y_i=1/x_i)=P_i$ i=1,2,3, . . ., n

Methods most often used for the logistic regression model's parameter estimations are the maximum likelihood method and the method of weighted least squares. After the coefficient estimations in the logistic regression analysis, adequate variables must be assessed for significance. There are three commonly used tests to determine whether the variables are significant or not in a logistic regression model. These tests are; the likelihood ratio test, the Wald test, and the score test, respectively. After the tests, the general significance must be assessed. In order to assess the general significance, G-test statistics, a test similar to the F-test in the multi-linear regression model, must be used with k-1 degrees of freedom and chi-square distribution. The correct classification rate is used in order to test the fit of the predicted model.

The artificial neural network (ANN) is a parallel and distributed data processing system inspired by the human brain. It uses adapted weight connections to connect each processing element to one another and each has its own input memory. ANN_s, in other words, are computer programs that imitate biological neural networks (Elmas, 2003).

A neural network consists of many simple processing units also referred to as neurons or nodes. Each node combines a number of incoming signals and produces an outgoing signal. The output of the node is determined by a transfer function that summarizes the weighted inputs, and an activation function that produces the output value. Often, a node also uses a bias, also called threshold, which is an incoming signal with a constant value. An activation function often produces an output signal in the range [0, 1] or [−1, 1]. The output signal might be an input for another neuron. A schematic diagram of a neuron is presented in Figure 1.

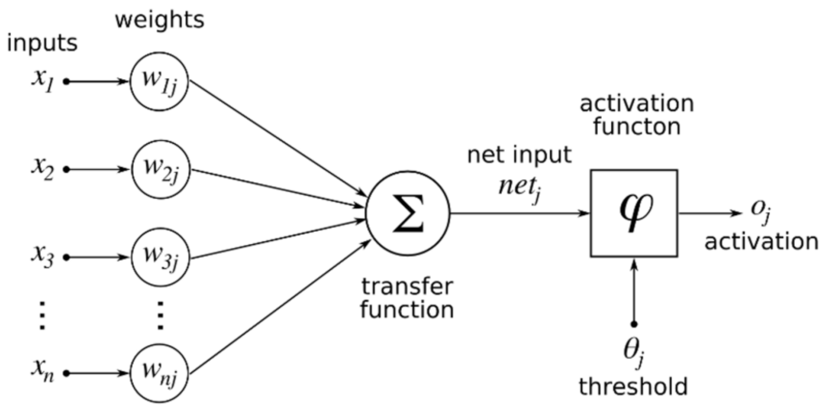

Figure 1. Model of a neuron in an artificial neural network

When artificial neurons congregated, they make up the artificial neural network. These neurons do not merge in a random order. Generally, most neurons come together in three layers and each layer comes together in parallel to one another to create the network.

The layer amount, the neuron amount in each layer, and the neurons' input and output links with one another are considered the architecture of an artificial neural network. ANN's are typically defined by three types of parameters; interconnections, learning processes, and layer amounts.

Currently, the most commonly used model of artificial neural networks is the multilayer perceptron network. Multilayer perceptron (MLP) is required to be trained before being used for prediction. Briefly, the learning method In MLP is to determine the weight connections by a calculation of the expected output. There are many enhanced learning algorithms in the literature, backpropagation algorithm as being the most commonly used algorithm among them.

Backpropagation algorithm minimizes the total of errors by optimizing the weights, with the gradient descent method (Bayramoğlu, 2007). There are also many non-linear optimization methods in learning other than the gradient descent method. Some of these methods can be listed as The Gradient Descent method, the Conjugate Gradients method, the Quasi-Newton methods, and the Levenberg-Marquardt method (Akın, 2001).

Neural networks offer a number of advantages, including requiring less formal statistical training, ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithms. Disadvantages include its "black box" nature, greater computational burden, proneness to overfitting, and the empirical nature of model development (Tu, 1996).

3. RESULTS and DISCUSSION

The process model for the consumer's decision to consume the private label food products is shown in Figure 2.

The factors involved in the model were examined in three groups: factors related to the important elements in food shopping, factors related to the reading habits of packaging and price tags when buying food products, factors related to the grocery shopping behaviors. Acknowledgements of consumers participating in the survey, of the appropriately prepared statements, were measured in five points Likert scale, prepared in three different ways.

First of all, the reliability of 14 statements, which were measured by the five-point Likert scale, was tested to determine the habits of grocery shopping. According to the results obtained, the level of homogeneity between 14 expressions is high. The Cronbach's alpha coefficient is 0.63 and is reliable. At the same time, there is a difference between the averages of 14 statements according to the results of Hotelling $T^2 = 2685.304$, $p = 0.000$ test, as well. According to these results, the scale used to determine the grocery shopping habits is reliable and valid. For this purpose, factor analysis was performed for 14 variables. As a result of the factor analysis, the problem of commonality and complex structure has been encountered. In order to overcome these problems, factor analysis deducted from 3 variable analyses was performed again. Expressions related to the risks of purchasing decisions of the consumers were prepared based on the risk descriptions stated in the works of Yurtgüder (2004) and Bardakci (2003).

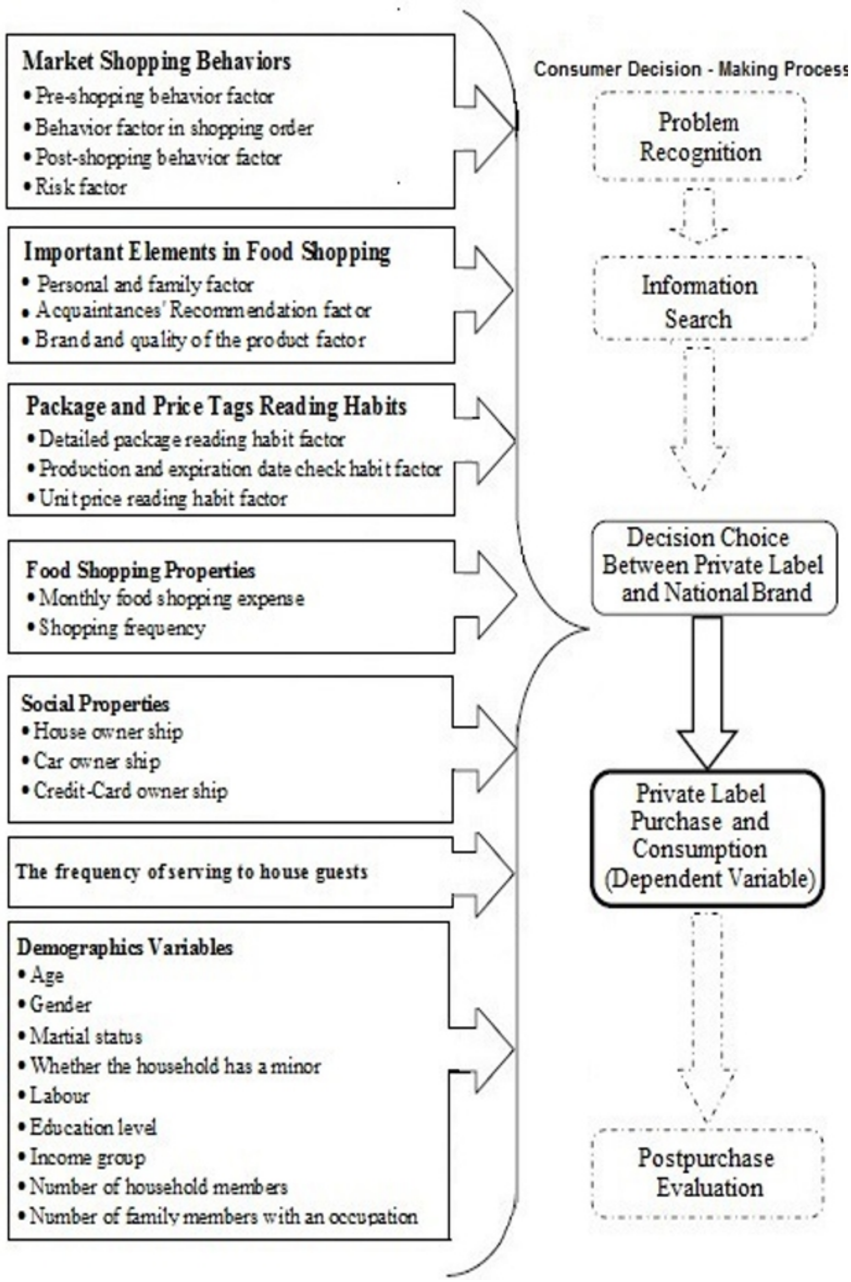

Figure 2. Consumer decision-making process model (Gan et al 2005)

The 10-statement scale used to identify the factors that consumers care about during grocery shopping; is reliable due to the resulting Cronbach's alpha coefficient of 77.6%. The difference between the averages of these statements is statistically significant (Hotelling T^2 = 1328.257, p = 0.000).

The price and unit price is the information contained in the price tags of the products that are on the shelf of the retailers. The other statements are on the packaging of food products. The 12-statement scale used to identify the packaging and price tag reading habits of the consumers during shopping; is reliable due to the resulting ratio of 0.76 and is valid according to the test results, as well (Cronbach = 0.76, Hotelling T^2 =4837.447, p=0.000).

As a result of the analysis, the factors related to important elements in grocery shopping, factors related to the habits of reading the packaging and price tags during grocery shopping and factors related to grocery shopping behaviors were determined (Table 1). Score test values on the factors obtained following the analysis were used in this model.

Table 1. Naming of Factor Groups

Grocery shopping behaviors	Pre-shopping behavior factor	Behavior factor in shopping order	Post-shopping behavior factor	Risk factor
I do my grocery shopping during discount days.	**0.792**	0.241	-0.016	-0.026
I examine the fliers of retailers and make price comparisons.	**0.791**	0.215	0.041	0.071
I go shopping to buy the cheapest price even if I do not need it.	**0.709**	0.024	0.03	-0.086
I buy the cheapest price because there are not big differences in quality due to legal regulations.	0.23	**0.831**	0.006	-0.11
I buy products in discount and in the promotion during grocery shopping without having to compare them with other products.	0.155	**0.823**	0.068	0.017
I definitely declare both my satisfaction and my complaints to the authority concerned.	-0.101	0.121	**0.882**	0.028
I tell both my satisfaction and my complaints to my close circle.	-0.003	0.072	**0.875**	-0.069
I return the product I purchased in cases if I am not satisfied with the product.	0.256	-0.205	**0.597**	0.228
I buy the products of the brand I bought and enjoyed before (Performance Risk)	0.187	-0.03	0.003	**0.713**
Since the satisfaction of my family and friends is important to me, I do not try new and different products and always use the same brand products (Social Risk)	-0.146	-0.34	0.163	**0.62**
I do not want to spend time buying a product with a brand that I don't know (Time Loss Risk)	-0.37	0.308	-0.039	**0.607**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.647
Bartlett's Test of Sphericity: 1606.363 (p: 0.000)

Important elements in food shopping	Personal and family factor	Acquaintances' Recommendation factor	Brand and quality of the product factor
Personal desires and wishes	**0.872**	0.031	0.182
Personal experiences	**0.728**	0.233	0.331
The wishes and desires of family members	**0.679**	0.373	0.226
Recommendations from experts in television programs	-0.044	**0.819**	0.144
Experiences of close friends	0.273	**0.774**	0.087
Personal desires and wishes	0.381	**0.674**	0.158
Brand of the Product	0.183	0.161	**0.899**
Quality of the Product	0.367	0.151	**0.813**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.827
Bartlett's Test of Sphericity: 1953.473 (p: 0.000)

Package and price tags reading habits	Detailed package reading habit factor	Production and expiration date check habit factor	Unit price reading habit factor
Nutritional value/Calories	**0.846**	0.070	-0.035
Origin of the product (country/region/city)	**0.795**	0.008	0.128
Ingredients list	**0.744**	0.234	-0.031
Manufacturer of the packaging	**0.677**	-0.071	0.323
Storage Conditions	**0.670**	0.249	-0.393
Expiry Date	0.069	**0.930**	-0.049
Manufacturing Date	0.128	**0.916**	0.024
Unit Price	-0.146	-0.009	**0.824**
Manufacturer	0.278	0.007	**0.761**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy : 0.731
Bartlett's Test of Sphericity: 1970.678 (p:0.000)

Two alternative methods have been used to determine the factors affecting the consumption of the private label food product: logistic regression and artificial neural network methods.

3.1. Determination of Factors by Logistic Regression Analysis

Assessments on dependent and independent variables used to estimate the model via the logistic regression analysis are shown in Table 2. The dependent variable in the model is derived from the answers "yes" or "no" given by the subjects to the question "Do you consume private label food products?" in the survey and for those who consume the private label food product, the dependent variable takes the value 1 while the value for the non-consumers is 0.

Table 2. Dependent and independent variables for model

Dependent Variables			
Do you consume private label food products?		Consume = 1 Not Consume = 0	
Independent Variables			
		Dummy1	Dummy2
Gender	male female	1 0	
Martial Status	married other	1 0	
Whether the household has a minor	yes no	1 0	
Labour	yes no	1 0	
House Owner	yes no	1 0	
Car Owner	yes no	1 0	
Credit Card Owner	yes no	1 0	
Educational Level	low medium high	1 0 0	0 1 0
Income Group	500-2.500 ₺ 2.501-4.500 ₺ 4.500 ₺ above	1 0 0	0 1 0
Monthly spending on food shopping	0-200 ₺ 201-400 ₺ 400 ₺ above	1 0 0	0 1 0
The frequency of serving to house guests	hardly ever day or night day and night	1 0 0	0 1 0
Shopping frequency	every day 1 or 2 times a week 1 or 2 times a month	1 0 0	0 1 0
Age			year
Number of household members			number of people
Number of family members with an labour			number of people
Pre-shopping behavior factor			factor score
Behavior factor in shopping order			factor score
Post-shopping behavior factor			factor score
Risk factor			factor score
Personal and family factor			factor score
Acquaintances' recommendation factor			factor score
Brand and quality of the product factor			factor score
Detailed package reading habit factor			factor score
Production and expiration date check habit factor			factor score
Unit price reading habit factor			factor score

The maximum likelihood method was used in order to estimate the model that was analyzed by the logistic regression analysis. In case of taking into consideration that the research in the study is cross-sectional; the predicted model's coefficient value (0.400) is quite a good level. Estimated model (Table 3) is significant according to the G-statistics result ($p(x^2(30)>223.179)=0.000$).

Table 3. Outcomes related to the model obtained as a result of the logistic regression analysis

	coefficient	standard error	Wald	significant	odds ratio
Constant **	-1.821	0.867	4.415	0.036	0.162
Pre-shopping behavior factor ***	0.533	0.115	21.543	0.000	1.705
Post-shopping behavior factor	0.066	0.105	0.389	0.533	1.068
Behavior factor in shopping order ***	0.743	0.122	37.259	0.000	2.102
Risk factor ***	-0.606	0.121	25.228	0.000	0.546
Personal and family factor	-0.093	0.114	0.660	0.416	0.911
Acquaintances' recommendation factor	-0.087	0.107	0.661	0.416	0.917
Brand and quality of the product factor ***	-0.408	0.113	12.951	0.000	0.665
Detailed package reading habit factor***	-0.610	0.111	30.000	0.000	0.544
Production and expiration date check habit factor***	0.308	0.109	8.025	0.005	1.361
Unit price reading habit factor	-0.062	0.124	0.250	0.617	0.940
Gender	-0.286	0.250	1.309	0.253	0.751
Age **	0.027	0.011	6.467	0.011	1.028
Martial status	-0.012	0.292	0.002	0.967	0.988
Educational Level			2.067	0.356	
Educational Level (Low)	-0.278	0.369	0.566	0.452	0.758
Educational Level (Medium)	0.115	0.287	0.161	0.688	1.122
Labour	-0.006	0.259	0.000	0.982	0.994
Number of household members	0.170	0.111	2.333	0.127	1.185
Number of family members with an labour	0.025	0.178	0.019	0.889	1.025
Whether the household has a minor	0.419	0.275	2.325	0.127	1.520
Income			4.391	0.111	
Income (500-2.500 ₺) **	1.056	0.523	4.079	0.043	2.875
Income (2.501-4.500 ₺)	0.722	0.511	1.992	0.158	2.058
Monthly food shopping expense			3.566	0.168	
Monthly food shopping expense (0-200 ₺) *	0.696	0.370	3.526	0.060	2.005
Monthly food shopping expense (201-400 ₺)	0.196	0.245	0.635	0.426	1.216
Shopping frequency **			8.594	0.014	
Shopping frequency (every day) **	0.948	0.386	6.032	0.014	2.581
Shopping frequency (1 or 2 times a week) **	0.665	0.258	6.643	0.010	1.944
The frequency of serving to house guests **			7.146	0.028	
The frequency of serving to house guests (hardly ever)	-0.647	0.463	1.951	0.163	0.524
The frequency of serving to house guests (day or night) ***	-0.701	0.264	7.049	0.008	0.496
House Owner	-0.105	0.225	0.217	0.641	0.901
Car Owner	0.032	0.229	0.020	0.888	1.033
Credit Card Owner	-0.206	0.221	0.875	0.350	0.813
G test-statistics	$P(\chi^2(30)>223.179)=0.000)$				
Nagelkerke R^2	0.400				
Hosmer & Lemeshow Test	$P(\chi^2(8)> 7.793)=0.454)$				

**** represent 1 % significant level, ** represent 5 % significant level, * represent 10 % significant level*

The model results stated that these variables (age, income, monthly food shopping expense, shopping frequency, the status of serving to houseguests, pre-shopping behavior factor, behavior factor in shopping order, risk factor, production, and expiration date check habit factor, brand and quality of the product factor and detailed package reading habit factor) have an impact on the probability of consumption for the private label food product and the impact rate can be observed below:

Income is the variable that has the most impact on the private label food product consumption. In the research for income variables that is divided into three categories, the reference group was the high-income group ₺ with an average 4,500 ₺ income. "Low income group" earns an income of 500-2,500, "middle income group" earns 2,501-4,500 ₺ and "high income group" receives 4,500 ₺ and above. The inclination towards consuming private label is 2.87 times higher for consumers in the in the low-income group compared to the consumers in high-income group.

While consumers increase their frequency of shopping, the likelihood of consuming private label food products also increases. Those who shop every day of the week has 2.58 times higher tendency towards purchasing private label compared to the consumers who shop once or twice a month whereas those who shop once or twice a week has 1.94 times higher consumption tendency.

Another significant factor following income and shopping frequency factors is the behaviors that consumers portrayed while shopping. Consumers may purchase their food products without paying attention to the brand. The existence of statutory regulations has led to the belief that there is no quality difference between the products. Along with the lower prices; promotions, discounts, and advertisements on the packaging, the consumer's decision to purchase private label is greatly affected. Every time the level of this impact rises by 1 unit; the consumer's tendency towards purchasing a private label increases 2.10 times, as well.

Another variable that affects the consumer's private label purchasing tendency is their average monthly spending on grocery. Consumers' average monthly spending on grocery has been examined through three categories and the reference group was a 400 ₺ high spending group. Compared to the families that spend 400 ₺ on market per month, the families who spend 200 ₺ and below on market per month had two times higher inclination towards purchasing private label.

Consumers may observe the supermarket brochures before going shopping and keep track of discount days, as a result, go to the supermarket for the cheapest prices. The consumers who have those frugal habits have 1.71 times higher inclination towards purchasing private label compared to those who do not have such habits.

As the habit of reading the package details increases, the private label consumption probability decreases by 45.60 %, as well. As expiration and production date checking habits rise, this probability grows 1.36 times higher.

The probability of purchasing private label rises as the consumer's age grows older. The consumer's private label consumption probability rises 1.03 times with every age.

As the importance of the brand and quality of the product in the eyes of the consumers increase, the probability of consuming the private label food product decreases by 33.50%.

Private label brand consumption and its risk factors for a product have a reverse connection within one another. As the social risk, performance, and time loss risk rates rise, the consumers' probability of private label consumption decreases. With each rate of risk factor that rises, the consumption probability of the consumers decreases by 45.50%.

For those households who host guests; as their guest visitation frequency rises, their probability to consume private label brand also rises. A family, who host guests both on day and night, has a probability to purchase store brand twice more than a family who hosts guests during just the day or the night.

In order to test the compatibility for the model estimation, the correct classification method was used. It is evident in the table of classification, shown in Table 4 that 495 out of a total number of 650 consumers had a 76.15 % rate of correct classification. The model has a 0.76 success rate of correct classification.

Table 4. Classification table estimated by the logistic regression method

Observed	Predicted: 0 No consumption	Predicted: 1 Consumption	Percentage Correct
0 No consumption	132	96	57.89%
1 Consumption	59	363	86.01%
		Overall Percentage	76.15%

3.2. Determination of Factors by ANN

The artificial neural network model characterized as such: Network topology; summation, and activation functions used; the learning paradigm; and the learning rule. A network that is available for research is a network that is made up of a multi-layered deterministic model with three layers and a feedforward connection.

All of the independent variables that are considered to affect private label consumption make up each input in the model. Continuous inputs are; factor scores obtained on essential groceries; factor scores on the habits of reading the packaging and the price tags during grocery shopping; factor scores on grocery shopping habits; the age of the individuals that deals with the shopping; the number of the family members; and the number of the family members who holds a job. Categorized inputs are; gender, job status, marital status, education level, whether there is a minor household member under 18 years of age, possession of a house, a car, and/or credit cards, the amount of the monthly spending on groceries, the shopping frequency, and the status of hosting guests. The total number of the inputs is 42. The middle layer, also known as the hidden layer, processes the attained data and transmits the data from the input layers to the next step. It has only one layer. The output that the network created is derived from the answers "yes" or "no" given by the subjects to the question "Do you consume private label food products?" in the survey. The subjects who consume private label had an output rate of 1 whereas those who did not consume had a rate of 0.

There was only one hidden layer used in the network's topology and after some testing, the number of processing elements in the hidden layer resulted in 28. In the input layer, there are 42 processing elements. Because there is only 1 dependent variable and the independent layer is a binary variable, there are 2 processing elements in the output layer. The logistic function was used in the network learning for the processing elements in the hidden layer and the processing elements in the output layer.

As a learning paradigm, one of the supervised learning methods, the Delta learning method and for the optimization of algorithms, the Conjugate Gradient method was used. The data pairs that were used for the network learning, made up the 70 % of all inputs and the test pairs used to test the network made up the other 30%. The total sample number is 650, learning pair number is 455, and the test pair number is 195.

The highest test success rate of 74.35 % was achieved when all of the samples on the network's learning pair at the end of 20 iterations was learned with a 25.6 of disturbance after the entire training and testing (Figure 3).

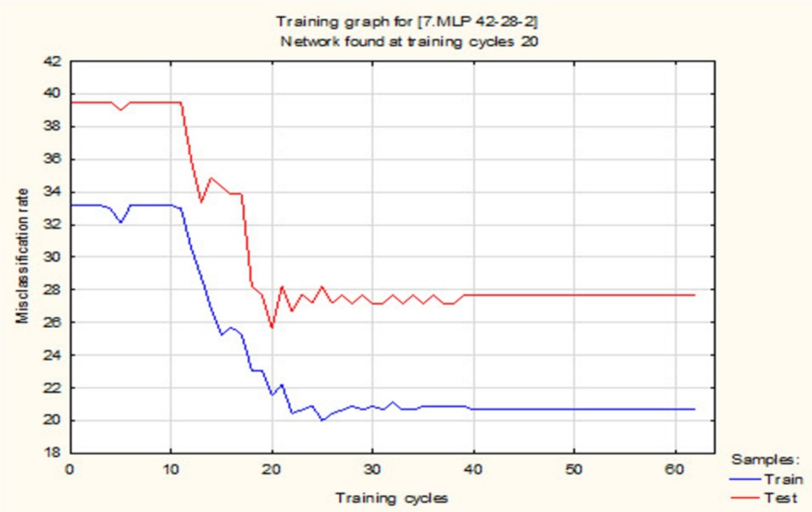

Figure 3. Error percentage by the iteration numbers for the training and testing set

The effect of the 25 independent variables examined on the consumption of private label food product (output) was calculated by sensitivity analysis. The results of this calculation are shown in Table 5 for each independent variable. As shown in the table, the consumption of private label food products is mostly influenced by the level of income, shopping frequency, and behavior factors during shopping.

Table 5. The importance of the inputs with the neural network model

Independent Variables	Relative İmportance	Rank
Income	1.118202	1
Risk factor	1.051764	4
Behavior factor in shopping order	1.066774	3
Shopping frequency	1.078587	2
The frequency of serving to house guests	1.032125	8
Pre-shopping behavior factor	1.036138	6
Monthly spending on food shopping	1.037523	5
Brand and quality the product factor	1.027994	9
Educational Level	1.005362	15
Detailed package reading habit factor	1.033341	7
Production and expiration date check habit factor	1.008823	13
Credit Card Owner	1.012923	12
Martial Status	1.004947	16
Age	1.008280	14
Number of household members	1.000817	18
Acquaintance’ recomendation factor	1.000812	19
Car Owner	0.992216	25
Number of family members with an labour	0.999247	21
Personal and family factor	1.003392	17
House Owner	0.995768	24
Gender	1.015718	11
Labour	0.998957	23
Unit price reading habit factor	1.000172	20
Post-shopping behavior factor	0.999017	22
Whether the household has a minor	1 021119	10

In order to test the estimated model's compatibility, the correct classification method is used. In Table 6, it can be said that the acquired model has a 0.77 rate of correct classification.

Table 6. Classification table estimated by the artificial neural networks method

	Predicted		
Observed	0 No consumption	1 Consumption	Percentage Correct
0 No consumption	107	121	46.92%
1 Consumption	27	395	93.60%
		Overall Percentage	77.23%

Although the logistic regression method gave weaker estimation results than the artificial neural network analysis, it still was able to clarify and define the examined variables that impact private label brand products, much more effortlessly. In fact, the results found through the logistic regression contributed in obtaining the parameter estimations, and the negative/positive degrees of influence for the analyzed variables. Kumar et al. (1995) Agrawal and Schorling (1996) evaluated their artificial neural network and logistic regression analyses approach similarly, relying on their experimental study results.

4. CONCLUSION

According to the results of both methods; While the most effective variable in the consumption of private label brand food products participating in the research is income variable, shopping frequency, and behavioral factors during shopping are other effective variables. The income variable, which is the most influential factor in the consumption of the private label food products; is very important regarding marketing managers. The target group for private label brands, which low and middle-income consumers prefer more than high-income consumers; should be low and middle-income groups. In addition, it is stated in the study that consumers who frequently do grocery shopping prefer private label brands more frequently. It will definitely be advantageous to spread the small store concepts spread among the neighborhood where the consumer can reach shopping easily and frequently, compared to the concept of the large-scale supermarkets within shopping centers. The fact, that the consumer behavior factor during shopping is one of the most influential factors, also supports the concept of the small grocery store. Consumers who follow the brochures, discount days and cheap price policies of the markets and thus go shopping; prefer private label brands in food products.

The results of this study, which includes other factors that affect the consumption of private label branded food products, will provide retailers and manufacturers with the opportunity to examine consumer behavior in detail, as well as to determine the differences they can create on the market. In addition; it is thought that this work incorporating the artificial neural network practice, which is rarely encountered these days despite being one of the most frequently used methods to determine the factors affecting the consumers' preference towards private label brand food products in different studies; may lead other studies to be done in the future.

REFERENCES

Agrawal, D. and Schorling, C. 1996. Market Share Forecasting: An Empirical Comparison of Artificial Neural Networks and Multinomial Logit Model, Journal of Retailing, 72(4): 383-407.

Akın, M., 2001. Yapay Sinir Ağları, İstanbul Üniversitesi Siyasal Bilgiler Fakültesi Dergisi, 25: s.7-19.

Akın, M. ve Yoldaş, A. 2010. Tüketicilerin psikografik özelliklerinin market markalı ürün satın alma eğilimlerine etkisi, Akademik Bakış Dergisi 22: s.1-18.

Akpınar, M.G., 2004. Market (süpermarket-hipermarket) markalı gıda ürünleri tüketici pazarının analizi: Antalya ili uygulaması, Doktora Tezi, Çukurova Üniversitesi Fen Bilimleri Enstitüsü, Adana.

Albayrak, M. ve Dölekoğlu, C. 2006. Gıda Perakendeciliğinde Market Markalı Ürün Stratejisi, Akdeniz İktisadi İdari Bilimler Fakültesi Dergisi 11: s.204-218.

Aydın, K., 2003. Müşterilerin Perakendeci Markalara Karşı Tutumlarının Ölçülmesine İlişkin Bir Çalışma, Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi 8(2): s.125-146.

Baltas, G., 1997. Determinants of store brand choice: a behavioral analysis, Journal of Product & Brand Management 6(5): 315-324.

Bardakçı, A., Sarıtaş, H., Gözlükaya, İ., 2003. Özel Marka Tercihinin Satınalma Riskleri Açısından Değerlendirilmesi, Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, Sayı: 21, ss. 33-42.

Bayramoğlu, F.M., 2007. Finansal Endekslerin Öngörüsünde Yapay Sinir Ağı Modellerinin Kullanılması, Yüksek Lisans Tezi, Zonguldak Karaelmas Üniversitesi Sosyal Bilimler Enstitüsü, İstanbul.

Elmas, Ç., 2003. Yapay Sinir Ağları (Kuram, Mimari, Eğitim, Uygulama), Seçkin Yayıncılık, Ankara.

Fettahlıoğlu, H. S., 2008. Tüketicilerin Satın Alma Davranışlarında Özel Markaların Tüketici Tutumları Üzerine Etkileri, Doktora Tezi, Dokuz Eylül Üniversitesi Sosyal Bilimler Enstitüsü, İzmir.

Frank, R. E., Boyd, J., Harper, W., 1965. Are private-brand-prone grocery customers really different?, Journal of Advertising Research 5(4): 27-35.

Gan, C., Limsombunchai, V., Clemes, M., Weng, A., 2005. Consumer Choice Prediction: Artificial Neural Networks versus Logistic Models, Journal of Social Sciences 1(4), 211-219.

Kumar, A.H., Rao, V.R., Soni, H., 1995. An Emprical Comparison of Neural Network and Logistic Regression Models, Marketing Letters 6(4), 251-263.

Kurtuluş, S., Kurtuluş, K., Yeniçeri, T., Yaraş, E., 2001. Perakendeci Markası Tüketicilerinin Tercihleri ve Bu Tüketicileri Ayırmada Kullanılabilecek Temel Değişkenler Üzerine Bir Pilot Araştırma, Yönetim 12(38): s.24-40.

Newbold, P., 1995. Statistics for Business and Economics. Prentice-Hall International, New Jersey, pages 867.

Orel, F.D., 2004. Market markaları ve üretici markalarına yönelik tüketici algılamaları, Çukurova Üniversitesi Sosyal Bilimler Enstitüsü Dergisi 13(2): s.157-174.

Richardson, P.S., Jain, A.K., Dick, A., 1996. Household Store Brand Proneness: Framework, Journal of Retailing 72(2): 159-185.

Savaşçı, İ., 2002. Tüketicinin perakendeci marka tercihleri: İzmir hipermarketleri kapsamında bir araştırma. Yüksek Lisans Tezi, Ege Üniversitesi Sosyal Bilimler Enstitüsü, İzmir.

Tatlıdil, H., 1992. Uygulamalı Çok Değişkenli Analiz, Ankara.

Tu, J.V., 1996. Advantages and Disadvantages of Using Artificial Neural Networks versus Logistic Regression for Predicting Medical Outcomes, J Clin Epidemiol, Vol.49, No:11, pp:1225-1231.

West, P.M., Brockett, P.L., Golden, L.L., 1997. A Comparative Analysis of Neural Networks and Statistical Methods for Predicting Consumer Choice, Marketing Science 16(4): 370-391.

Yurtgüder, Y., 2004. Perkandecilikte özel marka kullanımı ve tüketiciler tarafından benimsenme durumu, Yüksek Lisans Tezi, Dokuz Eylül Üniversitesi Sosyal Bilimler Enstitüsü, İzmir.