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Investigating some classification methods to evaluate efficiency results: A case study by using conjoint analysis

Etkinlik sonuçlarının değerlendirilmesi için bazı sınıflama yöntemlerinin incelenmesi: Konjoint analizi kullanarak bir örnek çalışma

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Investigating Some Classification Methods to Evaluate Efficiency Results: A Case Study by Using Conjoint Analysis

Araştırma Makalesi / Research Article

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ABSTRACT

A new product development is an important step of competitive advantage for producers. There are several issues to be considered during developing a new product from the point of view of both customers and producers. Costumer preferences require a great deal of consideration in order to able to address consumer needs in marketing. Conjoint Analysis (CA) is often preferred to reveal utility of the new product by means of customer preferences order on a certain type of product or service which is widely used to reveal how people value different attributes on a new product concept. On the other hand, Data Envelopment Analysis (DEA) can be used to determine efficient product concepts considering both utility and development expenses of the products. In this study, CA was applied with the aim of determining utilities of new car concepts. Then, DEA was used to reveal efficient and inefficient car concepts on a real data set. Finally, most commonly used classification methods Linear Discriminant Analysis (LDA), binary Logistic Regression (LR) and Artificial Neural Networks (ANN) were compared to validate the results of DEA in terms of accuracy.

Keywords: Conjoint analysis, data envelopment analysis, linear discriminant analysis, binary logistic regression, artificial neural networks.

Etkinlik Sonuçlarının Değerlendirilmesi İçin Bazı Sınıflama Yöntemlerinin İncelenmesi: Konjoint Analizi Kullanarak Bir Örnek Çalışma

ÖZ

Yeni bir ürünün geliştirilmesi, üreticiler için rekabet avantajının önemli bir adımıdır. Yeni bir ürün geliştirme süresince, tüketiciler ve üreticilerin her ikisi açısından da dikkate alınması gereken birçok konu vardır. Tüketici tercihleri, pazarlamada tüketici ihtiyaçlarını karşılayabilmek için dikkat gerektirmektedir. Konjoint Analizi (KA), belli bir ürün ya da servis üzerinde tüketici tercihlerinin aracılığı ile yeni bir ürünün faydasını ortaya çıkarmak için sık sık tercih edilmektedir. Öte yandan, Veri Zarflama Analizi (VZA) ürünlerin faydası ve geliştirme masraflarının her ikisini de dikkate alarak etkin ürün konseptlerini belirlemek için kullanılabilir. Bu çalışmada, yeni araba konseptlerinin faydalarını belirlemek amacıyla Konjoint Analizi uygulandı. Daha sonra, gerçek bir veri seti üzerinde, etkin ve etkin olmayan araba konseptlerini belirlemek için VZA kullanıldı. Son olarak, en yaygın sınıflama yöntemlerinden Lineer Diskriminant Analizi (LDA), ikili Lojistik Regresyon (LR) ve Yapay Sinir Ağları (YSA) doğruluk bakımından VZA sonuçlarının geçerliliğini incelemek için karşılaştırıldı.

Anahtar Kelimeler: Konjoint analizi, veri zarflama analizi, lineer diskriminant analizi, ikili lojistik regresyon, yapay sinir ağlar

1. INTRODUCTION

New product development is one of the most important processes for a company that is willing to increase both profit and competitiveness in market. Global competition, rapid technology change and shifting market opportunities in the world compel companies to invest in a new product that will ensure long-term growth and prosperity [1,2]. Although the new products open up new opportunities for companies, the substantial risk associated with these products should not be neglected. Empirical studies have pointed high failure rates of the new products, especially in consumer markets [3,4].

The degree of success or failure of a specific product is able to be measured through the acceptance of the new product [5]. This acceptance derives from the perceived value that a potential customer associates with the benefits delivered by the new product. A successful product can be mentioned as the product that has high perceived value from the point of view of the customer. However, a successful product from the point of view of customer might not be successful product from the point of view of the company to produce. Delightness of customers should not be taken as only factor which makes the new product successful, since the company

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develop these new products to make profit [6,7]. Thus, aim of the study is to take in consideration Conjoint Analysis (CA) with Data Envelopment Analysis (DEA) in order to deal with both customer preferences and company expenses.

An integrated approach for the evaluation and selection of the new product concepts using CA and DEA was suggested by [8]. The method consists of four main steps: Get product concepts, estimate the development expenses, determine the utility of the new product concepts, evaluate the efficiency of the product concepts. Their study suggests that development team determine all possible product concepts. However, determination of all possible concepts by development team might not be always possible because of the high number of attributes and levels of attributes. Besides, this evaluation process neglects the randomness of the design concepts. Therefore, we considered orthogonal main effects plan in order to determine possible concept cards randomly in this study. Decision Making Units (DMUs) can be classified into two different main groups as efficient and inefficient according to their efficiency scores by using DEA. The classification results obtained by DEA as efficient and inefficient can be evaluated since these two groups will be a guide by using Linear Discriminant Analysis (LDA), binary Logistic Regression (LR) and Artificial Neural Networks (ANN) in the next step. Therefore, we compared the validation of the DEA results by using most commonly used classification methods LDA, LR and ANN.

In this study, brand, price, equipment, engine type, engine size, fuel consumption, gear type, car type and colour were considered as nine car attributes, then utilities of each car concepts were computed by using CA. Thereafter, efficient and inefficient car concepts were determined by using DEA where production and selling expenses are inputs and utility of each car concept is output. Then obtained results were evaluated with the help of accuracy by using LDA, LR and ANN. In addition, sensitivity, specificity to evaluate accuracy results, which statistically measure the performance of the test, were computed after LDA, LR and ANN were applied. In Section 2, the steps of the our method were introduced. The application study was explained in Section 3. Then, conclusions were made in Section 4.

2. MATERIAL and METHOD

Determining efficient product concepts is our aim of the study. In this respect, we considered the rating based CA by using orthogonal main effects plan to create possible car concepts. The steps of our methodology are as follow:

Step I: Get product concepts by using orthogonal main effects plan

CA is an applicable multivariate statistical method revealing utility of the products with multiple attributes which can be decomposed into specific contributions of each attribute and possibly their interactions. CA is mainly seperated as rating based and choice based method [9]. Product concepts are able to be obtained by four different ways in rating based CA: full factorial design, fractional factorial design, orthogonal main effects plan, incomplete block design. Orthogonal main effects plan is one of the widely used particular type of fractional factorial design with some desirable properties. There are several advantages associated with orthogonal designs. First, these designs are parsimonious. Second, they enable estimation of all main effects of attributes in CA. These stimulus set construction designs can be blocked so that each individual receives a balanced subset of profiles. In the literature a good representative number of concepts is determined as at least 16 [9]. 32 product concepts were generated according to the orthogonal main effects plan in this study.

Step II: Determine the utilities of the new product concepts

Utilities of the new product concepts are determined using CA. This method can be used to obtain the consumer utilities for various aspects of multiple attributes stimuli on existing or new products [10]. CA is widely applicable method, especially in marketing research in order to measure the utility that a consumer associates with a new product concept [11,12,13].

The additive conjoint model is shown in Equation (1)

$$y_j = U_1(x_{j1}) + U_2(x_{j2}) + \cdots + U_r(x_{jr}) + Error \quad (1)$$

where $U_t(\cdot)$ is the component utility function specific to the *t* th attribute and is the level for the *j* th profile on the *t* th attribute [9]. No constant term is specified, but it could be included in any one of the component utility functions or assumed to be zero without any loss of generality. The form of these functions varies with respect to the scale used for the attributes.

The potential customers were requested to rank their preferences according to the orthogonal main effects plan before CA was applied. Then, the utilities of each product concepts were determined with the help of customer preference order.

Step III: Estimate the development expenses (production&selling expenses)

Cost estimation techniques can be classified into qualitative and quantitative techniques [14]. Qualitative cost estimation techniques utilize past historical cost data and expert experience to estimate project costs subjectively. Since relevant past historical information shares characteristics with the new product to be estimated in terms of design, process, data and knowledge, it can be helpful in forecasting the new product cost. A new product design expenses containing design, manufacturing, operation and proposal can be divided into two subgroups as production and selling expenses from the point of view of the company. In this study, production and selling expenses of each 32 product concepts were rated according to the scale of 1-10 where 1 shows the product concept has lowest expense whereas 10 shows the product concept has the highest expense.

Step IV: Determine the efficient product concepts

In DEA, it is assumed that a set of DMUs is to be evaluated in terms of their relative efficiencies in converting multiple inputs into multiple outputs [15]. DEA has been gained importance in marketing research studies due to the applicability of the methodology [16, 17, 18]. DEA models, in general, consist of Charnes-Cooper-Rhodes (CCR), Banker-Charnes-Cooper (BCC), multiplicative and the Slack-based measures (SBM) models. SBM model, which is also called the additive model or non-oriented model and this model based on variable return to scale, was considered in this study. SBM model quantify the improvements when both inputs and outputs can be modified simultaneously. It is assumed that companies are willing to maximize the utilities whereas minimizes the amount of development expenses simultaneously. Therefore, SBM model was considered in the study.

The SBM model is based upon input and output slacks is shown in Equation (2)

$$\min \rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{io}}{1+\frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{ro}} \quad (2)$$

subject to

$$\boldsymbol{x_0} = \boldsymbol{X\lambda} + \boldsymbol{s^-}$$
$$\boldsymbol{y_0} = \boldsymbol{Y\lambda} - \boldsymbol{s^+}$$
$$\boldsymbol{\lambda}, \boldsymbol{s^-}, \boldsymbol{s^+} \geq 0$$

$\mathbf{X}_{ij}$ represents multiple inputs (i=1,2,…,m)

Step V: Validation of the DEA result

One of the most important issues after grouping is the evaluation of the results to find the partitioning that best fits the underlying data. The most commonly used classification methods are LDA, LR and ANN. The detailed description of these methods can be found in the books of [19, 20]. At first, the grouping is extended to the individual observations. Then, these sets are separated by LDA, LR and ANN in order to obtain accuracy. DMUs can be classified into two different main groups as efficient and inefficient according to their efficiency scores. The validation of DEA grouping result is crucial, so these two groups will be a guide to evaluate LDA, LR and ANN in the next step.

2.1 Linear Discriminant Analysis (LDA)

LDA is a supervised multivariate statistical method concerned with separating distinct sets of objects or observations and with allocating new objects to previously defined groups. Discrimination terminology was introduced by [21] in the first separatory problems. G_1 and G_2 are the names of two groups and their number of observations are shown as $n_1$and n_2, respectively. $\boldsymbol{\bar{x}}_1$, $\boldsymbol{\bar{x}}_2$ and $\mathbf{S}_1$, $\mathbf{S}_2$ indicate sample mean vectors, and estimated variance-covariance a matrices based on sample sizes $n_1$and n_2, respectively. The prior probability of G_i is given as prior probability $p_i, i = 1{,}2$ and $p_1 + p_2 = 1$. This discrimination method requires that homogeneity of variance-covariance matrices of the groups. In Equation (3), LDA classifies an observation x_o to group G_1 if

$$(\boldsymbol{\bar{x}}_1 - \boldsymbol{\bar{x}}_2)'\boldsymbol{S}_{pooled}^{-1}\boldsymbol{x}_0 - \frac{1}{2}(\boldsymbol{\bar{x}}_1 - \boldsymbol{\bar{x}}_2)'\boldsymbol{S}_{pooled}^{-1}(\boldsymbol{\bar{x}}_1 + \boldsymbol{\bar{x}}_2) \geq ln\left(\frac{p_2}{p_1}\right) \quad (3)$$

where

$$\boldsymbol{S}_{pooled} = \frac{(n_1-1)\boldsymbol{S}_1+(n_2-1)\boldsymbol{S}_2}{n_1+n_2-2}$$

$\boldsymbol{S}_{pooled}$ is the pooled estimator of the common variance-covariance matrix.

2.2. Binary Logistic Regression (LR)

Binary Logistic Regression (LR) provides relation with one or more than explanatory variables when response variable has two possible outcome. LR does not have assumptions such as normality and homogeneity of the variances, therefore LR has been widely used in literature. The LR model is shown in Equation (4)

$$ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_i x_i \quad (4)$$

where p_i shows the probability of being efficient for concept cards. x_i and β_i denotes the explanatory variables and coefficients of related explanatory variables, respectively [22].

LR model presents the outcome as a probability whose value is restricted to between 0 and 1, with a threshold value of 0.5. If the probability is greater than 0.5 then LR classifies the observation has G_1. Otherwise, if the probability is less than 0.5 then LR classifies the observation has G_2.

2.3. Artificial Neural Network (ANN)

Artificial neural network (ANN) is a self-adaptive trainable process that is able to learn and resolve complex classification problems based on grouping knowledge. It is a supervised learning that the model initially learns from the training data set and then classifies the test image using the learnt knowledge. 70% of data set were selected for testing whereas 30% of data set were selected for training in this study.

An ANN behaves in the same manner as how the biological brain works since it is composed of interconnected processing elements that simulate neurons. Each neuron can pass information to another by using this interconnection. In the study, we studied with feed-forward neural network which is also called multilayer perceptrons (MLPs). The structure of MLPs consist of input layer, hidden layer and output layer, shown in Figure 1. Input layer, which can be classified into two types that provides receiving variables. In the first type of input layer, which we used, neurons have transfer functions, weights and biases delivering to the next stage after operations. Hidden layer is an interface between input layer and output layer which transfers signals from the input layer to the output layer. Output layer is the last layer that enables the equality of number of neurons and number of output variables needed [23, 24].

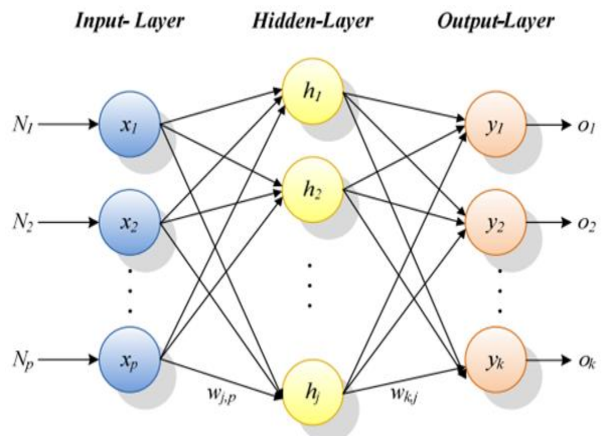

Figure 1. A diagram of multilayer perceptrons

3. APPLICATION STUDY

We proposed a multi-step process: first we applied CA to reveal utilities of product concepts according to the distinguish between the efficient and inefficient product concepts by using SBM model. orthogonal main effect plan. Then, DEA was applied to Later, LDA, LR and ANN were considered to evaluate the DEA results. Validation measurements such as accuracy, sensitivity and specificity were given for LDA, LR and ANN classification results.

In this study, 400 car customers were randomly selected who are incoming to car dealer, galery and car market in Ankara [25]. The main interests of this group of customers while purchasing a new car were determined as brand, price, equipment, engine type, engine size, fuel consumption, gear type, car type and color. Then, levels of the attributes were shown Table 1.

The proposed steps were able to be applied to the data set after attributes and the levels of each attributes were determined.

Step 1: 32 car concepts were created by orthogonal main effects plan. The obtained orthogonal design of the car concepts is shown in Table 2.

The proposed steps were able to be applied to the data set after attributes and the levels of each attributes were determined.

Table 1. Car attributes and levels of attributes

Attributes	Levels
Model of car	Car A Car B Car C Car D
Price (1000$)	<25 25-40 >40
Equipment	Standart Optional
Engine Type	Diesel Gasoline
Engine Size	1200-1599 1600-1999
Fuel Consumption (lt)	≤8 >8
Gear Type	Straight Automatic
Type	Sedan HB
Color	Light Colours Dark Colours

Step 1: 32 car concepts were created by orthogonal main effects plan. The obtained orthogonal design of the car concepts is shown in Table 2.

Step II: In the second step, customer preferences orders were obtained and a partial listing of customer preferences orders are given for only five customer in

Table 3. Customer preferences were analyzed by using CA, then utilities of 32 product concepts were computed as in Table 4

Table 2. Orthogonal design of the car concepts

Concept Number	Model of car	Price	Equipment	Engine Type	Engine Size	Fuel Consumption	Gear Type	Car Type	Colour
1	Car D	<25	Optional	Diesel	1200-1599	>8	Straight	HB	Dark
2	Car C	>40	Standart	Diesel	1200-1599	≤8	Straight	HB	Light
3	Car D	<25	Standart	Diesel	1200-1599	>8	Automatic	HB	Light
4	Car B	25-40	Standart	Diesel	1200-1599	>8	Automatic	Sedan	Light
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
29	Car A	<25	Standart	Diesel	1200-1599	≤8	Straight	Sedan	Light
30	Car D	>40	Standart	Gasoline	1200-1599	≤8	Straight	Sedan	Dark
31	Car B	<25	Optional	Gasoline	1200-1599	≤8	Automatic	HB	Light
32	Car D	25-40	Optional	Diesel	1600-1999	≤8	Straight	Sedan	Dark

Table 3. Preferences order of five customers

Customer Number	Customer Preference Order 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	3	5	7	15	9	11	1	2	8	14	10	4	16	12	13	6
2	16	2	3	8	4	11	7	15	12	5	10	6	14	1	9	13
3	12	2	9	8	13	11	4	10	14	15	16	7	3	1	6	5
4	5	12	1	8	10	13	9	3	15	14	16	4	11	7	6	2
5	10	3	14	11	8	9	7	6	15	5	16	12	13	2	1	4

Step III and Step IV: In the study, production and selling expenses were determined by a development team according to the scale of 1-10. Production and selling expenses were considered as input variables while utility was considered as output variable for DEA. Input and output variables for SBM model are shown in Table 5. SBM was applied to reveal the group of efficient DMUs (G_1) and inefficient DMUs (G_2) concept cards nd the results are shown in Table 6.

Table 4. Utilities of product concepts

Concept Card Number	Utility
1	9.25
2	1.88
3	7.25
4	3.38
⋮	⋮
29	4.00
30	5.13
31	7.75
32	7.88

Table 5. Input and output data for the SBM model

	Inputs		Outputs
Concept Card Number	Production Expenses	Selling Expenses	Utility
1	5	4	9.25
2	3	3	1.88
3	4	4	7.25
4	6	7	3.38
⋮	⋮	⋮	⋮
29	3	3	4.00
30	4	3	5.13
31	3	3	7.75
32	8	7	7.88

Table 6. Efficiency results of the product concept cards

	Efficiency Status	
	Group of efficient DMUs (G_1)	Group of inefficient DMUs (G_2)
Concept Card No	9, 12, 18, 19, 20	1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 13, 14, 15, 16, 17, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32

Step V: Before LDA was applied, assumptions of LDA were checked. Firstly, normality assumption was not violated when Kolmogorov-Smirnov normality test was applied (p-value=0.200). Secondly, Box's M test of equality of covariances matrices was applied to grouped data in Table 6. It was inferred from the Box's M result that the equality of covariances matrices assumption was not violated (p-value=0.475).

A confusion matrix of binary classification is a two by two table formed by counting of the number of the true positive, false positive, true negative and false negative of a binary classification method. The most commonly validation measurements are accuracy, sensitivity and specificity deriving from confusion matrix. Accuracy measures, which is also known as correctly classification rate, the degree of veracity of the classification method on a grouped data set. It is calculated as the number of all correct predictions divided by the total number of the dataset. Other basic measures, such as sensitivity and specificity, are also more informative. Sensitivity shows how correct negative predictions divided by the total number of negatives. In addition, sensitivity and specificity are measures to assess the accuracy. A classification method can be very specific without being sensitive, or it can be very sensitive without being specific. Both factors are equally important [26, 27].
It is seen that confusion matrices of LDA, LR and ANN classification results are given in Table 7, Table 8 and Table 9, respectively. In these tables, the group of inefficient DMUs are shown as "0" whereas the group of efficient DMUs are shown as "1".

Table 7. LDA Classification results

			Predicted Group Membership		Total
		Group	0	1	
Original	Count	0	22	5	27
		1	1	4	5
	%	0	81.50	18.50	100.00
		1	20.00	80.00	100.00

Table 8: LR Classification results

			Predicted Grup Membership		Total
		Group	0	1	
Original	Count	0	26	1	27
		1	2	3	5
	%	0	96.30	3.70	100.00
		1	40.00	60.00	100.00

Table 9: ANN classification results

Sample	Group	Predicted Group Membership 0	1	Total
Training	0	21	0	21
	1	2	2	4
	%	92.00	8.00	100.00
Testing	0	6	0	6
	1	1	0	1
	Overall Percent	100.00	0.00	100.00

As shown in Table 10, accuracy of LDA, LR and ANN were obtained as 81.30%, 90.60% and 92.00%. According to the results, the highest accuracy value were obtained from ANN, LR and LDA, respectively. Sensitivity and specificity are measures in order to evaluate accuracy results of the classification methods. The sensitivity and specificity values of ANN were obtained as 91.30% and 100.00%, respectively. These results support the accuracy result for ANN.

Table 10. Validation measurements for classification methods

Classification Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
LDA	81.30	95.65	44.44
LR	90.60	92.86	75.00
ANN	92.00	91.30	100.00

Grouping results according to DEA-LDA, DEA-LR and DEA-ANN were shown in Table 11, Table 12 and Table 13, respectively.

Table 11. Grouping results according to DEA and LDA

Concept card number	DEA grouping	LDA grouping	Probabilities of membership in G_2 (%)	Probabilities of membership in G_1 (%)
1	0	0	66.00	34.00
2	0	0	99.00	1.00
3	0	0	82.00	18.00
4	0	0	99.00	1.00
5	0	1	16.00	84.00
⋮	⋮	⋮	⋮	⋮
19	1	0	68.00	32.00
⋮	⋮	⋮	⋮	⋮
29	0	0	95.00	5.00
30	0	0	95.00	7.00
31	0	0	67.00	33.00
32	0	0	95.00	5.00

Table 12. Grouping results according to DEA and LR

Concept card number	DEA grouping	LR grouping	Predicted probabilities (%)
1	0	0	8.68
2	0	0	0.31
3	0	0	2.50
4	0	0	0.02
5	0	0	32.39
⋮	⋮	⋮	⋮
19	1	1	12.50
⋮	⋮	⋮	⋮
29	0	0	0.56
30	0	0	1.13
31	0	0	6.78
32	0	0	0.45

Table 13. Grouping results according to DEA and ANN

Concept card number	DEA grouping	ANN grouping	Probabilities of membership in G_2 (%)	Probabilities of membership in G_1 (%)
1	0	0	45.10	54.90
2	0	0	88.50	11.50
3	0	0	95.30	4.70
4	0	0	95.60	4.40
5	0	0	93.10	6.90
⋮	⋮	⋮	⋮	⋮
19	1	0	79.30	20.70
⋮	⋮	⋮	⋮	⋮
29	0	0	91.70	8.30
30	0	0	89.00	11.00
31	0	0	81.90	18.10
32	0	0	92.10	7.90

4. CONCLUSION

Car concepts with the highest utility may not be the efficient car concepts to develop as a new car. The issues in development of a new product from the point of both customers and producers should be taken into the consideration. Costumer preferences require a great deal of consideration to address consumer needs in marketing whereas companies require development expenses to be as less as possible. Therefore, the aim of the study is to take in consideration Conjoint Analysis with Data Envelopment Analysis in order to deal with both customer preferences and company expenses.

In this study, utilities of each car concepts with respect to the customer preferences were determined by using Conjoint Analysis according to the orthogonal main effects plan on a real data set. As a consequence of the Conjoint Analysis result, three most important attributes were found as price, motor type and brand, respectively. Customers demand low fuel consumption with HB, automatic gear, dark and optional car while they prefer the cars which have powerful motor.

Thereafter, two groups as efficient and inefficient car concepts were determined by using Data Envelopment Analysis where production and selling expenses were inputs and utilities of each car concepts were outputs. Finally, Data Envelopment Analysis grouping results were validated by using, which are most commonly used classification methods, Linear Discriminant Analysis, binary Logistic Regression and Artificial Neural Networks in terms of accuracy, sensitivity and specificity.

According to the results of Linear Discriminant Analysis classification, validation measurements were obtained with 81.30% accuracy, 95.65% sensitivity and 44.44% specificity. In the same way, binary Logistic Regression results were obtained with 90.63% accuracy, 92.86% sensitivity and 75.00% specificity. Finally, Artificial Neural Network results were obtained with 92.00% accuracy, 91.30% sensitivity and 100.00% specificity. This case study mentions that Artificial Neural Network has the best performance among the other classification methods when sensitivity and specificity were investigated for Artificial Neural Network accuracy result. On the other hand, binary Logistic Regression performs as good as Artificial Neural Networks.

The study shows that a product concept which is generated by orthogonal main effect plan has a high utility from the point of view of costumer may not be the efficient product concept to develop when the development expenses are considered. Besides, concepts cards which have the same utility can be classified considering development expenses by Data Envelopment Analysis. By this method, companies can distinguish the product concepts which have the same utility value.

Classification results for a new car concept indicates that low production and selling expenses with low utility cause a new car to be inefficient whereas low production and selling expenses with high utility cause a new car to be efficient. On the other hand, high production and selling expenses with low utility cause a new car to be inefficient whereas high production and selling expenses with high utility cause a new car to be efficient.

The major advantages of our study can be given briefly as follow: Generation of the concept cards before applying Conjoint Analysis is possible by using orthogonal main effects plan to provide randomness of the design. Afterwards, Conjoint Analysis results can be taken in consideration with Data Envelopment Analysis in order to deal with both customer preferenses and company expenses. Artificial Neural Networks method can be preferred in view of most commonly used classification methods Linear Discriminant Analysis and binary Logistic Regression.

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