AN INTEGRATED PERFORMANCE MEASUREMENT FRAMEWORK FOR RESTAURANT CHAINS: A CASE STUDY IN ISTANBUL

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Keywords

Categorical DEA, Dimension Reduction, Principal Component Analysis (PCA), Performance Measurement, Restaurants.

Abstract

Companies that continue to operate in a competitive market strive the most efficient use of their resources in order to remain competitive. Nowadays, with increasing customer feedback, properly analyzing customer needs and requests and producing services in accordance with expectations have become increasingly important due to the large number of companies competing in the same market, and this is especially important to be at the forefront of competitors in the food services industry. There are risks and uncertainties owing to the continuously changing demand for food service enterprises, the difficulty to regulate interest and comparable charges, the competitive environment, and currency rate hikes. In light of all of these circumstances, restaurants require a versatile tool to effectively measure and analyze their performance. Therefore, this study combines Principal Component Analysis (PCA) and Categorical Data Envelopment Analysis (CAT-DEA) to analyze the performance of 15 dealers in Istanbul, divided into three categories: steakhouse, kebab, and meatball-doner. The results demonstrate that each category has just one efficient restaurant, for a total of three efficient restaurants out of fifteen. In addition to the suggested CAT-DEA-based framework, three research hypotheses are constructed and analyzed to investigate the link between restaurant performance and various environmental factors (or relevant indicators) in the food service industry.

RESTORAN ZİNCİRLERİ İÇİN ENTEGRE BİR PERFORMANS ÖLÇÜM ÇERÇEVESİ: İSTANBUL'DA BİR VAKA ÇALIŞMASI

Anahtar Kelimeler

Kategorik VZA, Boyut İndirgeme, Temel Bileşenler Analizi (PCA), Performans Ölçme, Restoranlar

Öz

Rekabetçi bir piyasada faaliyet göstermeye devam eden şirketler, rekabetçi kalabilmek için kaynaklarını en verimli şekilde kullanmaya çalışırlar. Artan müşteri geri bildirimleri ile birlikte, aynı pazarda rekabet eden çok sayıda firma nedeniyle, müşteri ihtiyaç ve isteklerini doğru analiz etmek ve beklentilere uygun hizmet üretmek giderek daha önemli hale geldi ve bu durum özellikle gıda hizmetleri endüstrisinde rekabette ön planda olmak için önemlidir. Yiyecek hizmeti işletmelerine yönelik sürekli değişen talep, faiz ve karşılaştırılabilir ücretlerin düzenlenmesindeki zorluk, rekabet ortamı ve kur artışları nedeniyle bu sektörde riskler ve belirsizlikler bulunmaktadır. Tüm bu koşullar ışığında restoranlar, performanslarını etkin bir şekilde ölçmek ve analiz etmek için çok

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yönlü bir araca ihtiyaç duyarlar. Bu nedenle, bu çalışma, İstanbul'da et lokantası, kebap ve köfte-döner olmak üzere üç kategoriye ayrılmış 15 bayinin performansını analiz etmek için Temel Bileşenler Analizi (PCA) ve Kategorik Veri Zarflama Analizini (CAT-DEA) birleştirmektedir. Sonuçlar, her bir kategorinin yalnızca bir verimli restorana sahip olduğunu ve on beş bayiden toplamda üç bayinin verimli olduğunu göstermektedir. Önerilen CAT-DEA tabanlı yaklaşıma ek olarak, yemek hizmeti endüstrisinde restoran performansı ile çeşitli çevresel faktörler (veya ilgili göstergeler) arasındaki bağlantıyı araştırmak için üç araştırma hipotezi oluşturulmuş ve analiz edilmiştir.

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1. Introduction

Efficiency evaluation has long been believed to be essential for service-related businesses due to today's world's rising rivalry and economic reasons (Reynolds and Thompson, 2007; Özden, 2008). At this point, it is critical to observe and measure the extent to which the firm can convert its inputs into outputs. Because "if the result cannot be measured, the success/failure situation cannot be evaluated; if the success cannot be evaluated, it cannot be rewarded; if the success cannot be rewarded, it is most likely that the failure is rewarded; and if the failure cannot be defined, it cannot be corrected" (Yildirim, 2010). In this regard, the proper and optimal utilization of resources is crucial for organizations.

Researchers in the foodservice industry have mostly concentrated on partial factor productivity indices, which include the rate of output measured in specified units and any input component assessed in specific units. Sales per labor hour, revenue per available seat hour, and transactions per hour are examples of such metrics. In internal analyses, these variables are inadequate and do not accurately represent efficiency. Total factor productivity models are insufficient to evaluate several units with varying labor characteristics (Brown and Hoover, 1990). To put it another way, both total and partial factor ratios provide an average outcome. Comparisons yield the most accurate findings (Reynolds and Thompson, 2007).

For efficiency analysis, studies in the literature shows that Stochastic Frontier (Zou, Kwan, Hansen, Rutherford and Kafle, 2016; Chen, Wanke, Antunes and Zhang, 2017; Tsionas, Chen and Wanke, 2017), DEA (Saranga and Nagpal, 2016; Lee and Worthington, 2014; Lu, Wang, Hung and Lu, 2012; Mallikarjun, 2015; Rouse, Putterill and Ryan, 2002; Sakthidharan and Sivaraman, 2018), Multi-Criteria Decision-Making techniques (MCDM) (Barros and Wanke, 2015; Wanke, Azad, Barros and Hassan, 2016; Çalış, Özçelik and Gencer, 2016; Pineda, Liou, Hsu and Chuang, 2018; Dinçer, Hacıoğlu and Yüksel, 2017), regression (Bravo-Ureta et al., 2007), tobit (McDonald, 2009; Grmanová and Strunz, 2017), logit (He, Sun, Shen, Jian and Yu, 2019), and many more approaches are employed. Most studies base their performance evaluations on the assumption that the DMUs in the data set are of similar scale. As a result of this situation, the subgroups that may exist in the data set among DMUs are not included in the analysis, and the inherent features of the data are neglected. In the light of these considerations, this study employs categorical data envelopment analysis (DEA) whilst also avoiding potential the curse of dimensionality by dimension reduction employing principal component analysis (PCA). Curse of dimensionality is a general concept used for potential problems that may arise with an increase in the number of variables in the data set. As the number of variables in the data set increases, the probability of including variables that are correlated with each other in the data set also increases, and the presence of highly correlated variables in the DEA approach causes the approach to fail in separating efficent and inefficent units (Jothimani, Shankar and Yadav, 2017). In addition, the number of DMUs in the data set should be twice the product of the number of input and output variables. With the PCA-DEA integration, these two problems can be avoided by reducing the number of variables in the data set to the minimum number of variables that most explain the total variance. The main motivation of this study is to demonstrate the benefits of PCA-DEA integration

for researchers, especially in data sets with low number of DMUs. Furthermore, to the best of our knowledge, this is the first study in the literature that combines categorical DEA and PCA methodologies. This study proposes a performance evaluation tool that can be used with PCA-Categorical-DEA integration both for datasets that are heterogeneous in terms of sizes on the basis of variables and for datasets with a small number of DMUs despite having a large number of variables.

The purpose of this study is to use categorical DEA based on PCA to assess the efficient and inefficient restaurants of 15 dealers of a restaurant chain operating in Istanbul and overseas. In this study, a list of variables was established as a result of literature review in the first stage, and the study was carried out with the variables selected from these set of variables as a result of interviews with restaurant chain management in the variable selection phase. Employee Number, Manager Experience, Seating Capacity, Number of Managers, Working Hours, Advertising Expenses, and Area variables are used as inputs in this study, and the Average Account, Number of Transactions, and Number of Customers variables are used as outputs, in order to apply PCA-Categorical DEA hybrid approach to analyze efficiency of restaurants. In the final stage, research hypotheses are tested in order to observe the effects of some environmental factors which were requested by the restaurant chain management.

The remainder of this article is organized as follows. Section 2 outlines a review of DEA-based restaurant chains efficiency studies and dimension reduction studies with PCA. In Section 3, proposed methodologies are delineated for evaluating performance of restaurants. The application of proposed framework, research hypotheses and their results are reported and discussed in Section 4. Section 5 presents managerial implications and further research directions.

2. Literature Review

2.1 DEA-based Restaurant Chains Studies

In the literature, there are numerous DEA-based efficiency studies that have been conducted in many fields such as banking, healthcare (Karadayi, Ekinci, Akkan and Ülengin, 2017), agriculture and farm, logistics, education, tourism, energy, environment, …etc. But if we focus on DEA-based restaurant chains efficiency studies, there are limited studies that can be summarized as follows:

Tepe (2006) measured the performance of 20 Burger King branches in Istanbul with the data envelopment analysis. In the study, 8 models, including input and output-oriented BCC and CCR models, were used. Number of team members, number of managers, seating capacity, restaurant manager's experience was selected as inputs. Moreover, number of transactions, sales and customer satisfaction were selected as outputs.

Giménez-García, Matínez-Parra and Buffa (2007) used three-stage data envelopment analysis method for location analysis of 54 branches of a restaurant chain. The inputs used in the study were; wait and kitchen staff, number of seats, number of server counters, and outputs were sales and quality index, and context environmental variables were as follows; location, average bill amount ticket, number of competitors. Reynolds and Thompson (2007) measured the efficiency of a 62-unit restaurant chains with three-stage DEA in their study. The inputs used were, hourly server wage, restaurant seats, and a coding variable representing whether the restaurant is a stand-alone facility and outputs of the study are daily sales and tip percentage. Reynolds and Biel (2007) analyzed 36 same-branded corporate units of a restaurant chain in the USA with the DEA. In the study, revenue, controllable income, guest satisfaction and retention equity were used as inputs. Whilst, cost of goods sold, labor cost, employee satisfaction, rent, taxes and insurance, square footage, number of seats were selected as output variables.

By applying a Data Envelopment Analysis method in French hotel chains, Botti, Briec and Cliquet (2009) analyzed that plural form networks are, on average, more efficient than strictly franchised and fully owned chains. While the inputs used in the study were costs, territory coverage, chain duration, sales were used as an output.

Reynolds and Taylor (2011) tested a multidimensional holistic model with multiple variables using DEA and evaluated its validity using structural equation modeling (SEM) to examine from three units of a small full-service restaurant chain in the USA.

Gharakhani, Maghferati and Jalalifar (2012) combined DEA and Super Efficiency models to analyze the efficiency of 15 restaurants in Iran.

Monthly working hours, branch area (square meters) and years of experience as a manager were chosen as inputs. The number of customers who purchase monthly from the branch and monthly sales in USD were selected as outputs. Chou and Fang (2013) employed DEA to measure menu performance based on excess in 20 Chinese-Style Fast Food chains. Output oriented CCR and BCC were used. As inputs, average unit food cost, average selling price, number of food supplier and a dummy variable, cooking steps (1. Easy – need one step, 2. Middle –need two steps, 3. A little bit harder – need tree steps, 4. Complicated –need four or more steps), cooking time, average unit labor cost, average other operating expenses were included. Popularity and earnings were chosen as output variables.

Duman, Tozanli, Kongar and Gupta (2017) suggested an integrated approach, fuzzy AHP and DEA They listed efficient and inefficient retail stores in franchises.The inputs and outputs used in the study were as follows; store territory (Sq. Mile), population density (Population/Sq Mile), weekly expenses (dollars/week), total hours worked by in-store personnel (hours/week), total hours worked by delivery personnel (hours/week) , output criteria (per week) unit, total number of carry-out orders (number of orders/week), total number of delivery orders (number of orders/week), sales (dollars/week), Delivery On-time (percentage), Out to door time (percentage).

Hu, Chiu and Chu (2019) measured the efficiency of 10 resturants in Taiwan using output-oriented CCR and BCC models. Assets, number of employees and total salary are selected as inputs. Revenue was selected as output variable. Parte and Alberca (2019) used the data of 1071 Spanish bar companies, examined the effectiveness of Spanish bar companies with a dynamic multi-stage DEA.In the study, total assets, number of employees, labor costs and operational costs were used as inputs and total sales were used as outputs.

Chiang and Sheu (2020) proposed a new approach to measuring the level of sustainability from the perspective of a restaurant manager in the food service industry. They reached a conclusion by collecting data from forty-eight prescriptions and analyzing the data with DEA. Inputs used in the study were: food additives, processed food, meat, decoration of plates and dishes. Outputs were; local ingredients, in season ingredients, certified organic ingredients and vegetarian food.

As it can be seen from Table 1, most of the studies utilized conventional DEA models. The remaining studies used extended form of DEA such as multi-stage or super efficiency models to increase the discriminatory power of DEA. One study integrated DEA and MCDM method (AHP) to conduct efficiency analysis. Hence, there are limited DEA-based studies in the published literature to assess performance of restaurants.

Table 1.

Summary of DEA-based Restaurant Chains Studies

Authors	Methodology	Application Area
Tepe (2006)	Standard DEA	20 Burger King branches
Reynolds and Biel (2007)	Standard DEA	36 same-branded corporate units of a restaurant chain
Botti et al. (2009)	Standard DEA	16 Hotel chains in France
Chou and Fang (2013)	Standard DEA	20 Chinese-style fast food chains
Hu et al. (2019)	Standard DEA	10 resturants in Taiwan
Chiang and Sheu (2020)	Standard DEA	48 recipes were evaluated in terms of sustainability from the perspective of a restaurant manager
Giménez-García et al. (2007)	Three-stage DEA	54 branches of a restaurant chain
Reynolds and Thompson (2007)	Three-stage DEA	62-unit restaurant chains
Parte and Alberca (2019)	Dynamic Multi-Stage DEA	1071 Spanish bar companies
Reynolds and Taylor (2011)	DEA and SEM	Three units of a small full-service restaurant chain
Gharakhani et at. (2012)	DEA and Super Efficiency	15 restaurants in Iran
Duman et al. (2017)	Fuzzy AHP and DEA	20 franchise retail stores of a leading pizza restaurant chain stores

2.2. Dimension Reduction with PCA to enhance the Discriminatory Power of DEA

Principal Component Analysis (PCA) is widely conducted for the prior reduction of the variables for DEA.

Roh and Choi (2010) examined the efficiency of 121 restaurants using DEA and factor analysis. The inputs and outputs used in the study are as follows; sales, net income, total size, revenue generating space, total employees, overhead expenses.

Bal and Özsoy (2016) used DEA to measure the economic performance of 28 cities in China. In addition, the data set was selected by PCA. Employees, working capital and investments were selected as inputs. Gross industrial output value, profit and taxes, and retail sales were chosen as outputs.

Andrejić, Bojović and Kilibarda (2013) investigated the efficiency of seven distribution centers of a trading company operating in Serbia via integrating PCA and DEA. The inputs included in the study vehicles,forklifts,employees in warehouse, employees in transport , warehouse area , pallet places, energy fuel, electricity consumption,other energy costs (water,gas),utility costs, operational invoices (demands), warehouse overtime, driver's overtime, vehicle maintenance, driver's overtime/driver.Outputs were shipped pallets,distance, deliveries, order picking transactions, tour/driver, delivery/driver, tons/driver, pallets/driver, distance/driver, order picking trans./order picker ,Turnover , utilisation time truck utilization, space truck utilization, warehouse space utilisation, quality failures in warehouse, failures in transport ,write off expired goods,total failures.

Põldaru and Roots (2014) conducted a PCA-DEA study to evaluate the quality of life in 15 counties of Estonia.The inputs included population density, number of employed per 1000 citizen, number of people with university degree per 1000 citizen, quality of land, milk yield per cow. Outputs were gross domestic product (GDP) per capita, Life expectancy at birth, number of pupils per 1000 citizens.

Stoica, Mehdian and Sargu (2015) examined the relationship between internet services and bank efficiency for 15 resident banks in Romania with DEA and PCA.The input variables were the deposits, total operating costs, number of employees, value of equipments. The outputs used were net total revenues and daily "reach" average rate.

Andrejić, Bojović and Kilibarda (2016) conducted an integrated analysis with DEA and PCA to measure the efficiency of Serbian distribution centers and to identify the main factors affecting the transport efficiency. While the inputs used in the study are fuel consumption, the outputs used are number of delivers, distance driven and shipped pallets.

Jothimani et al. (2017) conducted a review with PCA and DEA to evaluate and select profitable stocks traded on the National Stock Exchange (NSE) for portfolio optimization. While the inputs used in the study were liquidity ratios, leverage ratios, asset utilization, the outputs were profitability ratio, growth ratio and valuation ratio.

Gnewuch and Wohlrabe (2018) employed PCA on standardized data to extract the main components to be used as inputs and outputs of the DEA model to evaluate 188 economics departments around the world. (Wu, Ke, Xu, Xiao and Hu, 2018) evaluated eco-efficiency coal-fired power plant using superefficiency DEA and PCA.

Nasser (2019) analyzed the efficiency of Hospitals in Lebanon with PCA-DEA method. The input variables were the number of hospitals, number of beds available, number of staff nurses, the population. Outputs were mumber of Ministry of Public Health (MOPH) subsidized admissions, number of MOPH subsidized in-patients, total caesarian sections conducted, number of MOPH subsidized hospitalized for cardiovascular cases, total cases benefiting from the Drug Dispensing Center.

Peixoto, Musetti and Mendonça (2020) aimed to measure the performance of Federal University Hospitals – Brazilian HUFs participating in the Restructuring National Program of Federal University Hospitals supported by PCA for the selection of inputs and outputs. While the inputs used in the study were SIR (Supervision of internship and residency), DH (Days of hospitalization), SPMH (Specific projects – Ministry of Health), TE (Type of equipment), the output was MR (Medicine residency).

Aydin, Karadayı and Ülengin (2021) assessed the performance of 45 airline companies via combining the balanced scorecard (BSC) approach and the network-based super-efficient data envelopment analysis (DEA). PCA was employed to increase the discrimination power of the DEA and to handle multidimensional data.

As can be seen from the literature review, even if there are performance evaluation studies such as Uslu Cibere, Başaran and Kantarcı (2020) and Singh, Torres and Robertson-Ring (2016) in the tourism industry, the performance evaluation of restaurant chains based on DEA is scarce. Moreover, PCA is widely employed for the selection of the input/output variables for DEA. One of the contributions of this study is to fill this gap combining PCA and DEA for assessing the performance of restaurant chains.

This paper proposes a new methodology that consists of two main stages; first stage uses the PCA to reduce the inputs and outputs number; second stage utilizes the categorical-DEA using the variables, which are formed by first stage, for performance evaluation. The proposed methodology not only improve the discrimination power of but also enable researcher to ensure having sufficient data set for DEA. Since DEA has a resriction that "the number of units to be at least 2 m × s, where m is the product of the number of inputs and number of outputs" this approach is a useful tool for researchers (Liu, Yang, Lu and Chauang, 2009). This study complied with research and publication ethics. Figure 1 summarizes the process of the proposed approach for performance assessment of restaurants:

3. Proposed Methodology

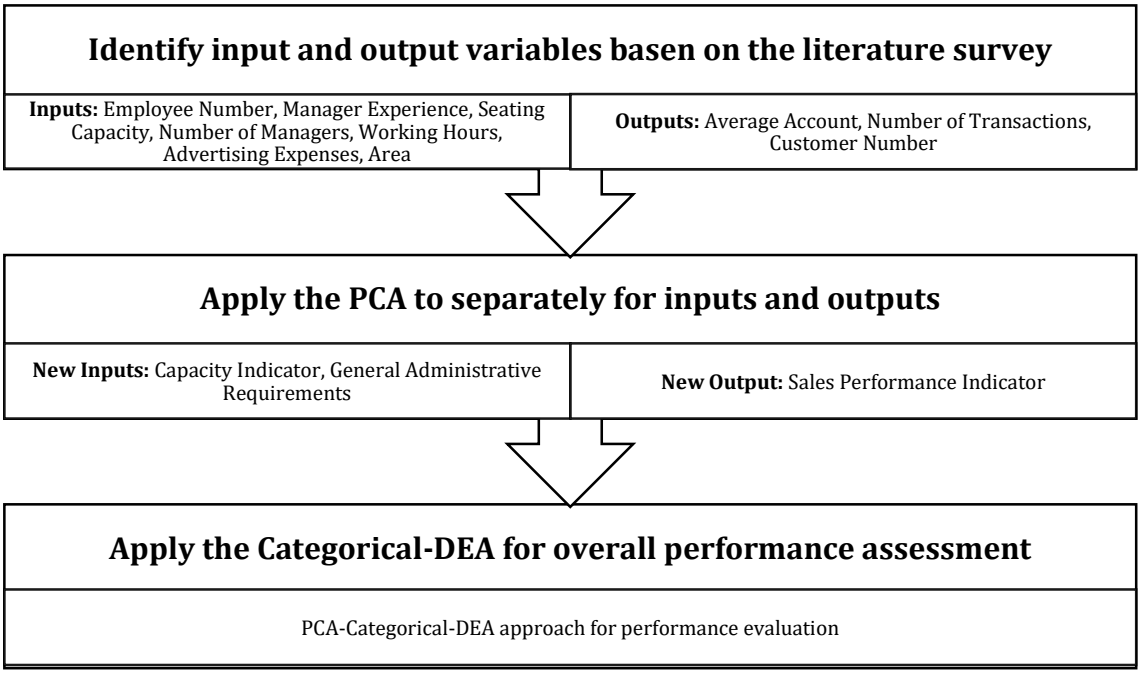

Figure 1. Proposed Methodology

3.1. Categorical DEA

DEA, which is based on LP's principles, calculates the relative efficiency of multiple DMUs, which have same targets and purposes, in a multiple input-output environment. This method enable researchers to calculate efficiencies of DMU's using desired number of inputs and outputs variable only if there are sufficient number of DMU's compared to number of inputs and outputs in the data set, and this leads decision makers to chose more this method comparing to other performance evaluation approaches. Basically DEA makes comparison among DMUs evaluating the proportions of the outputs and inputs and chooses the best ones as efficient according to the amount of outputs/inputs. The CCR model, which is the basic DEA model, was first developed by Charnes, Cooper, Rhodes in 1978, and six years later, Banker, Charnes, Cooper (BCC) introduced BCC models that measure the efficiency of DMUs under the assumption of variable returns to scale. More detail about the most preferred basic DEA models can be found in the studies of Charnes, Cooper and Rhodes (1978) and Banker, Charnes and Cooper (1984).

Classic DEA assumes that DMUs are homogeneous and can control all of the variables. However, this assumption is not valid in all cases and on DMUs since there are some external variables such as location, weather conditions, unemployment rate, advertising etc. cannot be controled by the administrator of DMUs. In 1986, Banker and Morey drew attention to the exogenous variables in inputs and outputs and studied the first examples of this situation in their study on the fast-food restaurant chain (Banker and Morey, 1986a). In efficiency analysis with classical DEA, input and output variables of DMUs are assumed to be continuous; however, it is not always possible for the variables to be continuous and in some applications one can see that some uncontrollable variables are categorical. Based on the idea that uncontrollable variables can be categorical, Banker and Morey developed the categorical DEA method in 1986 (Banker and Morey, 1986b). This approach enable researchers to divide DMUs to sub-groups according to the categorical variables for forming more homogenous groups and it's became possible to consider these sub-groups in efficiency calculations.

This paper utilizes the CAT-I-C specification, which is based on the version of CCR-I that is input oriented DEA approach, and the mathematical representation of dual form is shown below:

$$
\begin{aligned}
&Min\theta_k \\
&\sum_{j\in\cup_{f=1}^{L} D_f}^{n} \lambda_j X_{ij} \\
&\leq \theta_k X_{ik} \\
&\sum_{j\in\cup_{f=1}^{L} D_f}^{n} \lambda_j Y_{rj} \\
&\geq Y_{rk} \\
&\lambda_j \geq 0 \text{ ve } j \in \cup_{f=1}^{L} D_f
\end{aligned} \tag{1}
$$

where

Y_{rk} :output r produced by the *kth* DMU.

X_{ik} :input *i* used by the *kth* DMU.

Y_{rj} : output *r* produced by the *jth* DMU.

X_{ij} : input *i* used by the j*th* DMU.

n : number of DMUs.

λ_j : weight of the j*th* DMU.

D_f : set of number of categories that belong to the k*th* DMU $f = \{1, 2, \dots, l, \}$

L: number of the categories.

Since the input oriented DEA model is appropriate due to the fact that a manager of a restaurant can control the dealer's input level, this paper utilizes CAT-I-C specification.

3.2. The Integration of PCA and DEA

One can found different studies that evaluates performance of determined units using different types of methods such as SFA (Zou et al., 2016; Chen et al., 2017; Tsionas et al., 2017), MCDM methods (Barros and Wanke, 2015; Wanke et al., 2016; Pineda et al., 2018; Dinçer et al., 2017), regression (Bravo-Ureta et al., 2007) and traditional DEA (Saranga and Nagpal, 2016; Lee and Worthington, 2014; Lu et al., 2012; Mallikarjun, 2015; Rouse et al., 2002; Saranga and Nagpal, 2016; Sakthidharan and Sivaraman, 2018) in the literature; however, even if DEA is one of the most known nonparametric one, which is used for performance evaluation, this approach has some drawbacks. One of the most important weakness of

this method is the curse of dimensionality, which emerges when the data set includes larger number of inputs and outputs and this drawback causes the DEA fails to discriminate efficient DMUs from inefficient DMUs (Jothimani et al., 2017). The integration of PCA and Categorical-DEA forms an approach that is robust to large sample size (Yap, Ismail and Isa, 2013). In general, researchers utilize the dropping variables approach to deal with the curse of dimensionality; however, this approach causes the losing of the whole information that a unique variable has. PCA-Categorical-DEA approach creates new variables, which are the linear combination of the original variables, to use them as inputs and outputs; therefore, since this approach can shrink the data set with minimum loss of information for increasing discrimination power of DEA, one can say that this is a more powerfull tool than traditional DEA for efficiency calcutlaions.

PCA is a multivariate method that uses some rotations such as varimax to reduce variables to the uncorrelated components and these components generally explains 75-90 % variance of the original variables. Therefore, the new components, which have eigenvalues higher than 1 (in some cases 0.9) can substitutes the original variables because of the fact that the they can explains the huge amount of the variance of the original variables (Adler and Golany, 2001). One can find detail information about PCA in (Adler and Yazhemsky, 2010).

Applying PCA as a pre-analysis to the data set to be used in the DEA phase helps to eliminate some of the weaknesses of the DEA approach. The first of these, as mentioned before, is the increase in discrimination power. In cases where there are variables that correlate with each other in the data set, if traditional DEA is applied without applying PCA, it has been observed that some DMUs can be found efficient even if they are actually inefficient (Jothimani et al., 2017). However, when PCA is applied as a pre-analysis, non-correlated components will be obtained and these components help to increase the discrimination power of the traditional DEA approach. In addition, with the reduction of the number of variables used, efficiency analysis can be performed on data sets with fewer DMUs.

First step of implementation of PCA-Categorical-DEA is running the PCA method to inputs and outputs separately. After implementation of PCA, one can achieve the new components which are consist of regression factor scores; however, these components most probably include negative scores for some DMUs. Since DEA do not use the variables having negative values, a transformation such as adding the absoulte values of the most negative values to all cells of the variables can be needed.

4. Application of the Proposed Performance Assessment Framework

The variables to be utilized as input and output are determined in the initial stage of the study as a result of a literature review and face-to-face interviews with managers. The correlations between the input variables and also among the output variables are evaluated as a product of the first stage, and PCA is applied separately in the second stage, with the data set consisting of 7 input variables, 3 output variables, and 15 DMUs. The efficiency scores of the restaurants are obtained at the end of the second stage by reducing 7 input variables to 2 factors and 3 output variables to a single factor, then applying categorical DEA to the new data set of 2 inputs and a single output. Furthermore, in the final step, hypothesis tests are performed in order to analyze the environmental factors provided at the restaurant management's request.

4.1. The Selection of the Input and Output Variables

To the best of our knowledge, there is no research on the specific input/output sets for efficiency analysis of restaurant chain. This study initially determine input and output variables benefiting from the literature review and Table 2 shows the selected variables for the study.

Table 2.

Inputs and Outputs of the PCA-Categorical DEA Model

	Variables	Definiton of Variable	References
Inputs	I1: Employee Number	Number of employees working in the dealer	(Rouyendegh and Erol 2010); (Reynolds and Thompson, 2007); (Roh and Choi, 2010); (Andrejić et al., 2013)
	I2: Manager Experience	Manager's years of experience	(Tepe, 2006); (Gharakhani et al., 2012)
	I3: Seating Capacity	Seating area on a chair basis for each customer in the dealer	(Tepe, 2006); (Reynolds and Thompson, 2007); (Roh and Choi, 2010)
	I4: Number of Managers	Number of managers working in the dealer	(Tepe, 2006)
	I5: Working Hours	Total working hours per week at the dealer	(Reynolds and Thompson, 2007; (Gharakhani et al., 2012)
	I6: Advertising Expenses	Annual advertising expenses spent for the dealer	(Yürüşen, 2011)
	I7: Area	Dealers's acreage (m2)	(Reynolds and Thompson, 2007); (Gharakhani et al., 2012)
Outputs	O1: Average Account	Average account spent per desk	(Reynolds and Thompson, 2007); (Roh and Choi, 2010)
	O2: Number of Transactions	Number of monthly receipts at the dealer	(Tepe, 2006)
	O3: Customer Number	Number of people arriving to the dealer	(Gharakhani et al., 2012)

Table 2 summarizes the variables in the data set, the studies in the literature from which these variables were obtained, and the definitions of the variables. The data set in the study was filled as a result of face-to-face interviews with the restaurant management and is the data of 2019 in order to avoid the effect of the pandemic.

The study conducts an application based on the data of 15 restaurant chain dealers. First and foremost, international dealers affiliated with the chain were omitted from the data set, with the understanding that the current currency rate, variances in input prices, and cultural differences in the areas where the restaurants are located might all have an impact on the research. It was decided to continue working with 15 dealers in Istanbul who have the biggest business volume and who the restaurant chain management want to monitor their performance.

4.2. PCA-Categorical DEA Approach for Overall Performance Assessment

This study firstly implement PCA on the variables that form both input and output data set. The analysis shows that 7 variables can be reduced to 2 variables for the input set. Since the third component has 0.832 eigenvalue and also loading of variables to the components are practically satisfactory, regression factor scores are used to create new 2 variables as inputs for categorical-DEA implementation stage. Table 3 shows the PCA results for input variables:

Table 3.

PCA Results for Input Variables

Variables	Factor 1	Factor 2
Area (m^2)	**0.936**	0.119
Seating Capacity	**0.921**	0.207
Employee Number	**0.866**	-0.058
Number of Managaers	**0.802**	0.429
Manager Experience	**0.556**	0.087
Working Hours	0.174	**0.888**
Advertising Expenses	-0.077	**-0.791**
Eigenvalues	*3.749*	*1.333*
% of Variance	*54.197*	*19.038*

Table 3 shows that 2 components can explain the 73.23% of the total variance of 7 input variables and varimax rotation reveals that 5 variables of them can be associated with the capacity and named as capacity indicator. Additionally, since component 2 includes weekly working hours (0.888) and advertising expenses (-0.791) it can be said that this factor is a general administrative requirements indicator. In the PCA approach, the variables that are correlated with each other are reduced to components and the correlation coefficient can be positive or negative. Table 3 and Table 4 show that there is a negative correlation between some variables, and as a result, these negatively correlated variables with the obtained components are naturally expected to be negatively correlated.

The same approach is also conducted for output variables and 3 variables form 1 component as output. New component explains 81,42% of total variance of the 3 variables and can be called as sales performance indicator. Table 4 shows the factor loadings of the output variables on the new output component:

Table 4.

PCA Results for Output Variables

Variables	Factor 1
Number of Transactions	**0.983**
Average Account	**-0.871**
Customer Number	**0.848**
Eigenvalues	*2.443*
% of Variance	*81.422*

The integration of PCA and DEA enable researchers to decrease their data set to the more compact and the most important contribution of this approach is discrimination power to discriminate efficient and inefficient DMU's when it is compared to the traditional DEA (Jothimani et al., 2017; Wu and Li, 2017). Additionally, (Liu et al., 2009) highlights that number of the DMUs should be greater than two times of product of the number of inputs and outputs. PCA-DEA approach is also appropriate for such situation since it shrinks the data sets. The first stage enabled us to create new 2 components as inputs and 1 component as output using regression factor scores which come from PCA stage. The most minimum values were added to the all components and this transformation make all values of the components greater than zero. Table

5 shows the results of the categorical-DEA model after reduction:

Table 5.

Results of Reduced Categorical-DEA Model

DMU No	DMU	Score	Rank	Category
1	Steakhouse-1	7.23E-05	12	3
2	Steakhouse-2	6.98E-05	13	3
3	**Steakhouse-3**	**1**	**1**	**3**
4	Steakhouse-4	6.93E-05	14	3
5	Steakhouse-5	4.73E-05	15	3
6	Kebab-1	0.646	9	2
7	Kebab-2	0.961	5	2
8	**Kebab-3**	**1**	**1**	**2**
9	Kebab-4	0.703	7	2
10	Kebab-5	0.895	6	2
11	Meatball-Doner-1	0.693	8	1
12	**Meatball-Doner-2**	**1**	**1**	**1**
13	Meatball-Doner-3	0.991	4	1
14	Meatball-Doner-4	0.234	10	1
15	Meatball-Doner-5	7.72E-05	11	1

Table 5 reveal that Steakhouse-3, Kebab-3 and Meatball-Doner-2 are the DMUs that can achieve 1 efficiency score as efficient units and this means that each category has only 1 efficient DMU.

Table 6.

Hypothesis Tests

Research Hypotheses	Asymp.Sig. (2 tailed)	Statistical Decision
H1: There is a difference between dealers with few competitors in the environment and dealers with many competitors in the environment in terms of restaurant dealer efficiency.	0.611	Do not reject H0
H2: There is a difference between dealers with few years of service and dealers with many years of service for the restaurant in terms of restaurant dealer efficiency.	0.306	Do not reject H0
H3: There is a difference between the dealer having takeout service and the dealer not having takeout service in terms of restaurant dealer efficiency.	1.000	Do not reject H0

The results were obtained with the Mann Whitney U test, one of the non-parametric tests, using the SPSS-26 program to apply the hypothesis tests. Since the sample size is small, it was thought that the analysis with a non-parametric test would give more accurate results.

As seen in Table 6, two environmental factors (H1 and H2) and one variable (H3), which are thought to affect the efficiency in line with the company's request, were analyzed and the results were obtained.We read the values for each hypothesis from the Asymp Sig.(2-tailed) section in the table, it was checked whether this value is above 0.05. Number of competitors in the environment , number of years the restaurant has served and packet service Asymp Sig.(2-tailed) values are 0.611 , 0.306 , 1.000 respectively.

As a result, since all of these values are greater than 0.05, we decide to fail to reject H0. That is, we have observed that number of competitors in the environment, number of years the restaurant has served and packet service have no role in whether a dealer is effective or not.

5. Managerial Implication and Further Research Opportunities

In this study, 15 dealers of a restaurant chain operating in Istanbul were taken into consideration and 3 dealers were found to work effectively under the assumption of a fixed scale return. In the examination made for the 15 dealers of the restaurant, it is concluded that the branch in which it operates best is kebab. Although the study is limited to 15 dealers in terms of accessibility to the restaurant's data, the restaurant has more than 15 dealers, and a study can be done by considering all dealers in the future. With this study, in which all dealers are handled, event scores can be analyzed much more efficiently and better analysis can be made. By examining the activities of the overseas dealers of the restaurant in a different category, it can be possible to make an efficiency analysis on the basis of countries. Since DEA allows analysis on a yearly basis, the impact of the Covid-19 pandemic in restaurants can be examined with the 2020 data.

This study proposes an integrated framework combining PCA and categorical DEA approaches for evaluating performance of restaurants. Performance of 15 dealers of restaurant were analyzed due to limited data availability. In addition, in the second stage of the study, whether the environmental variables that are requested to be examined by the restaurant management have an effect on the efficiency were questioned by hypothesis tests. The study has been handled with a small number of DMUs. In future studies, the number of DMUs and the number of environmental variables whose effects on current performance are desired to be tested by the management can be increased. Nevertheless, the obtained results can be discussed in the light of new applications of the proposed methodology. In conclusion, this performance evaluation framework could provide an accurate roadmap not only for restaurant studies but also for studies carried out in similar institutions and organizations.

Contribution of Researchers

Conceptualization = Ayşegül Pınarbaşı, Melis Almula Karadayı, Umut Aydın; Data curation; Ayşegül Pınarbaşı; Formal analysis = Ayşegül Pınarbaşı, Umut Aydın; Funding acquisition = None; Investigation = Ayşegül Pınarbaşı, Melis Almula Karadayı, Umut Aydın; Methodology= Melis Almula Karadayı, Umut Aydın; Project administration = Melis Almula Karadayı, Hakan Tozan; Resources = Ayşegül Pınarbaşı, Umut Aydın; Software = Melis Almula Karadayı, Umut Aydın; Supervision= Melis Almula Karadayı, Hakan Tozan ; Validation= Melis Almula Karadayı, Umut Aydın; Visualization = Ayşegül Pınarbaşı, Umut Aydın; Roles/Writing- original draft = Ayşegül Pınarbaşı, Melis Almula Karadayı, Umut Aydın.

Conflict of Interest

The authors have no conflicts of interest to disclose.

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