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A hybrid stochastic data envelopment analysis and decision tree for performance prediction in retail industry

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ABSTRACT

Assessing the retail industry's efficiency is pivotal for economic growth and corporate productivity. This study employs a novel approach, utilizing a regression-based Stochastic Data Envelopment Analysis (SDEA) model, Balanced Scorecard (BSC), and Decision Tree. The integration of these methods is a pioneering effort in the retail sector. This is a data-driven decision-making framework, aiding managers in predicting efficient and inefficient Decision-Making Units (DMUs). Results from a case study in 44 retail store chains in Iran indicate that the accuracy of the SDEA model is 99%. The Decision Tree highlights low branch efficiency due to a low customer count, a unique finding in comparison to prior studies.

1. Introduction

Performance evaluation has become vital in modern business management (Ahmed et al., 2023; Gopal et al., 2018). It is a tool to identify the strengths and weaknesses of organizations (Danesh Asgari et al., 2017), as many organizations have problems achieving strategic goals due to the lack of a regular and targeted performance evaluation system (Chou, 2015). With the rapid development of information and communication technology, competition among companies, including the retail industry (Rouyendegh et al., 2020), has intensified, and firms require higher productivity to compete and survive (Fenyves and Tarnóczi, 2020; Mertens et al., 2016). The efficiency of chain stores is a key factor in the competition in the retail industry because the overall profitability of any chain company depends on the profitability of its constituent parts, that is, its branches (Morimura and Sakagawa, 2018). In addition, the effort to increase the productivity of a branch increases the efficiency of the entire company, which in turn creates competition among retailers (Lau et al., 2017; Sinik, 2017). Thus, the importance of evaluating retail performance is increasingly highlighted and has become the main topic of modern organizational management (Yinghui and Wenlu, 2015). However, despite its evident significance, there has been limited research on this facet of chain store management.

The retail industry has played a vital role in promoting the economy of developed countries so that it can impact the economy of those countries significantly (Gandhi and Shankar, 2014; Pande et al., 2020). The retail industry's productivity is important at the micro and macro economy levels. The effects of productivity at the national level can be mentioned as a factor in controlling inflation because the increase in wages in a country can be compensated by increasing productivity (Sinik, 2017). Gross Domestic Product (GDP) is one of the measures of countries' economic growth directly affected by the success of the retail industry. In examining the (GDP) and retail market share of countries in Southwestern Asia and the Global Retail Development Index (GRDI), it becomes evident that Iran, with a population exceeding 88 million, a GDP of 359 bn, and a retail market share of 9% of its GDP, exhibits a lower retail market share of GDP compared to other countries such as Turkey, which has a similar population. Furthermore, some countries like Saudi Arabia, India, and the United Arab Emirates rank among the top 35 countries in the GRDI, whereas Iran does not hold a position within this ranking (Kearney, 2021; WorldBank, 2023). The retail market in Iran can improve due to its population. The retail market can play a huge role in enhancing the GDP and improving its economy, as there is great potential in Iran's retail market. In addition, the size of Iran's retail market and its share of GDP has been in a downward trend from 2017 to 2020 (Serkland Invest, 2020). In such a case, the need to measure efficiency and its importance increases (Ko et al., 2017).

A review of performance evaluation studies in the retail industry reveals several key gaps. Data Envelopment Analysis (DEA) has emerged as a prominent tool for performance evaluation in the retail sector, with its effectiveness documented in numerous studies (Nong, 2022; Pachar

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et al., 2020; Sayar et al., 2021). This widespread adoption highlights its value in assessing retail industry performance (Perrigot and Barros, 2008). However, previous research primarily relies on classical DEA approaches Despite significant advancements in DEA methodology, limitations remain (de Melo et al., 2018). Classical models solely rely on historical data, hindering future performance prediction and their results cannot be directly extrapolated to the future. Additionally, classical DEA considers all inputs and outputs as fixed and deterministic, failing to account for potential randomness. To address these limitations, we propose utilizing the SDEA model. The SDEA model overcomes the limitations of classical DEA by employing probability distributions to predict efficiency, enabling future performance evaluation (Jahani Sayyad Noveiri et al., 2021; Sueyoshi, 2000). Suppose we know the reason for the effectiveness or ineffectiveness of a chain store in the future month. In that case, we can prevent inefficiency, significantly impacting the company's profitability and improving the retail industry. Due to the uncertainty in the environmental factors governing the store branches, the inputs and outputs of the branches are uncertain and forecasting efficiency and planning to improve their performance is a serious need of managers.

This study employed a modified version of the DEA future analysis model proposed by Sueyoshi (2000) to predict the efficiency of DMU. Sueyoshi's model relies on expert opinions and the PERT/CPM technique to predict expected values, which can be susceptible to errors and biases. Furthermore, branch manager transfers can disrupt the prediction process. Managers may lack sufficient knowledge about new branches, leading to inaccurate estimations. To overcome these limitations, we propose a novel approach that utilizes time series regression for predicting expected values. This method eliminates reliance on expert opinions and associated errors, leading to more accurate predictions. Our proposed model leverages readily available historical data to predict branch efficiency, eliminating the need for manager estimations. This ensures consistent and reliable predictions even with changes in branch management.

A comprehensive performance evaluation system requires indicators that capture the organization's overall performance (Gazi et al., 2022). However, existing research lacks a standardized method for selecting these criteria. To address this gap, we propose utilizing the BSC framework developed by Kaplan and David (1992). The BSC is a widely recognized and comprehensive approach that evaluates performance across four key perspectives: learning and growth, financial health, customer satisfaction, and internal processes (Mio et al., 2022). This structured approach ensures a holistic view of the organization's performance. The combined DEA and BSC method has proven effective in various fields (Basso and Funari, 2020; Jaberi Hafshjani et al., 2021; Zarei Mahmoudabadi and Emrouznejad, 2022). Studies suggest it empowers decision-makers with balanced, comprehensive, and unbiased evaluations (Hsu and Lin, 2021). The combined model leverages the strengths of both DEA and BSC, potentially overcoming their limitations (Dolasinski et al., 2019; Wu and Liao, 2014). Notably, no research has yet applied DEA-BSC to the retail industry.

While DEA excels at identifying inefficient DMUs, it has limitations. DEA is a mathematical tool and doesn't pinpoint the causes of inefficiency or account for external factors. Therefore, interpreting and utilizing DEA results relies heavily on managerial expertise (Pande et al., 2020). In contrast, data mining techniques used for performance prediction in retail can offer significant strategic advantages. These techniques empower companies to make more informed and nuanced strategic decisions (Morimura and Sakagawa, 2023). To address DEA's limitations and enhance retail performance evaluation, we propose integrating Decision Trees. Decision Trees are powerful tools for interpreting DEA findings and making data-driven decisions. The extracted rules can provide valuable insights for prediction, ultimately improving store efficiency and effectiveness.

This research seeks to (i) find and predict the efficiency or inefficiency of DMUs, (ii) find and predict the reason for their inefficiency, and (iii) suggest solutions for inefficient DMUs to increase their efficiency. This research makes several significant contributions to performance evaluation in the retail industry: (i) to the best of our knowledge, this research marks the first application of the SDEA method to evaluate the performance of DMUs in the retail industry, (ii) the BSC framework is employed in this research to identify relevant performance indicators within the retail industry, and (iii) most significantly, we present a novel approach that combines SDEA, BSC, and Decision Trees for a comprehensive efficiency evaluation in the retail industry. This marks a significant milestone in the field. This study utilizes the proposed SDEA-BSC model to evaluate the efficiency of 44 branches within Ofoq Kourosh Chain Stores, a leading Iranian retailer with over 20 million customers. The chain has grown significantly, expanding from just 8 branches in 2013 to over 3000 in just nine years. By leveraging Decision Trees, we analyze branch efficiency and provide improvement recommendations for underperforming units. Our research addresses existing limitations by proposing a novel and comprehensive methodology, aiming to bridge the gap in retail performance evaluation. This study contributes valuable insights to the broader literature on retail performance evaluation, offering a data-driven framework for decision-making regarding chain store performance.

The rest of this article is organized as follows. Section 2 examines the research on retail store performance evaluation. Section 3 presents data envelopment analysis models and our proposed model, and then the balanced scorecard and Decision Tree are discussed. Section 4 presents the balanced scorecard results, the efficiency of the DMUs obtained through the SDEA model, and the Decision Tree results. Section 5 presents theoretical and managerial insight. In section 6, the conclusion, limitations, and future recommendations are presented.

2. Literature review

Among the researches that have been conducted recently in the field of chain stores efficiency evaluation, Sayar et al. (2021) proposed a new form of the inverse DEA model by considering revenue (for planning) and budget (for finance and budget) constraints. The proposed model helps decision-makers to find the required value of each input and the revenue contribution of each output to meet the revenue or budget constraints. They used this model to analyze the efficiency of 58 supermarkets belonging to a chain. The area of supermarkets (in square meters) and working hours of employees (in hours) are considered as inputs, and sales and the number of loyal customers are considered as outputs. The result of the research highlights that every production system is faced with resource limitations regarding budgeting or planning. In addition, price availability allows for deeper analysis to gain more insight into the manufacturing process. Therefore, the proposed models help decision makers to take action in the process of input-output analysis considering budgeting or planning (whichever is required). The proposed models can be used to initiate and plan procedures not only for business sectors but also for any business and production system, considering the state of efficiency. (Baviera-Puig et al., 2020) calculated the efficiency of one of the Spanish supermarket chains using DEA and GIS concluded that membership programs in the loyalty scheme have a positive effect on the efficiency of the supermarket.

In another research, (Aggelopoulos and Lampropoulos, 2024) examined the impact of acquisition and organic growth on the total factor productivity change of retailing networks. They used data of newly opened stores of a large supermarket network in Athens, for a period (financial year 2014) where the network began to refocus on its organic growth after a two-year period of deep recession (financial years 2012–2013). To evaluate the performance effects of both strategies, they employed the bootstrap data envelopment analysis and the Malmquist productivity index DEA approach. They concluded that compared to organic growth, acquisitions lead to lower operating efficiency. The efficiency of food retail companies in the northern region of Hungary was analyzed by Fenyves and Tarnóczi (2020) The analysis was performed using time-series data from 2012 to 2017. This study suggests solutions to the stated problem. According to this study, the efficiency of companies shows a very different picture during the years under review. Also, the findings show that the use of developed DEA methods brings better results. That is, it is possible to have a better estimate of the efficiency of companies.

A comprehensive approach to evaluate the efficiency of retailers and rank the criteria that affect the efficiency of retailers was proposed by Okur and Ercan (2023). They conducted among the quantitative criteria, number of employees and profit before tax, and among the qualitative criteria, satisfied customers, qualified staff, and branding respectively have priority. Silva Junior et al. (2020) conducted a research aimed at analyzing the efficiency of a sample of 31 supermarkets in Brazil, using data envelopment analysis. The variables used in the research were gross sales, number of employees, sales area, and number of checkouts. Among the related findings, the sales area and the number of employees can be mentioned as variables that show inconsistency in order to reach the maximum efficiency of the DMUs. (de Melo et al. (2018) evaluated the technical efficiency and scale of the Brazilian supermarket sector through bootstrap data envelopment analysis, and measure changes in productivity using the Bootstrap-Malmquist index; concluded that small supermarket chains had lower levels of efficiency, but experienced higher levels of productivity growth. Also, Vyt and Cliquet (2017) evaluated the efficiency of store management of a French supermarket chain using two-stage data envelopment analysis and a geographic marketing approach. The results showed that retailers tend to have stores in an important sales area, with more employees, and in a more populated area with higher purchasing power.

We have summarized the findings of performance evaluation studies in the retail industry according to Table 1. The DEA model is divided into two columns: the "Classical" model, which includes CCR and BCC, the foundational and classical models introduced in 1979 and 1984, respectively, and the "Developed" model, which encompasses non-classical and newer models like Network DEA or stochastic models. In the second column, the data used in previous studies have been categorized into two groups: "Deterministic" and "Stochastic". "Deterministic" refers to data that are real and not stochastically generated or unforeseen. The "Anticipation" column denotes the use of methods capable of prediction, such as the SDEA model or decision trees. The "BSC" column signifies the utilization of the Balanced Scorecard in the examined study. The last column relates to the ability to extract rules for future decision-making, primarily achievable through machine learning methods. For instance, (Reiner et al., 2013) analyzed the performance of stores by utilizing simulation. Using this method, they dissected the factors influencing the efficiency of retail outlets and proposed rules to

Table 1
Review of performance evaluation in the retail sector using DEA.

Studies		DEA Model		Data		Anticipation	BSC	Deriving rules
		Classical	Developed	Deterministic	Stochastic			
1	Mateo et al. (2006)		✓	✓				
2	Barros (2006)	✓		✓				
3	Sellers-Rubio and Mas-Ruiz (2006)	✓		✓				
4	Sellers-Rubio and Mas-Ruiz (2007)		✓	✓				
5	(C. Yang et al., 2007)		✓	✓				
6	(de Jorge Moreno, 2008)		✓	✓				
7	Yu and Ramanathan (2008)	✓	✓	✓				
8	Joo et al. (2009)	✓		✓				
9	Yu and Ramanathan (2009)	✓	✓	✓				
10	Vaz et al. (2010)		✓	✓				
11	Mostafa (2010)	✓	✓	✓		✓		
12	(Akanksha Gupta and Mittal, 2010)	✓		✓				
13	Vaz and Camanho (2012)		✓	✓				
14	Reiner et al. (2013)	✓		✓				✓
15	Pande and Patel (2013)	✓		✓				
16	Uyar et al. (2013)		✓	✓				
17	Gandhi and Shankar (2014)	✓	✓	✓				
18	Zhang et al. (2014)		✓	✓				
19	Goic et al. (2015)		✓	✓				
20	Xavier et al. (2015)	✓		✓				
21	Duman et al. (2017)	✓		✓				
22	Ko et al. (2017)	✓		✓				
23	Sinik (2017)	✓		✓				
24	Vyt and Cliquet (2017)		✓	✓				
25	de Melo et al. (2018)		✓	✓				
26	Gupta et al. (2019)	✓	✓	✓				
27	Baviera-Puig et al. (2020)	✓		✓				
28	Pachar et al. (2020)		✓	✓				
29	Fenyves and Tarnóczi (2020)	✓		✓				
30	Pande et al. (2020)	✓	✓	✓				
31	Silva Junior et al. (2020)	✓		✓				
32	Rouyendegh et al. (2020)	✓		✓				
33	Sayar et al. (2021)		✓	✓				
34	Gafner et al. (2021)		✓	✓				
35	Nong (2022)	✓		✓				
36	Lu et al. (2022)		✓	✓				
37	Okur and Ercan (2023)	✓		✓				
38	Theeb et al. (2023)	✓		✓				
39	Aggelopoulos and Lampropoulos (2024)		✓	✓				
40	(Y. Yang et al., 2023)	✓	✓	✓				
41	Shi and Zhao (2023)	✓		✓		✓		
42	Costa Melo et al. (2023)	✓		✓				
43	Aggelopoulos et al. (2023)	✓	✓	✓				
44	This study (2023)	✓	✓	✓	✓	✓	✓	✓

enhance performance based on their findings. Although more studies have been identified in the relevant field, we have exclusively examined studies from 2006 onward.

This literature review shows that, to the best of our knowledge, there is no research analyzing supermarket or hypermarket efficiency with a stochastic DEA-BSC model and, as mentioned before, the combination of DEA and BSC can obtain highly balanced, complete, and unbiased evaluation results. Another gap in previous research is the lack of uncertainty in evaluating the performance of the chain stores in previous studies. Also, given the expressive power of data mining tools, they have not been used to analyze results and extract rules for predictive decisions in the retail industry assessment. Therefore, the main questions of this research include the following:

i. How to predict the efficiency of branches for future periods?
ii. How can we determine the reasons for the efficiency or inefficiency of a branch in retail industry in future months?
iii. Which performance evaluation indicators in the realm of chain stores possess strategic comprehensiveness?
iv. How can branch efficiency be increased using a method other than data envelopment analysis?

3. Methodology

The main objective of this research is to propose a new approach to performance measurement of chain stores in the retail industry. The proposed approach is implemented in three main phases (i) the identification of performance evaluation indicators in the framework of the Balanced Scorecard with the help of experts through the Fuzzy Delphi Technique and categorizing them into input and output by literature review, (ii) the evaluation of the efficiency of the stores by Stochastic Data Envelopment Analysis method, and (iii) concluding and providing solutions for inefficient branches with the help of a Decision Tree. The research framework is shown in Fig. 1. In the following the underpinning theories of Fuzzy Delphi Technique, Stochastic Data Envelopment Analysis, and Decision Three have been presented.

3.1. Fuzzy Delphi Technique

Given that human judgments are ambiguous and entail uncertainty, Fuzzy Delphi Technique has been utilized to account for the uncertainty in expert opinions, for the purpose of screening performance evaluation indicators (Esmaelnezhad et al., 2023). The steps of Fuzzy Delphi method are described below; adapted from (Kaufmann and Gupta, 1988):

Step 1: A questionnaire was designed using a linguistic scale to indicate the importance of performance evaluation indicators.
Step 2: Collecting opinions of the experts using the questionnaire. The questionnaires were completed by industrial and academic experts.
Step 3: The experts' opinions were converted into triangular fuzzy numbers. Calculating the fuzzy weight $(\widetilde{w}_j)$ of each strategy using (1):

$$\widetilde{w}_j = \left(\alpha_j, \gamma_j, \beta_j\right) \quad \forall j \in m \tag{1a}$$

Where:

$$\alpha_j = \min_{i \in n}\{a_{ij}\} \quad \forall j \in m \tag{2a}$$

$$\gamma_j = \left(\prod_{i=1}^{n} b_{ij}\right)^{1/n} \quad \forall j \in m \tag{3a}$$

$$\beta_j = \max_{i \in n}\{c_{ij}\} \quad \forall j \in m \tag{4a}$$

Step 4: The obtained weights are then defuzzified using the center of gravity method as follows:

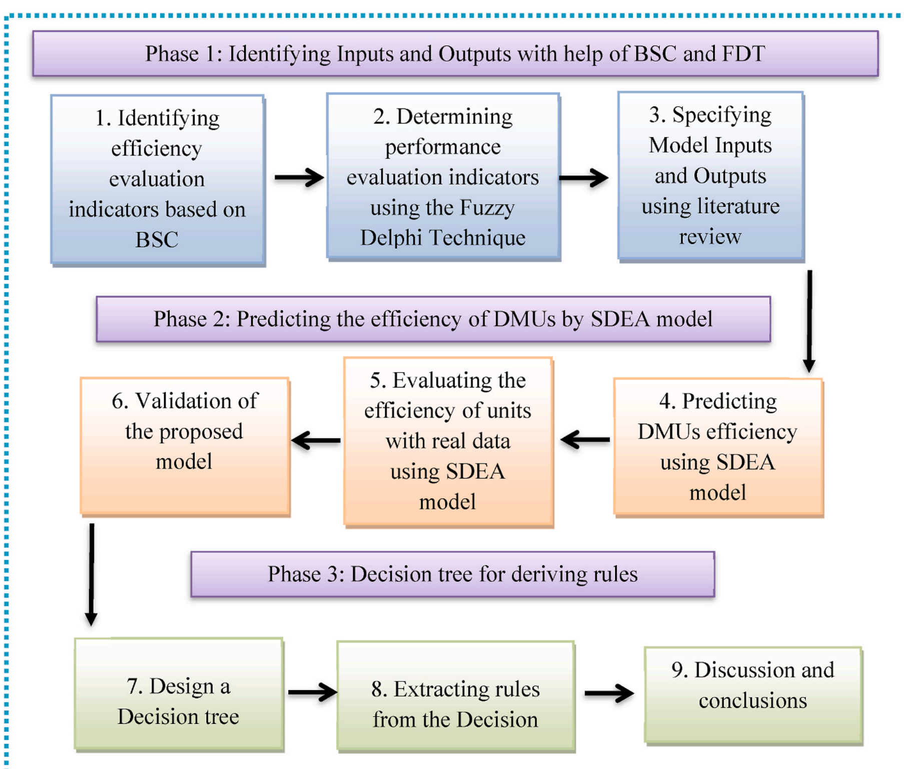

Fig. .1. Research framework.

$$S_j = \frac{\alpha_j + \gamma_j + \beta_j}{3} \quad \forall j \in m \tag{5a}$$

Step 5: Indicators with values greater than 0.7 are selected, and those with values less than 0.7 eliminated (Guttorp et al., 1990).

3.2. Stochastic data envelopment analysis

Deterministic DEA models, which are presented in the appendix, are based on the accuracy of all data, however, in some cases the data may be incomplete or contain uncertainty. For this reason, Charnes and Cooper (1959) proposed stochastic constraints in planning for the first time. The problem of classic DEA models, which are deterministic models, is to not consider measurement errors and incorrect data, and to not allow random deviations of input and output data. The result of this weakness is the occurrence of errors in the evaluation of the DMUs under review. This means that an efficient DMU may be erroneously introduced as inefficient and vice versa (Wei, 2001). In order to solve this problem and consider the random deviations of inputs and outputs, Sengupta (1982) developed the CCR deficit model as an objective function and stochastic constraints, and finally, SDEA models were proposed (Li, 1998). In 1993, the LLT model was proposed, in which the limits of the CCR coverage model were considered as random variables (Land et al., 1993). Later, Cooper et al. (1996) presented a new model using satisficing model of Simon (1957), which is a combination of the stochastic data envelopment analysis model with the concept of satisfactory decision-making.

Previous studies have used models that used past data sets to evaluate performance. Therefore, DEA has estimated past performance results. However, future planning is more important than evaluating past performance, so a model is needed that has the ability to predict the future performance of the investigated DMUs (Sueyoshi, 2000).

The SDEA model presented by Sueyoshi (2000) is a type of stochastic model that allows the use of both deterministic and stochastic data in the model. In this sense, SDEA not only allows analyzing the current state but also the future state of DMUs. In this model, it is assumed that there are n numbers of DMUs, whose entire set is represented by J. Each DMU is characterized by m inputs (X_{ij}) and s outputs (Y_{rj}). It is also assumed that all DMUs have input and output vectors, and all components of these vectors are positive. Therefore, the final SDEA-CCR secondary model will be as follows:

$$\begin{aligned} &\text{Min } \theta \\ &\text{St:} \end{aligned} \tag{6a}$$

$$-\sum_{j=1}^{n} (\beta_j x_{ij})\lambda_j + \theta x_{ik} \geq 0, i = 1, \ldots, m. \tag{7a}$$

$$\sum_{j=1}^{n} \left\{ \bar{y}_{rj} + b_{rj} F^{-1}(1-\alpha_j) \right\} \lambda_j \geq \bar{y}_{rk}, r = 1, \ldots, s. \tag{8a}$$

$$\lambda_j \geq 0 \;\; j = 1, \ldots, n. \tag{9a}$$

$$\theta : \text{free} \tag{10}$$

In the above model, v_i represents the weight of inputs and u_i represents the weight of outputs. Also, x_{ij} represents the i-th input and y_{rj} represents the r-th output associated with DMU_j. $\boldsymbol{\beta}_j$ also represents the expected efficiency level of the j-th decision-making unit, which can take values from 0 to 1. $\boldsymbol{\alpha}_j$ is also defined as the decision maker's risk tolerance. Also, θ is the binary variable of the first constraint and λ_j is the binary variable related to the second constraint.

Equations (11) and (12) are used to calculate the predicted values as well as their standard deviation, where (MLrj) is the Most Likely Estimate, (OPrj) is the optimistic estimate, and (PErj) is the pessimistic estimate.

$$\bar{y}_{rj} = \frac{(OP_{rj} + 4ML_{rj} + PE_{rj})}{6} \tag{11}$$

$$b_{rj}^2 = \frac{(OP_{rj} - PE_{rj})}{6} \tag{12}$$

As can be seen, the values of $\bar{y}_{rj}$ and b_{rj}^2 are calculated based on expert opinions and then substituted into the DEA model. In other words, the calculated efficiency values are directly influenced by expert opinions. To prevent this issue, we suggest calculating the expected values using a regression equation and utilizing past data. In this case, $\bar{y}_{rj}$ and b_{rj}^2 are calculated as follow:

$$\sum Y_{rj} = Na + b\sum X \tag{13}$$

$$\sum XY_{rj} = a\sum X + b\sum X^2 \tag{14}$$

$$\bar{y}_{rj} = a + bX \tag{15}$$

$$b_{rj}^2 = \frac{\sum \left(\bar{y}_{rj} - \mu_{\bar{y}_{rj}}\right)^2}{N} \tag{16}$$

In equations (13)–(16), Y_{rj} represents the deterministic output value, $\mu_{\bar{y}_{rj}}$ is the average output, "N" is the number of the relevant period, "X" is the time, and "a" and "b" are, respectively, the constant and slope of the line. In order to calculate $\bar{y}_{rj}$ and b_{rj}^2, the data of the last 6 periods were used because only the values of the last year were available.

3.3. Balanced scorecard

The balanced scorecard is a strategic tool and a framework for evaluating the performance of organizations that was presented by Kaplan and David (1992). The advantage of this approach is to consider financial and non-financial criteria in performance evaluation. The balanced scorecard examines the organization from four perspectives: financial, customers, growth and learning, and internal processes. Customer perception answers the question of how customers see the company. The internal processes perspective aims to provide answers to the question of where (in which activities) and how excellence can be achieved. A learning and growth perspective should answer the question of how to continue to innovate and create value, while a financial perspective is more concerned with stakeholder needs. All of these perspectives are presented in a strategy map that describes and connects them. In the combination of DEA and BSC models, BSC is used as a tool to evaluate performance indicators and the DEA model is used as a tool to evaluate the efficiency of DMUs.

3.4. Decision tree

Data mining includes various algorithms and techniques such as classification, clustering, regression, artificial intelligence, neural networks, association rules, decision trees, genetic algorithm, and nearest neighbor method, to discover knowledge from databases that are widely used (Dey et al., 2017). A decision tree is a flowchart-like tree structure in which each internal node represents a test on a feature, each branch represents the result of the test, and the class label is represented by each leaf node (or terminal node). Tree models where the target variable can take a limited set of values are called classification trees. In this tree structure, the leaves represent the class labels, and the branches represent the combinations of features that lead to those class labels (H. Sharma and Kumar, 2016). Since the output of the decision tree can be organized in the form of a tree or rules, the results are easy to understand and interpret. Decision tree algorithms include ID3 (Quinlan, 1986), C4.5 (Quinlan, 1993), and CART (Breiman et al., 1984). Because they are easy to understand, decision trees have been widely used in many fields, nevertheless, there is no application for predicting the performance of chain stores so far.

4. Results and discussions

To evaluate the performance of stores, we used cross-section data for the year 2023, obtained from one of Irans's leading hypermarket chains, on 44 of its retail outlets. The "Ofoq Kourosh" chain store is one of the major retailers in Iran that has experienced significant growth in terms of branch numbers and customers in recent years. The required data was collected through interviews with branch managers of this retail chain. The inputs and outputs that are considered in the analysis are those listed in Table 2.

4.1. Phase 1: identifying inputs and outputs

First, using the opinions of experts, 21 indicators were selected in the framework of the balanced scorecard. Then, using the Fuzzy Delphi Technique, the indicators were screened and after three rounds, a consensus was reached and the number of indicators were reduced to 10. The fuzzy Delphi results can be seen in Table 4.

In the following step, the obtained indicators using Fuzzy Delphi Technique were compared with the indicators utilized in previous studies. The literature survey is a way to ensure the validity of the inputs and outputs. Subsequently, the inputs and outputs of the SDEA model were identified and categorized through a literature review, and the resulting outcomes are presented in Table 3. Also, in Fig. 2, the inputs and outputs of the SDEA model, which are categorized based on the BSC, are presented.

In retail performance evaluation by DEA, key factors are categorized into inputs and outputs. Inputs, such as assets (inventory) and costs (wages, marketing, maintenance, and so on) represent resource utilization (Pande et al., 2020). Employee working hours (total recorded at the store) and number of employees (actively engaged staff) reflect workforce deployment (Sinik, 2017). The age of the branch indicates the time since its establishment, and managerial experience reflects the tenure of managers which contributes to operational maturity. Finally, store size refers to the floor area. On the output side, previous research consistently highlights sales volume as a crucial performance indicator (Gupta and Mittal, 2010). Similarly, the number of customers reflects purchase volume (Sinik, 2017). Finally, profit remains a widely recognized metric for retail store performance.

Table 3
Inputs and outputs.

Inputs and Outputs		
Inputs	Assets	(de Jorge Moreno, 2010; Fenyves and Tarnóczi, 2020; Gandhi and Shankar, 2014; Gupta et al., 2019; Uyar et al., 2013)
	Costs	(Fenyves and Tarnóczi, 2020; Pande et al., 2020; Pande and Patel, 2013; Uyar et al., 2013)
	Employees working hours	(Gupta and Mittal, 2010; Nong, 2022; Sayar et al., 2021; Sinik, 2017; Zhang et al., 2014)
	Number of employees	(de Melo et al., 2018; Gandhi and Shankar, 2014; Ko et al., 2017; Silva Junior et al., 2020; Uyar et al., 2013; Vaz and Camanho, 2012; Vyt and Cliquet, 2017)
	Age of the branch	(Assaf et al., 2011; Baviera-Puig et al., 2020; Gauri, 2013)
	Store size	(Baviera-Puig et al., 2020; Ko et al., 2017; Sayar et al., 2021; Vyt and Cliquet, 2017; Zhang et al., 2014)
	Manager experience	(V. Sharma and Choudhary, 2010)
Outputs	Sales	(Baviera-Puig et al., 2020; Gandhi and Shankar, 2014; Sayar et al., 2021; Uyar et al., 2013; Vaz and Camanho, 2012; Yu and Ramanathan, 2009)
	Number of customers	(Gupta and Mittal, 2010; Ko et al., 2017; Nong, 2022; C. Yang et al., 2007)
	Profit	(Gupta et al., 2019; Sellers-Rubio and Mas-Ruiz, 2006; Uyar et al., 2013; C. Yang et al., 2007; Yu and Ramanathan, 2009)

"Sales", "Profit", "Assets", and "Costs" were reported on a monthly basis, measured in million Tomans. The "Store size" was measured in square meters. Values related to the "Manager experience" and the "Age of the branch" were expressed on a monthly basis.

4.2. Phase 2: predicting the efficiency of DMUs

By identifying the inputs and outputs, the efficiency of the branches was calculated using the predicted values and with different values of α and β (as defined in section 3.2) using equations (6)–(10). The obtained results from the model need to be assessed for various parameter values and subjected to analysis. Accordingly, Tables 4 and 5 present and discuss the efficiency evaluation results of 44 branches for different values of alpha and beta.

Also, after a month, deterministic data was collected, and based on

Table 2
Fuzzy Delphi results.

First round			Second round		
Indicator	Average	Result	Indicator	Average	Result
Assets	0.817	Approval	Assets	0.867	Approval
Labor costs	0.650	Disapproval	Sales	0.800	Approval
Sales	0.750	Approval	Profit	0.758	Approval
Profit	0.825	Approval	Liquidity	0.542	Disapproval
Transaction Size	0.425	Disapproval	Stocks	0.483	Disapproval
Liquidity	0.725	Approval	Costs	0.842	Approval
Stocks	0.758	Approval	Number of employees	0.742	Approval
Advertising cost	0.617	Disapproval	Number of checkout's	0.500	Disapproval
Rental cost	0.667	Disapproval	Store size	0.767	Approval
Marketing cost	0.625	Disapproval	Employees working hours	0.758	Approval
Costs	0.750	Approval	Manager experience	0.733	Approval
Number of employees	0.783	Approval	Age of the branch	0.717	Approval
Number of checkout's	0.700	Approval	Number of competitors	0.558	Disapproval
Store size	0.767	Approval	Customer satisfaction index	0.792	Approval
Employees working hours	0.725	Approval	Number of customers	0.800	Approval
Manager experience	0.825	Approval			
Age of the branch	0.733	Approval			
Number of competitors	0.750	Approval			
Customer satisfaction index	0.742	Approval			
Number of customers	0.742	Approval			
Number of loyal customers	0.683	Disapproval			

Table 4
DMUs efficiency results.

DMU	$\beta = 0.7$			$\beta = 0.8$			$\beta = 0.9$		
	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.5$	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.5$	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.5$
1	0.6126	0.6347	0.7000	0.7001	0.7254	0.8000	0.7877	0.8160	0.9000
2	0.5876	0.6051	0.6913	0.6715	0.6915	0.7901	0.7554	0.7779	0.8888
3	0.4536	0.4644	0.5157	0.5184	0.5308	0.5894	0.5832	0.5971	0.6630
4	0.6851	0.6883	0.7000	0.7829	0.7867	0.8000	0.8808	0.8850	0.9000
5	0.6697	0.6753	0.7000	0.7654	0.7717	0.8000	0.8611	0.8682	0.9000
6	0.4345	0.4470	0.5036	0.4966	0.5108	0.5755	0.5586	0.5747	0.6475
7	0.4379	0.4502	0.5009	0.5005	0.5145	0.5725	0.5630	0.5788	0.6441
8	0.4311	0.4463	0.5040	0.4927	0.5100	0.5760	0.5543	0.5738	0.6480
9	0.4677	0.4815	0.5441	0.5345	0.5503	0.6219	0.6013	0.6191	0.6996
10	0.4557	0.4699	0.5273	0.5208	0.5371	0.6026	0.5859	0.6042	0.6780
11	0.6063	0.6244	0.7000	0.6929	0.7136	0.8000	0.7795	0.8028	0.9000
12	0.6119	0.6269	0.6953	0.6993	0.7164	0.7946	0.7867	0.8060	0.8939
13	0.5091	0.5153	0.5378	0.5819	0.5890	0.6147	0.6546	0.6626	0.6915
14	0.5295	0.5400	0.5797	0.6052	0.6171	0.6625	0.6808	0.6943	0.7454
15	0.4838	0.4948	0.5434	0.5529	0.5655	0.6210	0.6220	0.6362	0.6986
16	0.4759	0.4889	0.5472	0.5439	0.5587	0.6253	0.6119	0.6285	0.7035
17	0.5726	0.5928	0.6695	0.6544	0.6774	0.7651	0.7362	0.7621	0.8608
18	0.5633	0.5754	0.6289	0.6438	0.6577	0.7187	0.7243	0.7399	0.8086
19	0.5683	0.5808	0.6312	0.6494	0.6638	0.7214	0.7306	0.7467	0.8116
20	0.4674	0.4780	0.5201	0.5342	0.5463	0.5944	0.6010	0.6146	0.6687
21	0.5896	0.5957	0.6132	0.6738	0.6808	0.7007	0.7581	0.7659	0.7883
22	0.4341	0.4445	0.4950	0.4961	0.5080	0.5657	0.5581	0.5714	0.6364
23	0.6723	0.6783	0.7000	0.7683	0.7752	0.8000	0.8644	0.8721	0.9000
24	0.6424	0.6549	0.7000	0.7342	0.7485	0.8000	0.8260	0.8421	0.9000
25	0.5038	0.5144	0.5546	0.5758	0.5879	0.6339	0.6478	0.6614	0.7131
26	0.6507	0.6611	0.7000	0.7437	0.7555	0.8000	0.8366	0.8500	0.9000
27	0.5081	0.5199	0.5687	0.5807	0.5942	0.6499	0.6533	0.6685	0.7312
28	0.6682	0.6751	0.7000	0.7637	0.7715	0.8000	0.8591	0.8680	0.9000
29	0.6188	0.6346	0.7000	0.7072	0.7253	0.8000	0.7956	0.8159	0.9000
30	0.4818	0.4988	0.5650	0.5506	0.5701	0.6457	0.6194	0.6413	0.7265
31	0.6846	0.6880	0.7000	0.7824	0.7863	0.8000	0.8802	0.8846	0.9000
32	0.6638	0.6716	0.7000	0.7586	0.7675	0.8000	0.8535	0.8635	0.9000
33	0.4825	0.4987	0.5644	0.5514	0.5700	0.6451	0.6203	0.6412	0.7257
34	0.5241	0.5397	0.5952	0.5990	0.6168	0.6803	0.6739	0.6939	0.7653
35	0.2792	0.2891	0.3291	0.3191	0.3303	0.3761	0.3590	0.3716	0.4231
36	0.2997	0.3064	0.3341	0.3425	0.3501	0.3818	0.3854	0.3939	0.4295
37	0.5580	0.5776	0.6577	0.6377	0.6601	0.7517	0.7174	0.7426	0.8457
38	0.6474	0.6571	0.7000	0.7399	0.7509	0.8000	0.8323	0.8448	0.9000
39	0.5981	0.6121	0.6730	0.6835	0.6995	0.7692	0.7690	0.7869	0.8653
40	0.6166	0.6314	0.7000	0.7047	0.7216	0.8000	0.7928	0.8118	0.9000
41	0.4685	0.4791	0.5256	0.5354	0.5476	0.6007	0.6023	0.6160	0.6758
42	0.4943	0.4994	0.5175	0.5649	0.5707	0.5915	0.6355	0.6420	0.6654
43	0.3663	0.3699	0.3830	0.4186	0.4227	0.4377	0.4709	0.4756	0.4924
44	0.5024	0.5189	0.5851	0.5742	0.5930	0.6687	0.6460	0.6671	0.7523

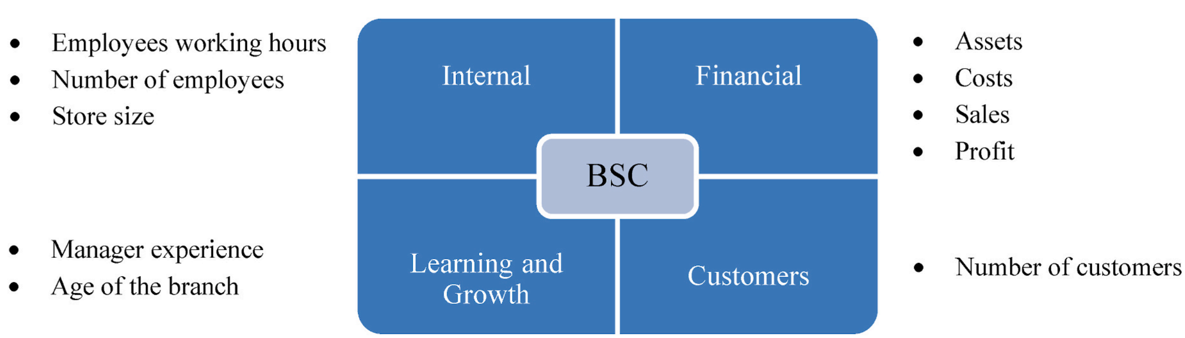

Fig. 2. Balanced Scorecard results.

that, the real performance of the branches was calculated by the SDEA model. Table 6 presents the computed real efficiency values of branches. This is imperative as the proposed model has the capability to predict branch efficiency, necessitating a comparison between the predicted and real efficiency values.

In order to compare the predicted efficiency with the real efficiency, after calculating the correlation between the predicted efficiency values of branches and the real efficiency values of branches, it was inferred that using the T-test at a significance level of 0.05, the correlation between the predicted efficiency of each branch in relation to the real efficiency value of branches is 0.99.

According to Tables 4 and 5, we can infer that:

1. The predicted efficiency of the DMUs increases by increasing (α) and (β).

Table 5
DMUs efficiency results.

DMU	$\beta = 1$						
	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.5$	$\alpha = 0.8$	$\alpha = 0.9$	$\alpha = 0.95$
1	0.8752	0.9067	0.9473	1.0000	1.0453	1.0732	1.0977
2	0.8394	0.8644	0.9031	0.9876	1.0890	1.1491	1.2037
3	0.6480	0.6634	0.6843	0.7367	0.8062	0.8447	0.8732
4	0.9786	0.9834	0.9890	1.0000	1.0699	1.1106	1.1472
5	0.9568	0.9647	0.9752	1.0000	1.1039	1.1674	1.2268
6	0.6207	0.6385	0.6618	0.7194	0.7888	0.8243	0.8526
7	0.6256	0.6431	0.6657	0.7156	0.7815	0.8215	0.8582
8	0.6158	0.6375	0.6639	0.7200	0.7853	0.8242	0.8495
9	0.6681	0.6879	0.7139	0.7773	0.8532	0.8991	0.9389
10	0.6510	0.6714	0.6982	0.7533	0.8156	0.8504	0.8805
11	0.8661	0.8920	0.9255	1.0000	1.1004	1.1616	1.2185
12	0.8741	0.8955	0.9258	0.9933	1.0724	1.1146	1.1528
13	0.7273	0.7362	0.7439	0.7683	0.8100	0.8377	0.8611
14	0.7564	0.7714	0.7886	0.8282	0.8836	0.9199	0.9523
15	0.6912	0.7068	0.7268	0.7762	0.8452	0.8857	0.9093
16	0.6799	0.6984	0.7236	0.7817	0.8499	0.8855	0.9118
17	0.8180	0.8468	0.8818	0.9564	1.0328	1.0715	1.1032
18	0.8048	0.8221	0.8458	0.8984	0.9655	1.0048	1.0315
19	0.8118	0.8297	0.8526	0.9017	0.9640	0.9995	1.0328
20	0.6677	0.6829	0.7022	0.7430	0.7967	0.8294	0.8573
21	0.8423	0.8510	0.8615	0.8759	0.8955	0.9096	0.9249
22	0.6201	0.6349	0.6564	0.7071	0.7748	0.8177	0.8570
23	0.9604	0.9690	0.9794	1.0000	1.0571	1.0897	1.1187
24	0.9178	0.9356	0.9562	1.0000	1.0643	1.1051	1.1408
25	0.7198	0.7349	0.7537	0.7923	0.8352	0.8596	0.8812
26	0.9296	0.9444	0.9627	1.0000	1.0495	1.0774	1.1020
27	0.7259	0.7428	0.7646	0.8124	0.8709	0.9072	0.9414
28	0.9546	0.9644	0.9764	1.0000	1.1002	1.1611	1.2178
29	0.8840	0.9066	0.9358	1.0000	1.0915	1.1464	1.1971
30	0.6882	0.7126	0.7438	0.8072	0.8781	0.9204	0.9593
31	0.9780	0.9828	0.9887	1.0000	1.0538	1.0844	1.1115
32	0.9483	0.9594	0.9730	1.0000	1.0485	1.0766	1.1012
33	0.6893	0.7125	0.7422	0.8063	0.8827	0.9288	0.9649
34	0.7488	0.7710	0.7965	0.8503	0.9120	0.9469	0.9782
35	0.3988	0.4129	0.4309	0.4701	0.5138	0.5338	0.5495
36	0.4282	0.4376	0.4499	0.4773	0.5113	0.5328	0.5533
37	0.7971	0.8252	0.8612	0.9396	1.0337	1.0910	1.1442
38	0.9248	0.9387	0.9560	1.0000	1.0473	1.0775	1.1050
39	0.8544	0.8744	0.8993	0.9615	1.0483	1.0988	1.1388
40	0.8808	0.9020	0.9330	1.0000	1.0954	1.1530	1.1979
41	0.6693	0.6845	0.7046	0.7509	0.7942	0.8172	0.8377
42	0.7061	0.7134	0.7222	0.7393	0.7563	0.7655	0.7733
43	0.5232	0.5284	0.5347	0.5471	0.5602	0.5673	0.5808
44	0.7177	0.7412	0.7712	0.8358	0.9123	0.9562	0.9845

Table 6
DMUs real efficiency results.

DMU	Efficiency	DMU	Efficiency
1	1.0000	23	1.0000
2	0.9813	24	1.0000
3	0.7782	25	0.7615
4	1.0000	26	1.0000
5	1.0000	27	0.7995
6	0.7430	28	1.0000
7	0.7449	29	1.0000
8	0.7623	30	0.8766
9	0.8096	31	1.0000
10	0.7389	32	1.0000
11	1.0000	33	0.8094
12	1.0000	34	0.8567
13	0.7947	35	0.4973
14	0.8288	36	0.4904
15	0.8150	37	0.9677
16	0.7887	38	1.0000
17	0.9862	39	1.0000
18	0.9394	40	1.0000
19	0.9202	41	0.7770
20	0.7512	42	0.7314
21	0.8468	43	0.5392
22	0.7480	44	0.8627

2. As long as $\boldsymbol{\alpha} < 0.5$, the efficiency of none of the DMUs reaches 1, in other words, the efficiency of all DMUs is less than 1 and inefficient. When the value of $\boldsymbol{\alpha}$ reaches 0.5, some DMUs reach the efficiency level of 1, although most of the DMUs still have an efficiency of less than 1. Also, when $\boldsymbol{\alpha} > 0.5$ is considered, the predicted efficiency of some DMUs is more than 1.

Based on the mentioned cases, it can be inferred that the above findings are consistent with the findings of (Sueyoshi, 2000).

4.3. Phase 3: decision tree

DEA is a potent tool for assessing the efficiency of DMUs, effectively revealing their efficiency and inefficiency levels. However, when it comes to providing explanations for inefficiencies, DEA falls short, necessitating the use of supplementary tools for dissecting and interpreting results from the SDEA model. To address this need, numerous studies have employed a combination of DEA models and data mining, as it has been demonstrated that these tools hold considerable power for data analysis. In this study as well, the Decision Tree has been utilized to analyze the outcomes of the SDEA model.

Researchers utilize the C4.5 algorithm for classification, recognized as a solution for decision-making, which can simplify and expedite the decision-making process (Arifin and Fitrianah, 2018). When the sample size is small and the samples do not fully represent the population, bootstrapping resampling technique can be used (Adèr, 2008; Emrouznejad and Anouze, 2010). To achieve this, we randomly sample from the dataset of 44 branches and repeat this process 100 times, resulting in a total of 4400 branches. The efficiency of branches results in two groups: efficient branches and inefficient branches, which are considered as the target variable in the decision tree. Additionally, the indices obtained from fuzzy Delphi technique are taken into account as explanatory variables in the decision tree. After entering the information into the RapidMiner software, a decision tree model was designed. In this model, the C4.5 Decision Tree was used to extract the rules. To design the tree, 70% of the training data and 30% of the test data were used to learn the model. Also, a validation module was incorporated to validate the tree, confirming that the model accuracy is 100%. The results of the decision tree are shown in Fig. 3.

In order to draw the decision tree, we considered the "Assets", "Costs", "Employees working hours", "Number of employees", "Age of the branch", "Store size", "Manager experience", "Sales", "Number of customers", and "Profit" as inputs and branch efficiency classification as output. The results of Decision Tree can be summarized as following:

- The root of the decision tree is the "Number of customers", and it indicates that among the 10 indicators in the model, the "Number of customers" has been identified as the most important attribute. The "Number of customers" represents a dimension of the "Customers" category in the balanced scorecard. Therefore, it can be concluded that the "Customers" dimension holds special importance in evaluating chain stores.
- "Assets", "Sales", "Costs", "Store size", and "Number of customers" have been of higher importance compared to other indicators.
- Branches whose "Number of customers" is less than or equal to 11250 are inefficient. These branches can encourage customers to make purchases by creating sales festivals, various discount schemes, and advertising.
- Branches whose "Number of customers" is more than 11250 and "Sales" is less than or equal to 2240 are inefficient. These branches can encourage customers to make purchases by creating sales festivals, various discount schemes, and advertising.
- Branches whose "Number of customers" is more than 11250, "Store size" is more than 195, "Sales" is less than or equal to 6050, and "Costs" is more than 202.500 are inefficient. In addition to the previous suggestions, it is suggested to these branches to reduce the area

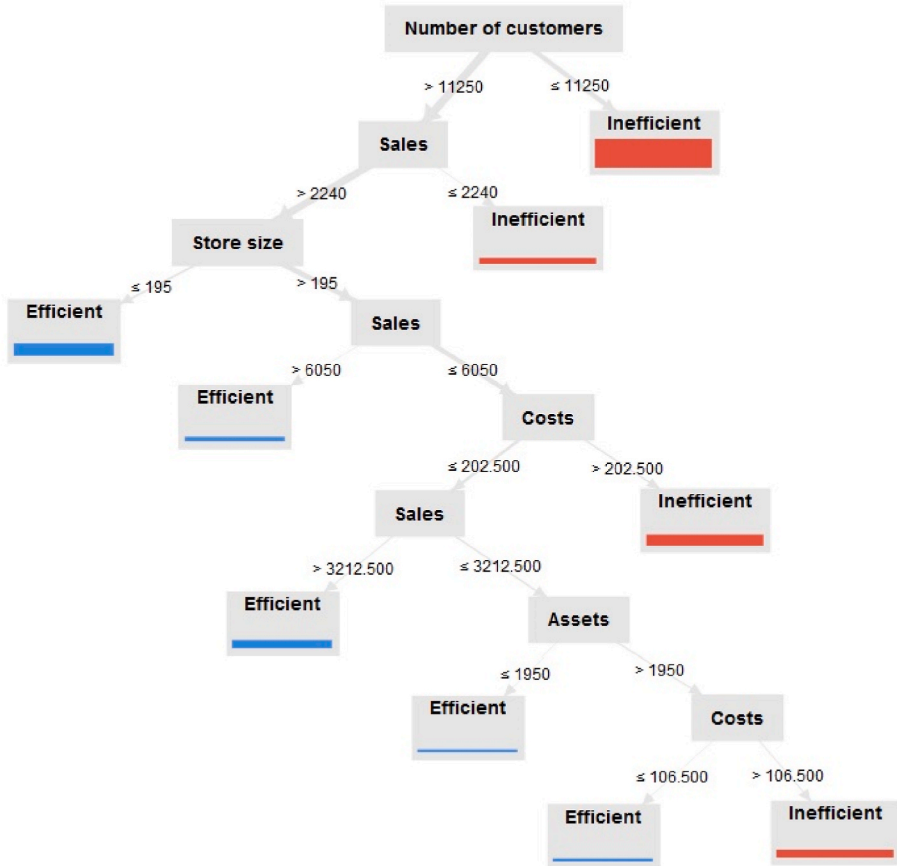

Fig. 3. Decision tree.

of the store in order to increase its efficiency, nonetheless, to keep the amount of store assets, which in a way represents the variety of products, and by using management approaches, to improve the placement of shelves and make optimal use of the store space. Additionally, reducing the store size has a direct correlation with cost reduction.

- Branches whose "Number of customers" is more than 11250, "Store size" is more than 195, "Sales" is less than or equal to 3212.500, "Assets" is more than 1950, and "Costs" is more than 106.500 are inefficient. It is suggested to these branches to reduce their area in addition to advertising and attracting customers. This will reduce their costs and assets and help them become more efficient. Of course, reducing assets does not mean reducing the variety of goods, and they should maintain the variety of their goods by improving the shelves and interior space of the store.
- Branches whose "Number of customers" is more than 11250, "Sales" more than 2240, and "Store size" is less than or equal to 195 are efficient.
- Branches whose "Number of customers" is more than 11250, "Store size" is more than 195, and "Sales" more than 6050 are efficient.
- Branches whose "Number of customers" is more than 11250, "Store size" is more than 195, "Costs" is less than or equal to 202.500, and "Sales" is more than 3212.500 are efficient.
- Branches whose "Number of customers" is more than 11250, "Store size" is more than 195, "Costs" is less than or equal to 202.500, "Sales" is less than or equal to 3212.500, and "Assets" is less than or equal to 1950 are efficient.
- Branches whose "Number of customers" is more than 11250, "Store size" is more than 195, "Sales" is less than or equal to 3212.500, "Assets" is more than 1950, and "Costs" is less than or equal to 106.500 are efficient.

5. Theoretical and managerial insight

DEA has been employed in various sectors such as banking, schools, hotels, hospitals, and notably in the retail industry. However, it is noteworthy that no studies conducted in the retail industry have considered uncertainty, despite the stochastic nature of many phenomena. Diverse SDEA models exist, one of which is the model presented in this study, capable of predicting the efficiency of DMUs. The SDEA model introduced in this research is 99% accurate, was capable of predicting the efficiency of DMUs. This could represent a significant advantage for company managers to forecast the performance of DMUs for future periods and make the necessary decisions based on their performance. This predictive capability creates a significant competitive advantage for managers, enabling them to make better decisions at the right time. These decisions may vary depending on the nature of the company. They may involve investment, hiring or workforce adjustment, product or service development, and resource management. Additionally, managers, by knowing future performance, can devise business strategies that can assist in the sustainable growth of the company. This ability allows the company to respond more rapidly to market challenges and exhibit agility.

Another notable aspect in performance evaluation studies within the retail industry is the absence of a specific framework for selecting performance evaluation indicators. Through the integration of DEA and BSC, we have forecasted the performance of branches based on the four dimensions of the Balanced Scorecard, which encompass various organizational aspects and exhibit strategic comprehensiveness. The outcome of the Balanced Scorecard presented ten performance indicators for evaluating efficiency in the retail industry, maintaining the expected comprehensiveness in performance assessment. In other words, one of the achievements of this study is the presentation and introduction of these ten indicators, which should be considered for a comprehensive evaluation of the retail industry's performance and have the potential for generalizability to other studies in this field. This research demonstrates that the BSC framework can effectively encompass the required indicators for evaluating efficiency. This is a developed technique that was absent in previous studies.

Leveraging machine learning techniques, due to their capability to extract valuable insights from raw data, alongside the DEA methodology, can establish a robust framework for performance evaluation. DEA identifies efficient and inefficient units, while the reasons behind them are elucidated by Machine Learning techniques. We identified the reasons for the efficiency and inefficiency of branches using decision trees and provided recommendations for improving their efficiency. From the perspective of the decision tree, the factors influencing branch efficiency are, in order, the number of customers, sales, area, costs, and assets, where their levels above or below a threshold contribute to efficiency or inefficiency. The analysis of the decision tree illustrates that attention to balanced scorecard dimensions, including the financial dimension (such as costs, assets, and sales), internal dimension (such as store size), and customer dimension (such as the number of customers and customer satisfaction level), as well as the strategic and tactical design of logistics processes in the store (such as geographical location and store layout, and product arrangement), can lead to performance improvement. Although this method was implemented on a specific case, it is applicable to other cases, with threshold values adjusted according to the case. This is another achievement of this study that was not found in previous research.

Our findings, similar to the research results of Silva Junior et al. (2020), De Melo Sampaio and Sampaio (2018), and Sellers-Rubio and Mas-Ruiz (2006) show a small number of stores with efficiency 1. Therefore, there is a need for managers to optimize the stores by taking a deeper look at the performance of their stores. At first glance, it may seem that a larger floor area would attract more customers, leading to increased sales. However, this study did not yield such a conclusion. According to our results, the average area of stores was 230 square meters, while the average area of efficient stores was 190 square meters. This result shows that branches with a smaller area are more efficient, as Didonet et al. (2006) and Nong (2022) also pointed out, however, this does not mean that the smaller the branch area, the more efficient it is; rather, it could be due to its specific geographical location (de Melo et al., 2018). Also, the other rationale reason could be that stores with smaller areas incur lower costs. Finally, the findings of this article are in line with the findings of Raman et al. (2001) and Reiner et al. (2013) regarding the existence of problems in the non-optimal design of store space and the non-optimal arrangement of shelves.

6. Conclusion

This paper was conducted to develop a framework for evaluating the efficiency of branches of a chain retail store using the hybride SDEA-BSC model and Decision Tree. First, performance evaluation indicators were determined using BSC and Fuzzy Delphy Technique. Then, the efficiency of DMUs was determined using Stochastic Data Envelopment Analysis, and based on that, inefficient and efficient DMUs were determined. Finally, using the Decision Tree, implicit rules were extracted from the relevant data. The results showed that the proposed model has high accuracy and interpretation in predicting efficiency, which can help managers with making better decisions to increase efficiency. Regarding the limitations that can be attributed to this research, it can be pointed out that in this study, a BSC was used to select performance evaluation indicators, one of which was customer satisfaction, however, it was removed due to a lack of information. Also, Economic inflation has influenced the research results, so it is suggested to consider this case in future research, or to use the Malmquist index in evaluating the efficiency of branches. It would be also interesting to first classify the DMUs according to a set of characteristics, before performing the efficiency evaluation, and then evaluate the efficiency of the DMUs in each class. In this study, the working hours of the branch employees were the same and did not play a role in the evaluation of efficiency. Therefore, in future research, it is suggested that this index be considered or that the case study has different employees' working hours. Further research can use a neural network and the results can be compared with Decision Tree results. Furthermore, the utilization of this model in other domains that require probabilistic analysis and future performance assessment, due to the influence of stochastic variables, can prove valuable and credible for the proposed research.

CRediT authorship contribution statement

Mohammad Dana Lagzi: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Seyed Mojtaba sajadi:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Mohammadreza Taghizadeh-Yazdi:** Writing – review & editing, Supervision, Software, Formal analysis, Conceptualization.

Declaration of competing interest

I confirm that have no conflicts of interest to disclose, and all authors are aware of the submission and agree to its publication.

Data availability

Data will be made available on request.

Appendix

1. Data Envelopment Analysis

DEA is a well-known and non-parametric technique for efficiency evaluation that uses linear programming techniques to calculate the efficiency of the investigated DMUs. Classical models include CCR and BCC models, which have develop by Charnes et al. (1979) and Banker et al. (1984) respectively. Charnes et al. (1979) presented a model that was capable of setting up a function with multiple inputs and outputs. This model was used under the name of data envelopment analysis. If we consider the number of DMUs to be evaluated as n, each DMU has m input and s output, x_{ij} represents the i-th input, y_{ij} the r-th output, u_r the r-th output weight, and v_i the i-th input weight, In this case, the efficiency is calculated from the following equation:

$$MAX\ Z_0 = \sum_{r=1}^{s} u_r y_{r0} \tag{1b}$$

St:

$$\sum_{i=1}^{m} v_i x_{i0} = 1 \tag{2b}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} x_{ij} v_i \leq 0 \tag{3b}$$

$$u_r, v_i \geq 0 \tag{4b}$$

Banker et al. (1984) created a new model by changing the CCR model, and it was named the BCC model (their names' initials). This model follows the assumption of variable returns to scale. The difference between the BCC model and the CCR model is in the presence of the variable W, which induces returns to different scales in the model during different signs.

- If W > 0, returns to scale are increasing.
- If W = 0, returns to scale are constant.
- If W < 0, there are diminishing returns to scale.

$$MAX\ Z_0 = \sum_{r=1}^{s} u_r y_{r0} + W \tag{5b}$$

St:

$$\sum_{i=1}^{m} v_i x_{i0} = 1 \tag{6b}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} x_{ij} v_i + W \leq 0 \tag{7}$$

$$u_r, v_i \geq 0 \tag{8b}$$

$$W : \text{free} \tag{9b}$$

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