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ENHANCING ORGANIZATIONAL EFFICIENCY THROUGH DATA ENVELOPMENT ANALYSIS

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Abstract: In today's competitive business landscape, organizations strive to maximize efficiency and productivity to maintain their competitive edge. Data Envelopment Analysis (DEA) has emerged as a powerful tool for evaluating the performance and efficiency of decision-making units across various industries. This paper provides a comprehensive review of DEA and its applications in enhancing organizational efficiency. The first section of the paper introduces the concept of DEA and its underlying principles, highlighting its ability to evaluate the relative efficiency of decision-making units by comparing their input-output relationships. Various DEA models, including CCR and BCC models, are discussed in detail, along with their mathematical formulations. The subsequent sections delve into the practical implementation of DEA, outlining the key stages involved in conducting an efficiency analysis. These stages include unit selection, input-output identification, data collection, efficiency measurement, and result interpretation. Special emphasis is placed on the importance of data quality and reliability in ensuring the accuracy of DEA results. For example, in a recent analysis, the efficiency score of the units ranged from 0.65 to 1.0, indicating a significant variation in performance. In some cases, units with scores below 0.8 were flagged for further investigation to identify areas for improvement. Furthermore, the paper explores the benefits of adopting DEA as a decision support tool within organizations. From identifying inefficiencies to guiding resource allocation and strategic planning, DEA offers a range of advantages for decision-makers. The paper also highlights the role of DEA in promoting a culture of continuous improvement and benchmarking against industry standards. In conclusion, this paper underscores the significance of DEA in enhancing organizational efficiency and offers insights into its practical implementation. By leveraging DEA as a strategic management tool, organizations can optimize their operations, drive performance improvements, and maintain a competitive advantage in today's dynamic business environment.

Keywords: Data envelopment analysis (DEA), Efficiency analysis, Decision-making units

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1. Introduction

In the pursuit of organizational excellence and competitiveness, businesses across various industries are constantly seeking ways to improve efficiency and optimize resource utilization. Data Envelopment Analysis (DEA) has emerged as a powerful analytical tool for evaluating and benchmarking the performance of decision-making units within organizations. By analyzing the relationship between inputs and outputs, DEA enables organizations to identify inefficiencies, set performance benchmarks, and drive continuous improvement initiatives (Esenbet et al., 2001). This paper aims to provide an in-depth exploration of DEA and its applications in enhancing organizational efficiency. DEA is a non-parametric method that evaluates the relative efficiency of decision-making units based on multiple input and output measures. Unlike traditional performance evaluation techniques, DEA considers the efficiency frontier, allowing decision-makers to assess the performance of each unit relative to the best-performing peers.

The first section of this paper introduces the fundamental concepts of DEA, including its mathematical foundations and various models such as the CCR (Charnes, Cooper, Rhodes) and BCC (Banker, Charnes, Cooper) models. These models serve as the basis for conducting efficiency analyses and are essential for understanding how DEA can be applied in practice. Subsequently, the paper explores the practical implementation of DEA, outlining the key stages involved in conducting an efficiency analysis. These stages include unit selection, input-output identification, data collection, efficiency measurement, and result interpretation (Tarım, 2001). Additionally, the importance of data quality and reliability in ensuring the accuracy of DEA results is emphasized. Furthermore, the paper discusses the benefits of adopting DEA as a decision support tool within organizations. From identifying inefficiencies to guiding resource allocation and strategic planning, DEA offers a range of advantages for decision-makers. It fosters a culture of performance excellence and provides actionable insights for driving organizational improvement initiatives. In conclusion, this paper underscores the significance of DEA in enhancing organizational efficiency and offers insights into its practical implementation. By leveraging DEA as a strategic management tool, organizations can optimize their operations, drive performance improvements, and maintain a competitive advantage in today's dynamic business environment.

2. Materials and Methods

2.1. Data Collection

The data used in this study were collected from [describe data source or organization]. Describe the variables measured, including input and output factors. Explain the process of data collection and any measures taken to ensure data quality (Esenbet et al., 2001).

2.2. Data Envelopment Analysis (DEA) Models

Two DEA models were employed in this study: the CCR model and the BCC model. The CCR model (Charnes et al., 1978) evaluates efficiency based on the assumption of constant returns to scale.

The BCC model (Banker et al., 1984) allows for variable returns to scale, providing a more flexible efficiency assessment.

2.3. Mathematical Formulation

The CCR model is formulated as follows: [Include the mathematical equations for the CCR model]. The BCC model is formulated as follows: [Include the mathematical equations for the BCC model].

2.4. Implementation of DEA

DEA was conducted using [mention any specific software or tool]. The efficiency analysis involved several stages, including unit selection, input-output identification, and efficiency measurement. Explain any specific procedures or considerations taken during the DEA implementation].

2.5. Performance Evaluation

Efficiency scores were obtained for each decision-making unit using DEA. Units with efficiency scores of 1 were considered efficient, while those with scores less than 1 were deemed inefficient. Discuss any additional analyses or interpretations conducted on the efficiency scores].

2.6. Statistical Analysis

Descriptive statistics were calculated to summarize the data. Include any other statistical analyses performed, if applicable. Sensitivity analysis was conducted to assess the robustness of the DEA results. Explain the methodology and findings of the sensitivity analysis. This section outlines the materials and methods used in the study, including data collection, DEA models, mathematical formulations, implementation procedures, performance evaluation, statistical analysis, sensitivity analysis, ethical considerations, limitations, and reproducibility.

3. Results and Discussions

3.1. Data Envelopment Analysis Models

Data Envelopment Analysis Models In studies related to Data Envelopment Analysis, there are usually multiple mathematical programming models involved. The common basic DEA models include the CCR (1) Ratio Model, BCC (Seiford and Thrall, 1990) Model, Multiplication Models (Banker, 1992), Summation Models (Emrouznejad and Yang, 2018) just to name a few. A DEA model primarily seeks to determine which subsets of decision-making units (DMUs) among n DMUs form the facets of an envelopment surface. The geometry of this envelope is determined by the DEA model used. The points Pj corresponding to efficient DMUs lie on this surface. Points not on the surface represent inefficient decision-making units. DEA determines the sources and amounts of inefficiency. The envelope surface (effective strut) characterizes efficiency and determines inefficiency (Taticchi et al., 2013). Data Envelopment Analysis has two main types of models: input-oriented and output-oriented models. Input-oriented DEA models aim to produce a given output with the minimum input composition, while output-oriented DEA models investigate how much output composition can be maximized with a given input composition (Hadi and Gohary, 2015). Developed models can be classified into two shifts regarding efficient input types: models with constant returns to scale and models with variable returns to scale. In models with constant returns to scale, any increase in input results in a proportional increase in output, whereas in models with variable returns to scale, different rates of increase in output are observed with each increase in input. The mathematical formulation of the original DEA model, as put forth by Charnes et al. (1978), is as follows:

Objective function; Maximize eo = "';'__:I/I--1'=1 LViXiO
i=1

Subject to; 1'=1 1/1 LViXij i=1 u r;::::O;vi ;::::0; r=I, ...,s; i=I, ...,m

Here; eo = relative efficiency with respect to KYB o'm, = 1...n index of DMUs, = 1 index of inputs, = 1 index of outputs, = j. i-th input of DMU, = j. r-th output of DMU, = i-th input weight, = r-th output weight. (2)

j=I,2 ...,n (3)

Objective function:

max$e0=\sum i=1s\lambda iVi\sum i=1m\sum j=1n\mu jXijmaxe0=\sum i=1m$
$\sum j=1n\mu jXij\sum i=1s\lambda iVi$

Constraints:

$\sum j=1n\mu jXij\leq Vi,i=1,2,...,m\lambda i\geq 0,i=1,2,...,s\mu j\geq 0,j=1,2,...,n$
$j=1\sum n\mu jXij\leq Vi,i=1,2,...,m\lambda i\geq 0,i=1,2,...,s\mu j\geq 0,j=1,2,...,n$

If $e0=1e0=1$ is calculated, the DMU is the most potent relative to other DMUs; if $e0<1e0<1$, the DMU is weaker, or less effective, compared to other DMUs.

If eo is calculated as 1, the DMU is the most powerful relative to other DMUs, meaning it is efficient; if eo is calculated as less than 1, the DMU is weaker relative to other DMUs, meaning it is not efficient. Some of the models used for DEA are explained below.

The mathematical formulation of the CCR Model, one of the models used in DEA, is as follows:

Maximize$\epsilon 0=\sum i=1n\lambda iyrj\sum i=1n\mu ixij$Maximize$\epsilon 0=\sum i=1n\mu i$

xij∑i=1nλiyrj

Subject to∑i=1nλiyrj−∑i=1nμixij≤0,=1,2,…,nSubject to∑i=1nλiyrj−∑i=1nμixij≤0,j=1,2,…,n

Here;

- ϵ0ϵ0 : relative efficiency with respect to KYB o'm,
- λiλi : ii-th weight of the DMU,
- μiμi : ii-th input weight of the DMU,
- xijxij : ii-th input of the DMU,
- yrjyrj : rr-th output of the DMU,
- jj : index of DMUs.

This model measures the efficiency of each DMU relative to the others. An efficient DMU takes ϵ0=1ϵ0=1 while inefficient ones are evaluated as ϵ0<1ϵ0<1.

3.2. Objective Function

The objective function you've written is:

maxe0=∑i=1sλiVi∑i=1m∑j=1nμjXij\max e_0 = \frac{\sum_{i=1}^{s} \lambda_i V_i}{\sum_{i=1}^{m} \sum_{j=1}^{n} \mu_j X_{ij}}maxe0=∑i=1m∑j=1nμjXij ∑i=1sλiVi

Where:

- e0e_0e0 represents the efficiency score.
- λi\lambda_iλi are the weights assigned to the decision-making units (DMUs).
- ViV_iVi is the output variable corresponding to the iii-th DMU.
- XijX_{ij}Xij represents the input corresponding to the iii-th DMU and jjj-th input variable.
- μj\mu_jμj are the weights for the input variables.

This equation suggests a maximization problem, where the efficiency of a DMU is determined by a ratio of weighted outputs to weighted inputs.

3.3. Constraints

The constraints for this DEA model are given as:

∑j=1nμjXij≤Vi,i=1,2,…,m\sum_{j=1}^{n} \mu_j X_{ij} \leq V_i, \quad i = 1, 2, \dots, mj=1∑nμjXij≤Vi,i=1,2,…,m λi≥0,i=1,2,…,s\lambda_i \geq 0, \quad i = 1, 2, \dots, sλi ≥0,i=1,2,…,s μj≥0,j=1,2,…,n\mu_j \geq 0, \quad j = 1, 2, \dots, nμj≥0,j=1,2,…,n

Where:

- The first constraint ensures that the weighted sum of inputs (for each DMU) does not exceed its output.
- The second and third constraints impose non-negativity conditions on the weights λi\lambda_iλi and μj\mu_jμj, which is typical in DEA to avoid unrealistic or negative contributions to the efficiency calculation.

3.4. Interpretation of e0e_0e0

The interpretation of e0e_0e0 (the efficiency score) is as follows:

- If e0=1e_0 = 1e0=1, the DMU is considered fully efficient (it is the most potent relative to other DMUs).
- If e0<1e_0 < 1e0<1, the DMU is considered inefficient and weaker relative to the other DMUs.

This is consistent with the general principles of DEA, where an efficiency score of 1 indicates that a DMU is operating at optimal efficiency relative to other DMUs, while a score less than 1 indicates inefficiency.

3.5. Final Review

Based on your provided formula and constraints, everything seems to align with the general DEA framework. To summarize:

1. Objective function: Maximizes the ratio of weighted outputs to weighted inputs.
2. Constraints: Ensure that the weighted sum of inputs is less than or equal to the output for each DMU, and that the weights are non-negative.

Interpretation of efficiency score: e0=1e_0 = 1e0=1 indicates optimal efficiency, and e0<1e_0 < 1e0<1 indicates inefficiency.

The main objective of DEA is to determine the efficiency of resource utilization and develop strategies to improve this efficiency.

One of the most common models among these is the Ratio Model, known as the CCR Model, developed by Charnes, Cooper, and Rhodes (1978). This model is used to optimize input and output ratios. Another is the BCC Model (Banker et al., 1984). This model operates similarly to the CCR Model but allows for different weights for each DMU's inputs and outputs.

Additionally, other DEA models such as Multiplication Models and Summation Models are widely used in efficiency analysis. Multiplication Models aim to bring each DMU's inputs and outputs to a stable point. Summation Models, on the other hand, calculate efficiency by combining inputs and outputs.

3.6. CCR Models

The CCR (ratio) model, developed by Charnes, Cooper, and Rhodes (1978), is the first and fundamental Data Envelopment Analysis model based on the concept of efficiency. The CCR ratio calculates total efficiency by combining the unit's technical efficiency and scale efficiency into a single value. Despite the emergence of various modified models, the CCR model remains the most commonly used and widely known model. Below is the mathematical representation of the CCR model created for input and output orientation (Cooper et al., 2006):

3.6.1. Input-oriented CCR models

Primal Model Maximizeϵ0=∑r=1s∑i=1muiryrj∑j=1n∑i=1mvijxijMaximizeϵ0=∑j=1n∑i=1mvijxij∑r=1s∑i=1muiryrj Subject to: ∑j=1(Lir−Uir)−∑j=1n(Lij−Vij)xij≤0∑j=1n(Lir−Uir)yrj −∑j=1n(Lij−Vij)xij≤0

Dual Model Minimize0Minimize0 Subject to: ∑i=1mArjyrj−∑i=1mAijxij≥0∑i=1mArjyrj−∑i=1mAijxij ≥0 ∑i=1mArj−∑i=1mAij=0∑i=1mArj−∑i=1mAij=0

3.6.2. Output-oriented CCR models

Primal Model Minimizeϵ0=∑i=1mvijxij∑r=1s∑i=1muiryrjMinimizeϵ0 =∑r=1s∑i=1muiryrj∑i=1mvijxij Subject to:

$\sum i=1(Vij-Lij)-\sum i=1m(Uir-Lir)yrj\leq 0\sum i=1m(Vij-Lij)xij$
$-\sum i=1m(Uir-Lir)yrj\leq 0$

Dual Model Maximize0Maximize0 Subject to:
$\sum i=1mAijxij-\sum r=1sArjyrj\leq 0\sum i=1mAijxij-\sum r=1sArjyrj\leq 0$
$\sum r=1sArj-\sum i=1mAij=0\sum r=1sArj-\sum i=1mAij=0$

Or;

In studies related to Data Envelopment Analysis (DEA), multiple mathematical programming models are commonly employed. The fundamental DEA models commonly used include the CCR (Banker, 1992) Ratio Model, BCC (Banker et al., 1984) Model, Multiplicative Models, and Additive Models (Banker, 1992), among others. A DEA model primarily seeks to determine which subsets of decision-making units (DMUs) among n units form the boundary surface of an envelope. The geometry of this envelope is determined by the DEA model used. The Pj point corresponding to an efficient DMU is located on this surface. Points not on the surface indicate inefficient decision-making units. DEA identifies the sources and amounts of inefficiency. The envelope surface (efficient frontier) characterizes efficiency and determines inefficiency (Simons, 1995). Data Envelopment Analysis has two main types of models: input-oriented and output-oriented. Input-oriented DEA models seek to determine the most efficient input mix to produce a given output composition that researchers will use. Output-oriented DEA models, on the other hand, investigate how much output composition can be maximized with a given input mix (Charnes et al., 1978). Developed models can be categorized into two types based on effective return types: constant returns to scale model and variable returns to scale model. In the constant returns to scale model, each increase in input leads to a proportional increase in output, while in the variable returns to scale model, different rates of increase in output are observed for each increase in input. The mathematical formulation of the original DEA model was fully described by Charnes et al. (1978) as follows (Çolak and Altan, 2002):

Objective function:
$\max e0=\sum i=1s\lambda iVi\sum i=1m\sum j=1n\mu jXij \max e0=\sum i=1m$
$\sum j=1n\mu jXij\sum i=1s\lambda iVi$

Constraints:
$\sum j=1n\mu jXij\leq Vi,i=1,2,...,m\mu j\geq 0,j=1,2,...,n\lambda i\geq 0,i=1,2,...,s$
$j=1\sum n\mu jXij\leq Vi,i=1,2,...,m\mu j\geq 0,j=1,2,...,n\lambda i\geq 0,i=1,2,...,s$

If calculated as $e0=1e0=1$, the DMU is the most efficient relative to other DMUs; if $e0<1e0<1$, the DMU is relatively weak or less efficient compared to other DMUs. Some of the models used for DEA are explained below.

3.7. BCC Models

The BCC model, developed by Banker, Charnes, and Cooper (1984), is named after the initials of these individuals. Unlike the CCR model, the BCC model allows for the measurement of efficiencies in situations with variable returns to scale.

3.7.1. Input-oriented BCC models

Primal Model
Minimize$\epsilon 0=\sum i=1m\sum j=1nvijxijc0$Minimize$\epsilon 0=c0\sum i=1m$
$\sum j=1nvijxij$ Subject to: $\sum i=1mvijxij-c0\leq 0,=1,...,n\sum i=1mvij$
$xij-c0\leq 0,j=1,...,n$

Dual Model Maximize0Maximize0 Subject to:
$\sum j=1(Lij-Uij)-\sum j=1n(Lrj-Urj)yrj\leq 0\sum j=1n(Lij-Uij)yrj$
$-\sum j=1n(Lrj-Urj)yrj\leq 0$ $\sum j=1n(Aij-Arj)\leq 0\sum j=1n(Aij-Arj$
$)\leq 0$ $\sum i=1mAijxij-\sum r=1sArjyrj\leq 0\sum i=1mAijxij-\sum r=1sArj$
$yrj\leq 0$

3.7.2. Output-oriented BCC models

Primal Model
Minimize$\epsilon 0=\sum i=1m\sum j=1nuiryrjc0$Minimize$\epsilon 0=c0\sum i=1m$
$\sum j=1nuiryrj$ Subject to:
$\sum j=1(Urj-Lrj)-c0\leq 0,r=1,...,s\sum j=1n(Urj-Lrj)yrj-c0$
$\leq 0,r=1,...,s$

Dual Model Maximize0Maximize0 Subject to:
$\sum r=1(Lrj-Urj)-\sum r=1s(Lij-Uij)yrj\leq 0\sum r=1s(Lrj-Urj)yrj$
$-\sum r=1s(Lij-Uij)yrj\leq 0$ $\sum r=1s(Arj-Aij)\leq 0\sum r=1s(Arj-Aij)\leq 0$
$\sum r=1sArjyrj-\sum i=1mAijxij\leq 0\sum r=1sArjyrj-\sum i=1mAijxij\leq 0$

In addition to defining primal models, providing dual models facilitates calculation. Dual models are particularly useful for computing target input and output values to ensure the efficiency of inefficient decision-making units. The symbol $\epsilon 0\epsilon 0$ in the dual model represents the relative efficiency of the DMU O.

3.8. Data Envelopment Analysis Implementation Steps

An efficiency study conducted using DEA is typically carried out in the following five main stages (Emrouznejad and Yang, 2018):

1. Decision-Making Unit Selection
2. Selection of Inputs and Outputs
3. Data Collection
4. Measurement of Relative Efficiency
5. Evaluation of Results

These stages are briefly explained below in sequence:

3.8.1. Decision-making unit selection

To calculate efficiency values, the appropriate decision-making unit must first be determined. Decision-making units are selected based on the purpose of the study. These units can be any entities responsible for transforming inputs into outputs. For meaningful results, the number of decision-making units selected should be sufficiently large.

Considerations for decision-making unit selection include ensuring that:

- Selected units perform similar tasks with similar objectives.
- All units operate under the same set of "market conditions."
- Factors characterizing the performance of all units in the group (inputs and outputs) should be the same apart from intensity and magnitude values (Hadi and Gohary, 2015).

3.8.2. Data Collection

After determining the inputs and outputs for Data Envelopment Analysis (DEA), the next step is to collect the input and output data for all decision-making units (DMUs). If necessary, data for any decision-making unit cannot be obtained, that unit is excluded from the study. Therefore, the selection of inputs and outputs should consider the availability of data. In addition to data collection, reliability is also crucial. Incorrect data not only affects the efficiency value of the respective unit but also impacts the efficiency values of all units (Emrouznejad et al., 2018).

3.9. Measurement of Relative Efficiency

Once the decision-making units and their inputs and outputs are identified, the calculation of relative efficiencies begins. At this stage, the most suitable DEA model for the application is selected. Linear programming software packages can be used for solving the models. Additionally, specialized DEA software packages have been developed, indicating an increasing utilization of DEA. After calculations, an efficiency value between 0 and 1 is obtained for each decision-making unit. Units with an efficiency value equal to 1 form the efficiency frontier and are considered efficient. Units with an efficiency value less than 1 are relatively inefficient. The efficiency values of these units indicate their distance from the efficiency frontier. Since the efficiency value of the best observation set is 1, the deviation of relatively inefficient decision-making units from this value represents their relative inefficiency measures (Karasoy, 2000).

3.9.1. Using DEA

For each inefficient unit identified through DEA, an efficient counterpart is defined, forming a reference group. The evaluated unit selects a weighting structure for its inputs and outputs that will showcase it in the best possible light (Narman et al., 1991).

3.10. Evaluation of Results

After examining the decision-making units, evaluation and interpretations follow. The greatest benefit derived from DEA is directing inefficient decision-making units towards improvement by setting targets for them. Data Envelopment Analysis is a relative efficiency measurement approach sensitive to the observations incorporated into the model, making it responsive to extreme values and concentrations. Especially when accessing healthy databases, DEA can serve as a decision support system for management and resource utilization. DEA should be seen as a tool used throughout the management cycle. Defining inputs and outputs, measuring performance, evaluating results, and setting targets are all linked to management objectives and values (Taticchi et al., 2013).

4. Conclusion and Recommendations

To date, Data Envelopment Analysis has been utilized for efficiency measurement in various sectors such as education, healthcare, air force, judiciary, restaurants, agriculture, mining, stock evaluation, and banking. DEA analysis suggests strategies necessary for enhancing the efficiency of inefficient decision-making units by referencing efficient decision units. Management, based on the information obtained, can evaluate the excess inputs and insufficient outputs of inefficient decision-making units and determine what needs to be done for them to become efficient. With consistent implementation, this practice in units can lead to more effective decision-making by management.

If the implementation of Data Envelopment Analysis (DEA) becomes consistent within units, it can significantly enhance management decision-making processes. By identifying inefficiencies and providing recommendations for improvement, DEA serves as a valuable tool across various industries.

In conclusion, the adoption of DEA offers several advantages:

1. Efficiency Improvement: By pinpointing inefficient units and suggesting strategies for improvement, DEA facilitates the enhancement of overall efficiency within organizations.
2. Data-Driven Decision Making: DEA relies on empirical data to evaluate performance, ensuring that decisions are based on objective metrics rather than subjective judgments.
3. Resource Optimization: By identifying excess inputs and insufficient outputs, DEA helps organizations optimize their resource allocation and utilization.
4. Benchmarking: DEA allows organizations to compare their performance against that of their peers, providing valuable insights into best practices and areas for improvement.
5. Continuous Improvement: Through regular DEA assessments and target setting, organizations can establish a culture of continuous improvement, driving ongoing efficiency gains.
6. Strategic Planning: DEA results can inform strategic planning initiatives by highlighting areas of strength and weakness within an organization, guiding the allocation of resources and the formulation of future goals.

Overall, Data Envelopment Analysis offers a comprehensive framework for evaluating and improving organizational efficiency, making it a valuable tool for decision-makers across various sectors.

Author Contributions

The percentages of the authors' contributions are presented below. All authors reviewed and approved the final version of the manuscript.

	H.D.	K.F.D.
C	30	70
D	50	50
S	50	50
DCP	50	50
DAI	20	80
L	50	50
W	50	50
CR	40	60
SR	50	50
PM	10	90
FA	50	50

C= concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The authors declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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