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Integrated Optimization Strategies for Enhanced Coffee Retail Store Efficiency with DEA Variants, Taguchi Signal to Noise, and Randomized Block Design

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ABSTRACT

By integrating Data Envelopment Analysis (DEA) variants, Taguchi, and randomized block design techniques, this research addresses a substantial deficiency in the existing body of knowledge by evaluating the collective performance of coffee retail establishments situated on university campuses. The research considers undesirable output such as customer complaints by conducting an analysis of five operational inputs of OPEX, CAPEX, staff count, sitting capacity, and shop size with two desirable outputs of cup production and total income. DEA and its derivatives, super efficiency CCR and BCC were extremely efficient. The BCC infeasible efficiency score was improved by incorporating a modified super-efficiency BCC. The investigation further enhances the methodology for determining the optimal Decision-Making Units (DMUs) among various DEA variations by incorporating Taguchi signal-to-noise and randomized block design as additional components. The most effective decision-making units (12, 9, and 5) demonstrated consistent and outstanding performance in all three DEA variants, as indicated by the results that succinctly outline the key results. Conversely, DMUs 2, 10, and 14 have been identified as prospective improvement areas.

Keywords: Constant returns to scale; Data Envelopment Analysis (DEA); Randomized block design; Taguchi method; Undesirable outputs; Variable returns to scale

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1. Introduction

The retail coffee industry is characterized by constant competition, where the preservation of operational efficiency is key to ensuring sustained success. Thus, maintaining operational efficacy becomes critical for long-term viability. This report undertakes an in-depth analysis of the intricate operational facets, unique to the coffee retail sector, essential for navigating the challenges of an exceptionally competitive market environment. The investigation focuses on the intricacies encountered by coffee retailers as they contend with the rigors of this competitive landscape. Achieving desirable outputs while balancing operational inputs and outputs, including operational expenses (OPEX), capital expenses (CAPEX), number of employees, seating capacity, and store size, poses a significant challenge. This entails the efficient utilization of resources to maximize desirable outcomes such as cup sales and overall revenue, while simultaneously mitigating unfavorable outputs, with a particular emphasis on reducing customer complaints (Table 1).

To confront these challenges thoroughly, our research utilizes a dual-method methodology. Initially, Data Envelopment Analysis (DEA) [1] serves as a mechanism for quantifying efficacy. This approach meticulously evaluates various factors, encompassing OPEX, CAPEX, employee count, seating capacity, and store dimensions, for every decision-making unit (DMU). It simultaneously assesses favorable outcomes, such as revenue generated from cups and overall sales, along with unfavorable outcomes, with a particular focus on customer grievances. Furthermore, integrating the Taguchi method with DEA provides a robust optimization perspective. This integration facilitates the identification of optimal input-output combinations, thereby enhancing overall efficiency. In the context of the coffee retail sector, the Taguchi method not only aims to optimize favorable results but also to mitigate the consequences of unfavorable ones, catering specifically to the sector's requirements.

Table 1. Coffee retail store indices.

Indices	Definition
Input	
OPEX	Operational expenditure is the money a company or organization spends on an ongoing, day-to-day basis to run its business.
CAPEX	Capital expenditures are funds used by a company to acquire, upgrade, and maintain physical assets such as property, plants, buildings, technology, or equipment
Seat	Seat is number of chairs in store and arrangement can also be adapted to the type of customers that the coffee shop expects.
Area	Area is size of store, depend on space utilization or decoration area in café to satisfy customers
Employee	Employee is number of employees, such as Barista or Cashier.
Output	
Indices	**Definition**
Cups	Cups is number of cups, only customers who come to order coffee or beverage menu.
Income	Income is money received in exchange for list of your order in coffee shop.
Complaints	Complaint is responses from consumer feedback in both of positive and negative opinion.

Through the use of DEA [2], this research intends to identify the finest coffee retail store and provide improvement guidelines for coffee retail stores. The analysis will consider both favorable and unfavorable results, with the objective of maximizing performance in accordance with inputs including operating expenses, capital expenditures, employee count, seating capacity, and store dimensions, in order to reconcile the current state of relative efficacy in relation to the thirteen other coffee retailers. Although previous research has comprehensively examined the internal factors that impact efficiency across different industries, there is a significant knowledge void regarding the analysis of external factors that affect efficiency. Insufficient attention has been paid to the influence of external factors, including market trends, regulatory modifications, and economic conditions, on the operational efficacy of businesses, particularly within the coffee retail sector.

Recent research often exhibits a bias towards internal operations, neglecting the intricate and ever-changing relationship that exists between the efficacy of a business and external environmental factors. The existence of this research is an enclosed indicating that a more thorough comprehension of the ways in which external factors impact operational efficiency and performance in the coffee retail industry is required [3-5]. The research holds considerable importance due to its capacity to provide a comprehensive comprehension of the coffee retail industry. This research provides advantages to all fourteen decision making units (DMUs) involved in the coffee retail industry by conducting a comprehensive examination of inputs and outputs, excluding any external factors. Through the use of DEA, this study aims to identify the highest-performing coffee retail establishment and provide actionable improvement recommendations [6-9].

This study aims to investigate methods to enhance efficiency in the coffee retail industry, taking into account the continuous rivalry within this market. The goal is to enhance operational efficiency via the use of DEA variants, Taguchi signal to noise, and randomized block design methodologies. The primary objective is to address the intricacies of coffee retail operations and highlight the need of improving efficiency to attain sustained success in a fiercely competitive sector. The research seeks to enhance operational inputs and outputs, such as operating costs, capital expenditures, personnel count, seating capacity, and store dimensions, in order to increase revenue and customer happiness while reducing customer complaints. The research seeks to provide practical strategies for coffee retail businesses to improve efficiency and maintain competitiveness in the dynamic market, assuring long-term viability and satisfying changing consumer preferences.

This paper presents and analyzes the integrated optimization strategies for coffee retail outlets in university contexts in a methodical and organized fashion. Section 2 delves into an extensive examination of the distinct operational obstacles encountered by coffee retail establishments, thereby imparting valuable perspectives on the complexities inherent in the fiercely competitive market environment. Section 3 provides a comprehensive explanation of the research methodology, encompassing the integrated optimization strategies implemented, such as randomized block design (RBD), the Taguchi signal-to-noise ratio, and data envelopment analysis (DEA) and its variants. The numerical findings are examined in detail in Section 4, providing insight into the results of the research. This segment additionally incorporates a sensitivity analysis that is contingent upon the quantity of seats, thereby offering a more intricate comprehension of the way in which the capacity of seating affects the overall efficacy of coffee retail establishments. In summary, the principal discoveries are consolidated in Section 5, which also presents conclusions and commences dialogues regarding the ramifications of the study. This final segment not only provides a summary of the results but also presents recommendations for potential enhancements in coffee retail establishments in light of the integrated optimization strategies that were investigated.

2. Coffee Retail Store

In order to achieve long-lasting success in the dynamic and fiercely competitive coffee retail industry, it is essential to possess a thorough understanding of the operational complexities involved. This section offers a comprehensive examination of the operational complexities inherent in a typical coffee retail establishment, with a particular emphasis on the pivotal inputs and outputs that have a substantial impact on the overall efficacy of the store.

Operating expenses (OPEX) refer to the recurrent costs incurred for operational inputs that are critical for the proper functioning of the store. The aforementioned expenditures consist of investments in essential elements of the organization, including marketing, supplies, utilities, and employee compensation. Capital Expenses (CAPEX) comprise monetary disbursements for tangible resources that are essential for the continuous administration of the store. The aforementioned enhancements and equipment, furnishings, and restorations comprise these investments. The personnel comprise a pivotal component that exerts a substantial influence on the quality of service rendered, the efficiency of procedures, and the overall contentment of customers. Ensuring optimal customer service and efficient administration of daily operations are contingent upon the maintenance of suitable personnel levels.

The acquisition of cups or the sale of cups, which comprise a critical output metric, serve as an indicator of the revenue-generating endeavors of the coffee retail establishment with respect to operational outcomes. There exists a clear and measurable correlation between the capacity to maximize cup sales and the overall operational efficacy of the organization. The establishment derives supplementary revenue from partnerships, product sales, and loyalty programs; these streams collectively contribute to the establishment's long-term viability and financial well-being. One of the revenue streams that contributes to the overall income is the sale of containers. Although it is undesirable, the number of customer complaints received is a crucial production estimation metric. The strategy implemented by the organization to manage and mitigate customer complaints demonstrates its dedication to providing a positive and satisfying experience for its customers.

The coordination of these inputs and outputs, which is critical for achieving a delicate equilibrium, presents an operational challenge. In order to attain favorable results, optimization techniques must take into account the optimal allocation of resources, encompassing both financial and human capital, while simultaneously aiming to maximize desired outputs and minimize undesired ones. The following sections will present a thorough examination of the methodologies used to assess and enhance these operational aspects with the aim of increasing the effectiveness of coffee retail establishments located in university settings.

DEA is an analytical instrument utilized to assess the efficacy of DMUs through the comparison of combinations of their input and output signals [10-12]. Within the framework of this case study, operational inputs (OPEX, CAPEX, number of employees, seating capacity, and store size), desirable outputs (number of cups produced, income generated), and undesirable outputs (customer complaints) are incorporated into the conceptual framework to establish criteria for defining DMUs. Developing a comprehensive model of the complex operations is the primary focus. By virtue of its non-parametric methodology, DEA offers the necessary adaptability to evaluate the comparative efficacy of DMUs within the intricate domain of coffee retail [14, 15]. Simultaneously, the Taguchi method provides a methodical framework for optimization, enabling the methodical investigation of variables that impact efficiency.

It is imperative to take thorough consideration of the data in this research. Particularly the process of choosing inputs and outputs. As a result, the inputs comprise a wide range of variables, such as CAPEX, OPEX, employee count, store size, and seat count. Undesirable output is quantified by the quantity of customer complaints; output consists of the quantity of containers sold and revenue generated. By offering this extensive assortment, a comprehensive assessment of operational performance is guaranteed.

The store's statistics data agency provides the data. The research evaluates coffee retail business efficiency using quantitative and qualitative methods. Quantitative measurements include OPEX, CAPEX, personnel count, seating capacity, store size, cup production, and total revenue. Quantifying complaints requires converting qualitative data into numbers. These metrics give objective numerical data for evaluating store operations and performance.

These quantitative and qualitative variables must be included into the optimization process to design efficient coffee retail shop efficiency methods. Quantitative benchmarks and performance indicators help discover areas for development and monitor progress. Qualitative metrics reveal consumer preferences, market trends, and competitive dynamics, helping the shop create strategies that connect with target customers and set it apart from rivals.

Integrating quantitative and qualitative measurements into the optimization process enables a comprehensive coffee retail shop efficiency assessment. This method enables initiatives that boost operational KPIs, customer happiness, and brand perception. These measurements help assess the tactics' efficacy by revealing their effects on store performance and competition.

An encoded narrative is concealed within the complex operational fabric of a coffee retail establishment, manifested in the data that has been processed using Taguchi signal-to-noise methodology. This segment provides a comprehensive analysis, revealing the latent nature of operational inputs and outputs as they are transformed by the Taguchi signal in relation to noise and normalization techniques.

3. Integrated Optimization Strategies

A variety of methodologies are utilized in the study to maximize efficacy in coffee retail locations. In order to determine the optimal DMU among all variants, DEA variants are employed, each possessing distinct advantages and disadvantages. By adopting this methodology, a thorough assessment of operational efficacy is guaranteed. The utilization of the Taguchi signal to noise method is intended to rectify undesired outputs, providing a notable edge over alternative approaches through the efficient conversion of these elements. In addition, randomization of block design is incorporated to guarantee the selection of the optimal strategy with robustness and dependability. The selection of these methodologies was based on their synergistic characteristics and capacity to furnish an all-encompassing comprehension of operational efficiency in the coffee retail industry. As a result, decision-making processes were improved and sustained success was facilitated. The specifics are provided below.

3.1 Taguchi signal to noise ratio

In the pursuit of improving operational processes and obtaining meaningful insights, the Taguchi signal-to-noise ratio [16] demonstrates itself to be an exceptionally efficient analytical tool. The methodology, formulated by Genichi Taguchi, exceeds traditional data analysis in that it offers an unparalleled perspective on the effectiveness and caliber of operational inputs and outputs.

Taguchi's methodology involves the transformation of raw data into a signal-to-noise ratio (SN), which goes beyond mere numerical values as an additional metric. Sensor Network technology is employed to distinguish between undesired operational noise, which has the potential to impede efficiency, and the optimal signal, which signifies the desired results. Taguchi's methodology elucidates underlying patterns and intricacies within data by prioritizing the signal over noise. This enables a more nuanced understanding of the dynamics of operations.

An additional stratum of insights becomes apparent upon closer inspection of the operational inputs, which comprise CAPEX, OPEX, and the Number of Employees, as revealed by Taguchi's SN methodology. Through the process of accentuating the optimized signal that is present in these inputs, the elements that contribute most positively to operational efficiency are illuminated. Simultaneously, the presence of noise that may potentially obscure these critical contributions is diminished.

When operational outputs such as customer complaints, overall income, or cup sales are taken into account, Taguchi's methodology outperforms conventional analyses. Through the reduction of operational noise and the isolation of the optimal signal, the SN provides a much clearer representation of the factors that affect these outputs. This procedure facilitates a heightened level of understanding, offering guidance for improvements and optimizations that lead to enhanced overall productivity.

In addition to serving as statistical instruments, the Taguchi Noise-to-Signal-to Ratios also function as metrics for assessing operational excellence. By implementing a process that entails deconstructing operational data and concentrating on the optimized signal, organizations have the ability to reveal latent efficiencies and arrive at well-informed decisions. As the discourse continues, Taguchi's SN will exert a significant impact, aiding in the formation of a more foundational understanding of the intricate operational dynamics that are intrinsic to the coffee retail industry.

Response analysis has traditionally utilized the mean of responses (y_i) for n replicates; nevertheless, there is an increasing contemporary interest in the variability of the response. Taguchi produced an extra modification of the repeatability data, which functions as a measure of the available variance. The aforementioned occurrence is denoted by the acronym SN, which stands for Signal to Noise Ratios. As a consequence, SN amasses an excessive amount of redundant information. The SN is established based on the characteristics of the nominal is optimal (NTB), smaller is better (STB), and larger is better (LTB) data classes. The following are the specific mathematical models of the SN utilized in this study for the LTB (SN_{LTB}) and STB (SN_{STB}):

$$SN_{LTB} = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{y_i}\right)^2\right], \qquad (3.1)$$

$$SN_{STB} = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right], \qquad (3.2)$$

A distinguishing characteristic of this method, apart from the concealed data, is the inclusion of undesirable as well as desirable outputs. Although favorable outcomes do indeed enhance efficiency, unfavorable outcomes, including societal impact and environmental burden, pose obstacles that necessitate attention in order to conduct a thorough assessment.

3.2 Normalization

As one of the pre-processing techniques, data normalization involves scaling or transforming the data so that each feature contributes equally. The efficacy of machine learning algorithms in generating a generalized predictive model for a classification problem is contingent on the data's quality. Numerous studies have demonstrated the significance of data normalization in enhancing the quality of data and, consequently, the efficacy of machine learning algorithms. In order to ensure that the value is contained within a predetermined range and to modify its size, data normalization is implemented. The principal aim of enhancing data normalization is to ascertain the relative importance of each criterion in relation to the others. Mean normalization [17, 18] is a significantly efficient technique utilized to decrease the magnitude of data sets while maintaining consistency or similarity in their dimensions.

$$Vnorm_{ki} = \frac{V_{ki}}{V_i}, \qquad (3.3)$$

where $Vnorm_{ki}$ are the normalized value for the value associated with the k[th] DMU and input or output in column i, V_{ki} is the value of the i[th] factor in each DMU k[th], and V_i is the average value of the i[th] factor.

3.3 Data Envelopment Analysis and its variants

The DEA analysis utilizes two prevalent models: the Variable Returns to Scale model, which Banker, Charnes, and Cooper (BCC) developed and the Constant Returns to Scale model, which was developed by Charnes, Cooper, and Rhodes (CCR). The functions of these models vary according to the specific data and intended outcome. The evaluation in this study is conducted using two models: the CCR model and the BCC model. The CCR model operates under the assumption that the scope of operation is consistent throughout all DMUs. The efficiency boundary is a hyperplane generated by the CCR model. A DMU is considered operationally effective if it is positioned on the boundary line; conversely, if it is situated below the boundary line, it has not yet achieved efficiency. The performance score diminishes as the distance from the boundary increases for that particular DMU.

This model offers a preliminary evaluation of efficiency that does not account for the magnitude of operations. It establishes the Best Practice Frontier, which serves as a benchmark for other DMUs in terms of efficiency $\left(\theta^k_{CRS}\right)$. In this calculation, the mathematical model of the k[th] DMU based on all m inputs and s outputs appears as follows:

$$\text{Min } \theta^k_{CRS} \qquad (3.4)$$

$$\text{S.T.}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta^k_{CRS} x_{ik}\ ;\ i = 1, 2, \ldots, m,$$

$$\sum_{j=1}^{m} \lambda_j y_{rj} \geq y_{rk};\ r = 1, 2, \ldots, s,$$

$$\theta, \lambda_j \geq 0\ , j \neq 0.$$

It relaxes the assumption of constant returns to scale, in contrast to the BCC Model. The BCC model aims to determine the efficiency value while assuming variable returns (VRS, or Variable Returns to Scale; this model is also referred to as VRS). This is due to the presence of competition within the business environment. Insufficient or financial constraints consequently, the DMU is incapable of functioning at a suitable level. The metric utilized to assess the effectiveness of BCC models is referred to as the Pure Technical Efficiency Score (TEVRS). Thus, by taking into account prospective level inefficiencies, this model offers a more adaptable framework for assessing performance. Similar to the CCR model, it establishes a Best Practice Frontier that facilitates a comprehensive comprehension of performance when applied at scale.

This model offers a preliminary evaluation of efficiency that does not account for the magnitude of operations. It establishes the Best Practice Frontier, which serves as a benchmark for other DMUs in terms of efficiency (θ^k_{VRS}). In this calculation, the mathematical model of the k[th] DMU based on all m inputs and s outputs appears as follows:

$$\text{Min } \theta^k_{VRS}$$

$$\text{S.T.}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta^k_{VRS} x_{ik}\ ;\ i=1,2,\ldots,m, \qquad (3.5)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk} \;; r = 1, 2, \ldots, s,$$
$$\sum_{j=1}^{n} \lambda_j = 1,$$
$$\theta, \lambda_j \geq 0 \;; j \neq 0.$$

In situations where both desirable and undesirable outputs are present, the DEA model integrates undesirable output factors [19-22] into the production process as desired input factors. The aim is minimize the desired input factors and undesirable output factors to the greatest extent possible, while maximizing the output factors and undesirable input factors, beginning with the efficiency of the decision-making unit. This viewpoint places emphasis on the favorable input variables, the unfavorable output variables, and the favorable ones. To determine efficiency (θ^k_{Un}), the consideration of undesirable output is taken into account. In this calculation, the mathematical model of the k^th^ DMU based on all m inputs, s desirable outputs and l undesirable output appears as follows:

$$\text{Min } \theta^k_{Un}$$
$$\text{S.T.}$$
$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta^k_{VRS-Un} x_{ik};\; i = 1, 2, \ldots, m,$$
$$\sum_{j=1}^{n} \lambda_j y^g_{rj} \geq y^g_{rk};\; r = 1, 2, \ldots, s, \qquad (3.6)$$
$$\sum_{j=1}^{n} \lambda_j y^b_{tj} \leq y^b_{tk} \;; t = 1, 2, \ldots, l,$$
$$\theta^k_{VRS-Un}, \lambda_j \geq 0 \;; j \neq 0.$$

For CCR model append nothing

For BCC model append $\sum_{j=1}^{n} \lambda_j = 1.$ (3.7)

In a recent development, the super efficiency DEA [23-25] ranks the top organizations according to scores derived from an exhaustive analysis of relevant data and factors. Nevertheless, the results acquired through the implementation of data enveloping techniques in the BCC model will be partitioned into two categories: efficiency scores of 1 and -1. Consequently, this configuration renders the ranking of optimal organizations unattainable. To determine efficiency (θ^k_{SE}), the super efficiency method is considered. In this calculation, the mathematical model of the k^th^ DMU based on all m inputs and s outputs appears as follows:

$$\text{Min } \theta^k_{SE}$$
$$\text{S.T.}$$
$$\sum_{\substack{j=1 \\ j\neq 0}}^{n} \lambda_j x_{ij} \leq \theta^k_{VRS-SE} x_{ik} \;; i = 1, 2, \ldots, m,$$
$$\sum_{\substack{j=1 \\ j\neq k}}^{n} \lambda_j y_{rj} \geq y_{rk};\; r = 1, 2, \ldots, s, \qquad (3.8)$$
$$\lambda_j \geq 0,\; j = 1, 2, \ldots, n \text{ and } j \neq k,$$
$$\theta^k_{VRS-Un}, \lambda_j \geq 0 \;; j \neq 0.$$

For CCR model append nothing

For BCC model append

$$\sum_{\substack{j=1 \\ j\neq 0}}^{n} \lambda_j = 1. \qquad (3.9)$$

Infeasible efficiency [26, 27] may result from calculating the Super Efficiency Score under variable returns (VRS) assumptions. Due to the fact that Super Efficiency models may be incapable of determining performance values, zero values are present in the dataset. An essential requirement for input-focused Super efficiency calculations to fail in determining the efficiency of the BBC model is that the evaluation of the decision-making unit must produce at least one output factor that exceeds the correct bound, which is established by other decision-making units. Therefore, to address the aforementioned issue, a Two-Stage Procedure for Super Efficiency score [28] is introduced, distinct from the conventional BCC model's capability for super efficiency. By utilizing this approach, one can achieve the same Super Efficiency score that is derived from the model, while also optimizing DMUs that cannot be resolved using conventional methods (Infeasibility). The ultimate goal is to develop an efficiency metric that demonstrates input savings and output surpluses.

To determine the output surpluses (s_r), in this calculation, the mathematical model of the k[th] DMU, considering all *s* outputs, is expressed as follows:

$$\text{Min} \sum_{r=1}^{s} s_r \qquad (3.10)$$

S.T.

$$\sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j y_{rj} + s_r y_{rk} \geq y_{rk};\ r = 1, 2, \ldots, s,$$

$$\sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0,\ j = 1, 2, \ldots, n,\ \ j \neq k, r = 1, 2, \ldots, s.$$

For the input-oriented Variable Returns to Scale (VRS) super-efficiency model, the only circumstance in which it is considered impossible is when S_r is greater than 0. Importantly, these $S_r^* y_{rk}$ values, which are separate from the conventional DEA output slacks, indicate output surpluses in DMUs in relation to the frontier that has been formed by the remaining DMUs. As a consequence of this, a unit-invariant modified VRS super-efficiency model is presented.

This model establishes the Best Practice Frontier, which serves as a benchmark for other DMUs in terms of efficiency ($\widehat{\theta}_k$); the modified super efficiency method is considered. In this calculation, the mathematical model of the k[th] DMU based on all m inputs and s outputs appears as follows:

$$\text{Min } \widehat{\theta}_k$$

S.T. (3.11)

$$\sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j x_{ij} \leq \widehat{\theta}_k x_{ik};\ i = 1, 2, \ldots, m,$$

$$\sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j y_{rj} + S_r^* y_{rk} \geq y_{rk};\ r = 1, 2, \ldots$$

$$\sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0\ ,\ j = 1, 2, \ldots, n,\ j \neq\ k.$$

In the realm that lies beyond the Best Practice Frontier, the ideas of Super Efficiency and Modified Super Efficiency come into play. The term "Super Efficiency" refers to the identification of DMUs that not only function on the efficient frontier but also outperform other DMUs operating on that frontier. The notion of Modified Super Efficiency is an extension of this idea that takes into consideration the possibility of outliers and changes in the data, so providing a more reliable measurement of efficiency. Table 2 displays the coefficients and variables utilized in assessing and optimizing the efficiency of decision-making units through Data Envelopment Analysis (DEA) and its variants.

Table 2. Definition of DEA coefficients and variables.

Coefficients and Variables	Definition
λ_j	Intensity of DMU j[th]
x_{ij}	Value of input factor i[th] at DMU j[th]
x_{ik}	Value of input factor i[th] at DMU k[th]
y_{rj}	Value of output factor r[th] at DMU j[th]
y_{rj}^{g}	Value of desirable output factor r[th] at DMU j[th]
y_{tj}^{b}	Value of undesirable output factor t[th] at DMU j[th]
y_{rk}	Value of output factor r[th] at DMU k[th]
y_{rk}^{g}	Value of desirable output factor r[th] at DMU k[th]
y_{tk}^{b}	Value of undesirable output factor t[th] at DMU k[th]
θ_{CRS}^{k}	Overall efficiency rating value of DMU at k[th]
θ_{VRS}^{k}	Pure technical efficiency value of DMU at k[th]
θ_{Un}^{k}	Efficiency value of DMU at k[th] of Undesirable output
θ_{SE}^{k}	Efficiency value of DMU at k[th] of Undesirable output - super efficiency
s_r	The optimal solution to model
$\widehat{\theta}_k$	Pure technical efficiency value of DMU at k[th] of Undesirable output – Modified super efficiency

3.4 Randomized Block Design (RBD)

An imbalanced randomized block design (RBD) was constructed so that we could compare the efficiency ratings of different decision-making units that were determined by applying different assessment methodologies [29]. The incorporation of an imbalanced RBD was done with the primary intention of accommodating any fluctuations in the amount of observations or treatments within each block. This was done in order to ensure that our experimental design was flexible. Retail establishments that sell coffee were categorized into blocks according to the primary characteristic of the evaluation techniques that were used. This grouping technique assures that each block represents a unique mix of assessment methods, and that any changes in efficiency ratings that are noticed are directly linked to the assessment method that was used.

Treatments were distributed at random to the decision-making units within each block of the study. The treatments represent the specialized application of several assessment methodologies, such as the Super Efficiency CCR, the Super Efficiency BCC, and the Modified Super Efficiency BCC. The use of random assignment of assessment techniques within each block helps avoid any biases associated with certain features and guarantees that any changes in efficiency scores that are detected are directly due to the assessment method that was used.

4. Numerical Results

After the inquiry into the complexity and concealed information of operational inputs (Table 3) and outputs (Table 4) has been finished, the next step is to carry out the numerical assessment of the findings that have been made. A detailed analysis of the operational performance of the coffee retail business is revealed via the utilization of the transformative potential of the Taguchi signal-to-noise ratio and the process of normalization. The numerical data that are shown below offer a comprehensive perspective of signals that have been optimized and noise that has been removed. Additionally, these findings provide insights into the effectiveness of a great deal of operational components. When it comes to optimizing OPEX and complaints, the Taguchi Method, also known as SN, takes a "Smaller the better" approach. On the other hand, when it comes to maximizing cups and revenues, the Taguchi Method has a "Larger the better" strategy.

The process of normalization, which is an essential part of our technique, guarantees that comparisons and assessments are fair and objective. A thorough knowledge of the complex efficiency environment in the coffee retail industry may be obtained through the selection of the Mean normalization, which allows for the standardization of a variety of measures. By aligning the data around a common mean, this approach makes it possible to conduct an in-depth analysis of the operational effectiveness of each and every coffee retail business independently.

Table 3. Optimized signals and minimized noise in operational inputs via Taguchi SN and normalization.

DMU (k)	Input				
	OPEX (x_{1k})	CAPEX (x_{2k})	Seat (x_{3k})	Area (x_{4k})	Employee (x_{5k})
1	1.010	1.612	1.393	1.405	1.885
2	0.992	0.992	0.488	0.499	1.077
3	1.019	0.620	0.000	0.729	1.077
4	1.030	2.108	2.786	1.823	0.808
5	0.986	0.744	0.000	0.449	0.808
6	1.002	0.496	0.348	0.528	0.808
7	1.039	1.736	0.488	0.934	0.538
8	0.999	1.736	0.975	0.528	0.808
9	0.958	0.744	0.279	0.324	0.808
10	0.972	0.868	1.254	0.726	0.808
11	1.033	0.149	1.672	1.157	1.077

DMU (k)	Input				
	OPEX (x_{1k})	CAPEX (x_{2k})	Seat (x_{3k})	Area (x_{4k})	Employee (x_{5k})
12	0.971	0.087	0.836	0.803	0.808
13	1.050	0.372	2.647	3.170	1.346
14	0.941	1.736	0.836	0.924	1.346

Table 4. Optimized signals and minimized noise in operational outputs via Taguchi SN and normalization.

DMU (k)	Desirable Output		Undesirable Output
	Cup (y_{1k})	Sale (y_{2k})	Complaints (y_{3k})
1	1.051	1.030	0.614
2	1.020	1.017	0.895
3	1.072	1.053	0.895
4	1.085	1.054	1.530
5	0.895	0.960	0.979
6	1.003	0.990	2.155
7	1.001	0.991	0.713
8	1.043	1.020	0.614
9	1.014	1.002	0.807
10	0.905	0.927	0.713
11	1.029	1.019	1.530
12	0.966	0.970	0.807
13	1.032	1.043	0.614
14	0.884	0.925	1.135

There are doing this numerical investigation in order to investigate the scores of Technical Efficiency that were computed by employing both the Constant Returns to Scale (CCR) and the Variable Returns to Scale (BCC) models [30]. It did disclose an encompassing concept of efficiency that encompassed all of the DMUs in their entirety. It is possible to gain an understanding of these scores by delving into the complexities of operational inputs, which include everything from operational and capital expenditures to the number of employees, seating capacity, and store size. Additionally, it is possible to comprehend the desired and undesirable outputs, which include the number of cups, overall incomes, and the challenging realm of customer complaints.

At the beginning of the process, the CCR model reveals its evaluation of efficiency, which paves the way for the determination of Super Efficiency (B1) among a subset of DMUs. As part of the investigation, the BCC model is investigated in further depth, and both Super Efficiency (B2) and Modified Super Efficiency (B3) are utilized in order to get information. When numerical findings are used, they become a compass that helps navigate the efficient landscape. There are certain DMUs that are extremely efficient, surpassing the standards that were anticipated, while there are others that provide potential for improvements that are more focused.

Table 5. Technical efficiency score assessed via super efficiency CCR (B1), super efficiency BCC (B2) and modified super efficiency BCC (B3).

DMU (k)	DEA Variants		
	Super Efficiency CCR (B1)	Super Efficiency BCC (B2)	Modified Super Efficiency BCC (B3)
1	1.005	1.079	1.079
2	0.972	0.975	0.975
3	1.428	infeasible	infeasible
4	1.009	infeasible	1.350
5	1.493	1.624	1.624
6	1.052	1.053	1.053
7	1.459	1.5	1.5
8	1.248	1.309	1.309
9	1.560	1.642	1.642
10	0.935	1.010	1.010
11	0.996	2.443	2.443

DMU (k)	DEA Variants		
	Super Efficiency CCR (B1)	Super Efficiency BCC (B2)	Modified Super Efficiency BCC (B3)
12	1.830	1.920	1.920
13	1.316	1.544	1.544
14	0.923	1.018	1.018

According to the Super Efficiency CCR model's evaluation of technical efficiency scores, DMUs 3, 5, 7, 9, 12, and 13 have super efficiency scores exceeding 1 (Table 5). This not only signifies effective functioning at the frontier but also surpasses the performance of alternative DMUs. The super efficiency scores of 1, which indicate efficient operations but do not necessarily surpass those of the aforementioned DMUs, are observed in DMUs 1, 4, 6, 8, 10, and 11. On the other hand, DMUs 2 and 14 exhibit Super Efficiency scores inferior to 1, which suggests that there may be prospects for enhancing their efficiency.

According to the Modified Super Efficiency BCC model, technical efficiency scores indicate that DMUs 3, 5, 7, 9, 12, and 13 have Modified Super Efficiency scores above 1. It is worth mentioning that DMU 3 fails the evaluation for infeasibility; however, it undoubtedly attains a score exceeding 1. The Modified Super Efficiency scores for DMUs 1, 4, 6, 8, and 10 are in proximity to 1, indicating that these DMUs operate efficiently, albeit with a lesser degree of superiority in comparison to the other DMUs. DMUs 2 and 14, conversely, have Modified Super Efficiency scores inferior to 1, which suggests the existence of possible domains that could be enhanced.

To achieve a thorough examination and acquire valuable insights regarding the variations in efficiency scores among decision-making units, the randomized block design (RBD) method was selected as the analytical framework. By employing this methodology, we are able to methodically examine and consider potential obstacles or constraints that could affect fluctuations in efficiency. As a result, we are equipped with a structured and resilient strategy to discern the subtle complexities present in the dataset. This analysis utilizes an unbalanced randomized block design (RBD), which accounts for the inherent variability in the number of interventions or observations contained within each block (B1, B2, and B3).

When constructing the hypothesis for the RBD, the null hypothesis states that efficiency scores do not differ across all entities involved in all DMUs, while the alternative hypothesis confirms the existence of such differences. The findings will be assessed with a 95% confidence level through the definition of statistical significance, thereby establishing a rigorous criterion for determining the influence of assessment methodologies on efficiency scores.

The results of the analysis conducted using the RBD indicate a p-value below 0.05. As a result, the null hypothesis can be rejected with 95% confidence (Table 6). This finding suggests that there is a significantly different efficiency score distribution across the DMUs.

Table 6. Analysis of variance for the RBD with three blocks of B1, B2 and B3.

Source of Variation	Degree of Freedom	Sum of Squares	Mean Squares	P-Value
DMUs	13	4.0562	0.31202	0.000
Block	2	0.3246	0.16229	0.062
Error	23	1.1829	0.05143	
Total	38	5.5466		

Following a comprehensive examination using the RBD, this research augments the comprehension by incorporating the signal-to-noise ratio (SN) in an effort to maximize efficiency (larger values are regarded as more favorable). By incorporating this further stage, we are able to enhance and optimize the efficiency results acquired via the evaluation techniques—Super Efficiency CCR, Super Efficiency BCC, and Modified Super Efficiency BCC. Our objective is to utilize SNR in order to determine and rank the conditions or factors that have the greatest impact on improving efficiency. This will provide a valuable optimization viewpoint that complements the RBD analysis. By adopting this holistic approach, efficiency dynamics are thoroughly investigated, as statistical insights from RBD and optimization considerations from SN are incorporated (Table 7).

Table 7. Best so far performance measures via Taguchi signal to noise ratio.

DMU (k)	DEA variants			Larger the Better	Rank
	B1	B2	B3		
1	0.995	0.927	0.927	0.443	11
2	1.029	1.026	1.026	-0.230	14
3	0.700	-	-	3.092	7
4	0.991	-	0.741	1.160	9
5	0.670	0.616	0.616	3.952	3
6	0.951	0.950	0.950	0.444	10
7	0.686	0.667	0.667	3.440	5
8	0.801	0.764	0.764	2.197	8
9	0.641	0.609	0.609	4.155	2
10	1.070	0.990	0.990	-0.149	13
11	1.004	0.409	0.409	3.491	4
12	0.546	0.521	0.521	5.522	1
13	0.760	0.648	0.648	3.258	6
14	1.083	0.983	0.983	-0.148	12

Technical efficiency scores, which have been meticulously examined for optimization purposes within SN, emphasize the remarkable efficiency scores of 5.522, 4.155, and 3.952 for DMUs 12, 9, and 5, respectively (Fig. 1). These units distinguish themselves as the most efficient processes that were evaluated. Conversely, the efficacy scores of DMUs 2, 10, and 14 are comparatively lower, suggesting potential areas for enhancement. DMU 2 exhibits the lowest efficiency score of -0.230, while DMU 10 and DMU 14 follow suit with -0.149 and -0.148, respectively.

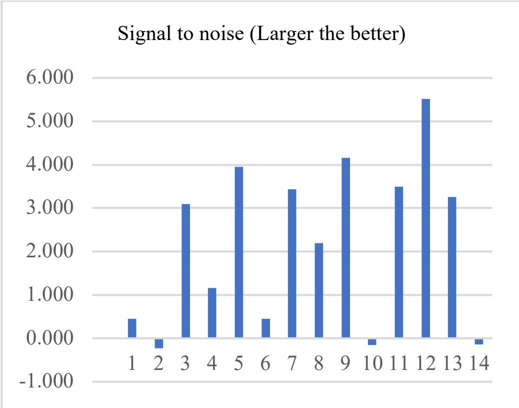

Fig. 1. Performance measures via Taguchi signal to noise ratio.

When confronted with the intricacies of this research, it is critical to not only provide definitive results but also investigate alternative analytical approaches in order to strengthen our conclusions. This research methodology is strengthened by the incorporation of a sensitivity analysis, in fact. In order to rectify the identified impracticability in the BCC model for DMU3 as it pertained to the research framework, a methodical and iterative approach was adopted.

Recognizing the extent of the impracticability challenge, the approach involved a progressive increase in the value assigned to the input factor of seats across all DMUs. To be more specific, the sensitivity analysis was performed on seating factor levels that were added arbitrarily to the dataset. The levels included values of 1, 15, and 40, with 1 signifying the minimum, 15 the average, and 40 the maximum. The primary objective was to eliminate any negative values from the seating factor that included all DMUs. The objective of this deliberate and gradual alteration was to investigate the impact of variations in the seating factor on the overall outcomes of efficiency. This facilitated a comprehensive examination of the ways in which these modifications could potentially mitigate the issue of impracticability (Table 8).

Table 8. Sensitivity analysis for technical efficiency score based on the seating factor levels.

DMU (k)	Increment of Seats			
	+0	+1	+15	+40
1	1.079	1.135	1.200	1.150
2	0.975	0.984	1.361	1.227
3	infeasible	39.732	3.053	3.053
4	1.350	1.345	3.678	2.011
5	1.624	1.509	1.134	1.103
6	1.053	1.061	1.199	1.144
7	1.5	1.500	1.500	1.500
8	1.309	1.317	1.449	1.364
9	1.642	1.535	1.535	1.535
10	1.010	1.010	1.010	1.010
11	2.443	2.443	2.443	2.443
12	1.920	1.873	1.841	1.841
13	1.544	1.473	1.653	1.494
14	1.018	1.018	1.024	1.023

The arbitrary addition of values—namely, 1, 15, and 40—was taken into account, which demonstrated that the BCC model's infeasibility concern for DMU3 could be effectively alleviated by removing zero values. By choosing factors that guaranteed the absence of zeros in the dataset, the DEA model evaluation was enhanced in its effectiveness. By adopting this strategic approach, the immediate impracticability was not only resolved but the DEA model's efficiency and dependability in assessing operational efficiency were also improved.

The meticulous examination of factors that do not contain zero values enhances the reliability and precision of the analysis conducted within the DEA framework. Furthermore, it is advantageous for scholars to undertake a comprehensive examination of the efficacy scores subsequent to the modifications made to the seating factor. Further examination of the efficiency scores, particularly subsequent to value increases, may yield supplementary knowledge regarding the intricate influence on the overall operation of every DMU. By incorporating an extra level of analysis, a more comprehensive comprehension of the impact of seating capacity adjustments on efficiency could be achieved. This, in turn, would enable more informed decision-making regarding the optimization of coffee retail operations.

5. Conclusions and Discussions

The investigation of the operational complexities of a coffee establishment has yielded significant findings through the implementation of a dual-methodology approach, which integrates RBD, DEA, and the Taguchi Method. The data preparation procedure was instrumental in guaranteeing the dependability of the data. The initial phase of the research methodology was dedicated to data preparation. This was accomplished by organizing and standardizing the data, utilizing the Taguchi method, and meticulously selecting the variables. Following this, the Constant Returns to Scale (CCR) and Variable Returns to Scale (BCC) models were selected as a secondary phase in the analytical strategy. This integration furnished a comprehensive comprehension of the operational efficacy of coffee shops. Furthermore, the inclusion of modified super efficiency and super efficiency as a third phase added an additional dimension to the analysis. The randomized block design (RBD) method compares efficiency scores in the fourth stage, with each Decision-Making Unit (DMU) serving as a factor and the evaluation method functioning as a block. The Taguchi method, which is also known as the "larger is better" technique, is implemented in the final stage to improve the performance score.

The implementation of diverse methodologies has yielded an all-encompassing outlook on efficiency scores. With their high efficacy ratings, the top three DMUs, 5, 9, and 12, establish a standard for achievement within a coffee establishment. Conversely, the domains of concern denoted by DMUs 2, 10, and 14 emerge as potential sites for improvement. The concern expressed by the BCC model regarding the impracticability of DMU 3 relates to the efficiency assessment. The difficulty of achieving infeasibility hinders the advancement of DMU 3 and, as a result, has an effect on the overall efficiency summary. This highlights the significance of rectifying the recognized impracticability in order to guarantee a thorough and precise evaluation of efficiency in relation to DMU 3. The discourse is further complicated by the sensitivity analysis predicated on seating capacity. Gaining insights into the intricate relationship between physical space, customer experience, and overall store performance is possible through an understanding of how fluctuations in seating capacity impact operational outputs. This investigation facilitates the development of customized approaches to enhance seating configurations, thereby promoting increased operational effectiveness.

Integrating many optimization methods into the study aims to improve coffee retail outlet efficiency holistically. Integration allows one to use the complementing benefits of each strategy to comprehensively address operational efficiency. DEA variations help evaluate coffee retail establishments by selecting the best DMU among many models. This strategy provides a holistic perspective of operational performance by considering several elements.

Additionally, the Taguchi signal to noise technique prioritizes effectively reducing unwanted outputs. Mitigating and addressing these issues adds a crucial component to optimization efforts, ensuring efficiency in all areas. In conclusion, randomized block design promotes validity and consistency by controlling experimental error and external factors. This ensures that coffee retail shop efficiency optimization methods are durable.

These methods provide a complete coffee store operational efficacy solution. Every technique reinforces each other, filling knowledge gaps and deepening understanding of efficiency challenges and opportunities. They collaborate to create robust optimization tactics that can boost coffee retail prosperity and competitiveness. As the present study draws to a close, potential directions for future investigation become apparent. Further research could be conducted to examine the impact of external factors on operational efficacy, thereby filling in existing voids in the field. A more comprehensive understanding could be attained by examining the effects of economic conditions, regulatory changes, and market trends on the operational dynamics of the coffee retail industry. Optimization of project selection is crucial for coffee retail chains to maximize revenue and customer happiness across locations. Allocating resources to new projects while meeting corporate goals and consumer preferences is difficult. These issues are addressed with integrated optimization methodologies as DEA variations, Taguchi signal to noise, and randomized block design.

In addition, DEA analysis uses investment expenditures, resource needs, and predicted results to assess project efficiency, producing indicators like revenue growth, customer happiness, and brand exposure.

This allows intelligent resource allocation to high-return ventures. Taguchi optimization examines menus, retail layouts, marketing activities, and consumer interaction tactics to determine project success [31]. These characteristics are optimized to improve customer experience, sales, and coffee chain differentiation.

Randomized block design checks project selection and execution tactics across many sites, taking into account store demographics, market trends, and competition. This helps determine the best project execution and resource allocation methods. Integrated optimization solutions boost project selection efficiency, profitability, and customer happiness for the coffee retail chain. DEA variations, Taguchi optimization, and randomized block design provide educated decision-making, high-potential initiative prioritization, and sustained development in a competitive market.

Furthermore, the potential of expanding operational analysis by incorporating Taguchi's methodologies alongside other optimization techniques is considerable. This could facilitate further advancements and inspire further research endeavors aimed at attaining operational excellence. An essential area for further investigation pertains to the examination of how external environmental factors impact the operational efficacy of coffee retail establishments. This necessitates a comprehensive analysis of the complex interplay between consumer sentiment, regulatory environments, market trends, technological progress, competitive dynamics, and global events. Constantly altering market preferences, alterations in regulatory frameworks pertaining to the retail industry, fluctuations in the economic climate, and the incorporation of technological advancements collectively shape the intricate external milieu in which coffee retailers function. A comprehensive comprehension of the ways in which these elements interact to influence operational strategies and efficiency is crucial for organizations aiming to adjust to dynamic external influences and prosper in the perpetually evolving coffee retail sector. A comprehensive investigation into the qualitative dimensions of these interactions requires a nuanced methodology that integrates quantitative analyses for assessing particular variables and qualitative methods for exploring the aforementioned aspects.

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