IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 17 May 2025, accepted 2 July 2025, date of publication 7 July 2025, date of current version 12 August 2025.

*Digital Object Identifier 10.1109/ACCESS.2025.3586417*

RESEARCH ARTICLE

# An Integrated Approach to Stock Selection and Ranking: Combining Shannon Entropy Technique, DEA, and Inverse DEA

**TEMITOPE OLUBANJO KEHINDE[1], (Member, IEEE), SAI-HO CHUNG[1], AND OLUDOLAPO A. OLANREWAJU[2]**

[1]Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong
[2]Institute of Systems Science, Durban University of Technology, Durban 4058, South Africa

Corresponding author: Temitope Olubanjo Kehinde (temitope.kehinde@connect.polyu.hk)

This work was supported by The Hong Kong Polytechnic University, Hong Kong.

**ABSTRACT** This study proposes a novel, integrated framework that combines Shannon Entropy Technique (SET), Data Envelopment Analysis (DEA), and Inverse DEA (IDEA) for the objective evaluation and ranking of equities, with a case application to the tourism sector of the Taiwan Stock Exchange (TWSE). SET is employed for data-driven variable selection to reduce dimensionality across five financial perspectives, enhancing the discriminatory power of DEA. DEA identifies efficient stocks, while IDEA ranks them based on adaptability to output perturbations, providing a dynamic and interpretable view of efficiency. Empirical analysis reveals that only five out of sixteen stocks achieved full efficiency. The IDEA-based ranking uncovered distinct adaptability profiles, with some firms requiring minimal input changes to accommodate output growth, indicating operational flexibility. Sensitivity analysis and model comparisons with super-efficiency and cross-efficiency DEA confirm the robustness and consistency of the proposed method, even under adverse scenarios. This work advances financial decision-making by offering a reproducible, bias-minimized, and scenario-sensitive ranking model. Its transparent structure makes it especially valuable for investors, policymakers, and portfolio managers navigating volatile or crisis-prone markets.

**INDEX TERMS** Data envelopment analysis, inverse DEA, efficiency, stocks, stock market, ranking.

## I. INTRODUCTION

Stocks, which represent fractional ownership in corporate assets and earnings, are among the most powerful tools in modern society for mobilizing savings, allocating capital, and distributing risk [1], [2]. When a firm issues equity, it gains financing for innovation, expansion, and job creation; when households buy that equity, they gain a liquid claim whose price reflects the collective wisdom of millions of market participants. At the macro level, vibrant stock markets accelerate economic growth by channelling capital from surplus sectors to high-productivity ventures; at the micro level, they encourage corporate transparency, discipline management through share-price monitoring, and promote wider wealth distribution through pension funds and individual portfolios.

Stock markets matter not merely to traders and investment bankers but to workers, entrepreneurs, consumers, and governments whose prosperity depends on efficient capital formation. Yet harnessing these benefits requires a critical intermediate step: selecting the right stocks. For an individual investor, poor selection erodes savings and jeopardises retirement security; for institutional asset managers, it threatens fiduciary credibility; for regulators and policymakers, misallocation of equity capital can starve socially valuable enterprises and inflate bubbles elsewhere. The problem has grown more acute as the global investable universe has exploded, thanks to low-cost online brokerages, exchange-traded funds, and cross-border listings, while the flow of financial data has become torrential. Faced with hundreds

The associate editor coordinating the review of this manuscript and approving it for publication was Frederico Guimarães.

of ratios, ratings, newsfeeds, and social-media signals, even sophisticated analysts struggle to separate signal from noise, recognize resilient business models, and build portfolios that withstand shocks.

The emergence of the COVID-19 epidemic posed unprecedented obstacles to the worldwide financial environment [3], [4]. For instance, between January and March 2020, the Taiwan Stock Exchange (TWSE) lost 29 percent of its value [5], and the tourism and hospitality segment, whose fortunes are tied directly to cross-border mobility, was hit hardest [6]. The tourism and hospitality industry plays a significant role in stimulating economic growth on a global scale. According to estimations from the United Nations World Tourism Organisation (UNWTO), its impact is comparable to global oil, food, or vehicle trade [7]. While tourism had previously outpaced global GDP growth for nine consecutive years and contributed an estimated USD 8.9 trillion (10.3 percent) to world GDP [8], border closures and travel restrictions abruptly reversed those gains. International arrivals collapsed by 74 percent in 2020, wiping out USD 1.3 trillion in export revenues and endangering more than 100 million tourism jobs worldwide [9]. Taiwan, ranked the 20th most-visited Asian destination in 2022 [10], experienced a near-total halt to inbound tourism for almost two years, providing a natural experiment in resilience.

Traditional stock appraisal methods rely heavily on qualitative judgment or single-ratio screens and therefore struggle to deliver transparent, reproducible rankings under crisis conditions. Data-Envelopment Analysis (DEA) improves on simple ratio analysis by benchmarking each decision-making unit (DMU) relative to a best-practice frontier [11], but two long-standing issues remain. First, selecting too many inputs and outputs dilutes discriminatory power, the so-called curse of dimensionality [12], [13]. Second, DEA yields multiple efficient DMUs with identical efficiency scores, yet offers no intrinsic way to rank them. Existing methods, such as super-efficiency and cross-efficiency, can be infeasible or overly sensitive to outliers.

In information theory, Shannon Entropy measures the information content of a variable [14]; high-entropy variables contribute more unique information than low-entropy ones. Applied to finance, the Shannon Entropy Technique (SET) can sift through a battery of financial ratios and retain only those with the greatest informational weight, thereby mitigating dimensionality problems without relying on subjective expert opinion [15]. Meanwhile, Inverse DEA (IDEA) extends standard DEA by asking the opposite question: If outputs increase by a given percentage, how much must inputs rise for each DMU to remain efficient [16]? The resulting input-expansion factors provide a natural, interpretable ranking of the originally efficient units, free from the infeasibility issues that plague super-efficiency models. Individually, each method solves part of the performance-measurement puzzle; combined, they promise a more robust, transparent, and crisis-resilient framework.

Sensitivity analysis is a fundamental method employed to ascertain the strengths and weaknesses of a model [17]. The inclusion of a "what-if" analysis is crucial in light of the intrinsic uncertainty and variability included in empirical data and parameters. Sensitivity analysis contributes to the validation, reliability, confidence level, and internal consistency of decision-making processes [18]. This is achieved by emphasizing the impact of variations in parameters and the resulting outcomes, hence ensuring the resilience and adaptability of models under various circumstances.

This work introduces SET-DEA-IDEA, an integrated three-stage framework that delivers (i) objective variable selection, (ii) efficiency benchmarking, and (iii) resilience-aware ranking of efficient stocks. We apply the framework to 16 publicly traded tourism companies on the TWSE for fiscal year 2021, the sector's first full year under pandemic restrictions, to answer three research questions:

1. Which financial ratios best characterise liquidity, asset utilization, leverage, profitability, and valuation for Taiwanese tourism stocks?

2. Which stocks operated efficiently, given those key ratios, during the height of COVID-19 disruption?

3. Among the efficient firms, which are most adaptable to output growth and therefore most attractive for investors seeking robust post-pandemic recovery plays?

Our contributions are as follows:

1. Methodological novelty: To our knowledge, this is the first equity-evaluation study that fuses SET for dimensionality reduction, classical DEA for efficiency measurement, and IDEA for post-efficiency ranking.

2. Practical robustness: Sensitivity tests, adding extra inputs, scaling inputs up by 20 percent, and scaling outputs down by 20 percent, confirm that efficiency scores and rankings remain stable, underscoring the framework's resilience.

3. Actionable insight: Of sixteen stocks analysed, five achieved full efficiency. IDEA then revealed distinct adaptability profiles.

4. Policy relevance: The transparent, data-driven nature of SET-DEA-IDEA makes it suitable not only for portfolio managers but also for regulators and policymakers tasked with stress-testing critical sectors during systemic shocks.

Three factors motivate our case selection. First, TWSE is the eighth-largest equity market in Asia and the seventeenth-largest globally by capitalisation, offering a rich yet under-examined dataset for methodological innovation [19]. Second, Taiwan's tourism firms display a wide dispersion in business models, from hotel chains to food-and-beverage groups, allowing a meaningful assessment of input–output heterogeneity. Third, the 2021 financial year represents a stress-test window in which every company faced identical external constraints (closed borders), sharpening the contrast between operationally agile and rigid firms.

By reframing variable selection, efficiency measurement, and ranking as a single coherent pipeline, SET-DEA-IDEA offers a reproducible blueprint for evaluating corporate resilience in volatile environments. For investors navigating post-pandemic recovery, for scholars seeking methodological advances, and for policymakers overseeing systemic stability, the framework delivers a concise, interpretable, and data-rich lens through which to judge firm performance, precisely when clarity and speed of insight are paramount.

The remaining part of this study is organized in the following manner: In section II, an examination is conducted on the current body of research, including SET, DEA, IDEA, and other decision-making techniques. Section III provides a comprehensive account of the methodology employed in this study. It encompasses a detailed discussion of the data sources, variable selection, and the sequential adoption of SET, DEA, and IDEA techniques. In Section IV, the findings of this study are presented and examined through tables, graphs, and statistical analysis. Section V discusses the validity, reliability, comparison, and robustness of the proposed method through sensitivity analysis. Section VI of this paper summarises and concludes the research work. In addition, it presents the limitations inherent in this study and, again, outlines potential paths for future research.

## II. LITERATURE REVIEW

The assessment of stock market efficiency, particularly in industries vulnerable to external disturbances such as tourism, has been the subject of extensive scholarly research. SET, DEA, and IDEA are notable multi-criteria decision-making (MCDM) techniques with broad applications across diverse sectors and domains. Hence, this section examines the current body of literature relating to these methodologies to identify existing research gaps and the obstacles that serve as the impetus for our investigation.

### A. SHANNON ENTROPY TECHNIQUE (SET)

In MCDM, determining the relative weights of indicators is a fundamental and essential step in the problem-solving process. Several methods are prominent and generally recognized for determining these weights, including expert opinion-based approaches, the least squares method, the special vector technique, and SET. Notably, the SET stands out as one of the most crucial methods for determining criteria weights [15]. Qualitative approaches such as the Analytic Hierarchy Process (AHP) [20], [21], Fuzzy AHP [22], Analytic Network Process (ANP) [23], PROMETHEE [24], and VIKOR [25], [26], are common methods that require expert opinions in their evaluation processes; however, these methods are often criticized for creating bias and subjectivity.

Principal Component Analysis (PCA) does not possess an inherent characteristic of being a tool for MCDM, yet the technique is typically used for dimensionality reduction, particularly in DEA evaluation [27]. Nevertheless, the utilization of PCA in this situation has its limitations. Applying PCA for dimension reduction in DEA models may lead to a reduction in the amount of original data, perhaps resulting in an oversimplification of the DEA model. The possible loss discussed above has the capacity to not only impact the assessment of DMU efficiency but also impose constraints on subsequent investigations, such as inverse optimization, as a result of the altered data. Moreover, the effectiveness of PCA is greatly impacted by the scaling of variables, rendering it susceptible to variations.

The concept of SET originated from information theory and was initially presented by Shannon in 1948 [28]. SET quantifies the level of uncertainty or unpredictability inherent in a given system or variable. The level of entropy increases proportionally with the degree of uncertainty or unpredictability exhibited by the system. SET has several applications across various disciplines, including cryptography, communication theory, physics, biology, ecology, economics, and statistics. One of the practical applications of SET is in the domain of feature selection. This process involves careful selection of a subset of relevant features or variables from a vast pool of accessible options tailored to address a given task or problem. The feature selection process of SET can decrease the dimensionality and intricacy of the data while also enhancing the effectiveness and precision of the models or techniques that rely on the chosen features or variables. One notable benefit of employing SET for feature selection is its independence from prior knowledge or expert judgments. Instead, it leverages the information content associated with each feature or variable to ascertain their significance and pertinence. Another benefit of utilizing SET for feature selection is its ability to effectively handle many features or variables, including numerical and categorical ones. Furthermore, it is capable of accommodating linear as well as nonlinear associations among these features.

Few studies have employed SET in portfolio stocks. Xie et al. [29] suggest a novel approach that integrates the efficiency of several variable subsets. These subsets are then weighted based on their respective degrees of relevance, which are determined using SET. The process yields a comprehensive efficiency score (CES), enabling a more precise and consistent ranking of all DMUs. The authors implement their methodology on several datasets from existing literature and conduct a comparative analysis with alternative DEA models. The authors demonstrate that their methodology can potentially enhance the discriminatory power of DEA while retaining valuable variable information. Furthermore, their versatile approach can be applied across various DEA assumptions and orientations.

A similar approach was adopted by Gupta et al. [30] to rank four distinguished DEA models. Peykani et al. [15] introduce a hybrid DEA–Shannon entropy (DEASE) method in their study. Their work addresses the issue of selecting appropriate input and output indicators within DEA models. The strategy employs SET to ascertain the weights of indicators and select the most significant ones from each cluster of comparable indicators. The approach considers negative data and values in some indicators, employing range directional measure DEA as the fundamental model. The paper showcases the practicality of the DEASE strategy through its implementation in a case study involving 15 equities from the food sector of the Tehran stock exchange. The findings indicate that the DEASE technique can potentially enhance the DEA model's discriminatory capability and achieve a more efficient stock ranking compared to a traditional DEA model. In a recent investigation, Karagiannis and Karagiannis [31] present a non-parametric model utilizing DEA to quantify the degree of overpricing for each brand in relation to its number of features. The authors additionally present a novel use of SET to aggregate vitamin and mineral items, thereby mitigating the curse of dimensionality.

### B. EFFICIENCY RANKING AND EVALUATION USING DEA

DEA is a non-parametric method utilized to assess the relative efficiency of DMUs by considering their weighted inputs and outputs. The DEA methodology has the capability to offer benchmarks and targets that can be utilized to enhance the performance of inefficient DMUs. Asides from stock selection, DEA has been extensively applied for performance improvement in other sectors, including blockchain operations, risk management, hotel management, telecommunication industry, banking, logistics, transportation industry, supply chain, cyberbullying detection, farm and agriculture, power, healthcare, production and manufacturing, tourism, automobile, construction, insurance, transportation, and education [32], [33], [34], [35], [36], [37], [38]. The notion of the DEA was originally proposed by Charnes et al. [39], drawing upon Pareto efficiency and linear programming principles. DEA has the capability to discern the most effective DMUs as efficient entities while categorizing the remaining ones as inefficient. The DEA methodology is capable of offering benchmarks and targets that can be utilized to enhance the performance of inefficient DMUs.

The technique of DEA offers numerous advantages in comparison to alternative methods when it comes to measuring efficiency and evaluating performance. One notable feature of this approach is its ability to generate an empirical frontier that encompasses all DMUs without relying on any assumptions regarding the functional form or distribution of the data. Instead, it utilizes the data itself to derive this frontier. An additional benefit is its ability to effectively manage many inputs and outputs that possess distinct units and scales without necessitating any pre-existing weights or preferences. A significant issue in implementing the DEA approach across different applications is the absence of consensus about selecting and determining appropriate input and output variables. Another crucial aspect when employing the DEA methodology is its discriminatory strength. Despite the lack of a universally accepted scientific norm or agreement in the existing literature about the optimal number of DMUs for a robust efficiency estimation, several researchers suggest employing Eq. (1) as a means to establish the minimal number of DMUs to be utilized in any standard DEA model [40]. In the given context, $a$ represents the minimum count of DMUs, $b$ represents the total count of inputs, and $c$ represents the total count of outputs.

$$a \geq max\left\{3 * (b + c)\,, b * c\right\} \tag{1}$$

Few studies have used DEA models and methodologies to determine the performance of portfolio stocks belonging to TWSE. Chen [41] conducts a survey that analyzed portfolios managed by DEA in eight prominent industries. The findings indicated that these portfolios demonstrated an incredible performance compared to industry averages and portfolios of small-sized enterprises. Hsu [42] introduces a novel methodology for portfolio optimization by integrating DEA with artificial bee colony (ABC) and genetic programming (GP). The effectiveness of this approach was demonstrated through a case study conducted in the semiconductor sub-sector of TWSE, where it successfully generated significant returns and mitigated investment risks. In addition, Huang et al. [43] introduce an integrated methodology combining DEA with multi-objective decision-making (MODM) methodologies to optimize stock investments in Taiwan. The methods employed encompass stock screening, portfolio selection, and capital allocation, demonstrating superior performance compared to benchmark indices regarding both return rate and Sharpe ratio across many testing intervals. Although some investigations have yielded valuable insights and implications for enhancing the efficiency of stocks, none of this research has developed a hybrid model such as SET-DEA-IDEA to perform efficiency evaluation and ranking, particularly in the tourism sector.

### C. INVERSE DEA (IDEA)

IDEA technique is widely utilized in conducting inverse optimization. This involves maintaining the efficiency score of DMUs at a constant level while systematically adjusting the input or output variables by a certain percentage. This adjustment allows examining the corresponding changes in the output or input variables. The notion of IDEA was initially introduced by Wei et al. [44]. This approach is rooted in inverse linear programming and sensitivity analysis principles.

The IDEA framework offers a distinctive approach to rate efficient DMUs by evaluating their capacity for improvement or decrease. Recently, researchers have developed and studied inverse optimization issues. Two major categories of models exist in this area, with the first focusing on resource allocation and the second on investment analysis [45]. IDEA concept has become the state-of-the-art analytical technique in energy and environmental studies [46]. Further, the utilization of IDEA has been established in the banking industry, particularly in mergers and acquisitions (M&A) scenarios. M&A in the banking industry often arises from the objective of attaining enhanced operational effectiveness, enlarging market share, and strengthening financial performance. IDEA framework provides a method for assessing the potential operational efficiency of a merged company before the merger and acquisition process is completed. Several notable works have employed the IDEA framework to assess the effectiveness of bank consolidations [45], [47]. In recent studies, scholars have investigated other industries using IDEA technique. These sectors encompass healthcare, education, transportation, supply chain, textile, and automobile. The works of [45] and [47] provide in-depth reviews of IDEA's advances and state-of-the-art applications in various domains.

In stock selection, IDEA is rarely used in the literature, making it a hotspot for investigators [16]. The two closely related articles in this regard include [48] and [49]. Çakır [48] presents a two-phase approach to address resource allocation issues within a fuzzy context. The initial stage involves selecting input and output variables for DEA using imprecise SET. This method can accommodate fuzzy and interval data while also facilitating the calculation of criteria weights. In the second phase, an interval IDEA model is utilized to estimate the optimal input values for DMUs in case of changes in some of their output values. This estimation is done while maintaining the efficiency score of the DMU. Their results showcase the practicality and effectiveness of the suggested technique by examining a genuine case study involving 16 cement companies in Turkey. However, the findings indicate that the hybrid model only addresses challenges related to input-output selection and resource allocation in situations characterized by fuzzy conditions. Another limitation is that the interval IDEA formulated could only be used for ranking purposes of input and output data but is not suitable for ranking efficient DMUs.

Similarly, Goyal et al. [49] put forth an IDEA approach by introducing a ranking system based on a super-efficiency IDEA model. The proposed model assesses and prioritizes 52 bus depots by considering their inputs and outputs. The study compares the suggested and conventional super-efficiency DEA models, revealing high consistency between their outcomes. The limitation of these studies is that the number of inputs and outputs considered does not compromise the discerning power of DEA. Also, it is worth noting that super-efficiency DEA and super-efficiency IDEA are sensitive to outliers and sometimes encounter infeasibility issues.

### D. RESEARCH GAPS AND CHALLENGES

Examining existing literature allows for identifying research gaps and issues that serve as the impetus for our investigation. The current body of literature lacks comprehensive research integrating SET, DEA, and IDEA (SET-DEA-IDEA) methodologies to evaluate and rank stocks. Furthermore, a scarcity of research employs IDEA to analyze the tourist industry. This sector is crucial since it is recognized as one of the most vital and rapidly evolving industries globally. Notably, Taiwan's tourism sector stands as one of Asia's most advanced and multifaceted, exhibiting considerable prospects for expansion and advancement. Furthermore, there is a scarcity of research that examines explicitly the financial year 2021, a period marked by the devastating impact of COVID-19 on the tourism industry and the closure of national borders to international tourists. This timeframe represents a crucial examination of the performance and effectiveness of tourism stocks to test the resilience of such stocks in any typical, unprecedented global crisis.

Although several hybrid DEA–MCDM frameworks exist, including integrations with PCA, AHP, TOPSIS, and VIKOR, many of these rely on subjective weighting schemes, which introduce bias and reduce reproducibility. SET was selected in this study due to its objectivity; it calculates weights based solely on data variability without requiring expert input. PCA, although statistically robust, often transforms variables into composite dimensions that may lack interpretability, which can hinder financial decision-making. Furthermore, PCA assumes linearity and is sensitive to variable scaling, which may distort DEA results in financial contexts. In contrast, SET operates directly on the original variable space, preserving interpretability and objectivity by assigning weights based on data entropy without requiring subjective input. Compared to PCA, SET retains the original variable structure, allowing for more straightforward interpretation and ensuring financial indicators maintain practical relevance. In contrast to AHP or Fuzzy AHP, SET eliminates reliance on decision-makers' preferences, enhancing model transparency. Furthermore, while some prior hybrid models use super-efficiency DEA or cross-efficiency evaluation for ranking, these methods may suffer from infeasibility or sensitivity to outliers. By integrating SET for variable selection, DEA for efficiency measurement, and IDEA for ranking, our proposed SET-DEA-IDEA framework offers a data-driven, interpretable, and robust method to handle uncertainty and preserve feasibility, particularly valuable in high-stakes financial decision-making environments.

Similarly, for ranking efficient DMUs, alternatives such as super-efficiency DEA or cross-efficiency evaluation are commonly used. However, these methods often face limitations, such as infeasibility issues in the presence of outliers or sensitivity to small data changes. On the other hand, IDEA provides a structured way to assess the stability and adaptability of efficient DMUs by quantifying how much input adjustment is required to maintain efficiency under changing output conditions. This approach yields deeper strategic insights and enhances the robustness of the ranking process. Consequently, the novel integration of SET, DEA, and IDEA in this study offers a transparent, reproducible, and data-driven framework that effectively addresses the dimensionality and ranking challenges inherent in financial performance evaluation.

## III. METHODOLOGY

This section provides an overview of the data sources, sample selection process, and variables employed in this study. It also comprehensively discusses the methods and step-by-step approach to implement the proposed SET-DEA-IDEA framework.

### A. DATA SOURCES AND COLLECTION

The primary data utilized in this study comprises the financial ratios of 16 stocks belonging to the tourist sector of the TWSE, specifically for the fiscal year 2021. The data utilized in this study were sourced from the Taiwan Economic Journal (TEJ) database, a reputable and comprehensive source of financial information on publicly traded firms in Taiwan. Sixteen companies from the tourist sector were chosen for analysis, taking into consideration their market capitalization and the availability of relevant data. The tourism industry encompasses a range of establishments and enterprises, such as hotels, restaurants, travel agents, airlines, and other interconnected entities. The study incorporates a collection of 13 financial ratios that assess different aspects of a firm's economic performance, including Liquidity, Asset usage, Leverage, Profitability, and Valuation. These ratios are frequently employed in financial analysis and stock appraisal [15], [48]. The definitions and formulas pertaining to these ratios are explained in Table 1.

### B. DIMENSIONALITY REDUCTION USING SET

SET quantifies the amount of information contained within a given set of variables. It serves as a valuable tool for identifying and selecting the most pertinent and representative inputs and outputs from a vast array of options. The utilization of SET can potentially decrease the dimensionality and redundancy of the variables while simultaneously enhancing the discrimination power and resilience of DEA. The process of employing SET for input and output variable selection involves the following procedures:

*Step 1:* First, we set up an Eq. (2) to create a decision matrix with $P$ alternatives and $Q$ criteria, where $p^{th}$ alternative and $q^{th}$ criterion denote the value of individual $n_{pq}$.

$$N = [n_{pq}]_{P*Q} = \begin{pmatrix} n_{11} & \cdots & n_{1Q} \\ \vdots & \ddots & \vdots \\ n_{P1} & \cdots & n_{PQ} \end{pmatrix} \tag{2}$$

*Step 2:* The second step involves applying the min-max normalization procedure to the data in order to mitigate the influence of varying units and scales. Eq. (3) is used to standardize the constructed matrix. The normalized estimate, $V_{pq}$, is calculated by expressing individual $n_{pq}$ on each column as a ratio of its sum.

$$V_{pq} = \frac{n_{pq}}{\sum_{p=1}^{P} n_{pq}}, \quad \forall p, q \tag{3}$$

*Step 3:* In the third step of the process, the entropy of each variable is determined by employing Eq. (4). The entropy, $e_q$, can be calculated by solving Eq. (4). The parameter is kept between 0 and 1 by having a fixed value.

$$e_q = -\left(ln\left(P\right)\right)^{-1} \sum_{p}^{P} V_{pq} \ln\left(V_{pq}\right), \quad \forall q \tag{4}$$

*Step 4:* In this step, we estimate the degree of deviation $d_q$ using Eq. (5). The magnitude of the deviation can be used to infer how much insight the relevant criteria provide into the decision.

$$d_q = 1 - e_q, \quad \forall q \tag{5}$$

*Step 5:* In the fifth step, the variables with the highest weight from each perspective are chosen as the inputs and outputs of the efficiency model. Since a low weight indicates that all the options perform equally, the one with the highest weight is chosen. Using Eq. (6), we divide $d_q$ by the total of $d_q$; the result gives the weight $w_q$.

$$w_q = \frac{d_q}{\sum_{q}^{Q} d_q}, \quad \forall q \tag{6}$$

In this study, 13 variables were grouped into five distinct views: Liquidity, Asset usage, Leverage, Profitability, and Valuation. The initial viewpoint to consider is Liquidity, which encompasses the assessment of various financial ratios, such as the current, quick, and cash ratios. The subsequent view pertains to Asset usage, wherein the available variables encompass asset and receivables turnover. The third perspective pertains to the concept of Leverage, which involves considering the factors of solvency ratio I and solvency ratio II when making choices. The fourth aspect pertains to Profitability, encompassing a range of factors such as return on equity, net profit margin, and earnings per share. Valuation constitutes the fifth perspective, wherein the available variables for consideration encompass the price-to-sales ratio, price-to-book ratio, and price-to-earnings-per-share.

**TABLE 1. Description of financial variables.**

| Ratio | Perspective | Formula |
|---|---|---|
| Current ratio (CR) | Liquidity ratio | Current assets / Current liabilities |
| Quick ratio (QR) | Liquidity ratio | (Current assets - Inventories) / Current liabilities |
| Cash ratio (CAR) | Liquidity ratio | Cash and cash equivalents / Current liabilities |
| Asset turnover (AT) | Asset utilization | Revenue / Total assets |
| Receivables turnover (RT) | Asset utilization | Revenue / Average accounts receivable |
| Solvency ratio I (SOL I) | Leverage ratio | Total debt / Total assets |
| Solvency ratio I (SOL II) | Leverage ratio | Total debt / Total equity |
| Return on equity (ROE) | Profitability ratio | Net Income / Average Equity |
| Net profit margin (NPM) | Profitability ratio | Net Income / Revenue |
| Earnings per share (EPS) | Profitability ratio | Net income / Weighted average number of common shares outstanding |
| Price to sales ratio (PSR) | Valuation ratio | Stock price / Revenue per share |
| Price to book ratio (PBR) | Valuation ratio | Stock price / Book value per share |
| Price to earnings ratio (PER) | Valuation ratio | Stock price / EPS |

In choosing the appropriate indicators for DEA, the selection of variables for input or output is determined by their respective weights, which are calculated using SET.

### C. INTEGRATED SET-DEA FOR EFFICIENCY ESTIMATION

One of the shortcomings of SET is its limitation in considering the objective or purpose of decision-making. To handle this limitation, SET is integrated with DEA to create an objective function. The selection of SET as a method for reducing dimensionality is notably significant. SET-DEA is a hybrid model for evaluating the performance level of stocks using a combination of DEA and SET to increase the model's discerning power when used to assess the performance of the DMUs. The required steps are presented as follows:

*Step 1:* The first step involves the establishment of clear definitions for the inputs and outputs of the DEA method. Variables are classified based on financial perspectives. The first perspective is Liquidity, and the indicators in this category include QR, CR, and CAR. The second perspective is Asset usage, and the indicators in this category include AT and RT. The third perspective is Leverage, and the indicators in this category include SOL I and SOL II. The fourth perspective is Profitability, and the indicators in this category include ROE, NPM, and EPS. The last perspective is Valuation, and the indicators in this category include PSR, PBR, and PER. The most weighted indicator using SET represents all the variables in each perspective.

*Step 2:* In the second step, selecting a suitable DEA model is necessary by considering the orientation and assumptions related to returns to scale. For this study, we have opted to utilize an input-oriented DEA model that incorporates the assumption of constant returns to scale (CRS). The input-oriented DEA model posits that DMUs can decrease their inputs while maintaining a consistent output level. The assumption of CRS posits that DMUs function at an optimal scale and that any proportional alteration in inputs will yield a proportional alteration in outputs.

*Step 3:* The third step involves formulating the chosen DEA model as a linear programming problem. In this paper, in a similar manner to [50] and [51], the classical input-oriented DEA model with CRS assumption is adopted as a base model, which is expressed as model (M1).

$$
\begin{aligned}
& Min\ \Psi_o^{CCR} \\
& s.t.\ \sum_{k=1}^{n} x_{jk}\lambda_k \le \psi_o^{CCR} x_{jo}, \quad j = 1, 2, \ldots, m \\
& \quad\ \sum_{k=1}^{n} y_{lk}\lambda_k \ge y_{lo}, \quad l = 1, 2, \ldots, s \\
& \quad\ \lambda_k \ge 0, \quad k = 1, 2, \ldots, n
\end{aligned} \tag{M1}
$$

$\psi_o^{CCR}$ = the efficiency score of $\mathrm{DMU}_o$
$x_{jk}$ = the j$^{\text{th}}$ input of $\mathrm{DMU}_k$
$y_{lk}$ = the l$^{\text{th}}$ output of $\mathrm{DMU}_k$
$\lambda_k$ = the assigned weight of $\mathrm{DMU}_k$
$n$ = number of DMUs
$m$ = number of inputs
$s$ = number of outputs

*Step 4:* In the fourth step, the DEA model is solved for each DMU by employing a linear programming solver. This work uses the deaR package of R software to evaluate the efficiency score of individual DMUs. The efficiency score of each DMU varies between 0 and 1. A DMU is deemed efficient if its efficiency score is equal to one, but a DMU is regarded as inefficient if its efficiency score is less than one.

*Step 5:* In the fifth step of the analysis, the results are interpreted by comparing the efficiency scores of various DMUs. This process involves identifying the efficient DMUs and those that exhibit inefficiencies.

### D. UTILIZING IDEA TO RANK EFFICIENT STOCKS

IDEA technique is utilized to conduct inverse optimization by maintaining the efficiency score of DMUs at a constant level. IDEA has proven in recent years that it can handle difficult decision-making situations. This involves adjusting the input or output variables by a specific percentage to observe the resulting changes in the related output or input variables. The IDEA methodology offers a distinctive approach to rate efficient DMUs by assessing their capacity for progress or decline. If a DMU output is perturbed, the classical IDEA problem asks for the necessary input level to keep the efficiency score the same. The IDEA model seeks to determine the necessary input level to reach a new level $x_o + \Delta x_o = \varphi_o$ that maintains DMU's efficiency score after the output is increased to $y_o + \Delta y_o = \beta_o$. The following MOLP model (M2) [50] can be used to achieve this goal:

$$
\begin{aligned}
& min\ (\varphi_{1o}, \varphi_{2o}, \ldots, \varphi_{mo}) \\
& s.t.\ \sum_{k\neq o}^{n} x_{jk}\lambda_k \le \psi^{CCR}\varphi_{jo}, \quad j = 1, 2, \ldots, m \\
& \quad\ \sum_{k\neq o}^{n} y_{lk}\lambda_k \ge \beta_{lo}, \quad l = 1, 2, \ldots, s \\
& \quad\ \varphi_{jo} \ge x_{jo} \\
& \quad\ \lambda_k \ge 0, \quad k = 1, 2, \ldots, n.
\end{aligned} \tag{M2}
$$

Soleimani-Chamkhorami et al. [50] created the first IDEA ranking model to rank Iranian banks. The IDEA implementation phase is carried out using Lingo software. The process for implementing the IDEA method to rank efficient DMUs consists of the following procedures:

*Step 1:* Normalization of inputs and outputs is required to put all variables on a standard scale. By so doing, the effect of noise and outliers are managed without compromising stability and accuracy. We apply Eq. 7-8 to normalize both the input and output variables.

$$\bar{x}_{jk} = \frac{x_{jk}}{max\ x_{jk}} \tag{7}$$

$$\bar{y}_{lk} = \frac{y_{lk}}{max\ y_{lk}} \tag{8}$$

*Step 2:* The second step involves creating sets A and B to categorize our DMUs into efficient and inefficient DMUs, respectively, using the selected input-oriented CCR model. In this study, we classify the DMUs with an efficiency score of one as efficient while the remaining DMUs are inefficient.

*Step 3:* Step 3 involves formulating the IDEA model as a linear programming problem, incorporating a constant percentage change denoted as c. Suppose all outputs of efficient DMUs are increased by c % (where $\beta = c$) to give Y+c%. Then, the corresponding increase in the input values is calculated using the inverse optimization model (M3). For mathematical proof, kindly refer to the work of [50].

$$
\begin{aligned}
&\varphi_o = min\ \varphi \\
&\quad s.t. \sum_{k \neq o}^{n} \bar{x}_{jk}\lambda_k \leq \bar{x}_{jo} + \varphi, \quad j = 1, 2, \ldots, m \\
&\quad\quad \sum_{k \neq o}^{n} \bar{y}_{lk}\lambda_k \geq \bar{y}_{lo} + c, \quad l = 1, 2, \ldots, s \\
&\quad\quad \bar{x}_{jo} + \varphi \geq \bar{x}_{jo} \\
&\quad\quad \lambda_k \geq 0, \quad k = 1, 2, \ldots, n
\end{aligned} \tag{M3}
$$

*Step 4:* The ranking order of $DMU_o$ where $o \in setA$ is computed using model (M3), sorted in descending order of $\varphi$. Fig. 1 details the summary of steps and methods of the proposed method.

## IV. EMPIRICAL ANALYSIS AND DISCUSSION

This section comprehensively evaluates the proposed SET–DEA–IDEA framework applied to 16 tourism-sector stocks listed on the TWSE. The key findings reveal that the SET method effectively reduced 13 financial variables to five representative indicators, maintaining information richness while addressing dimensionality concerns. The SET-DEA model identified five stocks as efficient, each achieving an efficiency score of 1, and provided benchmarks for improvement among the remaining stocks. IDEA was subsequently applied to rank these efficient stocks, revealing consistent performance patterns and adaptability across various simulated output increments. These findings highlight the practical value of the integrated approach for equity evaluation and decision-making under uncertainty.

### A. APPLICATION OF SET

SET methodology is applied to the datasets, and the results are then analyzed and discussed. The entropy values and corresponding weights for each financial ratio, categorized by their financial perspective, are displayed in Table 2.

Liquidity is a crucial aspect in financial analysis, and among the several liquidity ratios, QR holds particular significance with a weight of 0.4629, rendering it the most prominent variable within this category. While CR carries a significant weight of 0.4074, it is surpassed by QR. The CAR is assigned a weight of 0.1297, suggesting that it holds relatively less importance in capturing the Liquidity of the analyzed equities. Asset utilization is a crucial aspect to consider, and the variable that has the most significance in this regard is RT, which carries a weight of 0.8892. This weight underscores the importance of RT in accurately reflecting Asset utilization. AT exhibits a significantly reduced weight of 0.1108. SOL II holds greater significance in the context of Leverage, as indicated by its weight of 0.6940, compared to SOL I, which carries a weight of 0.3060. In terms of Profitability, the weight assigned to EPS is the greatest at 0.3370, closely followed by ROE and NPM, with weights of 0.3356 and 0.3275, respectively. In the context of Valuation, PSR holds significant importance as the primary variable, carrying a weight of 0.5952. PER and PBR carry weights of 0.3052 and 0.0995, respectively, signifying their relatively lower relevance when compared to PSR.

**TABLE 2. Indicator selection using SET.**

| Financial ratio | Perspective | Entropy ($E_j$) | Weight ($W_j$) |
|---|---|---|---|
| Current ratio (CR) | Liquidity | 0.7681 | 0.4074 |
| Quick ratio (QR) | Liquidity | 0.7365 | 0.4629 |
| Cash ratio (CAR) | Liquidity | 0.9262 | 0.1297 |
| Asset turnover (AT) | Asset utilization | 0.8898 | 0.1108 |
| Receivables turnover (RT) | Asset utilization | 0.1163 | 0.8892 |
| Solvency ratio I (SOL I) | Leverage | 0.9712 | 0.3060 |
| Solvency ratio I (SOL II) | Leverage | 0.9347 | 0.6940 |
| Return on equity (ROE) | Profitability | 0.7772 | 0.3356 |
| Net profit margin (NPM) | Profitability | 0.7826 | 0.3275 |
| Earnings per share (EPS) | Profitability | 0.7763 | 0.3370 |
| Price to sales ratio (PSR) | Valuation | 0.7413 | 0.5952 |
| Price to book ratio (PBR) | Valuation | 0.9567 | 0.0995 |
| Price to earnings ratio (PER) | Valuation | 0.8673 | 0.3052 |

Using SET, the variables inside each perspective have been appropriately sorted based on their weights. The weights assigned to each variable offer an impartial assessment of their significance, promoting a data-centric approach to variable selection that is free from subjective biases. By employing a strategy of picking the variable with the highest weight from each perspective, it is possible to efficiently decrease the number of dimensions and eliminate redundancy in the dataset. This approach guarantees that the most indicative variables are picked for the study using DEA. This technique improves the efficiency of the evaluation process and strengthens the ability to differentiate and withstand the challenges of DEA. Based on the weights derived from Table 2, the variables chosen for subsequent analysis are QR, RT, SOL II, EPS, and PSR. The liquidity metric known as the QR is utilized to assess the ability of a company to meet its short-term obligations. Asset utilization is evaluated

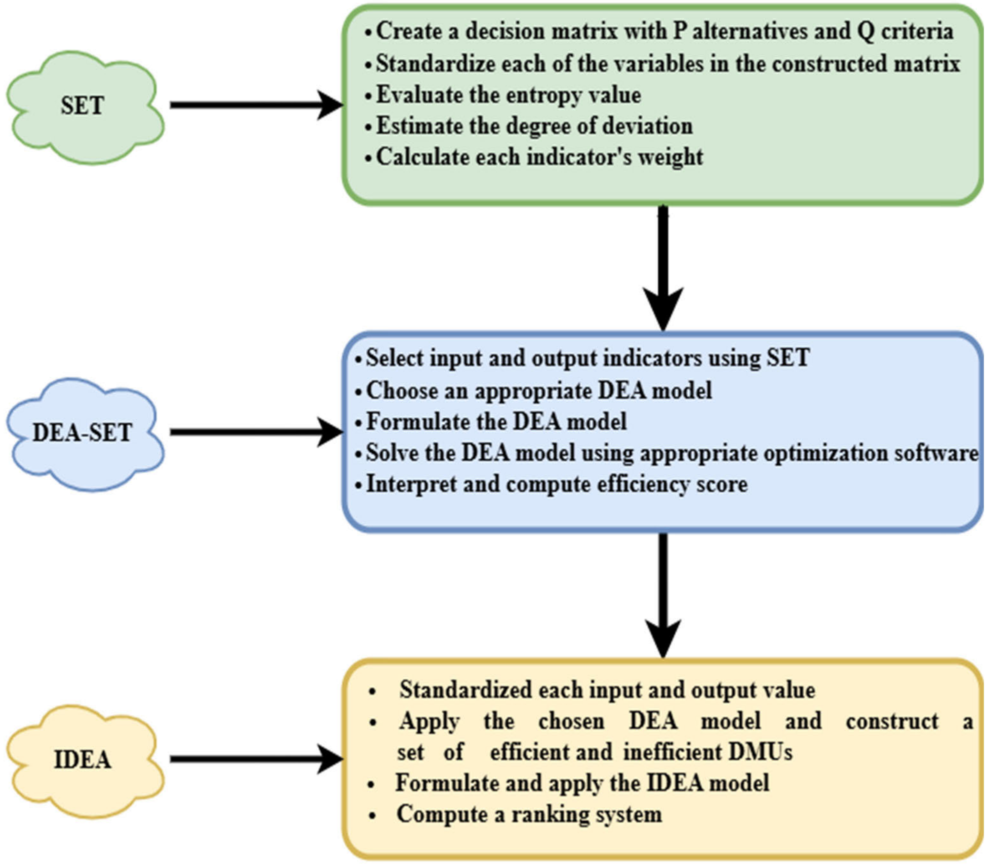


**FIGURE 1.** Summary of steps and methods.

through RT ratio, which measures the efficiency of a company in collecting its accounts receivable. Leverage is analyzed using SOL II, which provides insight into the proportion of total liability and equity financing employed by a company. Profitability is evaluated through the EPS metric, which indicates the amount of earnings generated per outstanding share of common stock. Lastly, the valuation metric known as PSR is employed to assess the market value of a company relative to its sales revenue. Table 3 depicts the final financial ratios chosen for each DMU (stock) using SET.

Liquidity, as measured by QR: The stocks demonstrate a diverse range of QR values, whereas DMU 4 (STOCK_ID 2706) stands out with an extraordinarily high QR of 1835.75 This observation indicates a robust short-term liquidity position. On the other hand, DMU 13 (STOCK_ID 3252) exhibits the lowest QR of 51.51, suggesting possible difficulties in fulfilling immediate financial obligations. Asset utilization, specifically RT, is a metric used to assess the efficiency with which a company manages its accounts receivable. The DMU 3 (STOCK_ID 2701) exhibits a notable RT of 13329.78, indicating proficient handling of receivables. Conversely, DMU 9 (STOCK_ID 2732) has a minimum value of 8.56 for the variable RT. The concept of Leverage, specifically SOL II, is a significant metric in financial analysis. DMU 11, identified explicitly by its STOCK_ID 2754, exhibits the highest SOL II of 215.04, indicating substantial financial Leverage. In contrast, DMU 3 (STOCK_ID 2701) and DMU 4 (STOCK_ID 2706) exhibit significantly low SOL II values of 16.25 and 16.20, respectively, suggesting a diminished dependence on external financing.

Profitability, measured explicitly by EPS, is a key metric to assess a company's financial performance. The company with the STOCK_ID 2707, known as DMU 5, demonstrates a notable level of Profitability, as seen by its EPS of 17.09. On the other hand, DMU 6 (STOCK_ID 2722) and DMU 4 (STOCK_ID 2706) exhibit the lowest EPS values, precisely 0.18 and 0.16, respectively. The valuation metric is represented as PSR. DMU 4, identified by its STOCK_ID 2706, exhibits the most significant PSR of 28.47, indicating a comparatively elevated valuation or market anticipation. The DMU 1 (STOCK_ID 1259) exhibits a PSR value of 0.44, which suggests a comparatively lower valuation in relation to its sales.

The variables chosen for analysis were picked based on their relevance as defined by SET. This selection process ensures that the variables chosen provide a concise

**TABLE 3. Final datasets based on SET.**

| DMU | ID | QR | RT | SOL II | EPS | PSR |
|---|---|---|---|---|---|---|
| 1 | 1259 | 116.24 | 49.66 | 152.79 | 3.07 | 0.44 |
| 2 | 1268 | 111.71 | 18.53 | 133.53 | 2.01 | 1.63 |
| 3 | 2701 | 1131.22 | 13329.78 | 16.25 | 0.19 | 22.88 |
| 4 | 2706 | 1835.75 | 319.90 | 16.20 | 0.16 | 28.47 |
| 5 | 2707 | 161.22 | 25.99 | 113.31 | 17.09 | 3.90 |
| 6 | 2722 | 117.91 | 43.61 | 33.84 | 0.18 | 6.07 |
| 7 | 2723 | 115.46 | 60.14 | 90.61 | 6.07 | 1.02 |
| 8 | 2729 | 83.51 | 14.81 | 167.85 | 7.04 | 1.21 |
| 9 | 2732 | 103.96 | 8.56 | 99.44 | 3.08 | 1.01 |
| 10 | 2752 | 210.90 | 10.37 | 83.04 | 6.68 | 1.95 |
| 11 | 2754 | 68.79 | 27.64 | 215.04 | 0.49 | 1.37 |
| 12 | 2755 | 129.98 | 53.57 | 110.58 | 3.65 | 0.70 |
| 13 | 3252 | 51.51 | 12.32 | 102.98 | 0.71 | 1.89 |
| 14 | 5704 | 186.36 | 32.23 | 30.29 | 1.51 | 3.22 |
| 15 | 5706 | 169.87 | 11.28 | 86.20 | 1.17 | 19.11 |
| 16 | 9943 | 145.82 | 70.60 | 52.88 | 0.43 | 5.29 |

**TABLE 4. Statistical representation of datasets.**

| Index | QR | RT | SOL II | EPS | PSR |
|---|---|---|---|---|---|
| count | 16.000 | 16.000 | 16.000 | 16.000 | 16.000 |
| mean | 296.263 | 880.562 | 94.052 | 3.346 | 6.260 |
| std | 482.762 | 3320.627 | 56.297 | 4.359 | 8.865 |
| min | 51.510 | 8.560 | 16.200 | 0.160 | 0.440 |
| 25% | 109.773 | 14.188 | 48.120 | 0.475 | 1.163 |
| 50% | 123.945 | 29.935 | 95.025 | 1.760 | 1.920 |
| 75% | 173.993 | 55.213 | 118.365 | 4.255 | 5.485 |
| max | 1835.75 | 13329.78 | 215.04 | 17.09 | 28.47 |
| variance | 233059.583 | 11026570.00 | 3169.384 | 18.997 | 78.583 |

yet complete depiction of each stock's performance based on financial perspective classification. Table 4 provides the statistical description of the final datasets selected for subsequent analysis.

### *B. SET-DEA*

By using the package deaR in R software, the CRS-DEA efficiency score of each DMU is evaluated. Individual DMU efficiency score (ES) is shown using Table 5. The DMUs with the highest level of efficiency, namely DMUs 3 (STOCK_ID 2701), 4 (STOCK_ID 2706), 5 (STOCK_ID 2707), 10 (STOCK_ID 2752), and 15 (STOCK_ID 5706), all exhibit ES of 1. This observation suggests that the equities above are positioned on the efficiency frontier, signifying their superior efficiency compared to other stocks in the sample.

**TABLE 5. Base model efficiency evaluation.**

| DMU | STOCK_ID | Stock Name | ES |
|---|---|---|---|
| 1 | 1259 | An-Shin | 0.24915 |
| 2 | 1268 | Hi-Lai Foods | 0.25812 |
| 3 | 2701 | Wan Hwa | 1.00000 |
| 4 | 2706 | First Hotel | 1.00000 |
| 5 | 2707 | Formosa Intl Hotels | 1.00000 |
| 6 | 2722 | Chateau | 0.73862 |
| 7 | 2723 | Gourmet | 0.49595 |
| 8 | 2729 | TTFB | 0.79526 |
| 9 | 2732 | La Kaffa | 0.56521 |
| 10 | 2752 | TOFU | 1.00000 |
| 11 | 2754 | Kura Sushi Asia | 0.22137 |
| 12 | 2755 | YoungQin | 0.26491 |
| 13 | 3252 | Haiwan | 0.41280 |
| 14 | 5704 | Chihpen Royal | 0.57776 |
| 15 | 5706 | PHX Tour | 1.00000 |
| 16 | 9943 | Holiday | 0.44165 |

These stocks function as reference points for the remaining equities within the dataset. The DMUs with moderate efficiency ratings include DMU 6 (STOCK_ID 2722), DMU 7 (STOCK_ID 2723), DMU 8 (STOCK_ID 2729), DMU 9 (STOCK_ID 2732), DMU 13 (STOCK_ID 3252), DMU 14 (STOCK_ID 5704), and DMU 16 (STOCK_ID 9943). These DMUs have efficiency values that fall between the range of 0.4 to 0.8. The efficiency of these stocks can be characterized as modest, with identifiable opportunities for enhancement to attain the efficiency frontier. The DMUs with the lowest efficiency ratings, specifically DMU 1 (STOCK_ID 1259), DMU 2 (STOCK_ID 1268), DMU 11 (STOCK_ID 2754), and DMU 12 (STOCK_ID 2755), exhibit efficiency scores below 0.3. The stocks in the sample exhibit a lower level of efficiency and possess considerable potential for enhancing their operational efficiency.

Table 5 presents a comprehensive overview of the comparative efficiency of the selected tourism stocks within TWSE during the financial year 2021. The efficiency scores obtained through the DEA analysis provide crucial insights into the operational performance of each stock compared to its counterparts. Stocks that possess an efficiency score of 1 are operating at their maximum potential, taking into account the inputs and outputs involved. These equities have the potential to function as benchmarks for other firms within the same sector, offering valuable insights into optimal strategies and streamlined operations. Conversely, equities exhibiting efficiency scores below 1 possess potential opportunities for enhancement. Through the examination of the disparities between these companies and the benchmark stocks, stakeholders can discern potential opportunities for operational

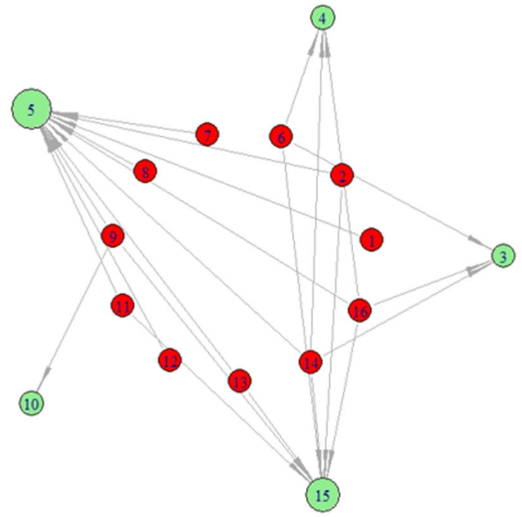


**FIGURE 2.** Network graph of DMUs.

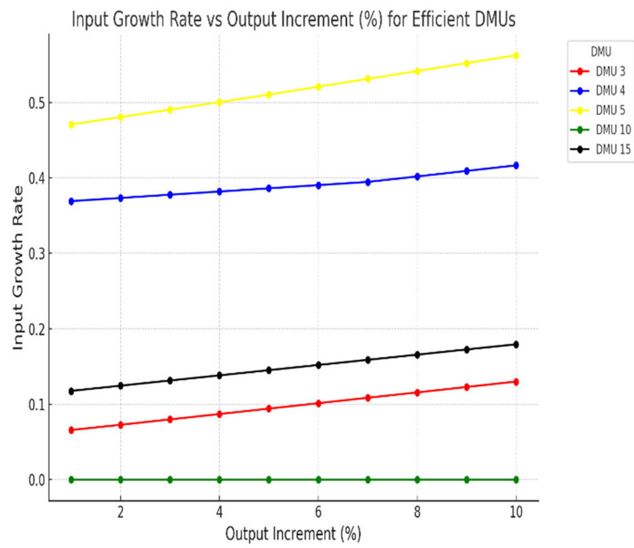


**FIGURE 3.** Input vs. Output growth curve.

improvements and strategic modifications. The efficiency scores serve as a basis for conducting additional analysis, such as IDEA, which allows for ranking efficient DMUs and provides more detailed insights into their performance. Fig. 2 displays the graphical results of DMUs efficiency analysis using the deaR package of R software. Fig. 2 depicts an efficiency graph and a network graph of efficiency evaluation. The green circles symbolize the efficient DMUs, while the red circles represent the inefficient ones. The graph illustrates the relationship between inefficient DMUs and efficient DMUs in generating an efficient frontier.

### C. IDEA

Table 6 and Fig. 3 display the findings of IDEA, where the outputs of efficient DMUs were increased by varied percentages (c = 1% to 10%), and the associated input growth rates were estimated.

#### 1) CONSISTENT RANKING

The rankings of the DMUs stay consistent throughout all percentages of output increment. DMU 5, identified by STOCK_ID 2707, routinely attains the top position in rankings, signifying the highest rate of input growth. This observation implies that when the level of outputs is augmented, DMU 5 exhibits the highest degree of input augmentation necessary to uphold its efficiency score of 1. In contrast, DMU 10 (STOCK_ID 2752) continuously occupies the lowest position in the rankings, suggesting the lowest rate of input increase. The order of ranking from highest to lowest is seen as DMU 5 > DMU 4 > DMU15 > DMU 3 > DMU 10

#### 2) GROWTH PATTERN

A positive correlation is observed between the percentage rise in output and the corresponding growth rate in input for all DMUs. This phenomenon is anticipated, as a larger increase in output typically necessitates a proportionately greater augmentation in inputs in order to sustain the same level of efficiency.

#### 3) VARIABILITY IN INPUT GROWTH

The analysis of DMU 10 (STOCK_ID 2752) reveals a lack of input growth, as seen by the negligible or non-existent increase in output for increments of up to 5%. This implies that DMU 10 has the capacity to accommodate higher levels of production without necessitating extra resources, up to a specific threshold. Nevertheless, it is essential to acknowledge that even when the output increments are increased to 6%, 7%, 8%, 9%, and 10%, the input growth for DMU 10 continues to exhibit little change.

Table 6 and Fig. 3 provide significant information on the robustness and adaptation of the effective DMUs. The IDEA analysis is a method that estimates the necessary output growth to achieve a specific rise in input growth. This approach provides valuable insights into how each DMU might react to output variations. DMU 5, identified by STOCK_ID 2707, exhibits a consistent pattern of leading input growth. The need for a proportional increase in outputs to achieve an increase in inputs renders it less flexible to changes than other DMUs. In contrast, DMU 10 (STOCK_ID 2752) exhibits notable resilience. The capacity to manage higher outputs without substantial increases in inputs implies the presence of untapped potential or resources, hence enhancing its adaptability to changes. The robustness of the IDEA method in assessing the adaptation and resilience of the DMUs is highlighted by the constant rankings seen across different output increments. In summary, it can be shown that although all DMUs listed in Table 6 exhibit an initial efficiency score of 1, their capacity to respond to increased output capacity differs. IDEA analysis uncovers the adaptability of the system, which offers supplementary insights

**TABLE 6.** Ranking of stocks using SET-DEA-DEA.

| Output increment (c) | DMU 3 | DMU 4 | DMU 5 | DMU 10 | DMU 15 | Ranking (DMU 3) | Ranking (DMU 4) | Ranking (DMU 5) | Ranking (DMU 10) | Ranking (DMU 15) |
|---|---|---|---|---|---|---|---|---|---|---|
| 1% | 0.0656 | 0.3693 | 0.4710 | 0.0000 | 0.1175 | 4 | 2 | 1 | 5 | 3 |
| 2% | 0.0725 | 0.3735 | 0.4808 | 0.0000 | 0.1244 | 4 | 2 | 1 | 5 | 3 |
| 3% | 0.0797 | 0.3778 | 0.4907 | 0.0000 | 0.1313 | 4 | 2 | 1 | 5 | 3 |
| 4% | 0.0868 | 0.3820 | 0.5006 | 0.0000 | 0.1381 | 4 | 2 | 1 | 5 | 3 |
| 5% | 0.0940 | 0.3863 | 0.5107 | 0.0000 | 0.1450 | 4 | 2 | 1 | 5 | 3 |
| 6% | 0.1012 | 0.3905 | 0.5211 | 0.0000 | 0.1519 | 4 | 2 | 1 | 5 | 3 |
| 7% | 0.1084 | 0.3948 | 0.5315 | 0.0000 | 0.1587 | 4 | 2 | 1 | 5 | 3 |
| 8% | 0.1155 | 0.4020 | 0.5419 | 0.0000 | 0.1656 | 4 | 2 | 1 | 5 | 3 |
| 9% | 0.1227 | 0.4094 | 0.5524 | 0.0000 | 0.1725 | 4 | 2 | 1 | 5 | 3 |
| 10% | 0.1299 | 0.4167 | 0.5628 | 0.0000 | 0.1793 | 4 | 2 | 1 | 5 | 3 |

**TABLE 7.** Dataset for sensitivity analysis.

| DMU | CAR | CR | QR | SOL I | SOL II | AT | RT | EPS | PSR |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.771 | 146.124 | 139.488 | 72.528 | 183.348 | 1.212 | 59.592 | 2.456 | 0.352 |
| 2 | 0.964 | 186.372 | 134.052 | 68.616 | 160.236 | 0.768 | 22.236 | 1.608 | 1.304 |
| 3 | 1.396 | 1358.904 | 1357.464 | 16.776 | 19.500 | 0.036 | 15995.74 | 0.152 | 18.304 |
| 4 | 2.584 | 2209.584 | 2202.900 | 16.728 | 19.440 | 0.024 | 383.880 | 0.128 | 22.776 |
| 5 | 0.190 | 197.052 | 193.464 | 63.744 | 135.972 | 0.540 | 31.188 | 13.672 | 3.120 |
| 6 | 0.336 | 148.404 | 141.492 | 30.348 | 40.608 | 0.264 | 52.332 | 0.144 | 4.856 |
| 7 | 0.974 | 161.028 | 138.552 | 57.048 | 108.732 | 1.104 | 72.168 | 4.856 | 0.816 |
| 8 | 0.698 | 115.596 | 100.212 | 75.204 | 201.420 | 0.924 | 17.772 | 5.632 | 0.968 |
| 9 | 0.715 | 154.644 | 124.752 | 59.832 | 119.328 | 1.152 | 10.272 | 2.464 | 0.808 |
| 10 | 1.940 | 263.688 | 253.080 | 54.444 | 99.648 | 1.404 | 12.444 | 5.344 | 1.560 |
| 11 | 0.641 | 90.000 | 82.548 | 81.912 | 258.048 | 0.852 | 33.168 | 0.392 | 1.096 |
| 12 | 1.449 | 172.212 | 155.976 | 63.012 | 132.696 | 1.572 | 64.284 | 2.920 | 0.560 |
| 13 | 0.358 | 176.940 | 61.812 | 60.876 | 123.576 | 0.132 | 14.784 | 0.568 | 1.512 |
| 14 | 1.269 | 238.944 | 223.632 | 27.900 | 36.348 | 0.636 | 38.676 | 1.208 | 2.576 |
| 15 | 0.291 | 209.520 | 203.844 | 55.560 | 103.440 | 0.072 | 13.536 | 0.936 | 15.288 |
| 16 | 0.576 | 183.660 | 174.984 | 41.508 | 63.456 | 0.348 | 84.720 | 0.344 | 4.232 |

to aid decision-makers in strategic planning and resource allocation.

## V. SENSITIVITY ANALYSIS AND MODEL COMPARISON

Sensitivity analysis is a reliable method for evaluating the robustness and flexibility of a model [52]. The introduction of additional input indicators from 3 to 7 increases complexity and possibly redundancy, potentially affecting the efficiency scores of the DMUs. This methodology will facilitate comprehension of the extent to which variations influence the efficiency scores and rankings in the inputs of the model. In this connection, we also augment the input values by 20% while reducing the output values by 20%. The augmentation of input variables results in heightened intricacy by subjecting our model to unfavourable conditions. This experiment is subjected to a sensitivity test to determine its impact on efficiency scores and rankings. It assesses the model's ability to rank and evaluate DMUs rigorously. Table 7 gives the new dataset based on the above conditions, while Table 8 details the efficiency scores of individual DMUs using the new dataset.

The findings presented in Table 8 offer strong evidence in favour of the feature reduction methodology utilized in this investigation. The persistent retention of efficiency scores, even when faced with more unfavourable conditions, serves as a strong testament to the resilience of our SET-DEA-IDEA

**TABLE 8.** Efficiency evaluation using a new dataset (Sensitivity data).

| DMU | STOCK_ID | Stock Name | ES |
|---|---|---|---|
| 1 | 1259 | An-Shin | 0.24915 |
| 2 | 1268 | Hi-Lai Foods | 0.25812 |
| 3 | 2701 | Wan Hwa | 1.00000 |
| 4 | 2706 | First Hotel | 1.00000 |
| 5 | 2707 | Formosa Intl Hotels | 1.00000 |
| 6 | 2722 | Chateau | 0.73862 |
| 7 | 2723 | Gourmet | 0.49595 |
| 8 | 2729 | TTFB | 0.79526 |
| 9 | 2732 | La Kaffa | 0.56521 |
| 10 | 2752 | TOFU | 1.00000 |
| 11 | 2754 | Kura Sushi Asia | 0.22137 |
| 12 | 2755 | YoungQin | 0.26491 |
| 13 | 3252 | Haiwan | 0.41280 |
| 14 | 5704 | Chihpen Royal | 0.57776 |
| 15 | 5706 | PHX Tour | 1.00000 |
| 16 | 9943 | Holiday | 0.44165 |

**TABLE 9.** Ranking of stocks using SET-DEA-IDEA (Sensitivity data).

| Output increment (c) | DMU 3 | DMU 4 | DMU 5 | DMU 10 | DMU 15 | Ranking (DMU 3) | Ranking (DMU 4) | Ranking (DMU 5) | Ranking (DMU 10) | Ranking (DMU 15) |
|---|---|---|---|---|---|---|---|---|---|---|
| 1% | 0.1150 | 0.4991 | 1.3326 | 0.0000 | 0.3175 | 4 | 2 | 1 | 5 | 3 |
| 2% | 0.1230 | 0.5054 | 1.3528 | 0.0000 | 0.3238 | 4 | 2 | 1 | 5 | 3 |
| 3% | 0.1324 | 0.5117 | 1.3730 | 0.0000 | 0.3301 | 4 | 2 | 1 | 5 | 3 |
| 4% | 0.1418 | 0.5180 | 1.3932 | 0.0000 | 0.3364 | 4 | 2 | 1 | 5 | 3 |
| 5% | 0.1512 | 0.5243 | 1.4134 | 0.0000 | 0.3428 | 4 | 2 | 1 | 5 | 3 |
| 6% | 0.1607 | 0.5308 | 1.4336 | 0.0001 | 0.3491 | 4 | 2 | 1 | 5 | 3 |
| 7% | 0.1701 | 0.5410 | 1.4538 | 0.0002 | 0.3554 | 4 | 2 | 1 | 5 | 3 |
| 8% | 0.1795 | 0.5512 | 1.4740 | 0.0002 | 0.3617 | 4 | 2 | 1 | 5 | 3 |
| 9% | 0.1889 | 0.5614 | 1.4942 | 0.0002 | 0.3680 | 4 | 2 | 1 | 5 | 3 |
| 10% | 0.1984 | 0.5716 | 1.5144 | 0.0002 | 0.3744 | 4 | 2 | 1 | 5 | 3 |

model and the appropriateness of employing SET for dimensionality reduction. The findings indicate that the initial selection effectively captured the essential elements of the DMUs' performance; meanwhile, the new variables or value revisions did not substantially impact the efficiency scores. The consistency seen in this study enhances the credibility of the research findings and underscores the reliability of the utilized SET-DEA model. Table 9 displays the ranking analysis of efficient stocks using SET-DEA-IDEA model, where the outputs of efficient DMUs were increased by varied percentages (c =1% to 10%), and the associated input growth rates were estimated. Table 9 and Fig. 4 provide significant insights into the resilience and adaptation of the efficient DMUs in light of the revised conditions, where consistent rankings were maintained as with the original dataset and conditions. The observed rankings consistently hold over various increments in output, indicating that the relative performance of these DMUs stays constant, even when exposed to multiple unfavourable conditions. In summary, the findings demonstrate robustness in ranking efficient DMUs across different scenarios, reinforcing the reliability of the proposed technique

Furthermore, a comparison test of the proposed SET-DEA-IDEA technique is conducted against classical ranking methods such as cross-efficiency and super-efficiency. The results of our model comparison are shown in Table 10. While all three models consistently identify DMUs 3, 4, 5, 10, and 15 as efficient, their relative rankings differ. For example, DMU

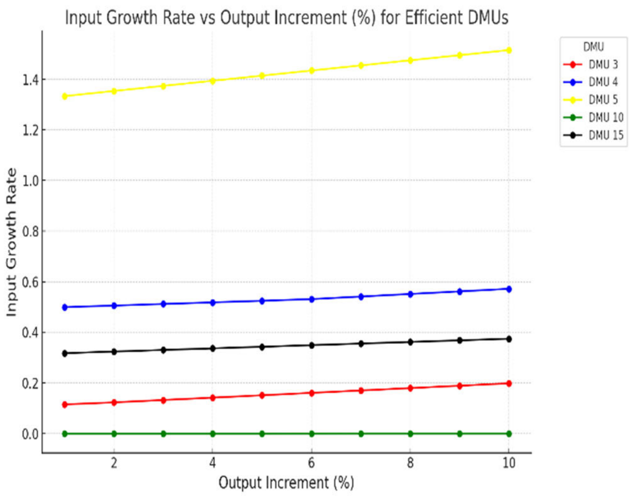


**FIGURE 4.** Input vs. Output growth curve (Sensitivity data).

**TABLE 10.** Comparison of SET-DEA-IDEA model with other methods.

| DMU | 3 | 4 | 5 | 10 | 15 |
|---|---|---|---|---|---|
| Cross efficiency rank | 3 | 4 | 1 | 5 | 2 |
| Super efficiency rank | 4 | 2 | 3 | 5 | 1 |
| SET-DEA-IDEA | 4 | 2 | 1 | 5 | 3 |

5 ranks first under both the cross-efficiency and proposed methods but only third under super-efficiency, suggesting the proposed method better captures its adaptability. DMU 15, conversely, holds the top position in the super-efficiency model yet drops to second and third in the cross-efficiency and proposed methods, respectively, implying that while it performs well under static assumptions, its flexibility under output variations may be more limited. Similarly, DMU 4 maintains a strong position (2nd) in the super-efficiency and proposed methods but drops in rank under the peer-sensitive cross-efficiency approach. This highlights potential bias introduced by evaluator dependencies in cross-efficiency models. The proposed SET–DEA–IDEA framework offers distinct methodological advantages. Unlike super-efficiency DEA, it avoids infeasibility issues, especially in small sample environments. Compared to cross-efficiency models, it eliminates peer-based scoring bias and provides a sensitivity-oriented ranking mechanism that evaluates how efficiently DMUs can adapt to output changes. This perspective is particularly valuable in dynamic or crisis-prone sectors such as tourism. Overall, the proposed model delivers more stable, interpretable, and resilience-aware rankings, demonstrating its superiority as a decision-support tool for robust stock selection.

## VI. CONCLUSION AND FUTURE RESEARCH

This study presents a novel, integrated SET-DEA-IDEA framework that combines SET, DEA, and IDEA to evaluate and rank equities within the Taiwan Stock Exchange (TWSE) tourism sector. Unlike traditional methods that often rely on subjective assessments or are vulnerable to infeasibility and inconsistency under volatile conditions, our approach offers a robust, objective, and reproducible model that significantly enhances stock evaluation processes, particularly under market disruption scenarios such as the COVID-19 pandemic. The novelty of this research lies in its first-time integration of SET, DEA, and IDEA into a unified model for stock analysis. SET is employed to address the curse of dimensionality by objectively selecting the most informative financial indicators across five key perspectives: Liquidity, Asset usage, Leverage, Profitability, and Valuation. DEA then computes efficiency scores to distinguish efficient from inefficient stocks, while IDEA provides a sensitivity-based ranking mechanism that reveals how well efficient stocks can adapt to incremental output changes without compromising performance. This dynamic assessment provides richer insights than static efficiency evaluations.

Empirical results demonstrate that only five stocks out of sixteen achieved an efficiency score of 1. These efficient stocks were further analyzed using IDEA across ten output increment scenarios, revealing consistent ranking behavior and adaptability, underscoring the stability and strategic value of the proposed model. Furthermore, sensitivity analyses and comparative evaluations with super-efficiency and cross-efficiency models confirmed the model's resilience and discriminatory strength, avoiding common pitfalls like infeasibility and peer bias. From a practical perspective, this framework offers reliable decision support for investors, policymakers, and portfolio managers, especially in crisis-prone or high-volatility sectors. It provides actionable insights on which stocks are efficient and which ones are flexible and robust under shifting market demands, an invaluable advantage in today's uncertain investment climate. Ultimately, this study establishes a scalable, data-driven foundation for transparent, defensible, and high-precision equity evaluation and ranking.

While this study contributes a novel and practical framework for stock evaluation and ranking, several limitations warrant consideration. First, the analysis is restricted to a single sector (tourism) within TWSE during a specific time period (2021). Although this sector was chosen due to its heightened exposure to external shocks, the findings may not be directly generalizable to other industries or broader markets without further validation. Second, the use of annual financial data limits the model's responsiveness to short-term fluctuations. Incorporating higher-frequency data (e.g., quarterly or monthly) could improve the model's sensitivity to real-time changes in market conditions. Third, the Inverse DEA model, though powerful in ranking efficient units, assumes proportional changes in input/output behavior. Future studies might explore non-radial or dynamic DEA models to capture more complex production structures and time-evolving efficiencies.

Future studies could apply the proposed SET–DEA–IDEA framework to cross-sectoral datasets, enabling broader benchmarking and comparison. Additionally, integrating machine learning and deep learning techniques such as ANN, LSTM, Helformer, and TabNet [53], [54], [55], [56] could enhance the framework's predictive capability, allowing for more proactive investment strategies. Finally, exploring the utility of this model in portfolio optimization, ESG (environmental, social, governance) investment screening, or in stress testing financial systems under hypothetical crises would significantly expand its practical relevance.

## REFERENCES


[1] D. O. Oyewola, T. O. Kehinde, S. A. Akinwunmi, and A.-M. Abdulrahim, "Stock market prediction with optimized PLSTM-AL in smart urban cities," *Finance Res. Open*, vol. 1, no. 3, Sep. 2025, Art. no. 100019.

[2] T. O. Kehinde, W. A. Khan, and S.-H. Chung, "Financial market forecasting using RNN, LSTM, BiLSTM, GRU and transformer-based deep learning algorithms," in *Proc. Int. Conf. Ind. Eng. Oper. Manage.*, Detroit, MI, USA, Oct. 2023, pp. 10–12.

[3] O. Soliku, B. Kyiire, A. Mahama, and C. Kubio, "Tourism amid COVID-19 pandemic: Impacts and implications for building resilience in the eco-tourism sector in Ghana's Savannah region," *Heliyon*, vol. 7, no. 9, Sep. 2021, Art. no. e07892.

[4] R. Verma, "Comovement of stock markets pre- and post-COVID-19 pandemic: A study of Asian markets," *IIM Ranchi J. Manage. Stud.*, vol. 3, no. 1, pp. 25–38, Mar. 2024.

[5] K.-J. Lee and S.-L. Lu, "The impact of COVID-19 on the stock price of socially responsible enterprises: An empirical study in Taiwan stock market," *Int. J. Environ. Res. Public Health*, vol. 18, no. 4, p. 1398, Feb. 2021.

[6] F. J. Sánchez-Sánchez and A. M. Sánchez-Sánchez, "Ecotourism and COVID-19: Impact on the efficiency of the Spanish hospitality industry," *J. Outdoor Recreation Tourism*, vol. 43, Sep. 2023, Art. no. 100680.

[7] R. Nurmatov, X. L. F. Lopez, and P. P. Coto Millan, "Tourism, hospitality, and DEA: Where do we come from and where do we go?" *Int. J. Hospitality Manage.*, vol. 95, May 2021, Art. no. 102883.

[8] S. Tewari and A. Arya, "Analyzing the efficiency of the Indian hotel industry using the Malmquist DEA approach," *Benchmarking, Int. J.*, vol. 31, no. 9, pp. 2839–2870, Nov. 2024.

[9] UNWTO. (Oct. 21, 2023). *Worst Year in Tourism History With 1 Billion Fewer International Arrivals*. [Online]. Available: https://www.unwto.org/news/2020-worst-year-in-tourism-history-with-1-billion-fewer-international-arrivals

[10] Yahoo_Finance. (Oct. 2023). *20 Most Visited Countries in Asia*. [Online]. Available: https://finance.yahoo.com/news/20-most-visited-countries-asia-192155445.html

[11] V. Pimentel and C. A. Mora-Monge, "Benchmarking the operational efficiency of Mexican hospitals—A longitudinal study," *Benchmarking, Int. J.*, vol. 31, no. 2, pp. 309–329, Feb. 2024.

[12] V. Charles, J. Aparicio, and J. Zhu, "The curse of dimensionality of decision-making units: A simple approach to increase the discriminatory power of data envelopment analysis," *Eur. J. Oper. Res.*, vol. 279, no. 3, pp. 929–940, Dec. 2019.

[13] M. G. Ünsal, D. Friesner, and R. Rosenman, "The curse of dimensionality (COD), misclassified DMUs, and Bayesian DEA," *Commun. Statist.-Simul. Comput.*, vol. 51, no. 8, pp. 4186–4203, Aug. 2022.

[14] A. Feutrill and M. Roughan, "A review of Shannon and differential entropy rate estimation," *Entropy*, vol. 23, no. 8, p. 1046, 2021.

[15] P. Peykani, F. S. Seyed Esmaeili, M. Mirmozaffari, A. Jabbarzadeh, and M. Khamechian, "Input/output variables selection in data envelopment analysis: A Shannon entropy approach," *Mach. Learn. Knowl. Extraction*, vol. 4, no. 3, pp. 688–699, Jul. 2022.

[16] T. O. Kehinde, F. T. S. Chan, and S. H. Chung, "Scientometric review and analysis of recent approaches to stock market forecasting: Two decades survey," *Expert Syst. Appl.*, vol. 213, Mar. 2023, Art. no. 119299.

[17] E. Aghakarimi, H. Karimi, A. Aghsami, and F. Jolai, "Evaluating and improving the performance of retailers' branches by considering resilience, sustainability and sales-marketing," *Int. J. Productiv. Perform. Manage.*, vol. 73, no. 5, pp. 1357–1386, May 2024.

[18] H. Tao, K. Shu, and C. Lv, "Eco-econo-efficiency based quota allocation towards coal de-capacity reform implementation: Case study from China," in *Proc. E3S Web Conf.*, Aug. 2023, p. 3011.

[19] Statista. (Sep. 25, 2023). *Largest Stock Exchange Operators Worldwide 2023, by Market Cap of Listed Companies*. [Online]. Available: https://www.statista.com/statistics/270126/largest-stock-exchange-operators-by-market-capitalization-of-listed-companies/

[20] R. Teixeira, J. J. M. Antunes, P. Wanke, H. L. Correa, and Y. Tan, "Customer satisfaction and airport efficiency in Brazil: A hybrid NDEA-AHP approach," *Benchmarking, Int. J.*, vol. 31, no. 7, pp. 2239–2266, Jul. 2024.

[21] Y. Hong and S. Qu, "Beyond boundaries: The AHP-DEA model for holistic cross-banking operational risk assessment," *Mathematics*, vol. 12, no. 7, p. 968, Mar. 2024.

[22] H. K. Chan, X. Sun, and S.-H. Chung, "When should fuzzy analytic hierarchy process be used instead of analytic hierarchy process?" *Decis. Support Syst.*, vol. 125, Oct. 2019, Art. no. 113114.

[23] S. Perçin, "Using the ANP approach in selecting and benchmarking ERP systems," *Benchmarking, Int. J.*, vol. 15, no. 5, pp. 630–649, Aug. 2008.

[24] N. Agrawal, "Multi-criteria decision-making toward supplier selection: Exploration of PROMETHEE II method," *Benchmarking, Int. J.*, vol. 29, no. 7, pp. 2122–2146, Aug. 2022.

[25] A. K. Sahu and R. D. Raut, "Benchmarking quality characteristics for road-mapping sustainability of higher educational institutes and capping Indian portfolio," *Benchmarking, Int. J.*, vol. 31, no. 9, pp. 3154–3189, Nov. 2024.

[26] D. Jing, M. Imeni, S. A. Edalatpanah, A. Alburaikan, and H. A. E.-W. Khalifa, "Optimal selection of stock portfolios using multi-criteria decision-making methods," *Mathematics*, vol. 11, no. 2, p. 415, Jan. 2023.

[27] S. Sarkar, "Application of PCA and DEA to recognize the true expertise of a firm: A case with primary schools," *Benchmarking: Int. J.*, vol. 23, no. 3, pp. 740–751, Apr. 2016.

[28] C. E. Shannon, "A mathematical theory of communication," *Bell Syst. Tech. J.*, vol. 27, no. 3, pp. 379–423, Jul. 1948.

[29] Q. Xie, Q. Dai, Y. Li, and A. Jiang, "Increasing the discriminatory power of DEA using Shannon's entropy," *Entropy*, vol. 16, no. 3, pp. 1571–1585, Mar. 2014.

[30] S. Gupta, T. Tanushree, and A. Rai, "Combined Shannon's entropy and data envelopment analysis model: Methods and applications," in *Proc. Int. Conf. Contemp. Comput. Appl. (IC3A)*, Feb. 2020, pp. 260–264.

[31] R. Karagiannis and G. Karagiannis, "Nonparametric estimates of price efficiency for the Greek infant milk market: Curing the curse of dimensionality with Shannon entropy," *Econ. Model.*, vol. 121, Apr. 2023, Art. no. 106202.

[32] A. Panwar, M. Olfati, M. Pant, and V. Snasel, "A review on the 40 years of existence of data envelopment analysis models: Historic development and current trends," *Arch. Comput. Methods Eng.*, vol. 29, no. 7, pp. 5397–5426, Nov. 2022.

[33] S. Jomthanachai, W.-P. Wong, and C.-P. Lim, "An application of data envelopment analysis and machine learning approach to risk management," *IEEE Access*, vol. 9, pp. 85978–85994, 2021.

[34] C.-N. Wang, T.-T. Dang, and N.-A.-T. Nguyen, "Location optimization of wind plants using DEA and fuzzy multi-criteria decision making: A case study in Vietnam," *IEEE Access*, vol. 9, pp. 116265–116285, 2021.

[35] B. A. H. Murshed, J. Abawajy, S. Mallappa, M. A. N. Saif, and H. D. E. Al-Ariki, "DEA-RNN: A hybrid deep learning approach for cyberbullying detection in Twitter social media platform," *IEEE Access*, vol. 10, pp. 25857–25871, 2022.

[36] Y.-T. Chen, T.-H. Dao, and N.-L. Nhieu, "Decoding efficiency in construction: A behavioral DEA approach to BRICS economies," *IEEE Access*, vol. 12, pp. 113165–113177, 2024.

[37] C. Wang, F. Yang, N. T. M. Vo, C. Duong, and V. T. T. Nguyen, "Optimizing efficiency in BaaS marketplaces: A DEA-Grey integration approach," *IEEE Access*, vol. 12, pp. 58532–58550, 2024.

[38] A. Mergoni, A. Emrouznejad, and K. De Witte, "Fifty years of data envelopment analysis," *Eur. J. Oper. Res.*, vol. 326, no. 3, pp. 389–412, Nov. 2025.

[39] A. Charnes, W. W. Cooper, and E. Rhodes, "Measuring the efficiency of decision making units," *Eur. J. Oper. Res.*, vol. 2, no. 6, pp. 429–444, Nov. 1978.
[40] ÿA. F. da Silva, R. D. C. Miranda, F. A. S. Marins, and E. X. Dias, "A new multiple criteria data envelopment analysis with variable return to scale: Applying bi-dimensional representation and super-efficiency analysis," *Eur. J. Oper. Res.*, vol. 314, no. 1, pp. 308–322, Apr. 2024.
[41] H.-H. Chen, "Stock selection using data envelopment analysis," *Ind. Manage. Data Syst.*, vol. 108, no. 9, pp. 1255–1268, Oct. 2008.
[42] C.-M. Hsu, "An integrated portfolio optimisation procedure based on data envelopment analysis, artificial bee colony algorithm and genetic programming," *Int. J. Syst. Sci.*, vol. 45, no. 12, pp. 2645–2664, Dec. 2014.
[43] C.-Y. Huang, C.-C. Chiou, T.-H. Wu, and S.-C. Yang, "An integrated DEA-MODM methodology for portfolio optimization," *Oper. Res.*, vol. 15, no. 1, pp. 115–136, Apr. 2015.
[44] Q. Wei, J. Zhang, and X. Zhang, "An inverse DEA model for inputs/outputs estimate," *Eur. J. Oper. Res.*, vol. 121, no. 1, pp. 151–163, Feb. 2000.
[45] A. Emrouznejad and G. R. Amin, "Advances in inverse data envelopment analysis: Empowering performance assessment," *IMA J. Manage. Math.*, vol. 34, no. 3, pp. 415–419, Jun. 2023.
[46] K. K. Orisaremi, F. T. S. Chan, and X. Fu, "An improved inverse DEA for assessing economic growth and environmental sustainability in OPEC member nations," *Mathematics*, vol. 11, no. 23, p. 4861, Dec. 2023.
[47] A. Emrouznejad, G. R. Amin, M. Ghiyasi, and M. Michali, "A review of inverse data envelopment analysis: Origins, development and future directions," *IMA J. Manage. Math.*, vol. 34, no. 3, pp. 421–440, Jun. 2023.
[48] S. Çakır, "Proposing integrated Shannon's entropy–inverse data envelopment analysis methods for resource allocation problem under a fuzzy environment," *Eng. Optim.*, vol. 49, no. 10, pp. 1733–1749, Oct. 2017.
[49] S. Goyal, M. S. Talwar, S. Agarwal, and T. Mathur, "Ranking of efficient DMUs using super-efficiency inverse DEA model," in *Proc. SocProS*. Cham, Switzerland: Springer, 2023, pp. 615–626.
[50] K. Soleimani-Chamkhorami, F. Hosseinzadeh Lotfi, G. Jahanshahloo, and M. Rostamy-Malkhalifeh, "A ranking system based on inverse data envelopment analysis," *IMA J. Manage. Math.*, vol. 31, no. 3, pp. 367–385, Jun. 2020.
[51] K. K. Orisaremi, F. T. S. Chan, S. H. Chung, and X. Fu, "A sustainable lean production framework based on inverse DEA for mitigating gas flaring," *Expert Syst. Appl.*, vol. 206, Nov. 2022, Art. no. 117856.
[52] F. Azizi, M. Hamid, B. Salimi, and M. Rabbani, "An intelligent framework to assess and improve operating room performance considering ergonomics," *Expert Syst. Appl.*, vol. 229, Nov. 2023, Art. no. 120559.
[53] T. O. Kehinde, O. J. Adedokun, A. Joseph, K. M. Kabirat, H. A. Akano, and O. A. Olanrewaju, "Helformer: An attention-based deep learning model for cryptocurrency price forecasting," *J. Big Data*, vol. 12, no. 1, pp. 1–39, Apr. 2025.
[54] T. Kehinde, S. H. Chung, and F. T. S. Chan, "Benchmarking TPU and GPU for stock price forecasting using LSTM model development," in *Proc. Sci. Inf. Conf.*, Sep. 2023, pp. 289–306.
[55] Y. K. Saheed, T. O. Kehinde, M. Ayobami Raji, and U. A. Baba, "Feature selection in intrusion detection systems: A new hybrid fusion of bat algorithm and residue number system," *J. Inf. Telecommun.*, vol. 8, no. 2, pp. 189–207, Apr. 2024.
[56] S. Ö. Arik and T. Pfister, "TabNet: Attentive interpretable tabular learning," in *Proc. AAAI Conf. Artif. Intell.*, vol. 35, May 2021, pp. 6679–6687.


**TEMITOPE OLUBANJO KEHINDE** (Member, IEEE) received the Ph.D. degree in industrial and systems engineering from The Hong Kong Polytechnic University, Hong Kong, in 2024.

He is currently a Postdoctoral Fellow with the Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University. He has authored and co-authored publications, including journals and conference proceedings. His research interests include finance, manufacturing, production, management, energy, machine learning, deep learning, and optimization.

Dr. Temitope is a member of many professional bodies, including European Operations Management Association (EurOMA), the Industrial Engineering and Operations Management (IEOM), the Institute of Industrial and Systems Engineers (IISE), the International Association of Engineers (IAENG), the International Society for Urban Informatics (ISUI), and the Production and Operations Management Society (POMS).

**SAI-HO CHUNG** received the Ph.D. degree in industrial and manufacturing systems engineering from The University of Hong Kong, Hong Kong, in 2007.

He is currently the Associate Head and an Associate Professor with the Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong. He has authored and co-authored more than 100 SCI journal articles. His research interests include logistics, supply chain management, finance, production scheduling, distribution networks, machine learning, container port terminals, and aviation.

Dr. Chung is an Editorial Board Member of TRE and has edited several special issues in SCI journals. His publications appear in POM, TR (Part B/C/E), DSJ, *Risk Analysis*, EJOR, IEEE TRANSACTIONS ON MOBILE COMPUTING, IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT, IEEE SYSTEMS JOURNAL, DSS, IJPE, IJPR, COR, and many more.

**OLUDOLAPO A. OLANREWAJU** received the Ph.D. degree in industrial engineering from Tshwane University of Technology, South Africa, in 2013.

He is currently an Associate Professor and the Head of the Department of Industrial Engineering, Durban University of Technology, South Africa. He is also a Rated Researcher with NRF. He has authored and co-authored more than 150 publications, including journals, conference proceedings, and book chapters. His research interests include, but are not limited to, energy and greenhouse gas analysis, artificial intelligence, modelling, and lean applications.

Dr. Olanrewaju has won many awards both locally and internationally.