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An Ideal-Point Goal Programming Data Envelopment Analysis Model for Ranking Productivity and Agility Improvement Enablers in the Ports and Maritime Organization

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Abstract

Extended project completion times and increased final costs of products and services are indicative of deficiencies in organizational productivity and agility when responding to environmental changes. Enhancing these two capabilities can significantly reduce the cost of organizational outcomes. One of the most effective approaches for simultaneously evaluating and improving productivity and agility is Data Envelopment Analysis (DEA); however, conventional DEA models generally suffer from limited discriminatory power. To address this limitation, the present study proposes an ideal-point-based model that integrates DEA with Goal Programming (GP). Using a multi-criteria set of evaluation factors, DEA is employed to assess relative efficiency, while GP is utilized to incorporate preference structures for prioritization. Ideal and anti-ideal reference points are introduced to enhance the model's discriminatory capability. The primary objective of this research is to identify and prioritize the key enablers of productivity and agility improvement within the Ports and Maritime Organization (PMO) through the proposed model. The research methodology consists of four stages and was implemented based on expert judgments from the organization. The proposed mathematical model incorporates project execution time and cost as input criteria, and the impacts of enablers on four organizational dimensions—efficiency, effectiveness, flexibility, and responsiveness—as output criteria. the model was applied to fourteen identified enablers, resulting in the prioritization of five key enablers: Enhancement of systems thinking capability within the organization, implementation of project portfolio management, implementation of business process management, implementation of project risk management, and deployment of business intelligence systems. The principal contribution of this study is the development of an ideal-point GP DEA model, which, according to the conducted analyses, demonstrates superior discriminatory power and ranking quality compared with existing alternative models. The proposed framework assists managers in allocating resources to enablers with the greatest potential impact on organizational productivity and agility, while also providing policymakers with a valuable decision-support tool for strategic planning. As a practical implication, the study recommends integrating the proposed model into a comprehensive organizational productivity cycle to facilitate the continuous and simultaneous improvement of productivity and agility.

Keywords: Productivity, Organizational agility, Enabler, Data envelopment analysis, Goal programming, Ideal-point goal programming data envelopment analysis model.

1 | Introduction

Government programs and projects in many developing economies have been confronted with significant implementation challenges due to a combination of inappropriate policymaking, economic sanctions, limited

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financial resources, inefficient managerial practices, and other institutional constraints [1]. As a result, many public-sector projects experience substantial delays, often extending over several years, and fail to achieve their intended objectives. These shortcomings have led to stakeholder dissatisfaction, increased costs for taxpayers, and numerous adverse economic and social consequences [2]. In today's dynamic environment, rapid advances in management science have made the establishment of effective performance evaluation systems indispensable. The absence of systematic evaluation across key organizational dimensions—including the utilization of resources, human capital, organizational objectives, and strategic initiatives—is widely recognized as an indicator of organizational dysfunction [3].

Productivity has long been regarded as a fundamental indicator for measuring organizational efficiency and supporting the optimal allocation of resources [4]. Its importance extends beyond organizational performance, as productivity plays a vital role in achieving organizational excellence [5] while simultaneously contributing to national economic growth, particularly within the framework of the resistance economy [6]. At the same time, organizations operate in increasingly volatile and uncertain environments characterized by rapid technological, economic, and competitive changes. Consequently, organizations must incorporate the principles of agility into their long-term strategies to respond effectively to these evolving conditions [7]. Organizational agility emphasizes continuous improvements in individual and organizational performance while maintaining the flexibility to respond rapidly to emerging opportunities driven by changing customer needs. Agile organizations are distinguished by their continuous learning capabilities and their readiness to adapt to both incremental and transformational changes, thereby improving their long-term competitiveness and profitability [8].

A critical step toward enhancing organizational agility is the identification of the key factors that influence it. Previous studies have identified numerous determinants of organizational agility, including knowledge management [9], [10], Enterprise Resource Planning (ERP) systems [11], business intelligence [12], [13], customer and supplier relationships [14], manufacturing excellence tools [15], organizational learning [16], and customer knowledge management [17]. Similarly, the literature has identified several factors that contribute to improving organizational productivity, such as knowledge management [18], value management [19], effective allocation of financial resources [20], project portfolio management [21], systems thinking among managers [22], organizational process management [23], continuous improvement practices [24], risk management [25], and the successful implementation of Project Management Information Systems (PMIS) [26].

Despite these advances, organizations continue to face a dual strategic challenge. On the one hand, they must maintain an adequate level of productivity to sustain operations and improve organizational performance. On the other hand, they require sufficient organizational agility to respond effectively to rapidly changing environmental conditions. Existing studies have generally proposed individual methods, initiatives, or organizational enablers for improving either productivity or agility. However, as revealed by the literature review, little attention has been devoted to developing an integrated portfolio of organizational enablers capable of simultaneously enhancing both productivity and organizational agility. This gap is particularly important for project-based organizations, where the achievement of strategic objectives depends on balancing operational efficiency with organizational adaptability.

The practical significance of this research stems from the challenges currently faced by project-based organizations. Government ministries, public agencies, affiliated companies, contractors, consultants, and other service providers have all been affected by delays, resource limitations, and managerial inefficiencies resulting from unfavorable economic and institutional conditions. Consequently, the primary concern of these organizations is to improve their productivity while simultaneously enhancing their agility to adapt to environmental changes. Accordingly, the practical objective of this research is to identify strategic initiatives, improvement actions, and organizational enablers that can support the simultaneous enhancement of organizational productivity and agility as two critical strategic objectives.

From a theoretical perspective, numerous studies have investigated the selection of revenue-generating project portfolios to improve productivity, while many others have examined the determinants of organizational agility. Nevertheless, an integrated framework for identifying and prioritizing a portfolio of organizational enablers that simultaneously improves both productivity and agility remains largely absent from the literature. Furthermore, previous productivity studies have employed a variety of analytical methods, including Data Envelopment Analysis (DEA) [27–29], linear regression [30], simulation [31], and fuzzy models integrated with artificial neural networks [32]. Although DEA has become one of the most widely used approaches for performance evaluation, conventional DEA models suffer from limited discriminative power and insufficient capability for ranking Decision-Making Units (DMUs) [33]. Goal Programming (GP), one of the most widely applied techniques in operations research, has proven effective for solving multi-objective optimization problems [34]. Integrating DEA with GP has been shown to improve the discriminative capability of DEA models while generating a common set of weights for all DMU [35]. Recent studies have further demonstrated the superiority of DEA-based GP models in enhancing discrimination and ranking performance [36], [37].

In light of these theoretical and practical considerations, this study aims to identify, prioritize, and rank the organizational enablers that simultaneously improve productivity and organizational agility. To achieve this objective, a case study was conducted within the Iran Ports and Maritime Organization (PMO), an organization operating under the ministry of roads and urban development and responsible for exercising governmental authority over the country's ports and coastal areas while facilitating maritime trade and coastal transportation. The PMO was selected because of its strategic importance, the researchers' consulting collaboration with the organization, and its need to develop a comprehensive roadmap for improving productivity and organizational agility. Accordingly, this study proposes a hybrid Data Envelopment Analysis–Goal Programming (DEA–GP) model to prioritize organizational enablers, thereby providing both a methodological contribution to the literature and a practical decision-support framework for enhancing productivity and agility in project-based organizations.

2 | Materials and Methods

This section provides a brief overview of the research methodologies employed in this study, including DEA and GP. These methods constitute the analytical framework used to identify, evaluate, and prioritize the organizational enablers for improving productivity and organizational agility.

2.1 | Data Envelopment Analysis

DEA is a widely used methodology for evaluating the relative efficiency of organizations and DMU. In DEA, the efficiency of each unit is assessed relative to a set of comparable units, where those exhibiting the highest level of performance are considered efficient [38]. Efficiency is defined as the ability to produce the maximum possible outputs or services using the minimum required level of resources—in other words, performing tasks in the most effective and resource-efficient manner.

Originally developed by Charnes et al. [39] based on the pioneering work of Farrell [40], DEA is a non-parametric operations research technique for evaluating the relative efficiency of a set of homogeneous DMU that utilize multiple inputs to generate multiple outputs. DEA provides an objective benchmarking framework by assigning each DMU a technical efficiency score, identifying efficient peer units as reference benchmarks, establishing performance targets for inefficient units, and quantifying the adjustments required in inputs and outputs to improve efficiency. Specifically, the method determines the extent to which input consumption can be reduced and/or output production can be increased to enable inefficient DMUs to achieve efficient performance [41].

2.2 | Goal Programming

GP is one of the most widely applied techniques in operations research, designed to achieve the optimal satisfaction of multiple objectives simultaneously [42]. The integration of DEA with GP has been emphasized as an effective approach for enhancing the discriminative power of DEA models while providing a common set of weights for all DMU [35].

3 | Proposed Mathematical Model

Several hybrid models integrating GP and DEA have been proposed in the literature. One of the most well-known models is that developed by Makuei et al. [35], which is based on minimizing the sum of the deviation variables and is formulated as follows.

$$
\begin{aligned}
&\text{MinZ} = \sum_{j=1}^{n} \text{dmax}_j,\\
&\text{s.t.}: \sum_{i=1}^{m} v_i x_{i1} = 1,\\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + \text{d}\max_j = \text{o}, j = 1,\ldots,n,\\
&\text{M} - \text{d}\max_j \geq 0,\\
&u_r, v_i \geq \varepsilon, \text{dmax}_j, \text{dmin}_j \geq 0, \text{dmax}_j, \text{dmin}_j \leq 1, r = 1,\ldots,s, i = 1,\ldots,m.
\end{aligned}
\tag{1}
$$

Although the above GP model provides greater discriminative capability than the classical CCR model [33], two modifications are introduced in the proposed model to improve further the discrimination of DMU efficiencies. First, the objective function is designed to maximize the deviation of each deviation variable from the average of all deviation variables relative to the total deviation. Second, the maximum efficiency value, θ_{max}, is calculated as the ideal point, while the minimum efficiency value, θ_{min}, is determined as the anti-ideal point. Accordingly, the efficiency of each DMU is evaluated within this interval. Since the maximum efficiency value exceeds one, the proposed approach enhances the discriminative power of the model. Therefore, these ideal and anti-ideal points, together with their corresponding coordinates, are incorporated into the proposed model.

To implement the proposed model, the ideal efficiency value (θ_{max}) must first be determined. This is accomplished by introducing an ideal point into the model, whose coordinates consist of a vector of the minimum input values and the maximum output values.

$$
\begin{aligned}
x_i^{min} &= \min_j \{x_{ij}\}, i = 1,..,m, j = 1,..,n,\\
y_r^{max} &= \max_j \{y_{rj}\}, r = 1,..,s, j = 1,..,n.
\end{aligned}
$$

The maximum efficiency value, θ_{max}, is calculated using *Model (2)*, as presented below.

$$\begin{aligned}
&\mathrm{Max}\,\theta_{max}=\sum_{r=1}^{s}u_r y_r^{max},\\
&\mathrm{s.t.}:\sum_{r=1}^{s}u_r y_{rj}-\sum_{i=1}^{m}v_i x_{ij}\le o,\ j=1,\dots,n,\\
&\sum_{i=1}^{m}v_i x_i^{min}=1,\\
&u_r,v_i\ge\varepsilon,\ r=1,\dots,s,\ i=1,\dots,m.
\end{aligned}\tag{2}$$

The maximum efficiency value, θ_{max}, is calculated as the ratio of the weighted sum of the maximum output values to the weighted sum of the minimum input values, as expressed in *Eq. (3)*.

$$\theta_{max}=\frac{\sum_{r=1}^{s}u_r y_r^{max}}{\sum_{i=1}^{m}v_i x_i^{min}}.\tag{3}$$

To implement the proposed model, the worst (anti-ideal) efficiency value, θ_{min}, must also be determined. For this purpose, an anti-ideal point is introduced into the model, whose coordinates consist of a vector of the maximum input values and the minimum output values.

$$x_i^{max}=\max_j\{x_{ij}\},\ i=1,..,m,\ j=1,..,n,$$
$$y_r^{min}=\min_j\{y_{rj}\},\ r=1,..,s,\ j=1,..,n.$$

The minimum efficiency value, θ_{min}, is calculated using *Model (4)*.

$$\begin{aligned}
&\mathrm{Max}\,\theta_{min}=\sum_{r=1}^{s}u_r y_r^{min},\\
&\mathrm{s.t.}:\sum_{r=1}^{s}u_r y_{rj}-\sum_{i=1}^{m}v_i x_{ij}\le o,\ j=1,\dots,n,\\
&\sum_{i=1}^{m}v_i x_i^{max}=1,\\
&u_r,v_i\ge\varepsilon,\ r=1,\dots,s,\ i=1,\dots,m.
\end{aligned}\tag{4}$$

The minimum efficiency value, θ_{min}, is calculated as the ratio of the weighted sum of the minimum output values to the weighted sum of the maximum input values, as expressed in *Eq. (5)*.

$$\theta_{min}=\frac{\sum_{r=1}^{s}u_r y_r^{min}}{\sum_{i=1}^{m}v_i x_i^{max}}.\tag{5}$$

In the proposed model, the ideal and anti-ideal points are first incorporated into the model. The proposed ideal-oriented DEA–GP model is formulated as *Model (6)* below.

$$\mathrm{MaxZ} = \frac{(\sum_{j=1}^{n}(\mathrm{dmax}_j - \mathrm{Meand\,max})\,\hat{}\,2)\,\hat{}\,1/2}{\sum_{j=1}^{n}\mathrm{dmax}_j} + \frac{(\sum_{j=1}^{n}(\mathrm{d\,min}_j - \mathrm{Meand\,min})\,\hat{}\,2)\,\hat{}\,1/2)}{\sum_{j=1}^{n}\mathrm{d\,min}_j},$$

s.t.:

$$\sum_{r=1}^{s} u_r y_{rj} - \theta_{max} * \sum_{i=1}^{m} v_i x_{ij} + \mathrm{d\,max}_j = o, j = 1,\ldots,n, n+1, n+2,$$

$$\mathrm{Meand\,max} = \frac{\sum_{j=1}^{n}\mathrm{d\,max}_j}{n}, \tag{6}$$

$$\mathrm{Meand\,min} = \frac{\sum_{j=1}^{n}\mathrm{d\,min}_j}{n},$$

$$u_r, v_i \geq \varepsilon, \mathrm{dmax}_j, \mathrm{dmin}_j \geq 0, \mathrm{dmax}_j, \mathrm{dmin}_j \leq 1, j = 1,\ldots,n, n+1, n+2, r = 1,\ldots,s, i = 1,\ldots,m.$$

In the above model, the parameters are defined as follows: n represents the number of DMU considered for efficiency evaluation, m denotes the number of inputs, $s$represents the number of outputs, x_{ij} indicates the value of input I for unit j, and y_{rj} represents the value of output rfor unit j.

The variables include u_r, which denotes the weight assigned to output r (or the value/price of output r), and v_i, which represents the weight assigned to input i. The efficiency score of unit jis denoted by θ_j. In addition, auxiliary variables d_j^{max} and d_j^{min} are considered to facilitate the required calculations.

After determining the weights using the aforementioned model, the initial efficiency score θ_j of each DMU is calculated using the following expression.

$$\theta_j = \frac{\sum_{r=1}^{s} u_r^* y_{rj}}{\sum_{i=1}^{m} v_i^* x_{ij}}, j = 1,..,n, n+1, n+2. \tag{7}$$

Since, according to the proposed model, the efficiency value θ_j is distributed within the interval $(\theta_{min}, \theta_{max})$, and the maximum efficiency value is θ_{max}, the calculated efficiency value should logically be adjusted based on the maximum efficiency value θ_{max}. However, because the efficiency values of the ideal and anti-ideal points are hypothetical and are not included among the actual DMU, the previously calculated normalized efficiency value should be divided by the maximum efficiency value among the actual DMU. Therefore, the final efficiency value θ_j^* is calculated according to the following expression.

$$\theta_j^* = \frac{\theta_j}{\max(\theta_j)}, j = 1,..,n. \tag{8}$$

To evaluate the proposed model, the aforementioned model is implemented and modeled using GAMS software. According to the objective function, the optimal efficiency values of the DMUs are obtained when the efficiency scores of individual DMUs are maximized as much as possible while maintaining an appropriate level of dispersion among them. This approach results in a higher discriminative power for efficiency evaluation, which is further assessed in the following sections.

4 | Research Methodology

To evaluate the proposed mathematical model and implement the research objectives, a case study was conducted in the Iran PMO to prioritize the enablers for improving organizational productivity and agility. The research methodology consists of the following steps:

I. Identification of evaluation criteria for DMUs.

II. Determination of enablers as DMU.

III. Collection of expert judgments regarding the evaluation criteria of enablers.

IV. Application of the proposed mathematical model to rank the enablers based on the evaluation criteria.

The data collection process was conducted through both library-based and field-based methods. Accordingly, the evaluation criteria and enablers for improving organizational productivity and agility were initially identified through a review of the literature and relevant secondary sources. Subsequently, a questionnaire was employed as the data collection instrument to determine the evaluation scores of the enablers according to the identified criteria. For this purpose, a team of nine experts from the Iran PMO was formed to complete the questionnaires and provide the required evaluation data.

5 | Finding

According to the research methodology, in the first stage, a set of six criteria was identified for prioritizing the enablers aimed at improving organizational productivity and agility based on the opinions of experts from the Iran PMO. As presented in *Table 1*, these criteria are categorized into two groups: Input criteria and output criteria. The identified criteria include various general criteria, organizational productivity criteria, and organizational agility criteria.

Table 1. Selected evaluation criteria for prioritizing enablers.

Number	Criterion Name	Criterion Category	Criterion Type	Criterion Reference
1	Duration of implementing the enabler project (months)	General	Input	[28], [43]
2	Cost of implementing the enabler project (Trillion Rials)	General	Input	
3	Relative impact on the efficiency of the organization's operational projects	Organizational productivity	Output	[44], [45]
4	Relative impact on the effectiveness of the organization's operational projects	Organizational productivity	Output	
5	Relative impact on organizational flexibility	Organizational agility	Output	[7], [8]
6	Relative impact on organizational responsiveness	Organizational agility	Output	

In the second stage, a set of 14 enablers for improving organizational productivity and agility was identified based on the reviewed literature presented in the Introduction section, as well as the opinions of experts from the Iran PMO, as shown in *Table 2*.

Table 2. List of enablers for improving productivity and agility in the PMO.

Number	Enabler Name	Impact on Productivity	Impact on Agility	Enabler Reference
1	Implementation of organizational knowledge management	*	*	[9], [10], [18]
2	Implementation of ERP system	+	*	[11]
3	Implementation of PMIS	*	+	[26], [46]
4	Supply chain integration	+	*	[47]
5	Implementation of customer knowledge management	+	*	[14]
6	Appropriate allocation of financial resources	*	+	[20]
7	Implementation of project portfolio management	*	+	[21]
8	Enhancement of organizational systems thinking	*	+	[22]
9	Implementation of project risk management	*	+	[25]
10	Implementation of organizational process management	*	+	[23]
11	Development of organizational learning	+	*	[16]
12	Implementation of continuous improvement approaches	*	+	[24]
13	Implementation of business intelligence	+	*	[7], [12]
14	Implementation of value management	*	+	[19]

According to the reviewed literature, for those enablers whose impacts on organizational productivity or agility have been explicitly identified, a star (*) is indicated in *Table 2*. Furthermore, based on the opinions of experts from the Iran PMO regarding the impacts of enablers on organizational productivity and agility, a plus sign (+) is used in the table.

In the third stage, to apply and implement the proposed model and rank the enablers based on the selected criteria, experts assigned scores ranging from 1 to 10 to the evaluation criteria of each enabler. Due to existing limitations, the corresponding table of scores is not presented.

In the fourth stage, according to the proposed model, the ideal point or maximum efficiency value $\theta_{\max}$ and the anti-ideal point or minimum efficiency value $\theta_{\min}$ must be calculated using *Models (2)* and *(4)*, respectively. The obtained values of $\theta_{\min}$ and $\theta_{\max}$ are as follows:

$$\theta_{\max} = 2.329, \theta_{\min} = 0.406.$$

By incorporating $\theta_{\max}$ and $\theta_{\min}$ into the proposed research model (*Model 6*), the initial efficiency values, final efficiency scores, and the ranking of the enablers are calculated and presented in *Table 3*.

Table 3. List of enablers for improving productivity and agility in the PMO.

Number	Enabler Name	Initial Efficiency θ_j	Final Efficiency θ_j^*	Ranking
1	Implementation of organizational knowledge management	0.769	0.735	8
2	Implementation of ERP system	0.666	0.637	11
3	Implementation of PMIS	0.627	0.599	13
4	Supply chain integration	0.752	0.719	10
5	Implementation of customer knowledge management	0.757	0.724	9
6	Appropriate allocation of financial resources	0.641	0.613	12
7	Implementation of project portfolio management	1.035	0.989	2
8	Enhancement of organizational systems thinking	1.046	1.000	1
9	Implementation of project risk management	1.015	0.970	4
10	Implementation of organizational process management	1.018	0.973	3
11	Development of organizational learning	0.952	0.910	6
12	Implementation of continuous improvement approaches	0.603	0.576	14
13	Implementation of business intelligence	0.985	0.942	5
14	Implementation of value management	0.944	0.902	7
15	Ideal point	2.329	--	--
16	Anti-ideal point	0.406	--	--

According to the above table, the priority ranking of the enablers for improving productivity and agility in the PMO is as follows:

Enhancement of organizational systems thinking, implementation of project portfolio management, implementation of organizational process management, implementation of project risk management, implementation of business intelligence, development of organizational learning, implementation of value management, implementation of organizational knowledge management, implementation of customer knowledge management, supply chain integration, implementation of ERP systems, appropriate allocation of financial resources, implementation of PMIS, and implementation of continuous improvement approaches.

6 | Model Validation

To validate the proposed model, other models were employed for comparison purposes, as presented in *Table 4*.

Table 4. Compared models.

Equations	Models
$\text{Max}\theta_0 = \sum_{r=1}^{s} u_r y_{r0}$, $\text{s.t.} \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq o, j = 1,\dots,n,$ $\sum_{i=1}^{m} v_i x_{i1} = 1,$ $u_r, v_i \geq \varepsilon, r = 1,\dots,s, i = 1,\dots,m,$	Model 1. CCR model [39]

Table 4. Continued.

Equations	Models
$\mathrm{Min}Z=\sum_{j=1}^{n} d\max_j,$ $\text{s.t.}\sum_{r=1}^{s} u_r y_{rj}-\sum_{i=1}^{m} v_i x_{ij}+d\max_j=0, j=1,...,n,$ $\sum_{i=1}^{m} v_i x_{i1}=1,$ $u_r, v_i \geq \varepsilon, d\max_j, d\min_j \geq 0, r=1,...,s, i=1,...,m,$	Model 2. Makuei et al. [35]
$\mathrm{Min}Z=M,$ $\text{s.t.}\sum_{r=1}^{s} u_r y_{rj}-\sum_{i=1}^{m} v_i x_{ij}+d\max_j=0, j=1,...,n,$ $\sum_{i=1}^{m} v_i x_{i1}=1,$ $M-d\max_j \geq 0,$ $u_r, v_i \geq \varepsilon, d\max_j, d\min_j \geq 0, r=1,...,s, i=1,...,m,$	Model 3. Moravati Sharif Abadi et al. [36]
$\mathrm{Min}Z=d\max_1,$ $\mathrm{Min}Z=\sum_{j=1}^{n} d\max_j,$ $\mathrm{Min}Z=M,$ $\text{s.t.}\sum_{r=1}^{s} u_r y_{rj}-\sum_{i=1}^{m} v_i x_{ij}+d\max_j=0, j=1,...,n,$ $\sum_{i=1}^{m} v_i x_{i1}=1,$ $M-d\max_j \geq 0,$ $u_r, v_i \geq \varepsilon, d\max_j, d\min_j \geq 0, r=1,...,s, i=1,...,m.$	Model 4. Mehrgan et al. [33]

The results of comparing the proposed model with the aforementioned models are presented in *Table 5*.

Table 5. Comparison of the results of the proposed model with different models.

Enabler Number	Enabler	Model 1	Model 2	Model 3	Model 4	Proposed Model
1	Organizational knowledge management implementation	0.767	0.742	0.716	0.742	0.735
2	ERP system implementation	0.786	0.681	0.623	0.683	0.637
3	Project information management system implementation	0.615	0.584	0.593	0.585	0.599
4	Supply chain integration	0.812	0.716	0.699	0.721	0.719
5	Customer knowledge management implementation	0.884	0.78	0.743	0.774	0.724
6	Appropriate allocation of financial resources	0.75	0.613	0.633	0.612	0.613

Table 5. Continued.

Enabler Number	Enabler	Model 1	Model 2	Model 3	Model 4	Proposed Model
7	Project portfolio management implementation	1	1	0.947	1	0.989
8	Enhancement of organizational systems thinking	1	1	1	1	1.000
9	Project risk management implementation	1	0.991	0.949	0.991	0.970
10	Organizational process management implementation	1	1	0.746	1	0.973
11	Organizational learning implementation	0.948	0.883	0.795	0.805	0.910
12	Implementation of continuous improvement approaches	0.798	0.636	0.612	0.634	0.576
13	Business intelligence implementation	1	1	1	1	0.942
14	Value management implementation	0.931	0.923	0.873	0.921	0.902
Number of efficient dMUs		5	4	2	4	1
Mean efficiency ($\overline{X}$)		0.878	0.825	0.781	0.819	0.806
Standard deviation of efficiencies (S)		0.1238	0.1625	0.1480	0.1615	0.1630
Coefficient of variation of efficiencies ($\frac{S}{\overline{X}}$)		0.1410	0.1970	0.1896	0.1972	0.2022

An examination of the aforementioned models reveals that, in most of them, a relatively large number of enablers, or equivalently DMU, are identified as efficient. This indicates a limited discriminative power in distinguishing the efficiency levels of the DMUs. For instance, in the CCR model, five DMUs are evaluated as efficient. Likewise, in *Models 2*, *3*, and *4*, the numbers of fully efficient DMUs are four, two, and four, respectively. In contrast, the proposed model identifies only one efficient DMU, demonstrating a superior discriminative capability.

Furthermore, compared with the other models, the proposed model exhibits the second-lowest mean efficiency score. The standard deviation of the efficiency scores obtained by the proposed model is the highest among all the compared models. Overall, the proposed model also yields the highest coefficient of variation, calculated as the ratio of the standard deviation to the mean efficiency. This finding indicates that the efficiency scores generated by the proposed model exhibit greater dispersion around their mean than those obtained from the standard DEA model and the other specified GP models, thereby providing a more effective discrimination among DMUs.

In addition, to further validate the proposed model, the dataset of 17 forest districts in Taiwan reported by Makui et al. [35] was re-evaluated using the proposed model developed in this study. The results obtained are presented in *Table 6* and are compared with those reported by Makui et al. [35] as well as the results of Kao and Hong [48].

Table 6. Comparison of results of different models with the proposed model.

DMU Number	CCR	Kao and Hung Model [48]	Makui et al. Model [35]	Proposed Model
1	1	1	1	1
2	1	1	1	0.249
3	1	1	1	0.193
4	1	1	1	0.360
5	1	0.9747	1	0.313
6	1	0.8524	0.9654	0.692
7	1	0.9244	0.8743	0.290
8	1	0.8954	0.8469	0.191
9	1	0.6619	0.6783	0.422
10	0.9403	0.8721	0.8779	0.216
11	0.9346	0.6398	0.6526	0.134
12	0.829	0.7456	0.7175	0.164
13	0.7997	0.6229	0.6227	0.127
14	0.7733	0.714	07126	0.149
15	0.7627	0.7245	0.7215	0.200
16	0.7435	0.6996	0.6696	0.141
17	0.6873	0.631	0.5925	0.126
Number of efficient dMUs	9	4	5	1
Mean efficiency ($\overline{X}$)	0.910	0.8211	0.8195	0.2922
Standard deviation of efficiencies (S)	0.11480	0.14712	0.15478	0.23157
Coefficient of variation of efficiencies ($\frac{S}{\overline{X}}$)	0.1261	0.1792	0.1889	0.7926

According to the results presented in *Table 6*, the proposed model yields the smallest number of efficient DMU compared with the models reported in the referenced studies. Specifically, only one DMU is identified as efficient by the proposed model. From another perspective, the proposed model also exhibits the lowest mean efficiency score among all the compared models, while producing the highest standard deviation and the highest coefficient of variation of the efficiency scores.

Based on the two validation procedures conducted—one using the dataset of the present study and the other using the external dataset reported in the literature—and through comparison with the aforementioned DEA GP models as well as the models proposed by Makui et al. [35] and Kao and Hong [48], it is evident that the proposed model achieves the smallest number of efficient DMUs together with the greatest dispersion in efficiency scores. These results indicate that the proposed model possesses superior discriminative power and provides a more effective framework for ranking DMU, thereby enhancing the resolution and reliability of efficiency evaluation.

7 | Conclusion

As discussed earlier, in conventional DEA models, DMU are classified into two categories: Efficient and inefficient. All efficient DMUs receive an efficiency score of one, and in most cases, several DMUs are simultaneously identified as efficient. Consequently, it is often impossible to determine the single best-performing unit.

In this study, a GP-based DEA model was developed to rank DMU. To enhance the discrimination power of efficiency evaluation by expanding the range of distinguishable efficiency scores, an ideal point and an anti-ideal point were introduced. Accordingly, the efficiency of each DMU is evaluated relative to these two reference points, allowing efficiency scores to be distributed between the maximum and minimum attainable efficiency levels while remaining normalized within the interval $[0, 1]$.

The results of the case study demonstrated that the proposed model, through its objective function and associated constraints, provides a more effective discrimination among DMU than the existing models considered in this study. This enhanced discriminative capability represents the primary contribution of the research. Furthermore, the proposed formulation eliminates the need to include the evaluated (reference) DMU in the optimization model while incorporating the ideal and anti-ideal points as benchmark units. Consequently, each DMU is evaluated relative to these two reference points, which reduces computational complexity and improves computational efficiency. Moreover, as demonstrated by the analytical results, the proposed model typically identifies a single top-ranked DMU, while the remaining units are ranked according to their relative performance. In addition, the higher coefficient of variation obtained for the efficiency scores indicates greater dispersion among the evaluated DMUs, resulting in a more informative and reliable ranking compared with existing DEA models. Collectively, these characteristics demonstrate the novelty and effectiveness of the proposed model for prioritizing DMU.

Based on the results of this study, which were obtained using expert judgments from the ports organization and the implementation of the proposed model, five enablers were identified as having the highest priority among the fourteen evaluated enablers for improving organizational productivity and agility. These enablers are: Enhancing organizational systems thinking, implementing project portfolio management, implementing organizational process management, implementing project risk management, and implementing business intelligence. As a practical implication, it is recommended that the proposed model be incorporated into a comprehensive productivity cycle framework to prioritize improvement initiatives aimed at simultaneously enhancing organizational productivity and agility.

Authors' Contributions

All aspects of the research and manuscript preparation were carried out by the author. The author has read and approved the final version of the manuscript.

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All data supporting the reported findings in this research paper are provided within the manuscript.

Conflict of Interest

The author declares that they do not have any conflict of interest.

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This article does not contain any studies with human participants performed by the author.

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