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Efficiency and Performance Stability Analysis of Nominated Suppliers in the Automotive Industry Using a Time-Series Data Envelopment Analysis Approach

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Abstract
Supplier management in the automotive industry often faces the dilemma of nominated suppliers, where suppliers are directly appointed by the Original Equipment Manufacturer (OEM), thereby limiting the company's bargaining power in ensuring operational efficiency. This study aims to analyze the technical efficiency and performance stability of 25 nominated suppliers at PT XYZ throughout 2025. The methodology employed is Data Envelopment Analysis (DEA) with the BCC model, input-oriented, and a monthly time-series approach, resulting in a total of 300 Decision Making Unit (DMU) observations. Input variables include Turnaround Time (TAT) and Price Index, while output variables consist of Delivery Rate, Quality Rate, and Response Rate. The results indicate significant fluctuations in technical efficiency scores across all suppliers, with no single supplier capable of maintaining a perfect efficiency level (1.00) consistently throughout the observation period. Slack analysis reveals that the dominant source of inefficiency is caused by TAT durations that exceed peer group reference benchmarks. These findings provide strategic implications for company management to implement a quantitative data-driven early warning system to mitigate late delivery risks and optimize coordination with OEMs.
Keywords: *automotive industry, bcc model, data envelopment analysis, nominated suppliers, technical efficiency*

Abstrak
Manajemen pemasok di industri otomotif sering menghadapi dilema pemasok yang ditunjuk langsung oleh Original Equipment Manufacturer (OEM), sehingga membatasi daya tawar perusahaan dalam memastikan efisiensi operasional. Studi ini bertujuan untuk menganalisis efisiensi teknis dan stabilitas kinerja 25 pemasok yang ditunjuk di PT XYZ sepanjang tahun 2025. Metodologi yang digunakan adalah Data Envelopment Analysis (DEA) dengan model BCC, berorientasi input, dan pendekatan deret waktu bulanan, menghasilkan total 300 observasi Unit Pengambilan Keputusan (DMU). Variabel input meliputi Turnaround Time (TAT) dan Indeks Harga, sedangkan variabel output terdiri dari Tingkat Pengiriman, Tingkat Kualitas, dan Tingkat Respons. Hasil menunjukkan fluktuasi signifikan dalam skor efisiensi teknis di seluruh pemasok, dengan tidak ada satu pun pemasok yang mampu mempertahankan tingkat efisiensi sempurna (1,00) secara konsisten sepanjang periode observasi. Analisis slack mengungkapkan bahwa sumber inefisiensi yang dominan disebabkan oleh durasi TAT yang melebihi tolok ukur referensi kelompok sejawat. Temuan ini memberikan implikasi strategis bagi manajemen perusahaan untuk menerapkan sistem peringatan dini berbasis data kuantitatif guna mengurangi risiko keterlambatan pengiriman dan mengoptimalkan koordinasi dengan OEM (Original Equipment Manufacturer).
Kata Kunci: *industri otomotif, model BCC, analisis pembungkus data, pemasok ditunjuk, efisiensi teknis*

1. Introduction

The automotive manufacturing sector is one of the main pillars of the global industrial structure, which relies heavily on supply chain efficiency to maintain competitiveness and operational sustainability. From a Supply Chain Management perspective, the effectiveness of inter-party coordination is a determining factor in creating competitive advantage, particularly in Just-in-Time (JIT) production systems that demand timeliness, high quality, and inventory minimization [1]. Close integration and coordination among supply chain entities are essential prerequisites for achieving overall system efficiency [2].

Within this ecosystem, PT XYZ, located in Karawang, faces a unique challenge in managing nominated suppliers — suppliers directly appointed by the Original Equipment Manufacturer (OEM). This mechanism creates a strategic dilemma, as it limits the company's bargaining power in vendor selection while simultaneously demanding maximum operational performance to mitigate late delivery risks that could disrupt the production flow[3].

Theoretically, organizational performance must be measured multidimensionally, encompassing operational aspects such as quality and timeliness [4]. Efficiency is understood as the optimal ratio between inputs consumed and outputs produced by a Decision Making Unit (DMU), as described in the frontier approach. To measure this relative efficiency, the Data Envelopment Analysis (DEA) method introduced by Charnes, Cooper, and Rhodes [5] has become the primary instrument. Over two decades of literature, DEA has proven effective for supplier evaluation and selection across various sectors [6]. Bibliometric analyses further confirm a strong trend in the use of DEA for sustainable supplier selection, taking both economic and environmental dimensions into account [7].

The application of DEA in the automotive industry has expanded significantly, ranging from hybrid DEA-AHP models for supplier benchmarking [8] to evaluations of vehicle assembly companies in developing countries [9]. Longitudinal studies have also been employed to measure the financial efficiency of relationships between OEMs and automotive suppliers [10]. Recent research even integrates DEA with AI-driven data approaches for strategic decision-making [11], as well as SCOR-based frameworks to evaluate automotive supply chain efficiency [12].

In a dynamic business environment, the effectiveness of supplier performance evaluation depends greatly on a model's ability to capture change and uncertainty [13]. Various approaches have been developed to address this challenge, including intelligent decision support systems for supplier benchmarking [14], stochastic cross-efficiency models under conditions of uncertainty [15], and the use of cross-efficiency for sustainable supplier ranking [16]. Additionally, non-radial super-efficiency DEA models enable more discriminative rankings by accounting for uncontrollable factors [17].

The urgency of this research lies in efficiency stability analysis. The concept of supplier stability has been advanced through multi-objective fuzzy models to simultaneously balance performance and risk [18]. The application of dynamic network DEA and periodic eco-efficiency assessments is crucial for monitoring long-term performance [19]. This aligns with sustainability and resilience frameworks that demand continuous performance measurement [20].

Despite the extensive DEA literature, a research gap remains in studies that specifically examine the technical efficiency stability of nominated suppliers in the automotive industry using a BCC model based on time-series data. The BCC model was selected because it accommodates the Variable Return to Scale (VRS) assumption, which is appropriate for the operational scale heterogeneity among suppliers [21]. Therefore, this study aims to analyze the technical efficiency and performance stability of 25 nominated suppliers at PT XYZ throughout 2025, covering a total of 300 time-based DMU observations. Input variables include Turnaround Time (TAT) and Price Index, while output variables consist of Delivery Rate, Quality Rate, and Response Rate. The findings are expected to provide practical contributions for managerial decision-makers in optimizing control over customer-designated suppliers through objective and measurable quantitative data.

2. Research Methodology

Research Object and Data Source

This study evaluates operational performance in the automotive manufacturing sector, with PT XYZ as the research object. The evaluation focuses on 25 Nominated Suppliers, defined as subcontract suppliers directly designated by the OEM. The data used consists of secondary quantitative data derived from simulated company procurement transaction records over a full calendar year, from January to December 2025. The research employs a monthly time-series approach, whereby each supplier's performance is evaluated separately for each month. By integrating 25 suppliers across 12 months of observation, this study produces a total of 300 analytical units, or Decision Making Units (DMUs). The use of longitudinal data aims to capture supplier technical efficiency stability more comprehensively than a single-period static approach would allow.

Research Variable Identification

Technical efficiency is measured through the identification of input and output variables that represent core activities within the automotive supply chain. The input variables in this model consist of two primary parameters: Turnaround Time (TAT) and Price Index. TAT is defined as the total material processing duration from the ordering stage to the receipt of goods at the warehouse, measured in days, while the Price Index reflects the ratio of actual price deviation relative to the established budget. The output variables, on the other hand, consist of three operational performance indicators: Delivery Rate, which measures the percentage of on-time deliveries; Quality Rate, which indicates the level of goods conformity to quality standards without defects; and Response Rate, which represents the speed of supplier communication in responding to company requests. Conceptually, efficiency is achieved when a supplier is able to minimize time usage and cost deviations to produce the maximum level of service and product quality.

Data Processing Procedure

The raw data processing procedure was carried out systematically using the Python programming language to ensure computational accuracy and efficiency for large-scale datasets. The first stage began with data cleaning to identify and remove null values or incomplete entries, thereby preserving the integrity of the analysis. This was followed by feature extraction to reformat the transaction data into relevant input and output variables. The final processing stage involved monthly data aggregation for each supplier using the groupby() function to construct an Input-Output matrix ready for processing within the DEA mathematical model. This entire procedure ensures that each DMU has a consistent and standardized data representation before the modeling stage is conducted. The complete data processing workflow is presented in Figure 1.

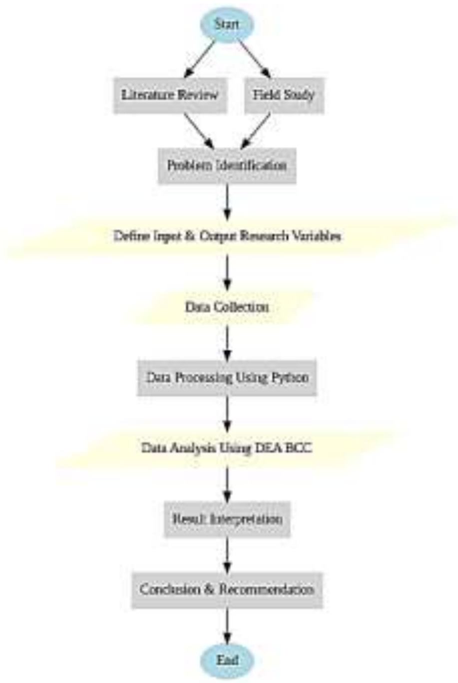

Figure 1. Flowchart of the Data Processing Workflow Using Python and DEA Analysis

Data Analysis Model

The data analysis technique employed is Data Envelopment Analysis (DEA) using the Banker, Charnes, and Cooper (BCC) model with an input-oriented approach [21]. The BCC model was selected on the grounds that each nominated supplier operates at a different economic scale; therefore, the Variable Return to Scale (VRS) assumption is considered more appropriate for reflecting pure technical efficiency than the Constant Return to Scale (CRS) assumption [5]. In the input-oriented approach, the model seeks to identify the maximum potential reduction in input variables without diminishing the current level of outputs [22]. Mathematically, DEA benchmarks each supplier against an efficiency frontier constructed by the best-performing suppliers in the dataset. The resulting efficiency scores range from 0 to 1, where a score of 1 indicates that the supplier has achieved optimal relative efficiency in the given period [23]. This analysis also incorporates slack value evaluation to provide specific and actionable improvement recommendations for suppliers positioned below the efficiency frontier [21].

3. Results and Discussion

The technical efficiency analysis in this study was conducted on 300 Decision Making Unit (DMU) observations representing the performance of 25 nominated suppliers over 12 months in 2025. Data processing was carried out systematically using the input-oriented BCC DEA method implemented in Python to ensure technical computational accuracy. The initial stage of analysis began with a descriptive statistical evaluation of all research variables to understand the distributional characteristics of supplier operational data. Both input variables TAT and Price Index and output variables Delivery Rate, Quality Rate, and Response Rate, exhibited diverse performance profiles reflecting the real dynamics of the

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automotive industry. This data distribution provides an initial indication of the complexity involved in managing suppliers with differing operational characteristics while being held to uniform quality standards.

Table 1. Summary of Supplier Input-Output Data Matrix for 2025

Supplier	Month	TAT	Price Index	Delivery Rate	Quality Rate	Efficiency Score
APA	January	3.62	0.93	0.93	0.73	0.9916
ACM	January	5.05	1.09	1.00	1.00	0.8899
IA	January	4.40	1.09	1.00	1.00	0.8899
AAM	January	4.00	1.12	1.00	1.00	0.8661
AIS	January	2.67	1.14	1.00	1.00	0.8696
AISS	January	2.97	1.14	0.80	0.71	0.8340
GCS	January	2.37	1.09	1.00	1.00	0.9562
GC	January	4.80	1.04	1.00	1.00	0.9327
DI	January	4.00	1.15	1.00	1.00	0.8435
…	…	…	…	…	…	…
CHHN	December	2.29	1.00	1.00	1.00	1.0000
PKN	December	2.31	1.12	1.00	1.00	0.9744
CTN	December	4.67	1.01	1.00	1.00	0.9604
PJMI	December	3.28	1.05	1.00	1.00	0.9238
PAP	December	2.58	1.18	1.00	1.00	0.8790
SI	December	3.77	1.08	1.00	1.00	0.8981
SIM	December	4.81	1.07	0.94	0.81	0.8629
FTC	December	3.15	0.96	0.83	0.88	0.9606
ITMI	December	4.07	1.01	1.00	1.00	0.9604

Measurements of the technical efficiency score (θ) reveal highly significant fluctuations among the 25 suppliers, with values distributed across the range of 0 to 1.00. Empirically, technical performance stability emerges as the primary challenge for the majority of suppliers, despite their status as customer-designated units. For instance, supplier GC achieved pure technical efficiency (θ = 1.00) in February, but experienced a sharp decline in October and December. A similar fluctuation pattern was observed for supplier APA, which reached an efficient score in May, and supplier DI, which was efficient in September; however, neither was able to maintain consistent performance across the remaining months of the observation period. This instability phenomenon indicates the presence of internal and external disruptions that affect suppliers' capacity to optimize resources toward the stipulated output targets.

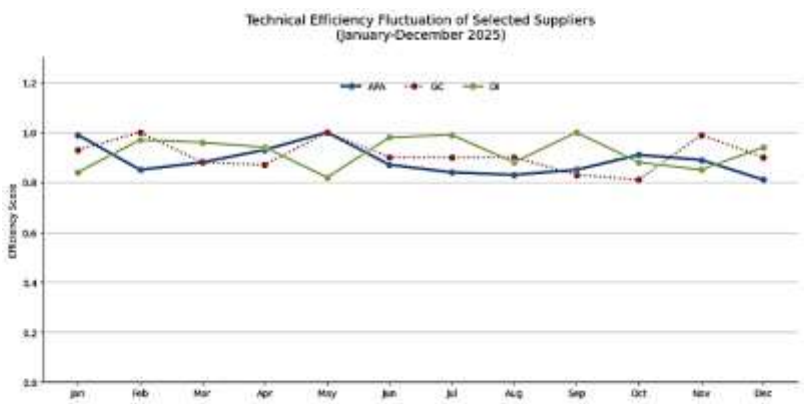

Figure 2. Technical Efficiency Fluctuation Chart for Selected Suppliers (January–December 2025)

Table 2. Recapitulation of Highest and Lowest Technical Efficiency Scores (θ)

Supplier	Min Score	Max Score	Frequency θ = 1.00
APA	0.810	1.000	1
ACM	0.822	0.980	0
IA	0.821	0.991	0
AAM	0.814	0.995	0
AIS	0.829	0.980	0
AISS	0.826	0.986	0
GCS	0.808	1.000	1
GC	0.808	1.000	2
DI	0.825	1.000	1
GUM	0.853	1.000	1
GUN	0.815	0.999	1
SATI	0.829	0.990	0
TBM	0.815	1.000	1
SKDM	0.815	1.000	1
IMI	0.819	0.996	0
CHHN	0.815	1.000	1
PKN	0.809	0.974	0
CTN	0.822	0.994	0
PJMI	0.808	0.986	0
PAP	0.815	0.998	0
SI	0.822	1.000	1
SIM	0.805	1.000	1
FTC	0.844	1.000	1
ITMI	0.815	0.983	0
YMM	0.808	1.000	1

The root causes of inefficiency for analytical units that did not achieve a score of 1.00 were subsequently identified through slack value analysis to determine the potential for input reduction without sacrificing output levels. Based on the simulation data findings, inefficiency in the majority of DMUs is dominated by significant slack values on the Turnaround Time (TAT) variable. Material processing durations that substantially exceed those of the efficient peer group benchmark were not offset by optimal Delivery Rate and Quality Rate achievements, positioning these suppliers below the efficiency frontier. These findings indicate that many suppliers still face serious constraints in lead time management, which directly impacts an overall reduction in technical efficiency scores.

Table 3. Average Efficiency Score and Slack Analysis per Supplier (January–December 2025)

Supplier	Avg. Score (θ)	TAT Slack (Days)	Delivery Slack (%)	Primary Root Cause (Systemic)
AISS	0.8978	0.6449	0.1203	Chronic constraints in processing duration and delivery timeliness.
APA	0.8680	0.6422	0.0557	Inefficiency in material processing duration (TAT).

Supplier	Avg. Score (θ)	TAT Slack (Days)	Delivery Slack (%)	Primary Root Cause (Systemic)
SIM	0.8729	0.5920	0.0318	Issues in logistics lead time and goods quality.
AAM	0.8799	0.6223	0.0087	Improvement focus on lead time management.
IMI	0.9013	0.5794	0.0176	Inefficiency in processing duration management.

The findings regarding stability and the root causes of inefficiency carry highly critical managerial implications for PT XYZ. Given that all 25 suppliers are nominated suppliers directly designated by the OEM, PT XYZ has limited bargaining power to unilaterally terminate contracts even when supplier performance is suboptimal. The efficiency fluctuation data and slack analysis therefore serve as an objective, quantitatively-grounded early warning system. This information provides a solid foundation for the purchasing department to conduct monthly vendor evaluations aimed at mitigating late delivery risks that could disrupt the main production flow. Through this approach, the company can direct strategic dialogue with the OEM based on real data to drive systematic supplier performance improvement, without undermining the established partnership relationships.

4. Conclusion

This study successfully analyzed the technical efficiency and performance stability of 25 nominated suppliers at PT XYZ throughout 2025, using an input-oriented BCC DEA time-series approach. Based on the analysis of 300 DMU observations, it can be concluded that the technical efficiency scores (θ) of the suppliers are highly fluctuating and dynamic. Not a single supplier was able to maintain a perfect efficiency level ($\theta = 1.00$) consistently every month. This confirms that the status of being an OEM-designated supplier does not automatically guarantee technical performance stability in practice.

The primary research finding reveals that the root cause of inefficiency in the majority of suppliers originates from large slack values on the Turnaround Time (TAT) variable. Material processing durations that exceed the peer group reference limits represent the main inhibiting factor, one that is not compensated for by optimal Delivery Rate and Quality Rate achievements. This indicates the existence of a significant improvement gap in suppliers' internal process time management systems, which in turn potentially threatens the sustainability of the company's Just-in-Time (JIT) production system.

From a managerial standpoint, the results of this analysis make an important contribution to PT XYZ as an objective and measurable vendor evaluation instrument. Despite its limited bargaining power over nominated suppliers, PT XYZ can leverage the efficiency fluctuation data and slack analysis as an early warning system to mitigate late delivery risks. Furthermore, these findings can serve as a real data-driven basis for the company to engage in strategic dialogue with the OEM, with the goal of driving systematic supplier performance improvement without disrupting established partnership relationships.

5. References

[1] M. Christopher, *Logistics and supply chain management: logistics & supply chain management*. Pearson UK, 2016.

[2] S. Chopra and P. Meindl, “Supply Chain Management. Strategy, Planning & Operation,” in *Das Summa Summarum des Management: Die 25 wichtigsten Werke für Strategie, Führung und Veränderung*, C. Boersch and R. Elschen, Eds., Wiesbaden: Gabler, 2007, pp. 265–275. doi: 10.1007/978-3-8349-9320-5_22.

[3] M. M. Abushaega, O. Y. Moshebah, A. Hamzi, and S. Y. Alghamdi, “Enhancing supply chain resilience with data envelopment analysis and temporal convolutional networks for supplier efficiency and late delivery risk prediction,” *Alexandria Engineering Journal*, vol. 128, pp. 231–246, Sep. 2025, doi: 10.1016/j.aej.2025.05.062.

[4] R. S. Kaplan and D. P. Norton, *The balanced scorecard: measures that drive performance*, vol. 70. Harvard Business Review Boston, MA, USA, 2005.

[5] 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, 1978.

[6] P. Dutta, B. Jaikumar, and M. S. Arora, “Applications of data envelopment analysis in supplier selection between 2000 and 2020: a literature review,” *Ann. Oper. Res.*, vol. 315, no. 2, pp. 1399–1454, Aug. 2022, doi: 10.1007/s10479-021-03931-6.

[7] K. Fotova Čiković, I. Martinčević, and J. Lozić, “Application of Data Envelopment Analysis (DEA) in the Selection of Sustainable Suppliers: A Review and Bibliometric Analysis,” *Sustainability*, vol. 14, no. 11, p. 6672, May 2022, doi: 10.3390/su14116672.

[8] S. Chul Park and J. H. Lee, “Supplier selection and stepwise benchmarking: a new hybrid model using DEA and AHP based on cluster analysis,” *Journal of the Operational Research Society*, vol. 69, no. 3, pp. 449–466, Mar. 2018, doi: 10.1057/s41274-017-0203-x.

[9] R. Restrepo and J. G. Villegas, “Supplier evaluation and classification in a Colombian motorcycle assembly company using data envelopment analysis,” *Academia Revista Latinoamericana de Administración*, vol. 32, no. 2, pp. 159–180, Aug. 2019, doi: 10.1108/ARLA-04-2017-0107.

[10] M. Brandenburg and G. J. Hahn, “Financial performance and firm efficiency of automotive manufacturers and their suppliers: A longitudinal data envelopment analysis,” *Logistics Research*, vol. 14, no. 1, pp. 1–26, 2021.

[11] H. Zareian Beinabadi, V. Baradaran, and A. Rashidi Komijan, “Sustainable supply chain decision-making in the automotive industry: A data-driven approach,” *Socioecon. Plann. Sci.*, vol. 95, p. 101908, Oct. 2024, doi: 10.1016/j.seps.2024.101908.

[12] S. Lim and Y. Luo, “A SCOR-Based Two-Stage Network Range-Adjusted Measure Data Envelopment Analysis Approach for Evaluating Sustainable Supply Chain Efficiency: Evidence from the Korean Automotive Parts Industry,” *Sustainability*, vol. 17, no. 19, p. 8607, Sep. 2025, doi: 10.3390/su17198607.

[13] B. O. Babatunde, A. R. Tella, and T. T. Onewo, “Efficacy Of Suppliers Performance Evaluation In A Dynamic Business Environment Using Data Envelopment Analysis (Dea),” *Zbornik radova-Journal of Economy and Business*, p. 164, 2021.

[14] M. Goswami, Y. Daultani, F. T. S. Chan, and S. Pratap, “Assessing the impact of supplier benchmarking in manufacturing value chains: an Intelligent decision support system for original equipment manufacturers,” *Int. J. Prod. Res.*, vol. 60, no. 24, pp. 7411–7435, Dec. 2022, doi: 10.1080/00207543.2022.2075811.

[15] M. Dotoli, N. Epicoco, M. Falagario, and F. Sciancalepore, “A stochastic cross-efficiency data envelopment analysis approach for supplier selection under uncertainty,” *International Transactions in Operational Research*, vol. 23, no. 4, pp. 725–748, Jul. 2016, doi: 10.1111/itor.12155.

[16] M. Hashemi Tabatabaei and A. Bazrkar, “Providing a Model for Ranking Suppliers in the Sustainable Supply Chain Using Cross Efficiency Method in Data Envelopment Analysis,” *Brazilian Journal of Operations & Production Management*, vol. 16, no. 1, pp. 43–52, Mar. 2019, doi: 10.14488/BJOPM.2019.v16.n1.a4.

[17] M. Taleb, R. Khalid, M. Attallah, R. Ramli, and M. K. Mohd Nawawi, “Evaluating efficiency and ranking of suppliers using non-radial super-efficiency data envelopment analysis with uncontrollable factors,” *International Journal of Computer Mathematics: Computer Systems Theory*, vol. 8, no. 2, pp. 108–127, Apr. 2023, doi: 10.1080/23799927.2023.2193177.

[18] M. Izadikhah, R. Farzipoor Saen, R. Zare, M. Shamsi, and M. Khanmohammadi Hezaveh, “Assessing the stability of suppliers using a multi-objective fuzzy voting data envelopment analysis model,” *Environ. Dev. Sustain.*, vol. 27, no. 9, pp. 22005–22047, May 2022, doi: 10.1007/s10668-022-02376-6.

[19] A. Torres-Ruiz and A. R. Ravindran, “Use of interval data envelopment analysis, goal programming and dynamic eco-efficiency assessment for sustainable supplier management,” *Comput. Ind. Eng.*, vol. 131, pp. 211–226, 2019.

[20] M. J. Ramezankhani, S. A. Torabi, and F. Vahidi, “Supply chain performance measurement and evaluation: A mixed sustainability and resilience approach,” *Comput. Ind. Eng.*, vol. 126, pp. 531–548, 2018.

[21] R. D. Banker, A. Charnes, and W. W. Cooper, “Some models for estimating technical and scale inefficiencies in data envelopment analysis,” *Manage. Sci.*, vol. 30, no. 9, pp. 1078–1092, 1984.

[22] W. W. Cooper, L. M. Seiford, and K. Tone, *Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software*, vol. 2. Springer, 2007.

[23] A. Emrouznejad and G. Yang, “A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016,” *Socioecon. Plann. Sci.*, vol. 61, pp. 4–8, 2018.