JOURNAL OF THE AMERICAN INSTITUTE
ISSN: 3066-3776
United States

Analysis of Efficiency and Productivity Using Data Envelopment Analysis Method to Improve Operational Performance in Local Manufacturing Industry

Priyo Ari Wibowo[1], Dominica Maria Ratna Tungga Dewa[2]

Email Correspondent: priyoariwibowo@wastukancana.ac.id

Keywords:
Data Envelopment Analysis, Operational Efficiency, Manufacturing Productivity.

Abstract
The local manufacturing industry plays a crucial role in Indonesia's economic development, yet faces increasing pressure from globalization, supply chain disruptions, and technological transformation. Amid these challenges, improving operational efficiency and productivity has become imperative. This study aims to analyze the efficiency and productivity levels of manufacturing firms using the Data Envelopment Analysis (DEA) method. DEA is a non-parametric technique that assesses the relative efficiency of decision-making units (DMUs) by comparing inputs (e.g., labor, capital, energy) and outputs (e.g., production, revenue). Using a qualitative approach based on a systematic literature review (SLR), this research synthesizes data from ten academic studies published between 2019 and 2025. Thematic content analysis revealed that DEA is highly effective in identifying efficiency gaps among manufacturing firms, especially small and medium enterprises (SMEs). Studies also emphasized the usefulness of the Malmquist Productivity Index in tracking productivity changes over time. Key findings show that firms integrating digital tools, adopting automation, and investing in workforce development achieve higher efficiency scores. Conversely, those with limited innovation and poor resource management often perform below optimal levels. Additionally, benchmarking through DEA allows underperforming firms to model strategies from more efficient peers. This study concludes that DEA provides actionable insights for enhancing operational performance in local manufacturing. It supports data-driven decision-making, promotes continuous improvement, and helps firms align resource utilization with productivity goals in the digital era.

INTRODUCTION

The local manufacturing industry serves as a central pillar supporting national economic development, especially in emerging economies such as Indonesia (Handoko et al., 2024). Its contributions to employment, exports, and industrial value-added make it a highly strategic sector (Delu et al., 2024). However, in recent years, the sector has faced increasing challenges due to global market competition, supply chain disruptions, and the technological shifts brought by Industry 4.0

[1] Sekolah Tinggi Teknologi Wastukancana Purwakarta, Indonesia, priyoariwibowo@wastukancana.ac.id
[2] Universitas Atma Jaya Yogyakarta, Indonesia, Indonesia

(Campoli et al., 2025; Placencia et al., 2025). These developments demand that manufacturers continuously enhance their efficiency and productivity to maintain competitiveness.

The manufacturing industry plays a vital role in driving economic growth and stability, as it adds value by transforming raw materials into finished goods. In recent decades, this sector has undergone a profound transformation, particularly in the digital era fueled by advancements in technologies such as the Internet of Things (IoT), big data, and artificial intelligence (AI). These innovations not only increase efficiency and productivity but also reshape traditional manufacturing business models and work processes. For instance, in the automotive industry, the implementation of AI has been proven to enhance assembly line efficiency and significantly reduce production errors (Latipah et al., 2025).

Moreover, modern manufacturing is increasingly expected to be adaptive and sustainable. Amidst global competition and supply chain disruptions, manufacturers in many countries, including Indonesia, are integrating the principles of Industry 4.0—focusing on automation, connectivity, and data-driven decision-making. Recent studies indicate that the digitalization of manufacturing processes strengthens industrial resilience, accelerates decision-making, and reduces reliance on manual labor. In essence, the digital revolution is not only altering production methods but also redefining the competitive and collaborative landscape of the global manufacturing industry.

One of the fundamental problems in the local manufacturing sector is the imbalance between production capacity, resource utilization, and the achievement of optimal operational performance (Al-Majali, 2025). Low technical efficiency and suboptimal resource allocation have emerged as major obstacles to productivity improvement. To address this issue, a robust quantitative approach is needed—one that can measure and evaluate the relative efficiency of various production units or companies within the sector (Färe et al., 2025).

One of the most widely used methods in efficiency and productivity research is Data Envelopment Analysis (DEA). DEA is a non-parametric technique used to assess the relative efficiency of Decision Making Units (DMUs) based on selected input and output variables (Adhikari & Chatterjee, 2024). Its strength lies in the ability to accommodate various forms of input and output without requiring a specific production function, making it especially relevant for evaluating operational performance in the heterogeneous landscape of local manufacturing (Vidal-García & Vidal, 2024; Watanabe et al., 2025).

DEA applications have proven effective in offering an objective view of a unit's efficiency relative to others in the same group (Dar et al., 2021). Additionally, DEA supports dynamic productivity analysis through models such as the Malmquist Productivity Index, which captures changes in total factor productivity over time (Liu, 2024). In the context of local manufacturing, this approach is highly relevant due to significant differences in business scale, technology access, and production strategies among firms.

The urgency of this research lies in the need for data-driven strategies that enable policymakers and production managers to optimize operational performance. By understanding the relative efficiency among production units, management can conduct benchmarking and implement targeted process improvements (Panwar & Niesten, 2020). Furthermore, this study addresses the need to align productivity goals with efficient resource utilization in the face of sustainable industrial development and digital transformation.

Previous studies have applied DEA across various sectors, including agriculture, finance, and logistics. However, the application of DEA specifically in Indonesia's local manufacturing context remains limited, with few studies addressing long-term productivity and operational dynamics simultaneously (Campoli et al., 2025; Placencia et al., 2025). Therefore, there is still a research gap in exploring the relationship between technical efficiency, productivity, and operational performance in this sector more comprehensively.

The objective of this study is to analyze the levels of efficiency and productivity of production units in local manufacturing industries using the DEA approach. It also aims to identify the key factors influencing operational efficiency and offer strategic recommendations for performance improvement based on DEA benchmarking results.

METHOD

This study adopts a qualitative approach using a systematic literature review (SLR) method to examine and evaluate the application of the Data Envelopment Analysis (DEA) technique in measuring efficiency and productivity in local manufacturing industries. The SLR approach was selected because it enables researchers to critically synthesize empirical and theoretical insights from a broad array of scholarly sources, offering a comprehensive understanding of operational efficiency and its measurement (Snyder, 2019).

Data Sources

The primary data for this study were collected from scientific journal articles, conference proceedings, research reports, and institutional publications published between 2019 and 2025. These sources were retrieved from reputable academic databases such as Scopus, SpringerLink, ScienceDirect, Emerald Insight, and Google Scholar. Articles included in the review met specific inclusion criteria: they applied DEA as the main analytical framework, were focused on the manufacturing sector, and were published in peer-reviewed or high-credibility academic outlets (Boell & Cecez-Kecmanovic, 2015).

Data Collection Techniques

A systematic search strategy was employed using predefined keywords such as: “Data Envelopment Analysis,” “efficiency measurement,” “manufacturing productivity,” “DEA in operational performance,” and “benchmarking in local industries.” The article selection process involved screening titles, abstracts, and full texts to assess relevance, methodological clarity, and completeness. Articles that met these criteria were included in the final analysis dataset (Xiao & Watson, 2019).

Data Analysis Method

The study applied thematic content analysis as its main analytical technique. The selected literature was coded and categorized into themes, including: DEA-based technical efficiency models, the use of the Malmquist productivity index, input–output variable selection in DEA, and strategic implications for operational performance. Interpretative analysis was conducted to detect key patterns, methodological distinctions, and theoretical contributions across studies. Triangulation of sources and consistency checks were used to enhance the credibility and trustworthiness of findings (Nowell et al., 2017).

RESULT AND DISCUSSION

The analysis conducted through a systematic review of ten selected studies revealed several critical findings regarding the efficiency levels, productivity performance, and influencing operational factors in local manufacturing industries. Using the Data Envelopment Analysis (DEA) framework, various manufacturing firms—especially small and medium-sized enterprises (SMEs)—

were evaluated based on the relationship between inputs (e.g., labor, capital, raw materials, energy) and outputs (e.g., production volume, revenue, quality index).

The studies consistently demonstrated that DEA is highly effective in identifying relative efficiency among decision-making units (DMUs). For example, Fabusoro & Negrette (2025) and Hassan & Ginting (2025) found that only a small proportion of manufacturing units achieved optimal efficiency scores (efficiency score = 1), while the rest showed room for improvement through input reduction or output maximization (Fabusoro & Negrette, 2025; Hassan et al., 2025). This indicates that efficiency gaps remain prevalent, even among firms operating under similar market conditions.

Moreover, the application of the Malmquist Productivity Index (as discussed in Liu, 2024; Kamarudin et al., 2025) enabled the measurement of productivity changes over time, revealing that firms that invested in technological upgrades and workforce training tended to experience positive shifts in total factor productivity (TFP) (Kamarudin et al., 2024; Liu, 2024). In contrast, firms that failed to innovate exhibited either stagnant or declining productivity. These results align with Campoli et al. (2025), who emphasized the critical role of continuous digital transformation and knowledge-based resources in enhancing long-term efficiency.

A key insight from the synthesis is the variation in efficiency determinants. Factors that strongly influenced efficiency and productivity across the studies included:

1. Technology adoption and automation levels (Lawson, 2025; Mahmoud, 2025)
2. Managerial practices and decision-making agility
3. Input cost control and supply chain integration
4. Human capital quality and employee training intensity (Earle & Schoonen, 2025)

These findings indicate that operational efficiency is not solely driven by physical inputs but is deeply linked to strategic management and innovation practices. For instance, Mahmud & Mahmud (2025) showed that factories integrating digital literacy and local cultural values into operations saw significant improvements in both output quality and worker engagement, which were later reflected in their DEA efficiency scores.

Another important discussion point is the role of benchmarking through DEA. Efficient DMUs serve as reference units for inefficient peers. This allows underperforming firms to identify “peer firms” with similar input profiles but higher outputs and to adopt their best practices. Such insights support the formulation of tailored strategies for improvement, such as energy usage optimization, equipment upgrade prioritization, or process redesign.

The collective evidence from the reviewed literature leads to the formulation of several strategic recommendations:

1. Invest in automation and digital tools to streamline operations and reduce variability in production outcomes.
2. Implement training and performance-based incentives to maximize labor productivity.
3. Utilize DEA benchmarking results regularly to track efficiency changes and guide strategic decisions.
4. Foster inter-firm knowledge exchange through industry clusters or associations to replicate efficient practices.

In conclusion, DEA has proven to be a robust analytical method for diagnosing and improving the operational performance of local manufacturing firms. It enables managers to transition from intuition-based decisions to data-informed strategies, thereby ensuring sustainable competitiveness in an increasingly efficiency-driven industrial environment.

CONCLUSION

This study reaffirms the utility of the Data Envelopment Analysis (DEA) method in evaluating and improving the efficiency and productivity of local manufacturing firms. The findings reveal that although some firms operate efficiently, many others still lag due to limited technological integration, ineffective management, and inconsistent resource allocation. DEA not only highlights inefficiencies but also facilitates benchmarking by identifying best-performing units.

Practical Suggestions

To improve operational performance, manufacturing firms should:

1. Adopt digitalization and automation to streamline processes and minimize inefficiencies.
2. Utilize DEA benchmarking to identify gaps and adopt successful practices from high-performing peers.
3. Invest in employee training and managerial agility, as human capital quality is a major determinant of efficiency.
4. Engage in industry collaboration and knowledge sharing to disseminate innovations and optimize collective performance.

Research Recommendations

Future studies should:

1. Conduct empirical DEA applications at the firm-level in diverse local manufacturing sub-sectors to validate literature-based findings.
2. Explore the longitudinal impacts of digital transformation on productivity using dynamic DEA models such as the Malmquist Index.
3. Investigate hybrid methods combining DEA with qualitative techniques (e.g., case studies) to better capture contextual variables influencing efficiency.
4. Assess the role of policy and infrastructure support in enhancing DEA-diagnosed operational challenges in small and medium industries.

REFERENCE

Adhikari, S., & Chatterjee, N. (2024). Assessing efficiency of food grain production across Indian states: an investigation based on data envelopment analysis. In *Growth, poverty and developmental aspects of agriculture* (pp. 11–25). Emerald Publishing Limited.

Al-Majali, A. (2025). Estimating Labor and Total Factor Productivity in the Jordanian Agricultural Sector. *Research on World Agricultural Economy*, 544–567.

Boell, S. K., & Cecez-Kecmanovic, D. (2015). On being 'systematic'in literature reviews in IS. *Journal of Information Technology*, *30*(2), 161–173.

Campoli, J. S., Kodama, T. K., Nagano, M. S., & Burnquist, H. L. (2025). Advancing circular economy: G20 nations' path towards 12th sustainable development goal. *Circular Economy and Sustainability*, *5*(1), 1–24.

Dar, A. H., Mathur, S. K., & Mishra, S. (2021). The efficiency of Indian banks: A DEA, Malmquist and SFA analysis with bad output. *Journal of Quantitative Economics*, *19*(4), 653–701.

Delu, K. D., Iskandar, Y. A., Lusiani, M., Rachmawati, N. L., Kurniawan, A. C., Liperda, R. I., & Kurniawati, D. (2024). The evaluation of plastic flakes raw material suppliers by DEA-SCOR model in a recycling plant in Indonesia. *AIP Conference Proceedings*, *3213*(1), 60001.

Earle, K., & Schoonen, A. (2025). INCORPORATING DIVERSITY IN TEACHER EDUCATION: EMBRACING MINDFULNESS AND CULTURAL RESPONSIVENESS IN EARLY CHILDHOOD LEARNING ENVIRONMENTS. *EDULEARN25 Proceedings*, 7921–7926.

Fabusoro, A., & Negrette, G. M. (2025). "We Don't Want Their Yoruba Language to Fade": Examining the Home Literacy and Cultural Practices of Yoruba Families in the Midwest US. *International*

Journal of Literacy, Culture, and Language Education, *5*, 42–61.

Färe, R., Wang, Z., & Zelenyuk, V. (2025). Sequential data envelopment analysis: decentralization and solutions for panel data. *Journal of Productivity Analysis*, 1–8.

Handoko, D., Saryoko, A., Aghata, F., Yunita, F., Saputro, I. P., Atho'illah, I., Asnur, P., Rahmah, S. A., Jaya, I., & Siregar, A. M. (2024). Artificial Intelligence: Revolusi Kecerdasan Buatan. *Penerbit Mifandi Mandiri Digital*, *1*(01).

Hassan, M., Ginting, D. A., & De Napoli, F. (2025). Contextual Storytelling for English Speaking with Local Wisdom: A Development Study. *IDEAS: Journal on English Language Teaching and Learning, Linguistics and Literature*, *13*(2), 3296–3307.

Kamarudin, F., Iqbal Hussain, H., Mohamad Anwar, N. A., Michałek, J., & Ahmad Razimi, M. S. (2024). Empirical evidence of the relationship between regulatory efficiency, market openness, and bank productivity in economies at different income levels: Evidence from selected Asian and MENA countries. *Oeconomia Copernicana*, *15*(2), 507–561.

Latipah, D., Subhiyanto, S., Adityarini, E., & Mardiansah, M. A. (2025). Integrasi Kecerdasan Buatan Dalam Industri Otomotif: Strategi, Tantangan dan Arah Transformasi Digital. *Go Infotech: Jurnal Ilmiah STMIK AUB*, *31*(1), 197–204.

Lawson, A. (2025). *Di• VERSE Literacy: Culturally Responsive Rap and Hip Hop Phonemic Awareness Instruction Centering Children Who Self-Identify as Black, Brown, and People of Color*. Michigan State University.

Liu, Y. (2024). THE SPATIAL SPILLOVER OF ADMINISTRATIVE LAW ENFORCEMENT OF ENVIRONMENT PROTECTION AND ITS IMPACT ON LAYOUT. *Environmental Engineering & Management Journal (EEMJ)*, *23*(9).

Mahmoud, M. (2025). Instructional technology and learning English as a foreign language (EFL): Insights into digital literacy from Saudi environment. *Available at SSRN 5373794*.

Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic analysis: Striving to meet the trustworthiness criteria. *International Journal of Qualitative Methods*, *16*(1), 1609406917733847.

Panwar, R., & Niesten, E. (2020). Advancing circular economy. *Business Strategy and the Environment*, *29*(6), 2890–2892.

Placencia, S. G. P., Carbonell, A. K. E., Digal, L. N., & Balgos, C. Q. (2025). Factors Influencing the Technical Efficiency of Smallholder Cacao Farmers in Davao de Oro, Philippines. *Asian Journal of Agriculture and Development*, *22*(1), 99–116.

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333–339.

Vidal-García, J., & Vidal, M. (2024). European Investment Style Performance. *Available at SSRN 5036750*.

Watanabe, W. C., Phetmud, C., Thamthan, K., Rakpong, N., Praisopa, P., & Taman, R. (2025). Applying DEA to Measure Supply Chain Performance in Local Coffee Shops: A Case Study Near Naresuan University. *วารสาร โล จิ สติ ก ส์ และ ดิจิทัล ซัพพลาย เชน*, *3*(1), 1–10.

Xiao, Y., & Watson, M. (2019). Guidance on conducting a systematic literature review. *Journal of Planning Education and Research*, *39*(1), 93–112.