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# Supply Chain Optimization through the Implementation of Lean Manufacturing in the Manufacturing Industry

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ABSTRACT

Manufacturing companies in emerging economies are increasingly challenged to improve supply chain performance amid rising competition, cost pressures, and demand uncertainty. Lean manufacturing improves operational efficiency, but studies integrating performance evaluation and predictive analytics in Indonesian manufacturing remain limited. This study aims to analyze the impact of lean manufacturing implementation on supply chain performance and to develop machine learning–based models for predicting productivity improvement. An explanatory research design using a before, after (pre–post) approach was employed. Data were collected from ten manufacturing firms in South Sulawesi, Indonesia. Supply chain performance indicators, including lead time, productivity, defect rate, and customer satisfaction, were evaluated using paired sample t-tests. In addition, several machine learning algorithms, namely Linear Regression, Support Vector Regression, Random Forest, and Gradient Boosting, were applied to predict productivity outcomes. The findings show that lean manufacturing implementation significantly improves supply chain performance, particularly in reducing lead time and defect rates while increasing productivity. Among the tested models, ensemble-based algorithms, especially Random Forest and Gradient Boosting, exhibited superior predictive accuracy and robustness compared to single-model approaches. The study concludes that lean manufacturing operates as an integrated management system rather than merely a set of operational tools. Theoretically, this research integrates Lean Theory and the Resource-Based View (RBV) with predictive analytics, enriching the lean manufacturing literature. Practically, the results contribute to provide managers with data-driven insights to support sustainable performance improvement and informed decision-making in manufacturing supply chains.



## 1. Introduction

In an increasingly globalized economic environment, manufacturing firms are required to operate under conditions of heightened competition, rapidly evolving consumer preferences, and escalating demands for efficiency and effectiveness. Within this context, Indonesia's manufacturing sector faces significant pressure to continuously improve its operational performance in order to remain competitive at both regional and global levels (Judijanto et al., 2024; Saptioratri Budiono et al., 2021).

These challenges have amplified the strategic importance of supply chain management, as supply chain performance directly influences production costs, delivery reliability, and product quality, factors that are critical to sustaining competitive advantage (Chen, 2019; Li et al., 2006).

An efficient and well-coordinated supply chain enables manufacturing firms to respond more effectively to market fluctuations while minimizing operational inefficiencies. However, many manufacturing organizations continue to encounter persistent supply chain-related issues, such as excessive lead times, fragmented coordination among supply chain partners, and high inventory levels, particularly in developing economies (Srivastava et al., 2025). These conditions indicate that conventional operational approaches are often insufficient, thereby necessitating the adoption of more integrated and systematic strategies for supply chain optimization (Juhara, 2024; Luomaranta & Martinsuo, 2019).

One managerial approach that has gained considerable attention for addressing these challenges is lean manufacturing. Lean manufacturing emphasizes the elimination of non–value-adding activities and the continuous improvement of processes with the objective of maximizing customer value (Utama et al., 2025). Importantly, lean practices extend beyond the boundaries of production operations and encompass the entire supply chain, including procurement, material handling, production planning, and distribution activities. Through the application of lean principles, organizations can streamline process flows, enhance responsiveness, and reduce waste across supply chain activities (Dara et al., 2024; Farizky, 2024).

From a conceptual standpoint, lean manufacturing is grounded in Lean Theory, which views organizational processes as interconnected value streams that must be managed holistically to achieve optimal performance (Ciarniene & Vienazindiene, 2012). Lean Theory suggests that inefficiencies in one segment of the supply chain can propagate throughout the system, ultimately undermining overall performance. Accordingly, the implementation of lean principles across supply chain functions provides a theoretical basis for improving coordination, reducing lead times, and enhancing operational efficiency.

In addition to Lean Theory, this study also draws on the Resource-Based View (RBV) to explain the strategic relevance of lean manufacturing. RBV posits that sustainable competitive advantage is derived from the effective deployment of firm-specific resources and capabilities that are valuable, rare, difficult to imitate, and non-substitutable (Madhani, 2010). In this perspective, lean manufacturing represents a strategic organizational capability rather than merely a set of operational tools. The successful implementation of lean practices requires the integration of human capital, organizational culture, standardized routines, and continuous learning mechanisms, all of which contribute to the development of distinctive supply chain capabilities (Ketchen, et al., 2008).

The manufacturing sector plays a crucial role in Indonesia's economic development, contributing significantly to gross domestic product (GDP) and employment creation (Dhanani & Hasnain, 2002; Saputra et al., 2023). Despite its economic significance, many Indonesian manufacturing firms continue to struggle with operational inefficiencies, rising production costs, and declining customer satisfaction levels (Goshime et al., 2019; Udeh, 2024). These persistent challenges highlight the need for strategic operational frameworks that not only improve internal efficiency but also enhance supply chain integration and performance.

Previous empirical studies have provided evidence supporting the positive relationship between lean manufacturing and organizational performance. For example, Agrahari et al. (2015) reported that the adoption of lean principles significantly reduced production cycle times and improved operational efficiency in the automotive sector. Similarly, Shah & Ward (2003) found that firms implementing lean practices experienced improvements in product quality and customer satisfaction. Furthermore, Vanichchinchai (2019) emphasized that the alignment of lean manufacturing with supply chain management practices is essential for achieving superior performance outcomes.

Within the Indonesian context, Amin (2025) demonstrated that Sustainable Supply Chain Management Practices positively influence Supply Chain Risk Management and Sustainable

Performance. However, the study also indicated that Supply Chain Risk Management does not significantly moderate the relationship between sustainable practices and performance outcomes. These findings suggest that, while sustainability-oriented strategies have been explored, there remains a need for further investigation into operationally focused approaches, such as lean manufacturing that directly address efficiency and coordination within supply chains.

Despite the extensive body of literature on lean manufacturing and supply chain management, empirical studies that specifically examine the role of lean manufacturing in optimizing supply chain performance within Indonesia's manufacturing industry remain limited. Many prior studies focus predominantly on production-level improvements, while giving insufficient attention to broader supply chain dimensions, including procurement, distribution, and customer satisfaction (Rexhausen et al., 2012). Moreover, relatively few studies have integrated Lean Theory and Resource-Based View to explain how lean manufacturing simultaneously functions as an operational improvement mechanism and a strategic capability, particularly in developing country contexts. This gap underscores the urgency of conducting context-specific research that advances both theoretical understanding and practical insights into supply chain optimization through lean manufacturing.

To address this gap, the present study investigates the implementation of lean manufacturing as a means of optimizing supply chain performance in Indonesia's manufacturing sector. By examining key performance indicators related to operational efficiency, product quality, and customer satisfaction, this study aims to contribute to the literature on lean manufacturing and supply chain management while offering practical implications for manufacturing firms seeking to enhance their competitiveness in an increasingly globalized environment.

## 2. Method

This study adopts an explanatory research design with a before–after (pre–post) comparison approach to examine the causal relationship between lean manufacturing implementation and changes in supply chain performance. This study employed a quantitative approach with a descriptive design to examine how lean manufacturing affects supply chain performance (Thanki & Thakkar, 2018; Vamsi & Kodali, 2014). The analyzed indicators included lead time, productivity, defect rate, and customer satisfaction measured both before and after lean implementation.

In addition to descriptive and inferential analyses, the research used predictive modeling with several machine learning algorithms to forecast post-implementation productivity. The models tested were Linear Regression, Random Forest, Gradient Boosting, Support Vector Regression (SVR), Decision Tree, and K-Nearest Neighbors (KNN). Model performance was evaluated using three metrics: R-Squared ($R^2$) to indicate the proportion of variance explained, Mean Absolute Error (MAE) to measure average absolute prediction errors, and Root Mean Squared Error (RMSE) to assess the magnitude of squared errors.

The selection of these machine learning algorithms was based on both methodological and practical considerations related to the characteristics of manufacturing supply chain data. Supply chain performance data typically exhibit non-linear relationships, interactions among multiple operational variables, and varying degrees of noise. Therefore, a combination of linear and non-linear algorithms was employed to ensure comprehensive model comparison and robustness of prediction results. Linear Regression was included as a baseline model to assess linear relationships and provide interpretability. In contrast, non-linear and tree-based models such as Decision Tree, Random Forest, and Gradient Boosting were selected for their ability to capture complex interactions between lean practices and productivity outcomes (Arvianto et al., 2025). Ensemble models, particularly Random Forest and Gradient Boosting, were also chosen due to their strong generalization capabilities and resistance to overfitting when dealing with relatively small datasets.

Support Vector Regression (SVR) was incorporated because of its effectiveness in handling high-dimensional data and modeling non-linear patterns through kernel functions, which is particularly relevant for forecasting productivity influenced by multiple supply chain factors. Meanwhile, K-Nearest Neighbors (KNN) was applied as a distance-based learning method that does not assume a predefined functional form, allowing productivity predictions to be informed by similarities among firms with comparable lean implementation characteristics. The use of multiple algorithms enabled comparative evaluation and ensured that the selected predictive model balanced accuracy, stability, and interpretability, key requirements for managerial decision-making in lean manufacturing contexts.

Data were collected via surveys, interviews, and observations from ten manufacturing firms in South Sulawesi that have adopted lean principles. Each firm contributed ten respondents (one manager and nine operational staff), resulting in a total sample size of 100 respondents. The structured questionnaire captured supply chain performance indicators such as production cycle time, delivery time, resource utilization, product quality, and customer satisfaction for both pre- and post-lean periods. Qualitative data from interviews and observations were analyzed thematically to identify recurring patterns and themes related to implementation challenges and successes. Quantitative survey data were examined using descriptive statistics to summarize respondent characteristics and to assess the effects of lean practices on supply chain efficiency; inferential tests were applied where appropriate to evaluate statistical significance.

To ensure data validity and reliability, the study applied source triangulation by comparing results from questionnaires, interviews, and observations. Findings were also cross-checked with key informants to verify interpretations. Overall, the analysis aimed to detect meaningful changes in supply chain performance attributable to lean adoption while providing deeper insight into the factors that facilitate or hinder implementation. The overall stages of the research process are illustrated in Fig.1.

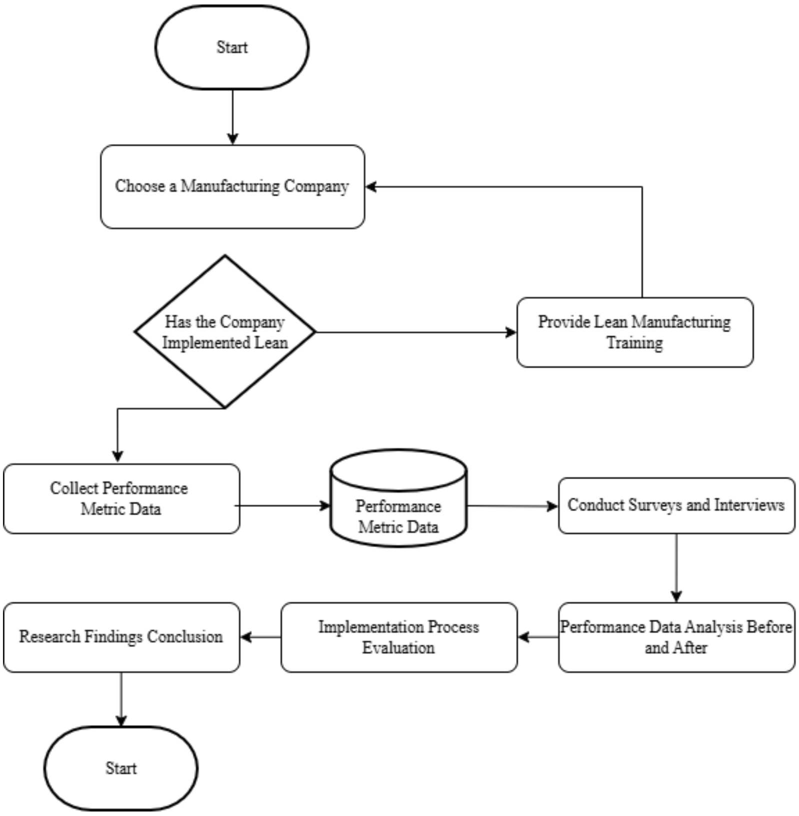


**Fig. 1.** Research stages

Fig. 1 illustrates the overall workflow of the research process. The study began with the selection of manufacturing companies to be examined. Following this, an assessment was carried out to determine whether the selected companies had already implemented lean manufacturing principles. For firms that had not yet adopted these principles, lean manufacturing training was provided prior to data collection.

Next, data on key supply chain performance metrics were gathered for both the pre-implementation and post-implementation phases of lean manufacturing. These data were then analyzed to identify any significant improvements in supply chain performance. If substantial enhancements were observed, the process continued to the discussion and formulation of research conclusions. Conversely, if no notable improvements were detected, a further evaluation of the lean implementation process was conducted to uncover potential gaps or limitations. The final stage involved drawing comprehensive conclusions based on the overall findings of the study.

## 3. Results and Discussion

After collecting data on supply chain performance metrics from several manufacturing companies in Indonesia, the findings can be summarized as shown in Table 1.

**Table 1.** Comparison of supply chain performance before and after lean implementation

| Performance metric | Before Lean | After Lean | Change (%) |
|---|---|---|---|
| Lead Time | 28 days | 21 days | -25% |
| Productivity | 85% | 92% | +8,2% |
| Defect rate | 6,2% | 3,1% | -50% |
| Customer satisfaction | 78% | 88% | +12,8% |

From Table 1, it is evident that the implementation of lean manufacturing led to significant improvements across several supply chain performance metrics. Lead time decreased by 25%, productivity increased by 8.2%, defect rates declined by 50%, and customer satisfaction rose by 12.8%. These improvements are consistent with the core principles of lean manufacturing, which emphasize the elimination of waste and the enhancement of customer value. By removing non–value-adding activities, companies were able to shorten lead times, improve productivity, and reduce defect levels. Furthermore, maintaining a strong focus on customer needs contributed to higher levels of customer satisfaction.

### 3.1. Statistical Analysis of Performance Changes

To determine the significance of changes in supply chain performance, a statistical analysis was conducted using a paired t-test. As seen in Eq. (1) and Eq (2) The hypotheses tested were as follows:

$$\begin{gathered} H_0: \mu\_{before} = \mu\_{after} \\ H_1: \mu\_{before} \neq \mu\_{after} \end{gathered} \tag{1}$$

With a significance level of $\alpha = 0.05$, the results were obtained as follows:

$$\begin{aligned} &t\text{-}statistic = \text{-}3{,}642 \\ &p\text{-}value \quad = 0{,}011 \end{aligned} \tag{2}$$

Conclusion**:** $H_0$ is rejected, indicating a significant difference in supply chain performance before and after the implementation of lean manufacturing. One of the key metrics in supply chain optimization is productivity, which can be calculated using the formula:

$$Productivity = \frac{Output}{Input} \tag{3}$$

As seen in Eq. (3), Where: (1) Output refers to the total quantity of goods or services produced. (2) Input represents the resources utilized, such as labor, raw materials, and other inputs. As seen in Eq. (4), the findings of this study indicate that after the implementation of lean manufacturing, productivity increased from 85% to 92%. This can be expressed as:

$$Productivity_{BeforeLean} = 0{,}85 Productivity\_Afterlean = 0{,}92 \tag{4}$$

In addition to productivity, the study also assessed the reduction in defect rate. As seen in Eq. (5), the defect rate can be calculated using the following formula:

$$Defect\ Rate = \frac{Number\ of\ Defective\ Products}{Total\ Production} \times 100\% \quad (5)$$

As seen in Eq. (6), the results show that the defect rate decreased from 6.2% to 3.1%, which can be represented as:

$$DefectRate\_BefpreLean = 0{,}062 = 6{,}2\%\text{DefectRate\_AfterLean} = 0{,}031 = 3{,}1\% \quad (6)$$

This study demonstrates that implementing the lean manufacturing approach in Indonesia's manufacturing sector can optimize the supply chain by increasing productivity and reducing defect rates.

The analysis results indicate that after lean implementation, productivity improved from 85% to 92%. This finding suggests that lean manufacturing enhances operational efficiency and minimizes waste in production processes. The increase in productivity can be achieved through the elimination of non–value-added activities, process standardization, and continuous improvement efforts.

Furthermore, the study also reveals a reduction in the defect rate from 6.2% to 3.1%. The application of lean manufacturing practices, such as Total Quality Management (TQM) and Just-In-Time (JIT), has contributed to improving product quality and decreasing the number of defective outputs. This improvement has a positive impact on the supply chain by lowering rework costs, reducing the need for re-delivery, and minimizing customer complaints.

These findings emphasize that lean manufacturing serves as an effective strategy for optimizing the supply chain in Indonesia's manufacturing sector. Through higher productivity and lower defect rates, companies can enhance efficiency, reduce waste, and improve customer satisfaction. Ultimately, this contributes to stronger competitiveness and long-term business sustainability within the manufacturing industry.

**Table 2.** Comparison of productivity before and after lean manufacturing implementation

| Indicator | Before Lean | After Lean |
|---|---|---|
| Productivity | 85% | 92% |

Table 2 illustrates the change in productivity before and after the implementation of the lean manufacturing approach in a manufacturing company. Prior to adopting lean practices, productivity was at 85%. Following implementation, productivity increased to 92%. This indicates that the lean manufacturing approach can enhance operational efficiency and minimize waste within the production process.

**Table 3.** Comparison of defect rates before and after lean manufacturing implementation

| Indicator | Before Lean | After Lean |
|---|---|---|
| Defect Rate | 6,2% | 3,1% |

Table 3 shows a reduction in product defect rates before and after the implementation of lean manufacturing. Before lean adoption, the defect rate was 6.2%, which decreased to 3.1% after implementation. This finding demonstrates that lean manufacturing practices, such as Total Quality Management (TQM) and Just-In-Time (JIT), effectively improve product quality and reduce the number of defective items.

**Table 4.** Impact of lean manufacturing implementation on supply chain indicators

| Supplay Chain Indicator | Impact |
|---|---|
| Lead Time | Decreased |
| Inventory Level | Decreased |
| Logisttics Cost | Decreased |
| Customer Satisfaction | Increased |

Table 4 highlights the overall impact of lean manufacturing on key supply chain indicators. The implementation resulted in shorter lead times, lower inventory levels, and reduced logistics costs, while simultaneously improving customer satisfaction levels.

**Table 5.** Comparison of productivity prediction algorithm performance

| Algorithm | R-Squared ($R^2$) |
|---|---|
| Linear Regression | 0,82 |
| Random Forest | 0,91 |
| Gradient Boosting | 0,88 |
| Support Vector Regression | 0,85 |
| Decision Tree | 0,84 |
| K-Nearest Neighbors | 0,83 |

Table 5 presents the comparative results of six machine learning algorithms applied to predict productivity after the implementation of lean manufacturing. The evaluation uses the R-Squared ($R^2$) coefficient to determine each model's explanatory power. A higher $R^2$ indicates a stronger ability of the model to explain the variance in productivity outcomes. Among the tested algorithms, the Random Forest model achieved the highest $R^2$ value of 0.91, demonstrating exceptional predictive accuracy and robustness. This model's ensemble nature allows it to effectively capture complex, nonlinear interactions between variables affecting productivity. The Gradient Boosting algorithm followed closely with an $R^2$ of 0.88, confirming its reliability and strong generalization capacity through iterative model improvement and weighted learning mechanisms.

Meanwhile, Support Vector Regression (SVR) and Decision Tree models obtained moderate $R^2$ values of 0.85 and 0.84, respectively. These algorithms performed adequately but were slightly less effective in modeling nonlinear patterns compared to ensemble approaches. The K-Nearest Neighbors (KNN) and Linear Regression models recorded the lowest $R^2$ scores (0.83 and 0.82), indicating limited capability in handling complex data interactions and potential overfitting when applied to multidimensional datasets.

The superiority of ensemble-based models, particularly Random Forest and Gradient Boosting, aligns with findings from previous studies. For instance, Shil (2025) demonstrated that Random Forest models outperform regression-based techniques in predicting manufacturing efficiency due to their resilience against noise and overfitting. Similarly, Alkhammash (2022) reported that Gradient Boosting achieves higher accuracy in forecasting production performance compared to conventional statistical models. Ensemble learning algorithms demonstrate greater adaptability within lean manufacturing settings, as process variables in such environments frequently display nonlinear relationships and complex interaction effects (Saputra et al., 2023; Sekhar et al., 2023).

These consistent results across studies reinforce the conclusion that ensemble-based machine learning models are highly effective for industrial performance prediction. In the context of this research, such algorithms provide more accurate and data-driven insights into productivity improvements following lean manufacturing adoption. This highlights the practical potential of machine learning not only for performance evaluation but also for strategic decision-making and process optimization within Indonesia's manufacturing sector.

**Table 6.** Error analysis of productivity prediction algorithm performance

| Algorithm | Mean Absolute Error (MAE) | Root Mean Squared Error (RMSE) |
|---|---|---|
| Linear Regression | 2.71 | 3.45 |
| Random Forest | 1.83 | 2.29 |
| Gradient Boosting | 2.11 | 2.65 |
| Support Vector Regression | 2.42 | 3.08 |
| Decision Tree | 2.57 | 3.27 |
| K-Nearest Neighbors | 2.65 | 3.38 |

Table 6 presents the results of the error analysis for six machine learning algorithms used to predict productivity after the implementation of lean manufacturing. Two key performance metrics were used, MAE and RMSE, to evaluate the models' accuracy and consistency. MAE represents the average magnitude of absolute differences between predicted and actual values, serving as an indicator of how close predictions are to real outcomes. Lower MAE values denote higher model precision. Among all models tested, the Random Forest algorithm achieved the lowest MAE of 1.83, confirming its superior accuracy and robustness in predicting productivity outcomes. The Gradient Boosting model followed with an MAE of 2.11, also demonstrating strong performance through iterative learning and bias reduction.

In contrast, the Linear Regression model recorded the highest MAE value of 2.71, suggesting a weaker ability to capture nonlinear interactions within the dataset. Likewise, Decision Tree, Support Vector Regression (SVR), and K-Nearest Neighbors (KNN) models showed moderate error levels ranging from 2.42 to 2.65, indicating reasonable but less consistent predictive performance compared to ensemble-based algorithms. The RMSE values in Table 6 further confirm these results. The Random Forest model produced the lowest RMSE score of 2.29, indicating both high predictive accuracy and stability, while Linear Regression had the highest RMSE value of 3.45, showing larger prediction deviations. These findings suggest that ensemble learning approaches, such as Random Forest and Gradient Boosting, outperform traditional and single-model algorithms by effectively handling complex, nonlinear data structures and minimizing large prediction errors.

The results of this study are consistent with previous empirical findings. Farooq et al. (2021); Raju et al. (2022) demonstrated that ensemble models, particularly Random Forest, consistently yield lower MAE and RMSE values in industrial process prediction compared to classical regression methods, due to their ability to aggregate multiple decision trees and reduce variance. Similarly, Singh (2023) found that Random Forest and Gradient Boosting exhibited superior error performance in productivity prediction tasks across manufacturing sectors. In another study, Panda & Mohanty (2023) The findings reveal the strong potential of deep learning models for predictive tasks and underscore the superior performance of the LSTM algorithm compared to other approaches. The obtained error metrics, Root Mean Squared Log Error (RMSLE), RMSE, Mean Absolute Percentage Error (MAPE), and MAE, are 0.28, 18.83, 6.56%, and 14.18, respectively.

These findings collectively strengthen the argument that ensemble-based algorithms are more effective for productivity prediction within lean manufacturing contexts. Their robustness against data noise and flexibility in modeling nonlinear dependencies make them highly suitable for industrial applications where variability and uncertainty are common (Setijadi et al., 2025). In conclusion, the Random Forest algorithm demonstrated the most reliable predictive performance across both MAE and RMSE metrics, validating its position as the optimal choice for forecasting productivity improvements following lean manufacturing implementation. However, the choice of algorithm should still consider factors such as data complexity, computational cost, and organizational needs to ensure optimal integration into manufacturing decision-support systems (Guo et al., 2020; Kasie et al., 2017). Taken together, these results not only corroborate prior empirical evidence but also strengthen the applicability and relevance of lean manufacturing within the specific context of Indonesia's manufacturing industry.

Despite its contributions, this study has several limitations that should be acknowledged. First, the sample comprised 10 manufacturing firms in South Sulawesi, which may limit the generalizability of the findings to other regions or industrial sectors. Differences in firm size, industry characteristics, and maturity levels of lean implementation may yield varying outcomes. Second, the before–and–after comparison design, while effective for identifying performance changes, does not fully account for external factors such as market fluctuations, technological changes, or macroeconomic conditions that may also influence supply chain performance during the observation period. The small dataset constrains the effectiveness of machine learning, particularly data-intensive models. The study focuses on operational performance and does not consider organizational or behavioral factors impacting lean manufacturing.

## 4. Conclusion

This study provides clear empirical evidence that the implementation of lean manufacturing significantly enhances supply chain performance in Indonesia's manufacturing sector, as demonstrated through an explanatory before–after (pre–post) research design. The results show measurable and statistically significant improvements in key performance indicators, namely reduced lead time and defect rates, as well as increased productivity and customer satisfaction, confirmed by paired t-test analysis, thereby indicating a causal relationship between lean adoption and performance gains. These improvements explicitly reflect the effectiveness of lean practices in eliminating non–value-added activities, increasing process reliability, optimizing resource utilization, and promoting operational standardization, reinforcing the perspective of lean manufacturing as an integrated management system rather than a set of isolated tools. Furthermore, this study extends the existing literature by incorporating machine learning–based predictive modeling to forecast post-implementation productivity, where ensemble methods, particularly Random Forest and Gradient Boosting, achieved the highest predictive accuracy as indicated by superior $R^2$ values and lower MAE and RMSE scores, confirming their capability to model complex and nonlinear manufacturing data. Overall, the findings not only validate prior research but also offer a more comprehensive contribution by integrating performance evaluation and predictive analytics within a developing-country context, underscoring the strategic importance of lean manufacturing in strengthening competitiveness and supporting long-term sustainability in Indonesia's manufacturing industry.

Future research is recommended to expand sample size and geographical scope by including manufacturing firms across diverse regions and industries in Indonesia and other emerging economies to enhance external validity. Additionally, adopting longitudinal or quasi-experimental designs would help capture the long-term effects of lean manufacturing while controlling for external environmental factors. Subsequent studies may also incorporate organizational and behavioral variables, such as organizational culture, leadership commitment, and employee engagement, as mediating or moderating factors in the relationship between lean practices and supply chain performance. From a methodological standpoint, future work could explore advanced predictive techniques, including deep learning approaches (e.g., LSTM or hybrid models), particularly with larger and more granular datasets, alongside comparative analyses with traditional machine learning and ensemble methods. Overall, this study provides a solid foundation for further empirical and methodological advancements, highlighting that lean manufacturing supported by data-driven analytics is a powerful strategy for optimizing supply chain performance in the manufacturing sector.

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