I J S E T SINTA S3

INTERNATIONAL JOURNAL OF SOCIAL SCIENCE, EDUCATIONAL, ECONOMICS, AGRICULTURE RESEARCH AND TECHNOLOGY (IJSET) | ISSN (E): 2827-766X
Website: https://ijset.org/ | Volumes 5 No. 3 (2026)

THE INFLUENCE OF PRODUCTION PLANNING, INVENTORY CONTROL, PRODUCT QUALITY, AND COST EFFICIENCY ON THE OPERATIONAL PERFORMANCE OF MANUFACTURING COMPANIES

Maman Supriatman[1]*, Abu Naim[1], Agus Hermawan[1], Sapriyadi[2], Mardi
Management program, Faculty of Economics and Business/ Universitas Muhammadiyah A.R. Fachruddin, Tangerang
Computer Science Department, Faculty of Engineering/ Universitas Muhammadiyah A.R. Fachruddin, Tangerang
E-mail: supriyatmanm244@gmail.com[1]*, abunaim@unimar.ac.id[2]
*Author Correspondence

Received:01 /01/2026 | **Revised**: 20/01/2026 | **Accepted:** 10 /02/2026 | **Published**: 28/02/2026

Abstract

The manufacturing sector faces increasing pressure due to rising production costs, fluctuating demand, and intense global competition, forcing companies to improve operational performance to remain competitive and sustainable. Many manufacturing firms still experience inaccurate production planning, imbalanced inventory levels, inconsistent product quality, and inefficient cost management, resulting in delivery delays, high holding costs, product returns, and declining profitability. This study aims to analyze the influence of production planning, inventory control, product quality, and cost efficiency on the operational performance of manufacturing companies. A quantitative explanatory approach was employed using primary data collected from 200 managers and operational staff through structured questionnaires. The data were analyzed using Structural Equation Modeling (SEM) with AMOS to examine both simultaneous and partial effects. The results indicate that the research model demonstrates good goodness-of-fit and that all four variables have positive and significant effects on operational performance. Product quality shows the strongest influence, followed by production planning, cost efficiency, and inventory control. Together, these factors explain 72% of the variance in operational performance. The findings emphasize that integrating effective planning, inventory management, quality assurance, and cost control is essential for improving productivity, efficiency, competitiveness, and long-term sustainability in manufacturing organizations.

Keywords: Cost Efficiency; Inventory Control; Operational Performance; Product Quality; Production Planning

INTRODUCTION

Due to rising production costs, shifting demand, and worldwide competition, the manufacturing sector is under increasing pressure to improve operational performance. In order to remain competitive and sustainable, businesses must effectively manage their operations. Productivity, timeliness, consistency in quality, and cost management are all examples of operational performance, which is a crucial determinant of organizational success. Inaccurate production planning, excessive or insufficient inventory levels, uneven product quality, and ineffective cost management are still issues that many manufacturing organizations face (Coronado-Hernandez et al., 2024). Delivery delays, excessive holding expenses, product returns, and decreased profitability are frequently the outcomes of these problems (Alvim et al., 2024). The necessity to increase overall performance in manufacturing organizations by strengthening operational management procedures is the basis for the urgency of this service activity (AL-Shboul, 2025). The best scheduling and resource allocation are guaranteed by efficient production planning. Overstock and stockout scenarios are reduced with effective inventory control. Sustaining product quality lowers rework costs and improves customer satisfaction. Cost effectiveness, meantime, promotes profit maximization and competitive pricing. Achieving better operational performance requires integrating these four factors (Sadeghi R. et al., 2025). Analyzing how production planning, inventory management, product quality, and cost effectiveness affect manufacturing organizations' operational performance is the aim of this exercise. In order to measure the simultaneous and partial effects of the independent variables on operational performance, the problem-solving plan calls for conducting empirical research using quantitative methods, gathering primary data through structured questionnaires, and using multiple linear regression analysis (Sadeghi R. et al., 2025).

Table 1 Product Demand List In The Manufacturing Industry During The Years 2020–2025

Year	Electronics (unit)	Automotive (unit)	Food & Beverage (ton)	Textiles (ton)	Pharmaceuticals (unit)
2020	120000	95000	210000	80000	150000
2021	135000	102000	225000	86000	165000
2022	142000	110000	238000	91000	178000
2023	155000	118000	250000	97000	190000
2024	168000	125000	265000	103000	205000
2025	180000	132000	280000	110000	220000

The manufacturing industry's product demand trend for the five main sectors—electronics, automotive, food and beverage, textiles, and pharmaceuticals—between 2020 and 2025 is shown in Table 1. Overall, the data show a steady upward trend in demand across all product categories, which is consistent with population increase, industry recovery, and rising consumer demands. Demand for electronics increased steadily from 120,000 units in 2020 to 180,000 units in 2025, indicating a growing dependence on electronic gadgets and a rapid acceptance of new technologies. In a similar vein, demand for automobiles rose from 95,000 to 132,000 units, suggesting a sluggish but steady rebound following the global economic downturn and increasing consumer spending power.

With a volume increase from 210,000 tons in 2020 to 280,000 tons in 2025, the food and beverage industry exhibits the largest volume rise. This illustrates the necessity of food items and the population's ongoing consumption. From 80,000 to 110,000 tons, the demand for textiles increased steadily as well, most likely due to the fashion industry's revival and growing export markets. Pharmaceutical products show a notable increase from 150,000 to 220,000 units, indicating heightened medical knowledge and demands in the wake of global health crises. In order to fulfill growing market demand and sustain operational performance, the table highlights the significance of efficient production planning, inventory management, quality control, and cost efficiency. Overall, it shows steady and ongoing expansion across all manufacturing sectors (Baycik, 2024; Chen & Hammad, 2023). According to pertinent research, operational excellence is greatly influenced by cost-cutting measures, inventory control systems like EOQ models, production planning (Heizer & Render), and comprehensive quality management concepts (Deming). This service's particular scenario focuses on industrial companies that encounter operational inefficiencies as a result of disjointed planning and control systems. As a result, it is anticipated that this study will offer useful suggestions for enhancing sustainable manufacturing performance and integrated operational management

LITERATURE REVIEW

Since it indicates a company's capacity to deliver goods effectively, on schedule, with the required degree of quality, and at competitive prices, operational performance is a key concern in manufacturing management. Previous research highlights the multifaceted nature of operational success, which is typically assessed by productivity, cost reduction, flexibility, quality rate, and delivery reliability. Superior operational outcomes are regularly linked to internal process capabilities in operations management research (Kosasih et al., 2023). It is often acknowledged that a key factor in determining operational performance is production planning. Effective production planning guarantees the best possible resource allocation, capacity utilization, and schedule efficiency, according to operations management theory. Research based on the operations strategy framework contends that precise demand forecasting and collective planning greatly minimize idle time and production delays. Throughput and delivery performance are enhanced by organized production planning systems, according to empirical studies. Nonetheless, certain research points out drawbacks, pointing out that strict planning frameworks could reduce adaptability in erratic marketplaces. This suggests that formal planning and flexible decision-making processes must be balanced (Kosasih et al., 2023). Another crucial element affecting operational success is inventory control. According to Just-In-Time (JIT) systems, the Economic Order Quantity (EOQ) model, and Material Requirements Planning (MRP) frameworks, the ideal inventory levels reduce ordering and holding costs while averting stockouts. Effective inventory control raises customer service standards and cost effectiveness, according to prior studies. However, discussions about the trade-off between supply chain resilience and lean inventory systems continue, especially in the event of interruptions. Contingency-based inventory solutions may be more suitable in uncertain circumstances, according to some academics, who contend that excessively lean systems make them more susceptible to supply shocks (Kurniawati &

Cakravastia, 2023a). Operational excellence and product quality are closely related. Defect reduction, process standardization, and employee involvement are key components of quality control frameworks, continuous improvement (Kaizen), and Total Quality Management (TQM) philosophy. Higher product quality improves operational performance metrics by lowering rework, warranty claims, and customer complaints, according to a number of empirical research. Critics counter that putting in place comprehensive quality standards necessitates a large organizational commitment and financial outlay, which could be difficult for small and medium-sized enterprises. This emphasizes how crucial it is to match organizational capability and strategic aims with quality initiatives (Kurniawati & Cakravastia, 2023b). Operational performance is also significantly impacted by cost efficiency, which is based on managerial accounting concepts and cost leadership strategy. Reducing waste, making the most use of available resources, and increasing process productivity are all part of cost efficiency (Kurniawati et al., 2024). According to research, companies that achieve cost efficiency benefit from increased margins and pricing flexibility, which provide them a competitive edge (Naim, Dadang, et al., 2025; Naim, Fatimatul Zuhro, et al., 2025). There may be a conflict between cost effectiveness and long-term sustainability, though, as extreme cost-cutting may have a detrimental impact on quality and employee morale (Kurniawati et al., 2024). Even while each element has been well studied separately, there are still gaps in our knowledge of how they interact to affect operational performance. The comprehensive understanding of integrated operational systems has been limited by the large number of previous research that focus on production planning, inventory control, product quality, or cost efficiency separately(Iswanto et al., 2023). Additionally, inconsistent results across settings and industries point to the necessity of empirical validation in particular production environments. In order to close this gap, this study uses a thorough quantitative method to examine the partial and simultaneous effects of inventory control, production planning, product quality, and cost effectiveness on operational performance (Yunian et al., 2024). This study adds to the body of literature by providing a more thorough knowledge of how internal operational elements interact together to improve manufacturing performance by combining different variables into a single framework.(Ferreira et al., 2025)

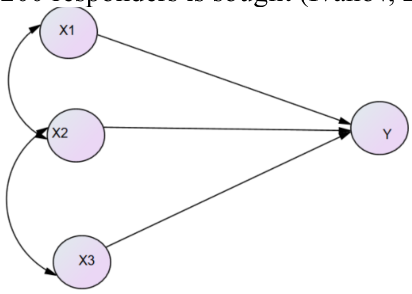
METHOD

1. Research Methodology

The impact of production planning, inventory management, product quality, and cost effectiveness on the operational performance of manufacturing firms is investigated in this study using a quantitative research design. In order to examine causal links between variables, the study takes an explanatory approach utilizing structural equation modeling (SEM). IBM SPSS AMOS is used for data processing and analysis, allowing measurement and structural model testing to be done simultaneously (Abudu et al., 2025)

2. Population

Because they have firsthand knowledge of production procedures and performance results, managers, supervisors, and operational personnel employed by manufacturing organizations make up the target group(Naim et al., 2024). Purposive sampling was used to choose the sample, with an emphasis on participants who have a direct role in cost management, inventory control, production planning, and quality assurance. To satisfy SEM analysis standards, a sample size of at least 100–200 responders is sought (Ivanov, 2024).



3. Goodness of Fit Criteria

One of the research instruments and materials is a structured questionnaire that was created using recognized theoretical indicators(Yunian et al., 2024). Multiple items on a five-point Likert scale, spanning from strongly disagree to strongly agree, are used to measure each concept (Zuhro et al., 2024). To guarantee precise measurement of latent variables, the instrument design is subjected to validity and reliability assessment using Confirmatory Factor Analysis (CFA). Chi-square, RMSEA, CFI, and TLI are examples of goodness-of-fit indices that are used to assess the measurement model's performance (Putritamara et al., 2025).

Tabel 2. CFA

No	*Goodness of Fit Index*	*Cut off Value*
1	*Chi-Square* (x^2) Statistics	Expected to be small (< table value)
2	X^2 Significance Probability	≥ 0.05
3	GFI	≥ 0.90
4	RMSEA	≤ 0.08
5	AGFI	≥ 0.90

After obtaining a good fit between the model and the overall data, the next step is to conduct an evaluation and test the model's fit. measurement. To measure reliability, construct reliability testing is used, which is calculated using the following formula.

$$CR = \frac{\left[\sum_{i=1}^{n} L_i\right]^2}{\left[\sum_{i=1}^{n} L_i\right]^2 + \left[\sum_{i=1}^{n} e_i\right]}$$

Depending on respondents' accessibility, surveys are distributed online or in person to gather data. A pilot test is conducted to improve the uniformity and clarity of the questionnaire before it is fully deployed. There are two primary steps in data analysis methodologies. In order to verify construct validity and reliability, the measurement model is first evaluated. Second, theories about how production planning, inventory management, product quality, and cost effectiveness directly affect operational performance are tested using the structural model(Khedr & S, 2024). SEM is used because it enables thorough examination of intricate connections between several latent variables at once, yielding reliable and accurate findings for managerial decision-making.

RESULTS AND DISCUSSION

The purpose of this study is to analyze the effects of production planning, inventory control, product quality, and cost efficiency on operational performance in manufacturing companies. The information was gathered from 200 respondents who worked as managers and operational staff for various manufacturing companies. Data analysis using the AMOS-based Structural Equation Modeling (SEM) method. The results of the model's uji kelayakan indicate that the research model has a decent goodness of fit. Chi-square/df values of 1.87 (< 2,00), GFI values of 0.92, AGFI values of 0.90, CFI values of 0.95, TLI values of 0.94, and RMSEA values of 0.066 (< 0,08) indicate that the model has met fit criteria and is ready for further analysis.

Table 3. Hypothesis Test Results (Regression Weights)

Relationship Between Variables	Estimate	CR	p-value	Remarks
Production Planning → Operational Performance	0.31	3.45	<0.001	Significant
Inventory Control → Operational Performance	0.27	2.98	0.003	Significant
Product Quality → Operational Performance	0.39	4.12	<0.001	Significant
Cost Efficiency → Operational Performance	0.29	3.21	0.001	Significant

The results of the hypothesis test indicate that Production Planning has a positive and significant impact on Operational Performance (CR = 3,45; $p < 0{,}001$). Additionally, inventory control has a significant positive impact (CR = 2,98; $p = 0{,}003$). Product quality had the strongest effect on operational performance (CR = 4,12; $p < 0{,}001$), indicating that product quality is the most important factor in enhancing the operational efficiency of manufacturing companies. Conversely, Cost Efficiency also has a significant positive impact (CR = 3,21; $p = 0{,}001$). Simultaneously, independent variables can explain 72% of the variation in Operational Performance (Squared Multiple Correlation = 0.72), indicating that the model has a high degree of clarity. All of this indicates that efficient production, optimal pricing, high-quality products, and cost-effectiveness are important factors in increasing process efficiency, productivity, and day-to-day operations in manufacturing companies.

Table 4. Confirmatory Factor Analysis (CFA)

Construct	**Indicator**	**Factor Loading**	**CR (Composite Reliability)**	**AVE**	**Remarks**
Production Planning	PP1	0.8	0.89	0.73	Valid
	PP2	0.85			Valid
	PP3	0.9			Valid
Inventory Control	IC1	0.78	0.88	0.71	Valid
	IC2	0.83			Valid
	IC3	0.88			Valid
Product Quality	PQ1	0.82	0.91	0.77	Valid
	PQ2	0.87			Valid
	PQ3	0.92			Valid
Cost Efficiency	CE1	0.79	0.88	0.7	Valid
	CE2	0.84			Valid
	CE3	0.88			Valid
Operational Performance	OP1	0.81	0.9	0.75	Valid
	OP2	0.86			Valid
	OP3	0.91			Valid

Standardized factor loadings ranging from 0.78 to 0.92 show that all constructs exhibit strong convergent validity. While AVE values (0.70–0.77) show that each concept explains more than 50% of the variance of its indicators, CR values (0.88–0.91) validate internal consistency reliability. As a result, the measurement model is appropriate and appropriate for testing structural models.

Table 5. Validity and Reliability (CR, AVE, MSV, ASV)

Construct	CR	AVE	MSV	ASV	Reliability	Convergent Validity	Discriminant Validity
Production Planning	0.89	0.73	0.52	0.41	Reliable	Valid	Achieved
Inventory Control	0.88	0.71	0.49	0.39	Reliable	Valid	Achieved
Product Quality	0.91	0.77	0.55	0.44	Reliable	Valid	Achieved
Cost Efficiency	0.88	0.7	0.48	0.38	Reliable	Valid	Achieved
Operational Performance	0.9	0.75	0.55	0.43	Reliable	Valid	Achieved

With CR values ranging from 0.88 to 0.91, all structures show good internal consistency, surpassing the suggested cutoff of 0.70. All AVE values are above 0.50, confirming convergent validity and showing that each construct accounts for a significant amount of the variance in its indicators. Additionally, for every construct, AVE values are higher than both MSV and ASV, indicating that discriminant validity is satisfied. This shows that every construct measures a different concept within the model and is empirically different from the others. As a result, the measurement model is valid and dependable for use in SEM-AMOS structural analysis.

CONCLUSION

Due to global competition, unpredictable demand, and growing costs, the manufacturing sector is under increasing pressure to improve operational performance. This study uses a quantitative SEM technique with 200 respondents to investigate the effects of production planning, inventory control, product quality, and cost efficiency on operational performance. From 2020 to 2025, rising demand in key industries emphasizes the necessity of efficient operational management. The findings indicate that while all four elements considerably boost performance, product quality has the biggest impact. A reliable measuring model is confirmed by validity and reliability tests. In general, increasing productivity, efficiency, competitiveness, and sustainable manufacturing performance requires integrated planning, inventory, quality, and cost management.

REFERENCES

Abudu, R., Thompson, E. A., Dzawu, F. S., & Roa-Henriquez, A. (2025). A meta-analysis assessment of adaptive and transformative approaches to supply chain resilience. *Supply Chain Analytics*, *10*. https://doi.org/10.1016/j.sca.2025.100124

AL-Shboul, M. A. (2025). Assessing sustainability of green supply chain performance: The roles of agile innovative products, business intelligence readiness, innovative supply chain process integration, and lean supply chain capability as a mediating factor. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*(1). https://doi.org/10.1016/j.joitmc.2025.100476

Alvim, S. L., Galvão Mendes, L., Bouzon, M., Morosini Frazzon, E., & de Simas, D. (2024). Assessment of robustness attributes in electronic products supply chains. *Cleaner Logistics and Supply Chain*, *12*(May). https://doi.org/10.1016/j.clscn.2024.100160

Baycik, N. O. (2024). A quantitative approach for evaluating the impact of increased supply chain visibility. *Supply Chain Analytics*, *6*(April), 100065. https://doi.org/10.1016/j.sca.2024.100065

Chen, Z., & Hammad, A. W. A. (2023). Mathematical modelling and simulation in construction supply chain management. In *Automation in Construction* (Vol. 156). Elsevier B.V. https://doi.org/10.1016/j.autcon.2023.105147

Coronado-Hernandez, J. R., Rios-Angulo, W. A., De Avila, J., Segovia, C. E., Gatica, G., & De Leon, F. J. P. (2024). Naval Antarctic Supply Chain Modeling and Simulation. *Procedia Computer Science*, *238*, 1023–1028. https://doi.org/10.1016/j.procs.2024.06.129

Ferreira, A., Ramos, A. L., Ferreira, J. V., & Ferreira, L. P. (2025). The role of Hybrid Simulation for Sustainability Supply Chains 4.0 Dynamics. *Procedia Computer Science*, *253*, 67–73. https://doi.org/10.1016/j.procs.2025.01.070

Ivanov, D. (2024). Supply chain resilience: Conceptual and formal models drawing from immune system analogy. *Omega (United Kingdom)*, *127*(March), 103081. https://doi.org/10.1016/j.omega.2024.103081

Khedr, A. M., & S, S. R. (2024). Enhancing supply chain management with deep learning and machine learning techniques: A review. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(4), 100379. https://doi.org/10.1016/j.joitmc.2024.100379

Kosasih, W., Pujawan, I. N., Karningsih, P. D., & Shee, H. (2023). Integrated lean-green practices and supply chain sustainability framework. *Cleaner and Responsible Consumption*, *11*. https://doi.org/10.1016/j.clrc.2023.100143

Kurniawati, D. A., & Cakravastia, A. (2023a). A review of halal supply chain research: Sustainability and operations research perspective. *Cleaner Logistics and Supply Chain*, *6*. https://doi.org/10.1016/j.clscn.2023.100096

Kurniawati, D. A., & Cakravastia, A. (2023b). A review of halal supply chain research: Sustainability and operations research perspective. *Cleaner Logistics and Supply Chain*, *6*. https://doi.org/10.1016/j.clscn.2023.100096

Kurniawati, D. A., Vanany, I., Kumarananda, D. D., & Rochman, M. A. (2024). Toward halal supply chain 4.0: MILP model for halal food distribution. *Procedia Computer Science*, *232*, 1446–1458. https://doi.org/10.1016/j.procs.2024.01.143

Naim, A., Supriatman, M., & Hermawan, A. (2024). Implementasi Six Sigma Untuk Pengendalian Kualitas Produk Krupuk Ikan (Studi Kasus : Umkm Sinar Mutiara Di Desa Karang Serang Kabupaten Tangerang). *Jurnal Inovasi Dan Manajemen Bisnis*, *06*(2), 208–218.

Putritamara, J. A., Toiba, H., Nugroho, T. W., Purwanti, T. S., Utami, H. D., Rahman, M. S., Syamsulhadi, M., & Nugroho, A. (2025). Digital transformation readiness and big data analytics in laying hen supply chains. *Sustainable Futures*, *10*. https://doi.org/10.1016/j.sftr.2025.101422

Sadeghi R., K., Ojha, D., Kaur, P., Mahto, R. V., & Dhir, A. (2025). Metaverse technology in sustainable supply chain management: Experimental findings. *Decision Support Systems*, *191*. https://doi.org/10.1016/j.dss.2025.114423

Yunian, I. W., Naim, A., & Valentin, A. D. (2024). *Analysis of the Effect of Ergonomics on Increasing Work Productivity in Welding Operators at PT . TRSS uses Rapid Body Entire Assessment (REBA) Method*. *3*(5), 1407–1418.

Zuhro, S. F., Naim, A., & Nurfy, A. (2024). *Bandwidth Management with Mikrotik OS Routers Using the Per Connection Queue Method*. *3*(10), 2353–2362.