Application of Artificial Intelligence in Production Planning and Supply Chain Management: Examining the Role of Machine Learning, Deep Learning, and Neural Networks in Optimizing Production Processes in the Electronics Industry of Iran

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Abstract

This research investigates the impact of artificial intelligence techniques, including machine learning, deep learning, and neural networks, on optimizing production processes in the electronics industry, focusing on companies based in Tehran. The research sample consisted of 243 managers and experts related to supply chain management within these companies. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the results indicated that each of these techniques positively and directly influences demand forecasting, inventory management, quality control, and cost reduction in production. The findings also highlight the importance of integrating these techniques to achieve synergistic effects and enhance overall production process performance. From a theoretical perspective, this study contributes to expanding the existing literature on the application of artificial intelligence in manufacturing and presents new models for examining the interactions of these techniques. On the other hand, the results are practical for managers in the electronics industry and other manufacturing sectors, enabling them to leverage artificial intelligence tools for process optimization, productivity enhancement, and cost reduction. Ultimately, this research demonstrates that artificial intelligence can act as a transformative factor in the manufacturing industry, guiding organizations toward sustainable competitiveness.

Keywords: *Supply Chain Management, Production Process Optimization, Artificial Intelligence, Machine Learning, Deep Learning, Neural Networks, Electronics Industry.*

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1. Introduction

The electronics industry, as one of the key sectors in the global economy, continually requires new and efficient solutions to optimize its processes due to high demand, rapid technological advancements, and the complexities of production. The increasing technological complexities in manufacturing electronic components, the pressure for continuous innovation, and the fluctuating demands of consumers have posed several challenges for this industry. In this context, the use of artificial intelligence (AI), particularly techniques such as machine learning, deep learning, and neural networks, can play a decisive role in enhancing productivity, improving quality, and reducing costs [1, 2]. Given the rapid development of these technologies and the adoption of AI techniques by large electronics companies, focusing on the application of these techniques for optimizing supply chain management and production planning has become an important area of both research and practice. Today, supply chain management (SCM) is influenced by various innovations, new technologies, and changes rooted in shifting company priorities and goals, as well as changes in the competitive environment, leading to increased complexity [3]. This complexity, especially in SCM, always requires the implementation of integrations, the selection of appropriate technologies for collaboration, and the establishment of profitable interaction practices. In fact, supply chains are referred to as arrangements of suppliers and customers where each customer can simultaneously be a supplier and vice versa, with each supplier potentially being a customer at higher levels. Consequently, a company needs to integrate its activities with its suppliers and customers for its survival. Although the use of new technologies in SCM is always faced with various challenges [4], previous research has also shown many benefits. For instance, Jeanneret Medina et al. (2024) state that AI applications in supply chains can reduce trust issues among chain members and enhance effectiveness [5]. In another study, Zimmerman et al. (2024) found that AI can foster innovation in supply chains [6].

In recent years, Iran's electronics industry has made efforts to adopt advanced technologies and smarten its production processes. However, this industry still faces challenges compared to global competitors. Infrastructure limitations, limited resources, and dependency on imported parts have further increased the need for optimizing production processes and reducing costs in Iran's electronics industry. In this context, AI and its advanced algorithms can assist Iranian electronics companies by providing data-driven solutions and optimizing production and supply chain processes, thereby improving productivity and enhancing their competitiveness in domestic and international markets. However, limited research has been conducted in the literature on the application of AI in SCM in developing countries like Iran. Notable studies in this field include research by Wong et al. (2020) in Malaysia and Meier et al. (2023) on blockchain applications in SCM in developing countries [7, 8]. This study aims to address this research gap by examining the applications of AI in SCM in electronics companies in Iran.

Based on the literature, one of the important AI techniques that can transform the electronics industry is machine learning [9]. Machine learning, by analyzing past data and identifying hidden patterns, can assist in various production and supply chain processes, from demand forecasting and inventory management to production line optimization. In fact, machine learning can prevent resource wastage and reduce production defects by improving the accuracy of forecasts and optimizing resource management. This technology, especially in the manufacturing of sensitive electronic components, which require high precision and constant monitoring, can have significant impacts on improving quality and reducing costs [10]. Deep learning, which leverages complex neural network structures, also holds a special place in advanced industries such as electronics [11, 12]. Deep learning can assist in identifying hidden patterns and relationships by analyzing massive and complex data, thus optimizing production planning and supply chain management. In the electronics industry, deep learning can be used to detect defects and errors in products, forecast seasonal demands, and even optimize assembly processes [13, 14]. Thus, electronics companies can achieve higher productivity and competitiveness by reducing costs associated with errors and increasing product quality. Additionally, based on previous studies, neural networks, as one of the most advanced AI techniques, offer a powerful and multi-layered structure for data processing, which in many cases can simultaneously process input data and produce accurate outputs [15]. Neural networks, especially in advanced and smart production processes, help electronics companies leverage complex processing and real-time data to efficiently manage processes such as production scheduling, energy optimization, and resource distribution [16]. In Iran's electronics industry, which faces resource limitations and demand fluctuations, neural networks can serve as a powerful tool for improving productivity and managing the supply chain intelligently.

The problem statement of this study is based on identifying the role and impact of AI techniques in improving production processes and supply chains in Iran's electronics industry, focusing on three techniques: machine learning, deep learning, and neural networks, which have not been studied before. One of the main challenges in the electronics industry is the need to reduce production time, increase productivity, and reduce waste. Along with the growing demand for high-quality and affordable products, the importance of optimizing production processes has become even more critical. This study focuses on electronics companies in Iran and aims to show, through detailed examination and analysis, the effectiveness of these techniques in improving and optimizing production processes. It also seeks to answer the question of how machine learning, deep learning, and neural networks influence the optimization of production processes, the most crucial part of SCM, in Iran's electronics industry. This research proposes three main hypotheses to answer this question. The first hypothesis states that the machine learning technique has a positive and direct impact on the optimization of production processes. This hypothesis examines the role of machine learning algorithms in improving productivity, reducing waste, and managing resources in the production of electronic components. The second hypothesis is based on the positive impact of deep learning on the optimization of production processes, focusing on how deep learning, by identifying hidden patterns in complex data, can assist in improving quality control and production management. The third hypothesis states that neural networks can have a positive and direct impact on optimizing production processes, and that this technology, by simulating production processes and optimizing scheduling and energy consumption, can play a crucial role in resource management. Ultimately, given the rapid advancements in AI technologies and the need for smartening production processes in various industries, this research can provide a better understanding of how AI can be effectively used in the electronics industry to optimize processes and improve competitiveness.

2. Methodology

This research is applied in nature, and its methodology is descriptive-analytical. It uses variance-based structural equation modeling (PLS-SEM) to examine the impact of machine learning techniques, deep learning, and neural networks on optimizing production processes. The reason for choosing PLS-SEM for this study is its suitability for analyzing complex models with relatively small sample sizes and its lack of requirements for data normality, making it ideal for predictive models and investigating causal effects. The statistical population of this study consists of 243 managers and experts from supply chain-related departments in electronic companies in Tehran. Given the characteristics of this population, the sampling method was purposive and based on access to individuals with sufficient experience and knowledge in supply chain and electronic production processes. Furthermore, the primary data collection tool in this research is a researcher-designed questionnaire, which is divided into two main sections: (1) The first section contains demographic questions to assess the respondents' demographic information, and (2) The second section includes questions related to the research hypotheses, designed to measure the various dimensions of machine learning, deep learning, and neural networks, and their impact on production process optimization. The questionnaire uses a five-point Likert scale (from strongly disagree to strongly agree) to assess the level of agreement or disagreement of respondents with each item. To evaluate the validity of the questionnaire, content validity and expert opinions in the fields of AI and SCM were used. After collecting feedback, the final questionnaire was reviewed, and 13 questions were finalized. Additionally, the reliability of the tool was assessed using Cronbach’s alpha coefficient, and for all constructs of the study, the Cronbach’s alpha coefficient was above 0.7, indicating adequate reliability of the tool.

For data analysis and hypothesis testing, variance-based structural equation modeling (PLS-SEM) was used. This method allows for the assessment of causal relationships between independent and dependent variables and is particularly suitable for predictive and exploratory models. In this study, data analysis is performed in two main stages:

- **Measurement Model Evaluation (Outer Model):** In this stage, the validity and reliability of the indicators and constructs of the study are examined. Indicators such as factor loadings, average variance extracted (AVE), and composite reliability are used to ensure the appropriateness of the measurement model.
- **Structural Model Evaluation (Inner Model):** In this stage, the research hypotheses and causal relationships between constructs are evaluated

through path coefficients, t-values, and R^2 values. The results of the structural model help analyze the impact of machine learning, deep learning, and neural networks on optimizing production processes.

Finally, for data analysis and structural equation modeling, the SmartPLS software was used. This software, compatible with PLS-SEM, is capable of conducting complex analyses on predictive models and hypothesis testing, making it the primary tool for data analysis in this research.

3. Findings and Results

The demographic characteristics of the sample show that 68% of the participants are male, while 32% are female. Regarding age, 27.6% are under 30 years old, 38.1% fall between 31 and 40 years, 22.3% are between 41 and 50 years, and 12% are over 50 years old. In terms of education, 25.7% have an associate degree or lower, 49% hold a bachelor's degree, 20.7% have a master's degree, and 4.6% have a doctoral degree or higher. Regarding job position, 26% of participants are managers, and 74% are experts or specialists.

In evaluating the reliability of the constructs, three indicators were used: factor loadings, Cronbach's alpha, and composite reliability. To confirm reliability, factor loadings should be greater than 0.7. Additionally, the values of Cronbach's alpha and composite reliability should also exceed 0.7. Table 1 shows the values of each of these indicators for the constructs examined in this study.

Table 1. Reliability Test Results

Construct	Indicator	Factor Loading	Cronbach's Alpha	Composite Reliability
Machine Learning	Q1	0.79	0.73	0.84
	Q2	0.84		
	Q3	0.78		
Deep Learning	Q4	0.85	0.79	0.87
	Q5	0.86		
	Q6	0.80		
Neural Networks	Q7	0.80	0.74	0.85
	Q8	0.78		
	Q9	0.85		
Production Process Optimization	Q10	0.83	0.86	0.90
	Q11	0.84		
	Q12	0.82		
	Q13	0.86		

To evaluate construct validity, convergent validity was assessed using average variance extracted (AVE). The AVE value ranges from zero to one, with values above 0.5 being acceptable. For discriminant validity, the Fornell and Larcker criterion can be used. This criterion states that the square root of the AVE for each construct must be greater than its correlation with other constructs. In other words, the diagonal values in the correlation matrix should be larger than all the other values in the respective column. The results of the convergent and discriminant validity tests are presented in Table 2.

Table 2. Validity Test Results

Variables	AVE	1	2	3	4
Machine Learning (1)	0.70	0.86	0	0	0
Deep Learning (2)	0.63	0.69	0.84	0	0
Neural Networks (3)	0.65	0.71	0.76	0.81	0
Production Process Optimization (4)	0.71	0.72	0.78	0.79	0.80

The R^2 coefficient measures the relationship between the variance explained by a latent variable and its total variance. This value ranges between zero and one, with higher values indicating better model fit. Generally, values of 0.67, 0.33, and 0.19 are interpreted as substantial, moderate, and weak, respectively. The Q^2 criterion indicates the predictive relevance of the model; if the value is greater than zero, the model is considered well-fitted. Values below zero indicate a poor model fit. Finally, the redundancy index shows the quality of the model, and for models with predictive power, this index should be greater than zero. These values are shown in Table 3.

Table 3. R^2, Q^2, and Redundancy Index

Construct	R^2	Q^2	Redundancy Index
Machine Learning		0.41	
Deep Learning		0.49	
Neural Networks		0.44	
Production Process Optimization	0.63	0.51	0.56

To assess the overall model fit in this study, the standardized root mean square residual (SRMR) index was used. The SRMR index shows the difference between the observed correlation and the implicit correlation matrix of the model and provides a measure of the average discrepancies between the observed and expected correlations, which serves as an absolute measure of model fit. SRMR is recognized as an appropriate metric for the Partial Least Squares (PLS-SEM) method and can help prevent incorrect model specification. If the SRMR value is below 0.1, the model fit is considered acceptable. In this study, based on the output from SmartPLS software, the SRMR value was found to be 0.067, indicating a good model fit.

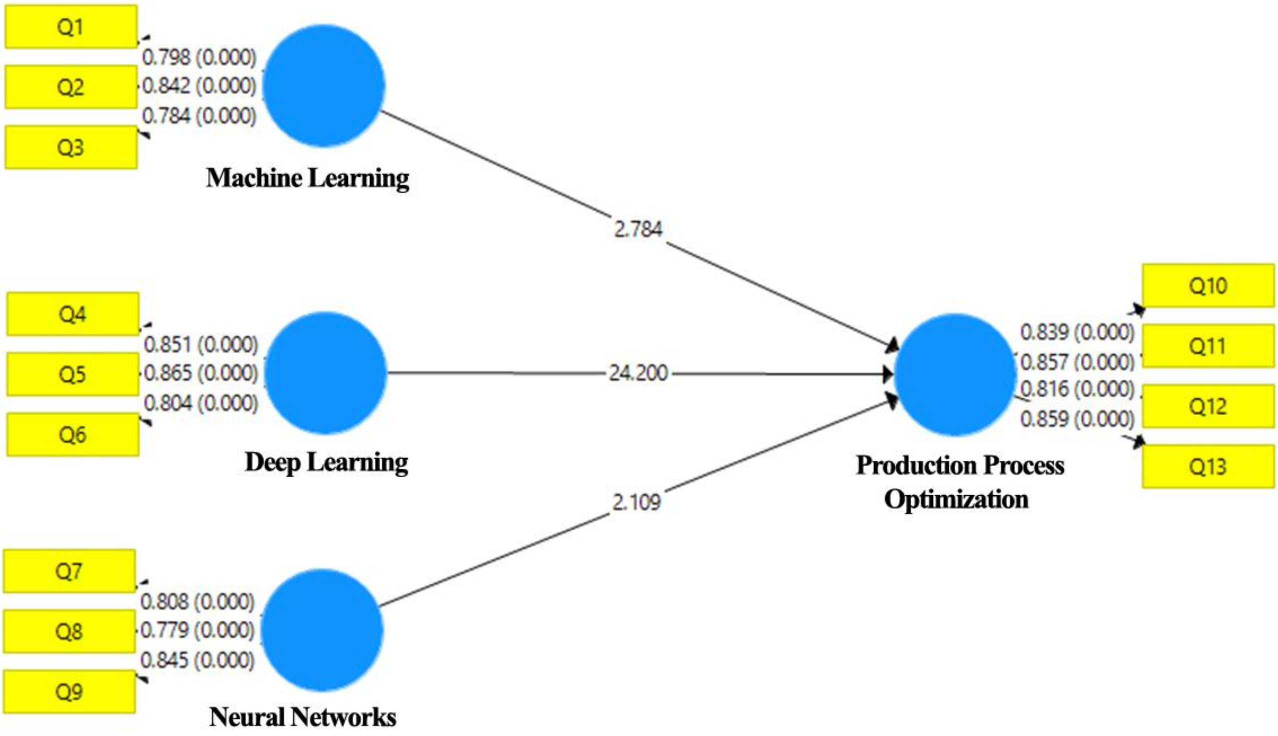

Figure 1. The results of model testing

Figure 1 displays the results of the Bootstrapping test, conducted with 5,000 iterations, showing the t-values. At a 95% confidence level, hypotheses are tested to evaluate the significance of the path coefficients between the variables. A t-value greater than 1.96 indicates a statistically significant path. The path coefficients represent the strength and direction of the relationships between the constructs. These results help to assess the influence of machine learning, deep learning, and neural networks on production process optimization. The t-values for the hypotheses, shown in Figure 1, confirm the robustness of the relationships between the independent variables (machine learning, deep learning, and neural networks) and the dependent variable (production process optimization).

Table 4. Hypothesis Testing Results

Path	Path Coefficient	t-value	p-value	Hypothesis Status
Machine Learning → Production Optimization	0.37	3.58	0.000	Supported
Deep Learning → Production Optimization	0.42	4.12	0.000	Supported
Neural Networks → Production Optimization	0.33	3.11	0.002	Supported

Table 4 presents the path coefficients, t-values, and p-values for the hypothesized relationships. As seen, all paths between the constructs are statistically significant, supporting the hypotheses that machine learning, deep learning, and neural networks positively affect production process optimization. The strongest relationship is between deep learning and production process optimization, with a path coefficient of 0.42, followed by machine learning at 0.37 and neural networks at 0.33.

4. Discussion and Conclusion

The results of the data analysis indicate that all three hypotheses of the study were confirmed. This means that machine learning techniques, deep learning, and neural networks have a positive and significant impact on the optimization of production processes. Confirmation of the first hypothesis shows that machine learning, as a tool for analyzing and processing complex data, has played a crucial role in improving predictions and optimizing production processes, thereby enhancing efficiency and reducing production costs. Additionally, the second hypothesis, which examines the impact of deep learning techniques on production process optimization, has successfully demonstrated the ability of deep neural networks to identify hidden patterns and provide more accurate analyses of production trends. The third hypothesis, regarding the role of neural networks in improving production processes, shows that neural networks, through advanced multi-layer algorithms, have played a fundamental role in optimizing quality and reducing waste. Overall, in line with the prior studies [17, 18], the results indicate that AI techniques have vast capabilities for improving performance and production efficiency in the electronics industry. This study has shown that AI techniques, particularly machine learning, deep learning, and neural networks, can have a significant impact on improving production processes.

Consistent with previous studies [2, 19], the findings of this study suggest that machine learning can effectively contribute to demand forecasting and production planning through modeling and analyzing historical data. This capability allows companies to more accurately estimate market needs and adjust production accordingly, thus preventing resource waste and reducing costs. Furthermore, the findings highlight the positive impact of machine learning on productivity improvement and production time reduction, enabling companies to perform better in competitive markets.

In addition, in line with previous studies [20, 21], the findings suggest that deep learning has an impact on quality control and production process optimization. Deep learning can be particularly useful in identifying and analyzing complex patterns, and this technique effectively identifies defective products and reduces production waste. Consequently, using deep learning helps companies improve their quality control processes and prevent the production of defective products. This, in turn, leads to increased customer satisfaction and brand reputation, which is of great importance to organizations.

On the other hand, in alignment with the prior research [22-24], the findings of this study also emphasize the role of neural networks in optimizing and smartening production processes. This technique, by processing data in a multi-layered manner and identifying hidden patterns, allows organizations to better control production trends and make smarter decisions. Thus, neural networks contribute to improving efficiency and reducing costs, helping organizations optimize their production strategies based on reliable data. These results indicate that these techniques not only assist organizations in improving product quality but can also lead to significant financial and productivity benefits.

This research contributes theoretically to the development of the existing literature on the application of AI in optimizing production processes. Previous research has mostly focused on AI techniques separately and examined the individual effects of each technique, whereas this research, for the first time in Iran, simultaneously investigates the impact of three techniques—machine learning, deep learning, and neural networks—on production processes in the electronics industry. This comprehensive review provides a more integrated understanding of AI functions in the manufacturing industry and offers a framework for future research. Furthermore, this study highlights the importance of investigating the combined impact of AI techniques. These findings can help theorists and researchers establish new frameworks for analyzing the synergistic effects of these techniques and explore the complex interactions between them. Thus, this study represents a new step in the literature on production optimization using AI and can serve as a foundation for future research in this field.

This study also theoretically emphasizes the importance of using variance-based structural equation modeling (PLS-SEM) in AI and production-related studies. By using this method, the research enables precise and transparent analysis of causal relationships and allows researchers to analyze the relationships between variables in more complex models that include various AI techniques. This aspect of the research contributes to the methodology literature in the field of AI applications in manufacturing and plays an essential role in enhancing the accuracy of predictive models.

From a practical perspective, this research offers valuable tools for managers in the electronics industry. Given the positive impact of machine learning on demand forecasting and inventory optimization, managers can use this technique to improve production planning and inventory management, thereby preventing issues such as stock shortages or excess inventory. This enables managers to optimize their production processes and reduce costs associated with inventory maintenance or shortages. Furthermore, deep learning techniques help managers identify defective products more accurately and improve quality control processes. This feature assists companies in achieving greater cost efficiency by reducing waste and improving product quality, leading to higher customer satisfaction. As a result, this study can provide valuable guidance for industrial managers and electronics manufacturers who are seeking smart, data-driven solutions.

Neural networks also provide a powerful tool for managers to analyze production data more accurately and identify hidden patterns. This enables managers to make more strategic decisions about their production processes and allocate resources more efficiently. This research can also assist managers in improving their supply chain by utilizing AI techniques to better analyze the flow of raw materials and reduce costs. In summary, these findings help managers confidently apply AI tools to improve performance and profitability.

This research is subject to several limitations. First, the statistical population of the study is limited to managers and experts in the supply chains of electronics companies in Tehran, which may not be applicable to other geographic regions or industries. Additionally, the data for this study were collected through self-reported surveys, which may introduce bias in the responses. Another limitation concerns the data collection tools, as the questionnaires were quantitative and may not fully capture all the complex aspects of production processes and supply chains.

- Use a broader statistical population, including companies across different regions and industries, to increase the generalizability of the findings.
- Conduct longitudinal studies to assess the long-term impacts of AI techniques on production optimization and performance.
- Explore the combined application of AI techniques in other sectors, such as automotive or pharmaceuticals, to compare their effectiveness across different industries.
- Investigate the role of AI in integrating sustainability practices within production processes, particularly in terms of energy consumption and waste reduction.
- Employ mixed-methods approaches that combine quantitative analysis with qualitative insights from managers and employees to obtain a more comprehensive understanding of the challenges and opportunities in applying AI to production processes.

In conclusion, the results of this study provide valuable insights into the role of AI techniques in optimizing production processes in the electronics industry. The positive effects of machine learning, deep learning, and neural networks on production efficiency, cost reduction, and quality control highlight the potential of AI to transform manufacturing practices. This research not only contributes to the theoretical understanding of AI applications in production optimization but also offers practical guidance for managers in leveraging AI tools to enhance productivity and competitiveness in the industry.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

References

[1] F. Kache and S. Seuring, "Challenges and opportunities of digital information at the intersectio n of Big Data Analytics and supply chain management," *International Journal of Operations and Production Management*, vol. 37, no. 1, pp. 10-36, 2017 2017, doi: 10.1108/IJOPM-02-2015-0078.

[2] E. Choi *et al.*, "Quantum machine learning for additive manufacturing process monitoring," *Manufacturing Letters*, vol. 41, pp. 1415-1422, 2024/10/1/ 2024, doi: 10.1016/j.mfglet.2024.09.168.

[3] A. S. Mahapatra, S. Sengupta, A. Dasgupta, B. Sarkar, and R. T. Goswami, "What is the impact of demand patterns on integrated online-offline and buy-online-pickup in-store (BOPS) retail in a smart supply chain mana gement?," *Journal of Retailing and Consumer Services*, vol. 82, p. 104093, 2025/1/1/ 2025, doi: 10.1016/J.JRETCONSER.2024.104093.

[4] A. K. Singh, V. R. P. Kumar, G. Dehdasht, S. R. Mohandes, P. Manu, and F. Pour Rahimian, "Investigating barriers to blockchain adoption in construction supply c hain management: A fuzzy-based MCDM approach," *Technological Forecasting and Social Change*, vol. 196, p. 122849, 2023/11/1/ 2023, doi: 10.1016/J.TECHFORE.2023.122849.

[5] M. Jeanneret Medina, C. Baudet, and J. F. Lebraty, "Blockchain and agency theory in supply chain management: A question of trust," *International Journal of Information Management*, vol. 75, p. 102747, 2024/4/1/ 2024, doi: 10.1016/J.IJINFOMGT.2023.102747.

[6] R. Zimmermann, A. Soares, and J. B. Roca, "The moderator effect of balance of power on the relationships between the adoption of digital technologies in supply chain management proces ses and innovation performance in SMEs," *Industrial Marketing Management*, vol. 118, pp. 44-55, 2024/4/1/ 2024, doi: 10.1016/J.INDMARMAN.2024.02.004.

[7] L. W. Wong, L. Y. Leong, J. J. Hew, G. W. H. Tan, and K. B. Ooi, "Time to seize the digital evolution: Adoption of blockchain in operati ons and supply chain management among Malaysian SMEs," *International Journal of Information Management*, vol. 52, p. 101997, 2020/6/1/ 2020, doi: 10.1016/J.IJINFOMGT.2019.08.005.

[8] O. Meier, T. Gruchmann, and D. Ivanov, "Circular supply chain management with blockchain technology: A dynamic capabilities view," *Transportation Research Part E: Logistics and Transportation Review*, vol. 176, p. 103177, 2023/8/1/ 2023, doi: 10.1016/J.TRE.2023.103177.

[9] M. Duquesnoy, I. Boyano, L. Ganborena, P. Cereijo, E. Ayerbe, and A. A. Franco, "Machine learning-based assessment of the impact of the manufacturing p rocess on battery electrode heterogeneity," *Energy and AI*, vol. 5, p. 100090, 2021/9/1/ 2021, doi: 10.1016/j.egyai.2021.100090.

[10] R. Sharma, A. Raj Paul, M. Mukherjee, S. Ram Krishna Vadali, R. Kumar Singh, and A. Kumar Sharma, "Forecasting of process parameters using machine learning techniques fo r wire arc additive manufacturing process," 2023/1/1/, vol. 80: Elsevier, 2023, pp. 248-253, doi: 10.1016/j.matpr.2022.12.081.

[11] S. Wang, J. Zhang, P. Wang, J. Law, R. Calinescu, and L. Mihaylova, "A deep learning-enhanced Digital Twin framework for improving safety a nd reliability in human–robot collaborative manufacturing," *Robotics and Computer-Integrated Manufacturing*, vol. 85, p. 102608, 2024/2/1/ 2024, doi: 10.1016/j.rcim.2023.102608.

[12] W. Wang, Y. Chen, Y. Wang, M. Deveci, S. Cheng, and P. R. Brito-Parada, "A decision support framework for humanitarian supply chain management – Analysing enablers of AI-HI integration using a complex spherical fu zzy DEMATEL-MARCOS method," *Technological Forecasting and Social Change*, vol. 206, p. 123556, 2024/9/1/ 2024, doi: 10.1016/J.TECHFORE.2024.123556.

[13] X. Sun, A. Beghi, G. A. Susto, and Z. Lv, "Deep learning-based quality prediction for multi-stage sequential hot rolling processes in heavy rail manufacturing," *Computers and Industrial Engineering*, vol. 196, p. 110466, 2024/10/1/ 2024, doi: 10.1016/j.cie.2024.110466.

[14] X. Sun, Y. H. Kuo, W. Xue, and Y. Li, "Technology-driven logistics and supply chain management for societal i mpacts," *Transportation Research Part E: Logistics and Transportation Review*, vol. 185, p. 103523, 2024/5/1/ 2024, doi: 10.1016/J.TRE.2024.103523.

[15] J. H. Fonseca, W. Jang, D. Han, N. Kim, and H. Lee, "Strength and manufacturability enhancement of a composite automotive c omponent via an integrated finite element/artificial neural network mu lti-objective optimization approach," *Composite Structures*, vol. 327, p. 117694, 2024/1/1/ 2024, doi: 10.1016/j.compstruct.2023.117694.

[16] M. Soori, B. Arezoo, and R. Dastres, "Artificial neural networks in supply chain management, a review," *Journal of Economy and Technology*, vol. 1, pp. 179-196, 2023/11/1/ 2023, doi: 10.1016/j.ject.2023.11.002.

[17] S. M. Ali *et al.*, "Drivers for Internet of Things (IoT) adoption in supply chains: Implic ations for sustainability in the post-pandemic era," *Computers and Industrial Engineering*, vol. 183, p. 109515, 2023/9/1/ 2023, doi: 10.1016/j.cie.2023.109515.

[18] S. Kunkel, M. Matthess, B. Xue, and G. Beier, "Industry 4.0 in sustainable supply chain collaboration: Insights from an interview study with international buying firms and Chinese supplie rs in the electronics industry," *Resources, Conservation and Recycling*, vol. 182, p. 106274, 2022/7/1/ 2022, doi: 10.1016/j.resconrec.2022.106274.

[19] R. Seidel, K. Schmidt, N. Thielen, and J. Franke, "Trustworthiness of machine learning models in manufacturing applicatio ns using the example of electronics manufacturing processes," 2022/1/1/, vol. 107: Elsevier, 2022, pp. 487-492, doi: 10.1016/j.procir.2022.05.013.

[20] X. Yan *et al.*, "Process-aware part retrieval for cyber manufacturing using unsupervise d deep learning," *CIRP Annals*, vol. 72, no. 1, pp. 397-400, 2023/1/1/ 2023, doi: 10.1016/j.cirp.2023.03.020.

[21] Y. Liang, Y. Wang, and J. Lu, "Extending cutting tool remaining life through deep learning and laser shock peening remanufacturing techniques," *Journal of Cleaner Production*,

vol. 477, p. 143876, 2024/10/20/ 2024, doi: 10.1016/j.jclepro.2024.143876.

[22] L. Huang, L. Zhen, J. Wang, and X. Zhang, "Blockchain implementation for circular supply chain management: Evaluating critical success factors," *Industrial Marketing Management,* vol. 102, pp. 451-464, 2022/4/1/ 2022, doi: 10.1016/J.INDMARMAN.2022.02.009.

[23] T. Hussain, J. Hong, and J. Seok, "A Hybrid Deep Learning and Machine Learning-Based Approach to Classify Defects in Hot Rolled Steel Strips for Smart Manufacturing," *Computers, Materials and Continua,* vol. 80, no. 2, pp. 2099-2119, 2024/8/15/ 2024, doi: 10.32604/cmc.2024.050884.

[24] G. Rumbe, M. Hamasha, and S. Mashaqbeh, "A comparison of Holts-Winter and Artificial Neural Network approach in forecasting: A case study for tent manufacturing industry," *Results in Engineering,* vol. 21, p. 101899, 2024/3/1/ 2024, doi: 10.1016/j.rineng.2024.101899.