

## Drivers of lean 4.0 and their impact on manufacturing performance: A PLS-SEM study in the Malaysian automotive sector

Dara Affyadah Mohd Affendi Lim<sup>1</sup>, Nazim Hanis Zainal Abidin<sup>2</sup>, Norhana Mohd Aripin<sup>3</sup>, Afdhal Junaidi<sup>4</sup>  
Norazlianie Szali<sup>1,5,6\*</sup>

<sup>1</sup>Faculty of Mechanical and Manufacturing Engineering, Universiti Tun Hussein Onn Malaysia (UTHM), 86400 Parit Raja, Batu Pahat, Johor, Malaysia.

<sup>2</sup>Faculty of Business, Economics and Social Development, Universiti Malaysia Terengganu, 21300 Kuala Terengganu, Terengganu, Malaysia.

<sup>3</sup>Faculty of Industrial Management, Universiti Malaysia Pahang, Al-Sultan Abdullah, 26300 Gambang, Kuantan, Pahang, Malaysia.

<sup>4</sup>Department of Chemistry, Faculty of Science and Data Analytics, Institut Teknologi Sepuluh Nopember, Sukolilo, Surabaya 60111, Indonesia.

<sup>5</sup>Mechanical Engineering Department, Sepuluh Nopember Institute of Technology Kampus Keputih Sukolilo, Surabaya, 60111, Indonesia

<sup>6</sup>Centre of Excellence for Advanced Research in Fluid Flow (CARIFF), Universiti Malaysia Pahang, Al-Sultan Abdullah, Lebuhraya Tun Razak, Gambang, Kuantan, Pahang, Malaysia; azlianie@uthm.edu.my (N.S.).

**Abstract:** This study aims to identify the key factors for implementing Lean 4.0 in the automotive manufacturing industry and to examine its impact on the performance of the automotive industry in Malaysia. A quantitative research design employing a cross-sectional approach was adopted for this study. Simple random sampling was utilized. Data were collected from 93 automotive manufacturing firms in Malaysia, with respondents comprising individuals from middle and senior management. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to investigate the relationship between the constructs. The main findings reveal that human, supplier, and customer factors positively influence Lean 4.0 implementation, while process factors do not have a significant effect. This research offers insight into the factors influencing Lean 4.0 implementation in automotive manufacturing. Moreover, this study assists policymakers and SMEs in planning training initiatives, facilitating knowledge transfer, and enhancing innovation and continuous improvement. This study addresses a critical gap in the empirical validation of Lean 4.0 implementation within the Malaysian automotive manufacturing context.

**Keywords:** *Automotive, Industry 4.0, Lean 4.0, Manufacturing, Structural equation modelling.*

### 1. Introduction

Lean manufacturing, initiated by the Toyota Production System (TPS), has long been recognized for its emphasis on waste reduction and value creation. It aims to optimize production by focusing on continuous improvement and eliminating waste in the operation [1]. The core principle of lean manufacturing is that these management approaches work together to deliver high-quality products at the speed of customer demand while minimizing or eliminating waste [2]. However, while lean manufacturing has delivered significant gains in efficiency and quality, its effectiveness is often constrained by a lack of real-time information, adaptability, and responsiveness to the complexities of modern production environments, particularly in highly digitalized manufacturing settings. Industry 4.0 signifies a transformative shift in the manufacturing sector. It is characterized by automation through the Internet of Things, cybersecurity, cloud computing, additive manufacturing, big data analysis, augmented reality, and artificial intelligence [3]. Despite these limitations, advancements in digital technologies have

introduced new opportunities to enhance manufacturing capabilities. Industry 4.0 is also transforming traditional manufacturing processes, encouraging innovation, and addressing challenges in complex production environments [4]. Since its emergence, Industry 4.0 has influenced the manufacturing sector, evident in the enhanced efficiency of operations management and improved business decision-making processes [5, 6].

Lean 4.0 integrates lean waste-reduction principles with advanced digital technologies to enhance manufacturing performance [7]. Unlike Industry 4.0, which primarily focuses on technological advancement, Lean 4.0 emphasizes the alignment of digital technologies with lean principles to ensure that technology adoption supports waste elimination and value creation. By incorporating real-time data, predictive analytics, and automation into lean practices, Lean 4.0 enables more responsive and data-driven operations [3]. This integration allows manufacturers to retain the discipline of lean while leveraging digital capabilities to strengthen decision-making and operational control [8]. While Lean 4.0 offers significant potential, its adoption comes with several challenges. Manufacturers encounter obstacles such as high implementation costs, a shortage of expertise, and resistance to change among employees [9, 10]. Together, they create a framework that improves current operations and prepares manufacturers for future challenges in a rapidly evolving industry [11].

Previous research from Bernhard et al. [12] reveals a critical gap in the lack of large-scale quantitative validation for Lean 4.0 frameworks and enablers. Their phased transformation methodology from case studies lacks empirical generalizability, necessitating robust quantitative studies in complex automotive contexts. Following that, Chivukula and Pattanaik [13] examined the enhancement of Industry 4.0 practices in general Jordanian manufacturing, supporting positive outcomes but not addressing Lean 4.0 integration. This limits applicability to automotive contexts, necessitating research on their combined effects within industry-specific settings. Additionally, research from Huang et al. [14] discussed the enhancement of Lean tools like Value Stream Mapping through real-time data and digital technologies, but did not explore how these innovations interact with human or organizational dynamics [15]. This suggests a gap in understanding how soft factors, including human factors, process factors, supplier factors, and customer factors, enable effective implementation of Lean 4.0 initiatives. Hence, this study addresses these gaps through quantitative validation of Lean 4.0 enablers specific to automotive manufacturing.

Therefore, this research addresses these identified gaps and corresponding research problems through three primary objectives: (1) to identify key factors influencing successful Lean 4.0 implementation in the automotive manufacturing industry, (2) to investigate the impact of Lean 4.0 implementation on automotive manufacturing performance, and (3) to provide empirical validation of the proposed framework using Partial Least Squares Structural Equation Modeling (PLS-SEM) within the Malaysian automotive manufacturing context.

## 2. Literature Review

Lean manufacturing, with its focus on reducing waste and maximizing efficiency, offers a strategic solution for lowering production costs, enhancing quality, and elevating technological capabilities [16]. Industry 4.0 introduces advanced technologies into manufacturing processes, aiming to create interconnected and smart factories that can transform production [17]. Industry 4.0 is a transformative trend that integrates advanced technological concepts to help industries achieve greater efficiency. It aims to maximize output while minimizing resource use by leveraging the latest manufacturing technologies [18]. Lean 4.0 is an integration between lean manufacturing and Industry 4.0, which can significantly enhance productivity levels and reduce costs in various production processes [19]. By adopting Lean 4.0, the automotive sector can achieve significant improvements in efficiency and sustainability, paving the way for smarter manufacturing.

## 2.1. The Factors of Lean 4.0 Implementation in the Automotive Manufacturing Industry

### 2.1.1. Human Factors

Human factors are critical for successful Lean 4.0 implementation in the automotive industry. Digital skills enable workers to leverage new technologies effectively, boosting process efficiency and decision-making [20]. Training programs enhance digital literacy, helping employees adapt to evolving manufacturing landscapes [21]. For example, Leesakul et al. [22] deployed continuous digital training modules across plants, accelerating technology adoption and Lean optimization. Transformational and participative leadership styles promote innovation, employee involvement, and a culture of empowerment and idea-sharing [23, 24], facilitating effective digital integration [25]. Empowering employees with access to advanced tools like augmented reality enables data-driven decisions, task ownership, and proactive issue resolution for better quality and fewer errors [26]. Continuous learning cultivates a growth mindset essential for tech adoption in a rapidly changing sector [27], creating a flexible workforce responsive to shifts and driving Lean 4.0 success. However, the adoption of Lean 4.0 may be hindered by resistance to digitalization and the presence of skill gaps among employees, particularly in organizations with limited digital readiness. Based on the literature reviewed, the following hypothesis is proposed:

*H<sub>1</sub>: There is a positive relationship between human factors and Lean 4.0 in the automotive manufacturing industry.*

### 2.1.2. Process Factors

Process factors prove essential for effective Lean 4.0 implementation in automotive manufacturing, requiring seamless integration of emerging technologies with workers' established knowledge and expertise. Pereira [28] highlights that human experience guides process adaptation, ensuring effective Lean principles while maintaining feasibility. However, reliance on experience alone may create inconsistencies, especially when informal practices conflict with Lean 4.0 standardization. Another essential process factor is continuous improvement, driven by feedback loops of data collection, analysis, and corrective action for ongoing benefits. Womack et al. [29] note that it is crucial for competitiveness by eliminating waste, improving resource efficiency, and boosting operational outcomes. Machine learning enables self-optimizing processes in Lean 4.0, with algorithms analyzing historical data for real-time adaptations that predict disruptions and minimize downtime across production lines and supply chains. Peretz-Andersson, et al. [30]. Khakifirooz et al. [31] explain that it optimizes production schedules and material flow across supply chains. Therefore, the following hypothesis is developed:

*H<sub>2</sub>: There is a positive relationship between process factors and Lean 4.0 in the automotive manufacturing industry.*

### 2.1.3. Supplier Factor

In the automotive industry, supplier factors are crucial for Lean 4.0 success. Supplier commitment to customer efforts aligns practices across the supply chain, based on mutual trust and continuous improvement, Liker and Morgan [32]. Invested suppliers boost efficiency, cut costs, and enhance sustainability. Collaboration fosters objective alignment, improving process flow and inventory management [33]. Prior studies have highlighted that leading automotive manufacturers adopt long-term supplier partnerships, digital platforms, and IoT-enabled systems to enhance real-time tracking, logistics coordination, and supply chain visibility [34, 35]. Improved data sharing optimizes production and supply chains via better forecasting, disruption response, and transparency [36]. Real-time data helps address inefficiencies and reduce waste. Appropriate logistics systems ensure seamless material flow, optimizing schedules, and are integrated with Lean 4.0 for efficiency gains, shorter lead times, and cost savings [36]. Therefore, the following hypothesis is developed:

*H<sub>3</sub>: There is a positive relationship between supplier factors and Lean 4.0 in the automotive manufacturing industry.*

#### 2.1.4. Customer Factors

Customer factors drive Lean 4.0 adoption in automotive manufacturing, aligning processes with dynamic market demands through digital-Lean integration for personalized, efficient production [16]. This encompasses the entire customer value chain, from design and fabrication to delivery and post-sale support [37]. Central to these factors is trust-building, where transparency, promise fulfillment, and superior performance cultivate loyalty in competitive landscapes [38]. Lean 4.0 delivers defect-free, timely outputs, minimizing waste, exemplified by Tesla's app-based production visibility, while maximizing consumer value through quality, affordability, customization, and sustainability [39, 40]. Lean 4.0 waste reduction allows for cost-competitive, high-quality offerings, as shown by BMW's modular architectures that support efficient variant production [41]. Data analytics and digital feedback mechanisms further bolster Lean 4.0 efficacy, refining demand forecasts, personalization, and responsiveness [42]. Automotive applications leverage connected vehicle telemetry and service feedback to optimize designs, maintenance, and planning [43], such as Ford's telematics-driven predictive servicing. Process flexibility, enabled by additive manufacturing, automation, and cloud systems, accommodates diverse demands without sacrificing throughput [44]. Accordingly, the following hypothesis is posited:

*H<sub>\*</sub> There is a positive relationship between customer factors and Lean 4.0 in the automotive manufacturing industry.*

### 2.2. The Integration between Lean Manufacturing and Industry 4.0

#### 2.2.1. Internet of Things

The Internet of Things serves as a cornerstone for integrating Lean manufacturing with Industry 4.0 in the automotive sector, embedding smart devices and sensors to enable real-time data collection, monitoring, and analysis [45]. This connectivity drives operational efficiency through predictive maintenance, optimized supply chains, and automated production lines [46]. Aligned with Lean methodologies, IoT facilitates internet-based error tracking in inventory, connecting machinery, tools, and vehicles to centralized networks for enhanced visibility and waste reduction [47]. Manufacturers track parts from suppliers to assembly, minimizing excess stock while bridging physical and cyber domains [48]. IoT sensors on assets like machinery and components support real-time data exchange, fostering responsive Lean strategies [49].

#### 2.2.2. Cybersecurity

Cybersecurity is vital in the automotive industry to protect connected vehicles, production systems, and sensitive data amid rising cyber threats. Modern cars with infotainment, navigation, and IoT-enabled factories are vulnerable to hacking, making encryption protocols essential for securing data transmission, such as location details or production schedules [18, 50]. Manufacturers employ access controls, secure coding, hashing, and digital signatures to ensure data confidentiality, integrity, and authenticity, preventing unauthorized access to proprietary designs, supply chains, and customer information [51, 52]. Regular software updates, vulnerability assessments, intrusion detection, and employee training mitigate risks, aligning with Lean principles by minimizing disruptions, waste, and inefficiencies in digital operations [53]. These measures foster trust, operational resilience, and efficient supply chains, enabling seamless IoT integration while safeguarding against breaches in an increasingly connected landscape [54].

#### 2.2.3. Cloud Computing

Cloud computing delivers on-demand IT services, including storage, servers, and software via internet infrastructure, eliminating physical asset ownership [55]. Service models encompass IaaS, PaaS, and SaaS across public, private, and hybrid deployments optimized for scalability and security. Within Lean 4.0 frameworks, cloud platforms enable real-time data processing essential for Industry 4.0 integration, supporting dynamic manufacturing environments [39]. In automotive manufacturing, cloud

systems transform inventory management and operational visibility. Real-time stock updates from warehouse scans provide ubiquitous access, minimizing manual errors consistent with Lean waste reduction [56]. Supplier integration via shared cloud data ensures just-in-time deliveries, averting production disruptions [57]. Remote accessibility through cloud-connected mobile devices facilitates global monitoring of production metrics, quality control, and equipment performance [58]. Instant alerts on smart devices accelerate maintenance responses and cross-functional collaboration, reducing downtime and enhancing throughput [59-61].

#### 2.2.4. Additive Manufacturing

Additive manufacturing (AM), or 3D printing, fabricates three-dimensional objects layer-by-layer from digital models, enabling complex geometries using plastics, metals, and ceramics [10]. In automotive Lean 4.0, AM facilitates rapid prototyping, customization, and just-in-time production, reducing inventory and lead times while minimizing material waste [62]. This flexibility supports responsive manufacturing without extensive retooling, producing unique components economically [63]. AM expands design possibilities for automotive parts, enabling small-batch customization unattainable via traditional methods Yang et al. [64]. Priarone et al. [65] demonstrated a 69% weight reduction in an iron bracket redesigned via powder bed AM in AlSi10Mg, optimizing topology for lightweighting. Integration with predictive analytics enhances customer requirement analysis, improving customization efficiency [66]. These capabilities align with Lean principles by eliminating excess inventory, accelerating iterations, and supporting material optimization, positioning AM as a transformative technology for automotive manufacturing agility and sustainability [67].

#### 2.2.5. Big Data Analytics

Big data analytics constitutes a cornerstone of Lean 4.0 integration, processing voluminous data from IoT sensors and digital systems to yield operational insights, trend identification, and data-driven decisions [68]. This capability underpins predictive maintenance, demand forecasting, and inventory optimization, aligning with Lean objectives of waste reduction, efficiency enhancement, and quality improvement. Synergistic integration with cloud computing and IoT fosters agile production environments conducive to continuous improvement [53]. In automotive manufacturing, robust data management systems accommodate diverse inputs from production lines, supply chains, and customer feedback, leveraging cloud-based big data platforms for pattern recognition and process optimization [39]. Real-time analytics mitigate bottlenecks, enable proactive market responses, and support predictive capabilities essential for Lean agility [69]. This strategic data infrastructure ensures operational responsiveness while upholding Lean manufacturing imperatives of resource efficiency and waste elimination [70, 71].

#### 2.2.6. Autonomous Robot

Autonomous robots constitute a pivotal element of Lean 4.0 integration within automotive manufacturing, executing repetitive tasks (assembly, material handling, and logistics) with precision, speed, and minimal human intervention [72]. By reducing cycle times, eliminating errors, enhancing safety, and generating real-time performance data, these systems align with Industry 4.0 smart manufacturing while operationalizing Lean waste reduction across motion, waiting, and defects [73]. Ford's deployment of autonomous mobile robots (AMRs) for intralogistics and Toyota's inventory tracking exemplify streamlined workflows that prevent overproduction and excess stock [74]. BMW further leverages advanced sensing for customized assembly, adapting seamlessly to variant configurations (interior layouts, paint specifications) without downtime, supporting just-in-time production and customer responsiveness [72]. This automation reallocates human resources to value-added functions like quality control and process innovation, maximizes equipment uptime, and delivers higher throughput, reduced costs, and consistent quality [75]. Ultimately, autonomous robots transform

traditional manufacturing into agile, data-driven systems that uphold Lean principles while meeting diverse market demands [76, 77].

### 2.2.7. Simulation

Simulation plays a pivotal role in Lean 4.0 within automotive manufacturing, enabling virtual modeling of assembly lines, machinery, processes, and product development to optimize efficiency pre-implementation [78]. Engineers simulate production flows to pinpoint bottlenecks, test workstation layouts, and evaluate robotic integrations without real-world disruptions, aligning with Lean waste minimization [79]. Digital twins of machinery facilitate root-cause analysis of performance issues, predictive failure modeling, and scenario testing under varying workloads or conditions, enhancing reliability and equipment effectiveness [80, 81]. Comprehensive process simulations map material intake through final assembly, quantifying cycle times, throughput, and resource utilization to eliminate waiting periods and resequencing operations optimally [36, 82]. In product development, virtual prototypes assess aerodynamics, crash performance, and structural integrity, curtailing physical iterations and material waste [83, 84]. This data-driven methodology fosters continuous improvement, reduces lead times, and ensures resource-efficient production consistent with Lean principles.

### 2.2.8. Augmented Reality

Augmented reality (AR) overlays real-time digital instructions and data onto physical work environments to enhance worker productivity and quality control [85]. AR headsets deliver step-by-step assembly guidance, safety protocols, and performance metrics directly into operators' field of view, accelerating training, minimizing errors, and reducing waste consistent with Lean principles [86]. In maintenance scenarios, AR provides instant access to manuals, analytics, and remote expert collaboration, slashing machine downtime through contextual troubleshooting [87]. Production floor applications visualize inventory levels, machine metrics, and bottlenecks for immediate decision-making, while quality control overlays compare physical assemblies against digital blueprints for defect detection [88]. New operators benefit from immersive 3D simulations of complex tasks, shortening learning curves without physical prototypes [89]. Managers leverage AR glasses for real-time line assessments and remote guidance, fostering data-driven agility and operational responsiveness [90]. By streamlining workflows, eliminating inefficiencies, and enabling continuous improvement, AR transforms traditional manufacturing into precise, worker-empowered systems aligned with automotive Lean objectives [91, 92].

## 2.3. Manufacturing Performance in the Automotive Manufacturing Industry

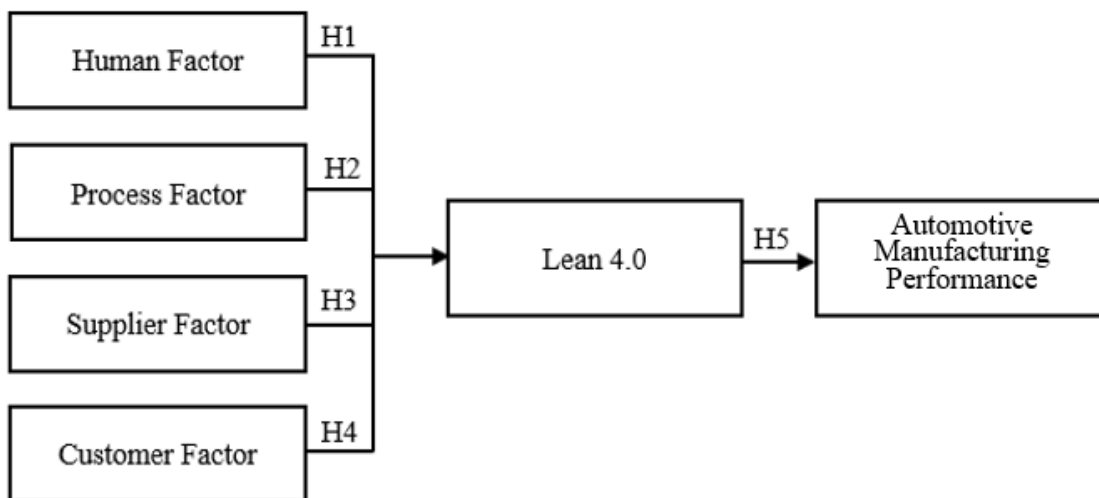
Manufacturing performance in the automotive industry is the key outcome of Lean 4.0 implementation, encompassing six validated dimensions: increased profits, reduced costs, faster decision-making, enhanced flexibility, higher productivity, and more capable employees. This framework highlights the integration of Industry 4.0 technologies with Lean principles, focusing on financial viability, operational excellence, and human capital development for competitiveness in digital transformation. IoT technology aids predictive maintenance to prevent costly equipment failures, while ERP systems can achieve zero inventory through just-in-time practices. Additionally, big data analytics can enhance customer relationship management, improving loyalty and ROI for marketing efforts [68, 93, 94]. Production costs systematically decline via Jidoka automation, ensuring human intelligence governs digital systems, autonomous robots eliminate just-in-time inventory waste, and additive manufacturing produces lightweight components with minimal scrap, emissions, and supply chain redundancies [95-97].

Decision-making accelerates through IoT-autonomous guided vehicle networks, providing real-time disruption intelligence and genetic algorithm-optimized scheduling, resolving shop-floor logistics complexities instantaneously [18, 98, 99]. Production flexibility manifests via autonomous robot reconfiguration, avoiding layout congestion, and simulation-Kanban hybrids dynamically adapting to

stochastic assembly demands and variable Kanban card configurations [72, 100]. Productivity increases through robotics-optimized line balancing, Jidoka-Industry 4.0 fusion extending production systems, and augmented reality augmenting lean methodologies digitally [73, 101]. Employees improve their skills through AR-guided training that immerses them in realistic scenarios. They use real-time data from IoT to develop strong diagnostic skills. Collaborative digital platforms help create a culture of continuous improvement [75, 102].

#### 2.4. Research Framework

Figure 1 illustrates the conceptual framework of this research, developed based on these five hypotheses and the relationships identified in the literature review.



**Figure 1.**  
Conceptual Framework.

### 3. Methodology

#### 3.1. Data Collection

The scale items for this study are human factor, process factor, supplier factor, and customer factor, following the automotive manufacturing construct. A five-point Likert scale was used for each question and subjected to content validity. Both academics and practitioners were included in the pre-test. This study adopted a simple random sampling approach, collecting 93 samples out of 507 Malaysian automotive manufacturing firms identified in the Federation of Malaysian Manufacturers (FMM) database. The sampling approach was chosen to provide an equal chance for all members of the Malaysian automotive manufacturing firms to be selected. Hence, with the capability of reducing representation bias, the method applied could increase the likelihood of population representation [103].

#### 3.2. Structural Equation Modelling

SmartPLS software was chosen because it efficiently handles small sample sizes and complex constructs, accommodates both reflective and formative measurement models, and provides high-accuracy parameter estimation [104]. The employability of a small sample size and exploratory-based study recognized the suitability of the partial least squares structural equation model (PLS-SEM) to be conducted rather than just using linear regression or covariance-based structural equation modeling (CB-SEM). Additionally, PLS-SEM is justified as being robust in predicting non-distributed data input, offering flexibility in handling complex relationship modeling [105]. This allows behavior predictions to deviate from bias based on normality and outliers, without testing them.

## 4. Data Analysis and Results

### 4.1. Sample Characteristics

Respondents were mainly represented by companies with more than 200 permanent employees (62%). Companies that have lasted longer than 5 years account for the majority (77%). The duration of lean manufacturing implementation exceeding 5 years by companies accounts for a large portion (68%). The majority are local companies (40%), and companies with a sales turnover of more than RM50 million have the upper hand (47%). Senior officers, executives, and engineers mainly participated in this survey (68%). Table 1 presents the overall demographic profile of the participating organizations.

**Table 1.**  
Demographic profile of the organizations participating.

| Demographic Category           | Category Details                  | Frequency | Percentage (%) |
|--------------------------------|-----------------------------------|-----------|----------------|
| Number of Permanent Employees  | > 200                             | 62        | 68.89          |
|                                | 75–200                            | 22        | 24.44          |
|                                | 5–75                              | 8         | 8.89           |
|                                | < 5                               | 1         | 1.11           |
| Years Established              | > 5 years                         | 77        | 85.56          |
|                                | 1–3 years                         | 8         | 8.89           |
|                                | 3–5 years                         | 6         | 6.67           |
|                                | < 1 year                          | 2         | 2.22           |
| Duration of Lean Manufacturing | > 5 years                         | 68        | 75.56          |
|                                | 1–3 years                         | 11        | 12.22          |
|                                | 3–5 years                         | 8         | 8.89           |
|                                | < 1 year                          | 6         | 6.67           |
| Ownership Type                 | Local                             | 40        | 44.44          |
|                                | Joint Venture                     | 35        | 38.89          |
|                                | Foreign                           | 18        | 20             |
| Sales Turnover                 | > RM 50 million                   | 47        | 52.22          |
|                                | RM 15 million to RM 50 million    | 17        | 18.89          |
|                                | RM 300,000 to RM 15 million       | 21        | 23.33          |
|                                | < RM 300,000                      | 8         | 8.89           |
| Organizational Positions       | Senior Officer/Executive/Engineer | 68        | 75.56          |
|                                | Manager/Deputy Manager            | 22        | 24.44          |
|                                | Director/Deputy Director          | 2         | 2.22           |

### 4.2. Measurement Model

Table 2 summarizes the convergent validity and reliability tests. Indicator reliability test passed, with all outer loadings for each item exceeding 0.6. Furthermore, the composite reliability (>0.8) indicates strong internal consistency among the indicators for each construct. The average variance extracted (AVE; >0.5) is slightly above the threshold for convergent validity, as per [104], indicating that the proportion of variance in the indicators is explained by their construct.

**Table 2.**  
Summary of Convergent Validity and Reliability Test.

| Construct              | Range of Outer | CR    | AVE   |
|------------------------|----------------|-------|-------|
| Human Factors          | 0.673 - 0.852  | 0.814 | 0.595 |
| Process Factors        | 0.673 - 0.814  | 0.829 | 0.550 |
| Supplier Factor        | 0.667 - 0.784  | 0.826 | 0.544 |
| Customer Factor        | 0.697 - 0.792  | 0.842 | 0.573 |
| Internet Of Things     | 0.770 - 0.866  | 0.872 | 0.695 |
| Cybersecurity          | 0.879 - 0.922  | 0.923 | 0.801 |
| Cloud Computing        | 0.859 - 0.879  | 0.900 | 0.751 |
| Additive Manufacturing | 0.876 - 0.867  | 0.903 | 0.757 |
| Big Data               | 0.812 - 0.910  | 0.905 | 0.761 |
| Autonomous Robot       | 0.864 - 0.923  | 0.923 | 0.799 |
| Simulation             | 0.864 - 0.904  | 0.920 | 0.793 |

Table 3 presents the discriminant validity test using the Heterotrait-Monotrait Ratio (HTMT). An HTMT value of 0.9 was employed in this study, as it is considered adequate. The HTMT formula assesses the relationship between items based on their true correlation, calculated by averaging standardized item scores [106]. Hence, as the cross-construct correlation ratios in the matrix are smaller than 0.9, the items are indeed distinct from each other, providing a stable measurement model. Overall, the tests for the measurement model showed adequate results.

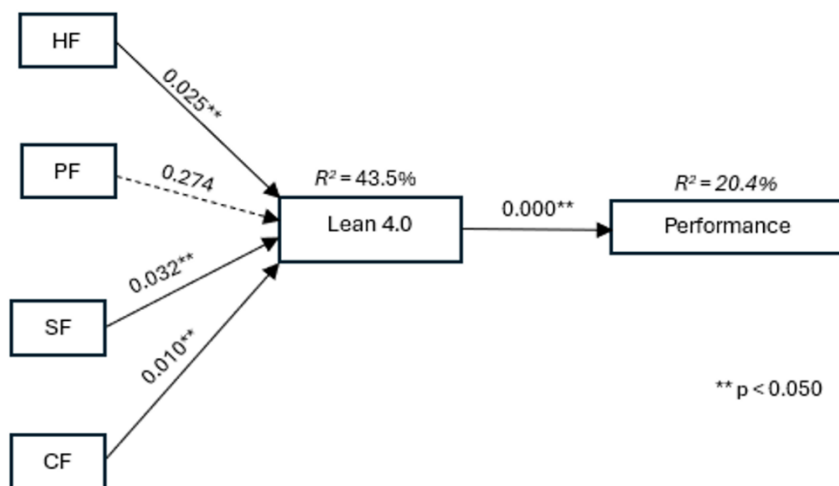
**Table 3.**  
Heterotrait-Monotrait Ratio (HTMT).

|          | AMP   | CF    | HF    | Lean 4.0 | PF    |
|----------|-------|-------|-------|----------|-------|
| AMP      |       |       |       |          |       |
| CF       | 0.441 |       |       |          |       |
| HF       | 0.557 | 0.682 |       |          |       |
| Lean 4.0 | 0.476 | 0.626 | 0.574 |          |       |
| PF       | 0.528 | 0.766 | 0.819 | 0.675    |       |
| SF       | 0.567 | 0.752 | 0.831 | 0.696    | 0.861 |

**Note:** AMP = automatic manufacturing performance, CF = customer factor, HF = human factor, PF = performance factor, SF = supplier factor.

#### 4.3. Structural Model and Results of the Hypotheses

The measurement model was sufficient in terms of reliability and validity. The structural model was then used to test the hypothesis relationships. Figure 2 shows the results of the structural model testing. The coefficient of determination ( $R^2$ ) for the constructs was used to assess the explanatory power of their respective latent variables. The  $R^2$  value of Lean 4.0 is considered weak (0.435). The  $R^2$  of automotive manufacturing performance explained by Lean 4.0 shows a weak explanatory variance with a value of 20.4%. Additionally, only the effect size ( $f^2$ ) for process factors was found to be nonexistent; the others showed small effects considering their relationships. To create many subsamples from the original data, the bootstrapping technique was used. Models were estimated for each subsample to calculate the standard errors needed for hypothesis testing [104]. It was found that process factors did not have a positive impact on Lean 4.0, as H2 was non-significant ( $\beta = 0.067$ ,  $p < 0.05$ ). Confidence intervals for each hypothesis were presented to provide insight into the stability of the estimated coefficient, offering a range of plausible population values for the parameter. Table 4 summarizes the hypothesis testing.



**Figure 2.**  
Structural Model Testing Results.

**Table 4.**  
Hypothesis testing.

| Hypothesis | Std. Beta | Std. Error | P values | T values | Confidence Interval |        | Decision        |
|------------|-----------|------------|----------|----------|---------------------|--------|-----------------|
|            |           |            |          |          | 5.00%               | 95.00% |                 |
| H1         | 0.257     | 0.131      | 0.025    | 1.954    | 0.053               | 0.492  | Significant     |
| H2         | 0.067     | 0.112      | 0.274    | 0.601    | -0.101              | 0.283  | Not Significant |
| H3         | 0.238     | 0.103      | 0.010    | 2.32     | 0.064               | 0.41   | Significant     |
| H4         | 0.208     | 0.112      | 0.032    | 1.857    | 0.023               | 0.391  | Significant     |
| H5         | 0.424     | 0.091      | 0.000    | 4.648    | 0.326               | 0.627  | Significant     |

## 5. Discussions

### 5.1. Human Factors and Lean 4.0

It is believed that human factors positively impacted the implementation of Lean 4.0 technology in manufacturing companies. The findings of this study align closely with earlier research, particularly Huang et al. [14], who emphasized that digital skills, employee adaptability, and human readiness are critical enablers of Lean 4.0 initiatives. Technology has evolved seamlessly throughout the generations. Hence, by improving digital skills and training employees with the latest technology, the company increases employee appreciation, yielding a positive return on investment. Leadership, as one of the human factors, has a significant impact on motivating employees to adapt to digital transformation. Excellent leadership values, trustworthiness, and involvement lead to a smoother Lean 4.0 implementation. Besides, the culture of self-improvement is an important part. Top management's empowerment is great, but the true champions are the employees themselves. Without the realization of learning and self-improvement, the culture of moving forward could be grounded. A study by Adiwaty and Moeins [25] confirmed that when leadership, empowerment, and an innovation culture work together, organizations are better able to adopt digital technologies effectively and sustain Lean 4.0 practices.

### 5.2. Process Factors and Lean 4.0

Process factors were found to have a non-significant impact on the Lean 4.0 initiative. The findings, however, are unexpected compared to previous studies, show a significant impact of process factors towards Lean 4.0. A study by Qureshi et al. [107] found the process factor to be at the top of the bar, indicating the most impactful factors influencing manufacturing SMEs' Lean 4.0 incorporations. The realization of the statistical results shown was made possible by an already robust framework that follows the tight international standards ISO 9001 and IATF 16949. Performance requirements were met by

having stable, mature processes, with or without significant influence from digital technologies. Lean 4.0 initiatives, such as real-time inventory tracking, are still in the early stages of implementation [16]. Occasionally, the infant-level of innovation requires significant investment to even change the majority of manufacturing processes. The perspective that if it is not broken, why change it, is believed to influence organizations' perceptions, leading them not to even interrupt stable manufacturing production while confirming steady income. Hence, the non-impact of process factors on Lean 4.0 implementation occurs.

### 5.3. *Supplier Factors and Lean 4.0*

The statistical results support our hypothesis that supplier factors influenced Lean 4.0 efforts. Such collaborative relationships lead to better process flow, improved inventory management, and greater agility in meeting changing customer demands [108]. Supplier involvement is critical, as it ensures Lean principles are integrated throughout the supply chain, fostering efficiency, cost-effectiveness, and sustainability. Technologies like RFID, IoT sensors, and GPS enable real-time tracking, providing visibility and traceability throughout the supply chain [109]. By integrating these technologies, automotive manufacturers can achieve better supplier performance, reduced lead times, and significant cost savings. A study by Sarangi and Ghosh [110] found that Industry 4.0 influenced the performance of the medical device industry, with supplier quality as a mediating factor. Although in the context of automotive manufacturing, the same concept could be applied through the rating process to select, if not the best, suppliers based on several criteria. Hence, supplier selection is crucial in reducing lead time while maintaining high-quality deliverables.

### 5.4. *Customer Factors and Lean 4.0*

Findings indicate that customer factors indeed influence the Lean 4.0 initiatives. Big data analytics, IoT, artificial intelligence, and cloud computing enable data-driven, intelligent decision-making across sectors such as demand forecasting, pricing optimization, product design, and development, thereby raising operational efficiency, which could then lead to better client satisfaction [111]. Sustainable customer demand is crucial in manufacturing businesses, especially in the automotive industry. Trust and loyalty from customers in reliability and quality in meeting demands can be cultivated when Lean 4.0 practices are implemented. Digital technology enables transparency in the manufacturing process, thereby enhancing customer awareness of how their goods are made [112]. The adaptability and responsiveness of Lean 4.0 systems enable manufacturers to quickly meet changing customer expectations, further strengthening relationships.

### 5.5. *Lean 4.0 and Automotive Manufacturing Performance*

Lean 4.0 was found to have a positive impact on automotive manufacturing performance. A study by Maware and Parsley [113] found that Industry 4.0, through the mediating effect of lean manufacturing, influenced sustainable performance. Based on the Indian automotive industry, Koteswarapavan and Pattanaik [111] found a positive influence of Industry 4.0 on organizational performance, with lean manufacturing as a mediator. Additionally, Industry 4.0 alone cannot influence sustainable performance. The combination of lean manufacturing and Industry 4.0 enables manufacturers to optimize operations, reduce waste, and streamline production processes, thereby increasing efficiency and cost-effectiveness. These advancements also allow manufacturers to respond dynamically to market challenges, maintain competitiveness, and achieve overall business success.

## 6. **Conclusions and Implications**

The objective of this study is to identify key factors of Lean 4.0 towards automotive manufacturing industry performance. The factors will then be examined to determine whether they supported or hindered the automotive manufacturing industry in Malaysia in implementing Lean 4.0 in its business operations. This study adopted four factors: human, process, supplier, and customer. All four factors were hypothesized to have a positive effect on Lean 4.0 implementation in automotive manufacturing

performance, based on a detailed literature review. Data collection was then performed, followed by data analysis through structural equation modeling. The findings then showed that three of the factors, human, supplier, and customer, did have an impact on Lean 4.0 implementation, thus influencing the performance of automotive manufacturing. However, the positive hypothesis regarding the process factor and Lean 4.0 was not significant.

Several theoretical and practical implications were observed. From a theoretical perspective, this study fills the methodological gap, where the quantitative design method was applied in this study. The lack of quantitative studies related to the Lean 4.0 research framework was identified, with most studies on strategies for Lean 4.0 implementation being qualitative and exploratory. Additionally, as shown throughout the literature review, there was a clear division between Industry 4.0 and Lean manufacturing. Therefore, this study contributes to the body of knowledge of Lean 4.0 as a unified operational strategy. The third contribution includes soft factors such as human, supplier, and customer factors within the Lean 4.0 framework, rather than focusing solely on technical tools and technological enablers.

As we examine practical perspectives, this study confirmed the need to incorporate human, supplier, and customer focus factors into Lean 4.0 efforts. This implies that a strategic focus on fostering a digitally skilled workforce, enhancing supplier collaboration, and prioritizing customer-centric practices could be leveraged to achieve higher performance across the automotive manufacturing industry, whether in inputs, processes, or outputs. Training programs, robust supplier partnerships, and data-driven customer engagement should be prioritized to fully leverage the potential of Lean 4.0 to improve manufacturing performance. Besides, this study provided policymakers with multiple insights into determining suitable initiatives to support conglomerates or even MSMEs, leading to targeted investments in digital infrastructure and standardized processes. As Malaysian GDP contributions are mostly from MSMEs, the factors identified in this study could aid in transferring knowledge and supporting the fragmented supply chain before Lean 4.0 implementation, thus unlocking higher manufacturing performance. Not only that, but stakeholders in general could be affected by the factors identified in this study. Given the market's dynamic nature, this study could boost innovation and continuous improvement across all stakeholders.

## 7. Limitations and Future Research

There are limitations to the quantitative side of the study. Hence, it is suggested to include a mixed-method approach, incorporating qualitative interviews or focus group discussions, which could enrich the findings by offering a deeper understanding of the factors influencing Lean 4.0 adoption and its impact on manufacturing performance. The sample size was relatively small, though considerable and adequate for this study; however, confidence in generalizability was believed to be limited. Future researchers could expand their focus to a more diverse demographic to capture a broader range of perspectives, particularly across different organizational roles and levels of experience.

Besides, the database collected in this study included only FMM-registered automotive manufacturing companies, rather than SMEs and non-registered manufacturing companies. Although it helps ensure reliable data from an established organization, the lack of representation of the Malaysian automotive manufacturing industry is believed to introduce bias. Lastly, internal factors identified for this study included scope limitations. Future researchers could incorporate external factors, such as government policies and economic conditions, to examine their moderating effects.

This study used a cross-sectional design, which means it takes a “snapshot” of a particular point in time. Although it fulfills this study's purpose by representing the population over a given period, it lacks representation across multiple time frames. The temporal bias could be due to the period during which the research was conducted. Hence, future research could adopt a longitudinal design, spanning multiple periods within the same conceptual model.

## Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

## Copyright:

© 2026 by the authors. This article is an open-access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## References

- [1] L. Naciri, Z. Mouhib, M. Gallab, M. Nali, R. Abbou, and A. Kebe, "Lean and industry 4.0: A leading harmony," *Procedia Computer Science*, vol. 200, pp. 394–406, 2022. <https://doi.org/10.1016/j.procs.2022.01.238>
- [2] S. Vinodh, J. Antony, R. Agrawal, and J. A. Douglas, "Integration of continuous improvement strategies with Industry 4.0: A systematic review and agenda for further research," *The TQM Journal*, vol. 33, no. 2, pp. 441–472, 2021.
- [3] B. K. Shukla *et al.*, "Modern approaches and implications toward industry 4.0," *Knowledge Management and Industry Revolution 4.0*, pp. 197–238, 2024.
- [4] B. Bajic, A. Rikalovic, N. Suzic, and V. Piuri, "Industry 4.0 implementation challenges and opportunities: A managerial perspective," *IEEE Systems Journal*, vol. 15, pp. 546–559, 2021. <https://doi.org/10.1109/JSYST.2020.3023041>
- [5] A. E. Alper, F. O. Alper, and G. Ozayturk, *Dynamics of technological unemployment, leadership, and entrepreneurship during the industry 4.0 revolution. Agile Leadership for Industry 4.0: An Indispensable Approach for the Digital Era*. Palm Bay, FL: Apple Academic Press, 2023.
- [6] P. Waghanna, A. Reddy, S. Deshpande, S. Chavan, V. R. Jaiswal, and V. Naranje, "Effects of adopting industry 4.0 on a manufacturing plant," in *2024 11th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions), ICRITO 2024*, 2024.
- [7] R. Vigneshvaran and S. Vinodh, "State of art review on lean integration with Industry 4.0," *International Journal of Services and Operations Management*, vol. 46, no. 2, pp. 182–208, 2023. <https://doi.org/10.1504/IJSOM.2023.134260>
- [8] F. D. Cifone, K. Hoberg, M. Holweg, and A. P. Staudacher, "Lean 4.0: How can digital technologies support lean practices?," *International Journal of Production Economics*, vol. 241, p. 108258, 2021. <https://doi.org/10.1016/j.ijpe.2021.108258>
- [9] A. Majumdar, H. Garg, and R. Jain, "Managing the barriers of Industry 4.0 adoption and implementation in textile and clothing industry: Interpretive structural model and triple helix framework," *Computers in Industry*, vol. 125, p. 103372, 2021. <https://doi.org/10.1016/j.compind.2020.103372>
- [10] M. Ryalat, "Smart additive manufacturing: An IoT-driven framework for predictive failure detection and sustainable operation," *Additive Manufacturing Frontiers*, vol. 5, no. 2, p. 200264, 2025. <https://doi.org/10.1016/j.amf.2025.200264>
- [11] E. Fallahiarezouard, M. Ahmadipourroudosht, M. H. Bagherian Rafi, and N. H. A. Ngadiman, "A systematic approach of maintenance 4.0 towards a sustainable manufacturing policy: A case study on an automobile company," *Process Integration and Optimization for Sustainability*, vol. 9, no. 4, pp. 1229–1251, 2025. <https://doi.org/10.1007/s41660-025-00505-y>
- [12] O. Bernhard, F. Dillinger, and M. Zäh, "Methodology for transformation processes in the context of lean 4.0 in manufacturing companies," *Procedia CIRP*, vol. 120, pp. 487–492, 2023. <https://doi.org/10.1016/j.procir.2023.09.024>
- [13] K. Chivukula and L. N. Pattanaik, "Effects of industry 4.0 technologies on lean manufacturing and organizational performances: An empirical study using structural equation modelling," *International Journal of Performability Engineering*, vol. 20, no. 6, 2024.
- [14] Z. Huang, C. Jowers, D. Kent, A. Dehghan-Manshadi, and M. S. Dargusch, "The implementation of Industry 4.0 in manufacturing: From lean manufacturing to product design," *The International Journal of Advanced Manufacturing Technology*, vol. 121, no. 5, pp. 3351–3367, 2022. <https://doi.org/10.1007/s00170-022-09511-7>
- [15] A. K. Suarno, N. Sazali, and A. Junaidi, "Implementation of value stream mapping techniques in improving the performance of service industry," in *Asia Pacific Conference on Manufacturing Systems and International Manufacturing Engineering Conference (pp. 219–231)*. Singapore: Springer Nature Singapore, 2024. [https://doi.org/10.1007/978-981-96-4353-0\\_20](https://doi.org/10.1007/978-981-96-4353-0_20)
- [16] A. H. Gooma, "Lean 4.0: A strategic roadmap for operational excellence and innovation in smart manufacturing," *International Journal of Emerging Science and Engineering*, vol. 13, no. 4, pp. 1–14, 2025.
- [17] R. F. S. Lizy, M. H. Ibrahim, and C. Manthiramoorthy, *Industry 4.0 in manufacturing, communication, transportation, healthcare. In Emerging technologies and security in cloud computing*. Amsterdam, Netherlands: Elsevier, 2024.
- [18] N. S. Aslan, N. Sazali, N. Sazali, and A. Junaidi, "The effect of lean manufacturing on production / operation for the small and medium enterprise in Malaysia," *Journal of Advanced Research Design*, vol. 121, no. 1, pp. 40–50, 2024. <https://doi.org/10.37934/ard.121.1.4050>

- [19] M. S. Amjad, M. Z. Rafique, and M. A. Khan, "Leveraging optimized and cleaner production through industry 4.0," *Sustainable Production and Consumption*, vol. 26, pp. 859-871, 2021. <https://doi.org/10.1016/j.spc.2021.01.001>
- [20] A. H. Trevisan, F. Acerbi, I. Dukovska-Popovska, S. Terzi, and C. Sassanelli, "Skills for the twin transition in manufacturing: A systematic literature review," *Journal of Cleaner Production*, vol. 474, p. 143603, 2024. <https://doi.org/10.1016/j.jclepro.2024.143603>
- [21] A. Guimaraes, E. e Oliveira, M. Oliveira, and T. Pereira, "Effects of Lean Tools and Industry 4.0 technology on productivity: An empirical study," *Journal of Industrial Information Integration*, vol. 44, p. 100787, 2025. <https://doi.org/10.1016/j.jii.2025.100787>
- [22] N. Leesakul, A.-M. Oostveen, I. Eimontaite, M. L. Wilson, and R. Hyde, "Workplace 4.0: Exploring the implications of technology adoption in digital manufacturing on a sustainable workforce," *Sustainability*, vol. 14, no. 6, p. 3311, 2022. <https://doi.org/10.3390/su14063311>
- [23] M. L. Kubjana, "Assessing the influence of leadership styles on the adoption of Construction 4.0 technologies in the South African construction industry," Master's Thesis, University of Johannesburg. Johannesburg, South Africa: University of Johannesburg, 2025.
- [24] J. L. Bindel Sibassaha, J. B. B. Pea-Assounga, and P. D. R. Bambi, "Influence of digital transformation on employee innovative behavior: Roles of challenging appraisal, organizational culture support, and transformational leadership style," *Frontiers in Psychology*, vol. 16, p. 1532977, 2025. <https://doi.org/10.3389/fpsyg.2025.1532977>
- [25] S. Adiawaty and A. Moeins, "Lean management in the era of industry 4.0: Challenges, opportunities, and strategic solutions," *Sinergi International Journal of Logistics*, vol. 2, no. 2, pp. 90-104, 2024. <https://doi.org/10.61194/sijl.v2i2.623>
- [26] E. de Carvalho Pereira *et al.*, "Soybean yield estimation in the Brazilian Midwest using Sentinel-2 imagery," *Big Earth Data*, pp. 1-25, 2026. <https://doi.org/10.1080/20964471.2026.2631900>
- [27] T. Gundu, "Learn, unlearn and relearn: Adaptive cybersecurity culture model," in *Proceedings of the International Conference on Cyber Warfare and Security (pp. 95-102)*. Reading, UK: Academic Conferences International Limited, 2024.
- [28] F. G. Pereira, "Improving controlling processes by applying Lean tools in a component manufacturing company for the automotive industry," Master's thesis, Universidade do Minho (Portugal), 2024.
- [29] J. P. Womack, D. T. Jones, and D. Roos, *The machine that changed the world: The story of lean production--Toyota's secret weapon in the global car wars that is now revolutionizing world industry*. New York: Simon and Schuster, 2007.
- [30] E. Peretz-Andersson, S. Tabares, P. Mikalef, and V. Parida, "Artificial intelligence implementation in manufacturing SMEs: A resource orchestration approach," *International Journal of Information Management*, vol. 77, p. 102781, 2024. <https://doi.org/10.1016/j.ijinfomgt.2024.102781>
- [31] M. Khakifirooz, M. Fathi, A. Dolgui, and P. M. Pardalos, "Scheduling in Industrial environment toward future: Insights from Jean-Marie Proth," *International Journal of Production Research*, vol. 62, no. 1-2, pp. 291-317, 2024. <https://doi.org/10.1080/00207543.2023.2245919>
- [32] J. K. Liker and J. M. Morgan, "The Toyota way in services: The case of lean product development," *Academy of Management Perspectives*, vol. 20, no. 2, pp. 5-20, 2006.
- [33] A.-N. A. Buabeng, "Supply chain cost drivers and operational performance of manufacturing firms in Ghana: Moderating effect of lean manufacturing," University of Cape Coast, 2023.
- [34] G. N. Kenyon, *Supply chain dimensions of quality. In The perception of quality: Establishing a competitive advantage through quality, value, and perception*. Cham, Switzerland: Springer, 2025.
- [35] G. Sindhu, "digital worlds in business management," *Era of Management: Adapting Strategies for a Changing Environment*, p. 38, 2025.
- [36] X. Su, J. Lu, C. Chen, J. Yu, and W. Ji, "Dynamic bottleneck identification of manufacturing resources in complex manufacturing system," *Applied Sciences*, vol. 12, no. 9, p. 4195, 2022. <https://doi.org/10.3390/app12094195>
- [37] V. Singh, M. Sharma, K. Jayapriya, B. K. Kumar, M. Chander, and B. Kumar, "Service quality, customer satisfaction and customer loyalty: A comprehensive literature review," *Journal of Survey in Fisheries Sciences*, vol. 10, no. 4S, pp. 3457-3464, 2023.
- [38] M. Anderson, "Building Trust Through Reliability: A Qualitative Approach to Understanding Customer Loyalty," 2025.
- [39] M. Javaid, A. Haleem, R. P. Singh, R. Suman, and E. S. Gonzalez, "Understanding the adoption of Industry 4.0 technologies in improving environmental sustainability," *Sustainable Operations and Computers*, vol. 3, pp. 203-217, 2022. <https://doi.org/10.1016/j.susoc.2022.01.008>
- [40] M. Ghouat, A. Haddout, and M. Benhadou, "Impact of industry 4.0 concept on the levers of Lean Manufacturing approach in manufacturing industries," *International Journal of Automotive and Mechanical Engineering*, vol. 18, no. 1, pp. 8523-8530-8523-8530, 2021.
- [41] F. Costa, N. Alemsan, A. Bilancia, G. L. Tortorella, and A. Portioli Staudacher, "Integrating industry 4.0 and lean manufacturing for a sustainable green transition: A comprehensive model," *Journal of Cleaner Production*, vol. 465, p. 142728, 2024. <https://doi.org/10.1016/j.jclepro.2024.142728>
- [42] E. O. Alonge, N. L. Eyo-Udo, B. C. Ubanadu, A. I. Daraojimba, E. D. Balogun, and K. O. Ogunsola, "Real-time data analytics for enhancing supply chain efficiency," *Journal of Supply Chain Management and Analytics*, vol. 10, no. 1, pp. 49-60, 2023.

- [43] T. A. Rainy, M. A. Rahman, and A. J. Mou, "Customer relationship management and data-driven decision-making in modern enterprises: A systematic literature review," *American Journal of Advanced Technology and Engineering Solutions*, vol. 4, no. 04, pp. 57-82, 2024.
- [44] O. Emma and S. Keller, "Interplay Between Consumer Demand and Advanced Manufacturing Adaptability: Strategies for Sustainable Innovation in a Rapidly Evolving Market," 2024.
- [45] A. G. Frank, M. Thürer, M. Godinho Filho, and G. A. Marodin, "Beyond Industry 4.0 – integrating Lean, digital technologies and people," *International Journal of Operations & Production Management*, vol. 44, no. 6, pp. 1109-1126, 2024. <https://doi.org/10.1108/IJOPM-01-2024-0069>
- [46] A. Hirsi *et al.*, "Artificial intelligence performance evaluation for URLLC of industrial IoT applications: A review, open challenges and future directions," *Physical Communication*, vol. 72, p. 102712, 2025. <https://doi.org/10.1016/j.phycom.2025.102712>
- [47] M. Soori, B. Arezoo, and R. Dastres, "Internet of things for smart factories in industry 4.0, a review," *Internet of Things and Cyber-Physical Systems*, vol. 3, pp. 192-204, 2023. <https://doi.org/10.1016/j.iotcps.2023.04.006>
- [48] L. Feng and X. Yu, "Hybrid manufacturing thermal environment cycle and industrial economic transformation based on artificial intelligence," *Thermal Science and Engineering Progress*, vol. 56, p. 103085, 2024. <https://doi.org/10.1016/j.tsep.2024.103085>
- [49] B. Kassem, M. Callupe, M. Rossi, M. Rossini, and A. Portioli-Staudacher, "Lean 4.0: A systematic literature review on the interaction between lean production and industry 4.0 pillars," *Journal of Manufacturing Technology Management*, vol. 35, no. 4, pp. 821-847, 2024. <https://doi.org/10.1108/JMTM-04-2022-0144>
- [50] A. Sudiarso, J. Juprianto, and R. A. Gultom, "Potential application of industry 4.0 with lean six sigma in Indonesia's defense industry: A Comprehensive Study: Potensi penerapan industri 4.0 dengan lean six sigma di industri pertahanan Indonesia: Sebuah Studi Komprehensif," *International Journal of Humanities Education and Social Sciences*, vol. 3, no. 2, pp. 1-10, 2023.
- [51] M. A. Rahman *et al.*, "A secure and intelligent framework for vehicle health monitoring exploiting big-data analytics," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 10, pp. 19727-19742, 2022.
- [52] L. B. Benjamin, P. Amajuoyi, and K. B. Adeusi, "Leveraging data analytics for informed product development from conception to launch," *GSC Advanced Research and Reviews*, vol. 19, no. 2, pp. 230-248, 2024.
- [53] U. C. Anozie, K. Pieterse, O. B. Onyenahazi, U. Chukwuebuka, and P. Ekeocha, "Integration of IoT technology in lean manufacturing for real-time supply chain optimization," *International Journal of Science and Research Archive*, vol. 12, no. 2, pp. 1948-1957, 2024.
- [54] B. Rahardjo, F.-K. Wang, R.-H. Yeh, and Y.-P. Chen, "Lean manufacturing in industry 4.0: A smart and sustainable manufacturing system," *Machines*, vol. 11, no. 1, p. 72, 2023. <https://doi.org/10.3390/machines11010072>
- [55] H. B. Patel and N. Kansara, "Cloud computing deployment models: A comparative study," *International Journal of Innovative Research in Computer Science & Technology*, vol. 9, no. 1, pp. 1-5, 2021.
- [56] H. Ran, "Construction and optimization of inventory management system via cloud-edge collaborative computing in supply chain environment in the Internet of Things era," *Plos One*, vol. 16, no. 11, p. e0259284, 2021.
- [57] Y. Tan, L. Gu, S. Xu, and M. Li, "Supply chain inventory management from the perspective of "cloud supply chain"—a data driven approach," *Mathematics*, vol. 12, no. 4, p. 573, 2024. <https://doi.org/10.3390/math12040573>
- [58] Y. Hao, P. Helo, and A. Gunasekaran, "Cloud platforms for remote monitoring system: A comparative case study," *Production Planning & Control*, vol. 31, no. 2-3, pp. 186-202, 2020. <https://doi.org/10.1080/09537287.2019.1631459>
- [59] J.-J. Heiskari, "Computing paradigms for research: cloud vs. edge," 2022.
- [60] C. B. Chrusciak, A. L. Szejka, and O. Canciglieri Junior, "Integrating digital transformation with human-centric factors strategies to enhance organisational process performance: The H.O.P.E. model," *Journal of Industrial Information Integration*, vol. 44, p. 100785, 2025. <https://doi.org/10.1016/j.jii.2025.100785>
- [61] C. J. Turner, J. Oyekan, L. Stergioulas, and D. Griffin, "Utilizing industry 4.0 on the construction site: Challenges and opportunities," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 2, pp. 746-756, 2020.
- [62] L. Driouach, K. Zarbane, and Z. Beidouri, "The impacts of additive manufacturing technology on lean manufacturing," *Journal of Achievements in Materials and Manufacturing Engineering*, vol. 120, no. 1, pp. 22-32, 2023.
- [63] A. M. Nayeem and M. M. N. Hossain, "Usage of additive manufacturing in the automotive industry: A review," *Bangladesh Journal of Multidisciplinary Scientific Research*, vol. 8, no. 1, pp. 9-20, 2023.
- [64] J. Yang, B. Li, J. Liu, Z. Tu, and X. Wu, "Application of additive manufacturing in the automobile industry: A mini review," *Processes*, vol. 12, no. 6, p. 1101, 2024. <https://doi.org/10.3390/pr12061101>
- [65] P. C. Priarone, A. R. Catalano, and L. Settineri, "Additive manufacturing for the automotive industry: on the life-cycle environmental implications of material substitution and lightweighting through re-design," *Progress in Additive Manufacturing*, vol. 8, no. 6, pp. 1229-1240, 2023. <https://doi.org/10.1007/s40964-023-00395-x>
- [66] M. Jayakrishna, M. Vijay, and B. Khan, "An overview of extensive analysis of 3D printing applications in the manufacturing sector," *Journal of Engineering*, vol. 2023, no. 1, p. 7465737, 2023. <https://doi.org/10.1155/2023/7465737>
- [67] C. G. Hussain, M. Qadeer, R. Keçili, and C. M. Hussain, *Additive manufacturing in the next world. In Medical additive manufacturing*. Amsterdam, Netherlands: Elsevier, 2024.

- [68] L. Hu and A. Basiglio, "A multiple-case study on the adoption of customer relationship management and big data analytics in the automotive industry," *The TQM Journal*, vol. 36, no. 9, pp. 1-21, 2023. <https://doi.org/10.1108/TQM-05-2023-0137>
- [69] P. Saraswat, R. Agrawal, and S. B. Rane, "Technological integration of lean manufacturing with industry 4.0 toward lean automation: Insights from the systematic review and further research directions," *Benchmarking: An International Journal*, vol. 32, no. 6, pp. 1909-1941, 2025. <https://doi.org/10.1108/BIJ-05-2023-0316>
- [70] M. Ryalat, H. ElMoaqet, and M. AlFaouri, "Design of a smart factory based on cyber-physical systems and Internet of Things towards Industry 4.0," *Applied Sciences*, vol. 13, no. 4, p. 2156, 2023. <https://doi.org/10.3390/app13042156>
- [71] L. B. Furstenu et al., "Internet of things: Conceptual network structure, main challenges and future directions," *Digital Communications and Networks*, vol. 9, no. 3, pp. 677-687, 2023. <https://doi.org/10.1016/j.dcan.2022.04.027>
- [72] G. Fragapane, D. Ivanov, M. Peron, F. Sgarbossa, and J. O. Strandhagen, "Increasing flexibility and productivity in Industry 4.0 production networks with autonomous mobile robots and smart intralogistics," *Annals of Operations Research*, vol. 308, no. 1, pp. 125-143, 2022. <https://doi.org/10.1007/s10479-020-03526-7>
- [73] J. E. Sordan, P. C. Oprime, M. L. Pimenta, F. Lombardi, and P. Chiabert, "Symbiotic relationship between robotics and Lean Manufacturing: A case study involving line balancing," *The TQM Journal*, vol. 34, no. 5, pp. 1076-1095, 2022.
- [74] S. Proia, R. Carli, G. Cavone, and M. Dotoli, "Control techniques for safe, ergonomic, and efficient human-robot collaboration in the digital industry: A survey," *IEEE Transactions on Automation Science and Engineering*, vol. 19, no. 3, pp. 1798-1819, 2021.
- [75] M. Javaid, A. Haleem, R. P. Singh, and R. Suman, "Significance of Quality 4.0 towards comprehensive enhancement in manufacturing sector," *Sensors International*, vol. 2, p. 100109, 2021. <https://doi.org/10.1016/j.sintl.2021.100109>
- [76] A. Rayhan, "Artificial intelligence in robotics: From automation to autonomous systems," *IEEE Transactions on Robotics*, vol. 39, no. 7, pp. 2241-2253, 2023.
- [77] J. Butt, "A strategic roadmap for the manufacturing industry to implement industry 4.0," *Designs*, vol. 4, no. 2, p. 11, 2020. <https://doi.org/10.3390/designs4020011>
- [78] M. Pekarcikova, P. Trebuna, M. Kliment, and M. Dic, "Solution of bottlenecks in the logistics flow by applying the kanban module in the tecnomatix plant simulation software," *Sustainability*, vol. 13, no. 14, p. 7989, 2021. <https://doi.org/10.3390/su13147989>
- [79] M. Sooria, B. Arezoob, and R. Dastresc, "Advanced virtual manufacturing systems: A review," *Journal of Advanced Manufacturing Science and Technology*, Review vol. 3, no. 3, p. 2023009, 2023. <https://doi.org/10.51393/j.jamst.2023009>
- [80] D. Roy, S. Tripathy, S. K. Kar, N. Sharma, S. K. Verma, and V. Kaushal, "Study of knowledge, attitude, anxiety & perceived mental healthcare need in Indian population during COVID-19 pandemic," *Asian Journal of Psychiatry*, vol. 51, p. 102083, 2020. <https://doi.org/10.1016/j.ajp.2020.102083>
- [81] P. Eirinakis, G. Kasapidis, I. Mourtos, P. Repoussis, and E. Zampou, "Situation-aware manufacturing systems for capturing and handling disruptions," *Journal of Manufacturing Systems*, vol. 58, pp. 365-383, 2021. <https://doi.org/10.1016/j.jmsy.2020.12.014>
- [82] S. Hassan, A. Amjad, M. U. Farooq, S. Anwar, and M. I. Ammarullah, "Applying lean production system philosophy to reduce patient waiting time in healthcare services: Simulation-based optimization and validations through experiment," *AIP Advances*, vol. 14, no. 9, p. 095022, 2024.
- [83] L. Rehberg and A. Brem, "Industrial prototyping in the German automotive industry: Bridging the gap between physical and virtual prototypes," *Journal of Engineering and Technology Management*, vol. 71, p. 101798, 2024. <https://doi.org/10.1016/j.jengtecman.2024.101798>
- [84] S. Shaw, J. M. Luckring, W. L. Oberkampf, and R. E. Graves, "Exploitation of a validation hierarchy for modeling and simulation," in *AIAA SCITECH 2023 Forum*, p. 2605, 2023.
- [85] P. T. Ho, J. A. Albajez, J. Santolaria, and J. A. Yagüe-Fabra, "Study of augmented reality based manufacturing for further integration of quality control 4.0: A systematic literature review," *Applied Sciences*, vol. 12, no. 4, p. 1961, 2022. <https://doi.org/10.3390/app12041961>
- [86] S. Balakrishnan, M. S. S. Hameed, K. Venkatesan, and G. Aswin, "Interaction of spatial computing in augmented reality," in *2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)*, 2021, vol. 1: IEEE, pp. 1900-1904.
- [87] L. Incarbone, "Mixed Reality for operator training and safety in Industry 4.0," 2022.
- [88] E. Marino, L. Barbieri, F. Bruno, and M. Muzzupappa, "Assessing user performance in augmented reality assembly guidance for industry 4.0 operators," *Computers in Industry*, vol. 157, p. 104085, 2024. <https://doi.org/10.1016/j.compind.2024.104085>
- [89] M. Yazdi, "Augmented Reality (AR) and Virtual Reality (VR) in Maintenance Training," in *Advances in Computational Mathematics for Industrial System Reliability and Maintainability*: Springer, 2024, pp. 169-183.
- [90] S. Poorani and L. Krishnan, "Manufacturing technology trends in auto sector guiding skill enhancement and employee retention," *Indian Journal of Training and Development*, vol. 51, 2021.
- [91] N. M. Aripin, G. Nawanir, S. Hussain, P. F. Muhamad Tamyez, M. A. Fauzi, and N. S. N. Alimin, "The path to sustainable lean implementation: A case study in automotive industry," *Operations Research Forum*, vol. 6, no. 1, p. 5, 2024. <https://doi.org/10.1007/s43069-024-00396-8>

- [92] G. Chantziaras *et al.*, "An augmented reality-based remote collaboration platform for worker assistance," in *International Conference on Pattern Recognition* (pp. 404–416). Cham: Springer International Publishing, 2021.
- [93] G. L. Tortorella, F. S. Fogliatto, P. A. Cauchick-Miguel, S. Kurnia, and D. Jurburg, "Integration of industry 4.0 technologies into total productive maintenance practices," *International Journal of Production Economics*, vol. 240, p. 108224, 2021.
- [94] B. ErKayman, "Transition to a JIT production system through ERP implementation: A case from the automotive industry," *International Journal of Production Research*, vol. 57, no. 17, pp. 5467–5477, 2019. <https://doi.org/10.1080/00207543.2018.1527048>
- [95] D. Romero, P. Gaiardelli, D. Powell, T. Wuest, and M. Thürer, "Rethinking jidoka systems under automation & learning perspectives in the digital lean manufacturing world," *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 899–903, 2019.
- [96] Z. Papulová, A. Gažová, and L. Šufliarský, "Implementation of automation technologies of industry 4.0 in automotive manufacturing companies," *Procedia Computer Science*, vol. 200, pp. 1488–1497, 2022. <https://doi.org/10.1016/j.procs.2022.01.350>
- [97] R. Lakshmanan, P. Nyamekye, V.-M. Virolainen, and H. Piili, "The convergence of lean management and additive manufacturing: Case of manufacturing industries," *Cleaner Engineering and Technology*, vol. 13, p. 100620, 2023. <https://doi.org/10.1016/j.clet.2023.100620>
- [98] F. Yao, B. Alkan, B. Ahmad, and R. Harrison, "Improving just-in-time delivery performance of IoT-enabled flexible manufacturing systems with AGV based material transportation," *Sensors*, vol. 20, no. 21, p. 6333, 2020. <https://doi.org/10.3390/s20216333>
- [99] J. Wang, Q. Chang, G. Xiao, N. Wang, and S. Li, "Data driven production modeling and simulation of complex automobile general assembly plant," *Computers in Industry*, vol. 62, no. 7, pp. 765–775, 2011. <https://doi.org/10.1016/j.compind.2011.05.004>
- [100] R. Pisuchpen, "Integration of JIT flexible manufacturing, assembly and disassembly using a simulation approach," *Assembly Automation*, vol. 32, no. 1, pp. 51–61, 2012. <https://doi.org/10.1108/01445151211198719>
- [101] J. Deuse, U. Dombrowski, F. Nöhring, J. Mazarov, and Y. Dix, "Systematic combination of Lean Management with digitalization to improve production systems on the example of Jidoka 4.0," *International Journal of Engineering Business Management*, vol. 12, p. 1847979020951351, 2020. <https://doi.org/10.1177/1847979020951351>
- [102] M. Moghaddam, N. C. Wilson, A. S. Modestino, K. Jona, and S. C. Marsella, "Exploring augmented reality for worker assistance versus training," *Advanced Engineering Informatics*, vol. 50, p. 101410, 2021. <https://doi.org/10.1016/j.aei.2021.101410>
- [103] D. Makwana, P. Engineer, A. Dabhi, and H. Chudasama, "Sampling methods in research: A review," *International Journal of Trend in Scientific Research and Development*, vol. 7, no. 3, pp. 762–768, 2023.
- [104] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *European Business Review*, vol. 31, no. 1, pp. 2–24, 2019. <https://doi.org/10.1108/EBR-11-2018-0203>
- [105] A. Chinnaraju, "Partial least squares structural equation modeling (PLS-SEM) in the AI Era: Innovative methodological guide and framework for business research," 2025.
- [106] G. W. Cheung, H. D. Cooper-Thomas, R. S. Lau, and L. C. Wang, "Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations," *Asia Pacific Journal of Management*, vol. 41, pp. 745–783, 2024. <https://doi.org/10.1007/s10490-023-09871-y>
- [107] K. M. Qureshi, B. G. Mewada, A. Yadav, N. Almakayeel, S. Y. Alghamdi, and M. R. N. M. Qureshi, "Analysing Lean 4.0 adoption factors towards manufacturing sustainability in SMEs: A hybrid ANN-Fuzzy ISM framework," *Scientific Reports*, vol. 15, no. 1, p. 17265, 2025.
- [108] D. M. Gligor, "The role of demand management in achieving supply chain agility," *Supply Chain Management: An International Journal*, vol. 19, no. 5–6, pp. 577–591, 2014. <https://doi.org/10.1108/SCM-10-2013-0363>
- [109] M. A. Al Mahmud *et al.*, "Reviewing the integration of RFID and IoT in supply chain management: Enhancing efficiency and visibility," *Journal of Posthumanism*, vol. 5, no. 3, pp. 409–437–409–437, 2025.
- [110] S. Sarangi and D. Ghosh, "The impact of industry 4.0 technologies enable supply chain performance and quality management practice in the healthcare sector," *The TQM Journal*, vol. 38, no. 2, pp. 297–323, 2026.
- [111] C. Koteswarapavan and L. Pattanaik, "A novel tool-input-process-output (TIPO) framework for upgrading to lean 4.0," *International Journal of Production Management and Engineering*, vol. 12, no. 1, pp. 65–77, 2024.
- [112] J. Barata and P. R. da Cunha, "Augmented product information: Crafting physical-digital transparency strategies in the materials supply chain," *The International Journal of Advanced Manufacturing Technology*, vol. 112, pp. 2109–2121, 2021. <https://doi.org/10.1007/s00170-020-06446-9>
- [113] C. Maware and D. M. Parsley, "Can industry 4.0 assist lean manufacturing in attaining sustainability over time? Evidence from the US organizations," *Sustainability*, vol. 15, no. 3, p. 1962, 2023. <https://doi.org/10.3390/su15031962>