INTERNATIONAL JOURNAL OF eBUSINESS AND eGOVERNMENT STUDIES
Vol: 14 **No:** 4 **Year:** 2022 **ISSN**: 2146-0744 (Online) (**pp.** 174-196) **Doi:** 10.34109/ijebeg. 202214208
Received: 21.09.2022 | **Accepted:** 30.01.2023 | **Published Online:** 28.02.2023

-RESEARCH ARTICLE-

INDUSTRY 4.0 ADOPTION AND LEAN MANUFACTURING PRACTICES FOR MANUFACTURING PERFORMANCE

Nazaruddin Matondang

Department of Industrial Engineering, Universitas
Sumatera Utara, Medan, Indonesia
Email: nazaruddin2@usu.ac.id
https://orcid.org/0009-0003-2444-4933

—Abstract—

The performance of its manufacturing companies could positively influence a province's economic development. Industry 4.0 is one factor that can enhance manufacturing companies' performance. The adoption of Industry 4.0 is intended to make the production process more efficient to reduce production cost inefficiency. To maximize the benefits and potential of Industry 4.0, manufacturers must implement Lean Manufacturing Practices effectively. The lean manufacturing concept aims to reduce lead time and increase output upon implementation by eradicating waste in manufacturing companies. Therefore, adopting Industry 4.0 and lean manufacturing practices can help companies achieve optimal manufacturing sector performance. Utilizing the Structural Equation Modeling – Partial Least Square (SEM-PLS) analysis, the effect of Industry 4.0 adoption and lean manufacturing practices on manufacturing performance was determined quantitatively. The data was collected by disseminating questionnaires to 35 manufacturing companies in the province of North Sumatra. Using a purposive sampling method, 135 respondents from 35 companies participated in the survey. The results indicated that lean manufacturing practices alone had the most significant impact on enhancing manufacturing performance, followed by adopting Industry 4.0. In addition, embracing Industry 4.0 can mediate the relationship between lean manufacturing practices and manufacturing performance, indicating that this will contribute to better performance improvements for the company's growth.

Keywords: Industry 4.0 Adoption, Lean Manufacturing Practices, Manufacturing Performance

Citation (APA): Matondang, N. (2022). Industry 4.0 Adoption and Lean Manufacturing Practices for Manufacturing Performance. *International Journal of eBusiness and eGovernment Studies*, 14 (4), 174-196. doi:10.34109/ijebeg.202214208

1. INTRODUCTION

Incorporating innovative production methods is essential for organizational effectiveness in global competition. Valamede and Akkari (2020) state that lean production is widely recognized as a highly effective strategy in contemporary manufacturing. (Tortorella et al., 2021). Organizations in a variety of industries and sizes across the globe have adopted lean production as a means to increase their overall productivity. According to the research, implementing lean production practices effectively produces a streamlined, high-quality system. Implementing this system results in a greater output of commodities and amenities, increased efficiency, decreased costs, accelerated turnover times, and enhanced adaptability to fluctuating production quantities (Cohen & Kouvelis, 2021). Collectively, these benefits improve the operational effectiveness of entities. However, according to previous research, lean production's prospective impact on competitiveness could be investigated. This study aimed to determine the effect of lean production methods on manufacturing productivity. As a result, we conducted a more thorough analysis of how the duration of lean production implementation affected the factory's productivity.

Over the past four decades, lean production (LP) has garnered increasing attention in operations management and production research (Januszek, 2022; Gayer et al., 2022). LP represents minimal production. On the one hand, it has been shown that LP can reduce waste production, abbreviate lead times, reduce inventory levels, and increase production. Nonetheless, there is a chance that it will boost employees' morale, facilitate communication, and promote openness to new ideas and solutions (Chanana, 2021). The advantages of utilizing LP will reduce costs and customer satisfaction initiatives. Due to the intense competition in modern markets, businesses must make rapid improvements. In addition, the sector faces difficulties due to the rapid growth in demand for highly customized products. (Na et al., 2023) LP faces several obstacles in the incorporation of novel technologies. Pull production must adapt to frequent schedule adjustments, and set-up time reduction frequently relies solely on human intuition. It is becoming increasingly difficult to ascertain precise customer requirements. To fully use the current information and communication technologies, novel approaches are required to manage the massive quantities of data generated by complex systems. In the scholarly literature, opportunities presented by Industry 4.0 (I4.0) to circumvent the limitations posed by LP when addressing these issues have been discussed (Jan et al., 2022). "using intelligent products and processes" is deemed "I4.0." This facilitates self-directed data acquisition, evaluation, and internet-based communication between products, procedures, providers, and consumers. Several recent studies indicate that implementing I4.0 technologies will be most beneficial in areas where flexibility and quality improvements are anticipated (Deshmukh et al.,2022; Tortorella et al.,2020; Nishal,2023).

According to the study's findings, Industry 4.0 (I4.0) demonstrates promising capabilities for mitigating the limitations of LP in addressing the issues mentioned above. "I4.0" refers to using intelligent products and processes that enable self-governing data collection and analysis and the interconnectivity of products, processes, suppliers, and consumers via the internet (Hahn,2020). Furthermore, numerous academic studies have demonstrated that incorporating Industry 4.0 technologies can significantly improve industrial performance, especially in flexibility, efficiency, lead time, costs, and quality (Chari et al.,2022; Javaid et al.,2021).

In 2020, the industry will account for 20.61 percent of the national GDP, making it the most economically significant sector. This percentage is anticipated to be attained in 2020. In North Sumatra, the manufacturing sector contributed only 18.09 percent of the gross regional product in 2020 (Hangler, 2020). In this era of accelerated industrialization, companies face intense levels of competition. (Nardo et al., 2020) To meet this challenge, manufacturing companies must adopt a new approach to enhance their manufacturing performance. Digitalization and artificial intelligence are crucial to modern manufacturing (Denicolai et al., 2021). The company's current business development should be capable of adopting Industry 4.0. Adopting Industry 4.0 aims to increase production process efficiency to reduce production waste and associated production costs. Industry 4.0 is founded on several principles, including decentralized systems, virtual applications, interoperability, modular production, service orientation, and real-time capabilities (Morgan et al., 2021).

The literature has not extensively studied the relationship between Industry 4.0 enabling technologies and manufacturing performance. Industry 4.0 comprises several pillars that can be adopted individually or concurrently in various permutations, with varying effects on businesses. In the last two decades, lean manufacturing has been the most pervasive strategy for enhancing the operational performance of manufacturing companies (Byrne et al., 2012). (Yamamoto et al., 2019) Lean manufacturing was designed to eliminate waste in every step of the production process by focusing on producing a product that provides value to the customer. This work focuses on all aspects of society that are least impacted by the outcomes of LM and, more recently, I4.0. Regarding this, there is considerable uncertainty. There are currently very few concerns in all aspects of society, such as those concerning the future of employment (Kramer & Kramer, 2020). Future research on LM and I4.0 can elucidate and demonstrate how this relationship affects the entire organization, differentiating its impact at each value chain level (Rossini et al., 2023). In contrast, if the process design is not robust and continuous improvement practices are not in place, the organization may not prioritize adopting new technologies (Tortorella et al., 2019).

2. LITERATURE REVIEW

2.1 Industry 4.0 Adoption

The term "digital manufacturing system" refers to the "digital manufacturing system" made possible by the seamless integration of production techniques, information technology, and information technology (Bi,2021). A new concept given the moniker "Industry 4.0" due to technological advancements and innovations has disrupted the global industrial sector. According to Rai et al. (2021), using advanced digital manufacturing techniques could enhance the utilization of supply chain resources. The primary objective of the Industrial Internet of Things (I4.0) initiative is to accelerate a transition toward leaner, more customer-centric, and more rapid manufacturing production. The entirely digital and automated production environment will benefit from this development. Utilizing the digital value chain also ensures reliable communication between products, machinery, and commercial partners. Industry 4.0 will be the driving force behind the future development of technologically sophisticated business models, according to Agrawal et al. (2023). The term "Industry 4.0" was introduced in a November 2011 article written and published as a direct consequence of a German government initiative on high-tech strategies for 2020 (Teixeira et al., 2022). "Industry 4.0," which refers to digitally networked manufacturing, encompasses 3D printing, robotics, and unconventional materials and production methods. According to a 2016 report, the growth of this industry is highly advantageous because it can digitally incorporate manufacturing systems, thereby simplifying and enhancing the supply chains used by businesses.

I4.0 is a broad and multifaceted concept that cannot be wrapped up in a single term (D'Orazio et al., 2020). There is no exhaustive definition of Industry 4.0 in the current research literature. In their study, Frederico et al. (2021) highlighted the importance of I4.0's reference to the interoperability of industrial actors and components. Hallioui et al. (2022) also highlighted this emphasis on the connection between elements, contending that the core of Industry 4.0 is the implementation of network-connected intelligent systems that can realize self-regulating production. Abbas et al. (2019) also emphasized the importance of the relationship between elements. Numerous authors, including these and countless others, have proposed a definition of I4.0 based on its combinatorial nature. They view it as an umbrella term for a collection of interconnected technological advancements designed to promote the digitalization of business. Several authors have proposed this definition.

2.2 Lean Manufacturing Practices

According to Ciliberto et al. (2021), lean manufacturing, or lean production, is one of the most widely utilized waste management principles in the manufacturing and service industries. (Shenshinov & Al-Ali, 2020:Shou et al., 2021). A lean enterprise is a company that implements lean across the entire organization. Lean applied to manufacturing is known as lean manufacturing, and lean applied to services is known as poor service. Lean applied to banks is known as lean banking, and lean in retail is known as lean retailing. (Madhani,(2020). The lean thinking principle is an extension of the lean definition, which is how to generate value efficiently throughout the entire production system by focusing on customers and essential competitiveness at all times. Lean

Vol: 14 **No:** 4 **Year:** 2022 **ISSN**: 2146-0744 (Online) (**pp.** 174-196) **Doi:** 10.34109/ijebeg. 202214208

Manufacturing is a waste elimination method focusing on creating lean production efforts. This method can be implemented effectively for engineering and administrative tasks. In lean, it is also referred to as 3M, which is derived from the Japanese Muda (waste), Mura (consistency), and Muri (irrationality).

Lean manufacturing is based on the elimination of waste and the addition of value. In lean production, "waste" refers to anything that does not immediately benefit the consumer (Ciliberto et al., 2021). Overproduction, waiting periods, unnecessary movement of materials, improper processing, inventory, defects, underutilized personnel, environmental waste, and underutilized facilities are among the most common types of waste. On the other hand, consumers perceive adding value tasks executed accurately on the first attempt and afforded significant importance by the organization. Rathi et al. (2022) provided a comprehensive description of lean production that included all aspects of manufacturing process performance, such as effectiveness and efficiency.

According to their claim, "lean production" is characterized by a reduction in resource utilization relative to mass production. This reduces the number of employees needed in the factory, the amount of manufacturing space required, the cost of tools, and the number of engineering hours required to develop a new product, hence the term "lean production." In addition, it reduces inventory levels, thereby improving quality management and enabling the production of a wider variety of products (Afonso et al., 2021).

The preceding definition includes the relationship between input and output and between production and the organization's goals. This definition is significant because it pertains to the system's effectiveness and efficiency. According to the definition provided by Debnath et al. (2023), the primary objective of lean production is to reduce supplier, customer, and internal process variability, with the end goal of eliminating waste.

The article "Lean Thinking" by Amaro et al. (2019) identifies the five fundamental pillars of lean implementation. The pursuit of perfection, value, value stream, flow, and value comprise these pillars. The value specification procedure facilitates an understanding of the buyer's requirements. The primary objective of a value stream analysis is to distinguish between essential and non-essential stages in the consumer product delivery process. During the progression of products and services through the value stream's value-adding techniques, there must be no interruptions, delays, defects, or other impediments (Ezzeldin et al., 2022). In business operations, the concept of "pull" refers to the production of products or services only upon the request or demand of customers. The term "perfection" emphasizes the significance of continuous production process improvements.

2.3 Manufacturing Performance

Manufacturing performance is the degree to which predetermined and agreed-upon standards, objectives, or other success indicators have been met over a specified period in the execution of delegated tasks. According to research conducted in 2020 by Delic and Eyer, the three components of manufacturing performance are qualitative performance, production adaptability, and operations cost.

Increasing a company's productivity typically requires financial investments in its production activities. Therefore, increasing the efficiency of the manufacturing process can result in a competitive advantage. Two fundamental procedures have been designated as essential for the success of a manufacturing enterprise. First, before competing with its primary competitors, a company must determine its competitive manufacturing priorities and evaluate its current standing in these domains. Before competing with its principal competitors, the company must complete this task (Tortorella et al., 2021). Therefore, to maintain or improve its manufacturing prowess, the business must thoroughly understand the fundamental manufacturing methodologies defining exceptional manufacturing parameters. Most academic studies that evaluate manufacturing performance employ a variety of success indicators, such as waste reduction, operational efficiency, delivery punctuality, product quality, employee motivation, customer satisfaction, and other comparable variables (Cohen & Kouvelis, 2021). In academic settings, reporting data for individual indicators is typical instead of presenting overall performance via an aggregate performance index. Therefore, giving performance data as a singular entity may lead to erroneous conclusions.

Moreover, research that focuses on the outcomes of operational activities frequently overlooks the rationale for investing time and resources in improvement efforts. Research integrating both outputs and inputs typically evaluates the performance by considering a single work, such as production volume, and a limited number of information, including capital and labor (Januszek, 2022). The justification is that research endeavors considering both factors concurrently assess efficacy based on a single outcome, typically about the amount of output generated. Typically, econometrics is the preferred approach for conducting such an investigation. However, such analyses overlook non-quantifiable factors such as quality, on-time delivery, and adaptability, which all play an important role in granting manufacturing firms a competitive advantage despite not being amenable to measurement (Gayer et al., 2022). In addition, inputs of manufacturing companies frequently fail to account for indirect costs, which have increased significantly due to the pervasive adoption of automation, system integration, and related technologies. This phenomenon persists despite a significant increase in indirect costs. As a result, individual performance metrics cannot adequately convey a comprehensive evaluation of a company's manufacturing competitiveness. This is because incomplete measurements depict only a portion of the overall situation.

2.4 Hypotheses Development

The relationship between industry 4.0 adoption, lean manufacturing practices, and manufacturing performance is depicted in Figure 1. Next, specific hypotheses will be discussed.

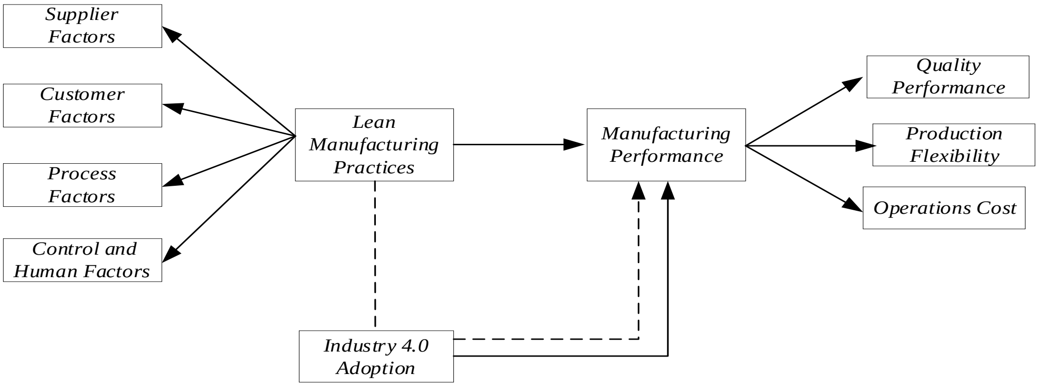


Figure 1. Research Model

2.5 Industry 4.0 Adoption and Manufacturing Performance

Industry 4.0 significantly impacts pricing, production flexibility, and product customization. The automation and digitization functions of Industry 4.0 adoption push producing organizations toward decreased lead times, lower production costs, and superior quality (Hahn, 2020). Thus, industry 4.0 experiences may enable manufacturing firms to optimize their performance. Taiichi Ohno, the founder of LP, advocated for automating repetitive value-adding processes to increase information flow and keep up with market demands. LP has a lengthy tradition of autonomization. This process was referred to as "autonomation" by Nardo et al. (2020) to characterize it.

Ciano et al. (2021) propose that LP methodology production processes suit Industry 4.0 implementation. This discussion is consistent with the concepts and examples presented in previous scholastic works (Morgan et al., 2021). Byrne et al. (2020) emphasized the importance of LP process orientation, clearly defined tasks and timelines for successfully implementing I4.0 autonomation and information exchange, and the mitigation of integration risks. Standardized procedures are essential for identifying and resolving issues, which are fundamental for effectively synchronizing processes. According to Yamamoto et al. (2019), there is a significant correlation between the successful implementation of Industry 4.0 and the widespread adoption of LP. Tortorella et al. (2019) have highlighted the significance of LP by proposing its incorporation as a fundamental strategy in an I4.0 implementation roadmap. This strategy was suggested by Bi (2021) as an essential tactic for an Industry 4.0 plan. According to Teixeira et al. (2022), the capacity to engage in LP requires technical proficiency. According to

Vol: 14 **No:** 4 **Year:** 2022 **ISSN**: 2146-0744 (Online) (**pp.** 174-196) **Doi:** 10.34109/ijebeg. 202214208

Ciliberto et al. (2021), LP can be a valuable asset for I4.0 because LP practitioners possess the knowledge to assess customer value and reduce inefficiencies. The authors also discussed how LP could optimize its products and protocols to increase the cost-effectiveness of Industry 4.0 applications. Shenshinov and Al-Ali (2020) suggest that using VSM can be advantageous in implementing Industry 4.0 due to its systematic approach to identifying improvement opportunities. VSM is recognized for this characteristic. According to Ozkan-Ozen et al. (2020), it is widely believed that LP is a crucial factor in implementing Industry 4.0. Ciano et al. (2021) have called attention to the absence of research on the facilitative effects of LP on I4.0. Current academic consensus regarding the positive impact of Industry 4.0 on Lean Production is encouraging. Nevertheless, our understanding of the fundamental mechanisms is still in its infancy.

H1: Industry 4.0 adoption will be positively associated with manufacturing performance.

2.6 Lean Manufacturing Practices and Manufacturing Performance

According to Dashtdar et al.(2021), the company increased productivity and maintained a competitive advantage due to LMP's lower operational costs and higher profits (Bakke & Claudio, 2023). This can be viewed internally as improving the product's overall quality. In addition, the management philosophy known as "lean manufacturing" won over many individuals and was ultimately adopted by many. Therefore, the implementation has been advantageous to the company's production. Productivity of a manufacturing plant that meets delivery deadlines and minimizes inventory loss It has been demonstrated that improvements in manufacturing performance enhance a company's capacity to compete in the manufacturing sector (Distelhorst & McGahan, 2022), with considerations such as labor and machine productivity.

Research has shown that implementing lean production practices can improve operational and lean performance by promoting consistency and optimizing operations (Sarta et al., 2012). The improvement in operating performance is attributable to concurrently implementing a series of lean production practices. Despite the variety of lean production methodologies, their fundamental principle remains to increase productivity through synergy. This holds regardless of the strategy employed. For example, Agyabeng-Mensah et al. (2021) discovered that the integration of Just-in-Time (JIT) and Total Quality Management (TQM) resulted in more significant performance improvements than the implementation of either approach separately. This information was included on page 1344 of their investigation. According to Hao et al. (2021), implementing lean production practices has a synergistic effect that improves manufacturing performance. It is, therefore, reasonable to assume that these practices will coexist. This claim is substantiated by the evidence presented on page 146. Lean production methodologies have been implemented for a very long time. In addition, Ciliberto et al. (2021) and Tortorella et al. (2019) discovered that implementing lean production techniques significantly and positively impacted operational performance.

H2: Lean manufacturing practices will be positively associated with manufacturing performance.

2.7 Industry 4.0 Adoption, Lean Manufacturing Practices, and Manufacturing Performance

The foundation of Industry 4.0 is founded on lean manufacturing principles. Industry 4.0 and lean manufacturing have the potential to create synergies and increase the precision with which they implement new practices when combined. Regarding lean manufacturing techniques, there is considerable potential for improvement in applying cutting-edge automation technologies. According to De Giovanni and Cariola (2021), lean-to and trade 4.0 yield the most outstanding results for enhancing manufacturing performance. A difference-in-difference, or DID, model was devised to examine the differences in function performance between the experimental and control groups. The samples originated from both of these categories. PSM-DID is a technique proposed by Fan and Zhang in 2021. This method can be used to identify appropriate control groups and the impact factor-induced difference. The DID model can determine whether or not Industry 4.0 impacts the extant performance gap between companies. With the PSM-DID technique, regulating the sample selection deviation and the endogenous problem in panel models is possible. Using the PSM-DID method, both of these issues can be addressed.

Six crucial performance indicators were identified due to the investigation into the effects of enterprise resource planning (ERP) on business outcomes. Return on equity (ROE) stands out because it is calculated by dividing operating income by net assets (Mareta et al., 2022). Patent applications serve as a measure of innovation. Capital market annual return is a measure of stock market returns. Sales profit margin is the ratio of operating profit to sales revenue. Inventory turnover rate, which is a measure of supply chain efficiency in terms of the efficient utilization of assets, and total asset turnover, which is a measure of supply chain efficiency in terms of the efficient utilization of assets, are the performance indicators of the supply chain. Additional supply chain performance indicators include total asset turnover, a measure of supply chain efficiency, and sales profit margin, the ratio of operating profit to sales revenue (Tovar & Aranon, 2021).

The research aims to determine whether the adoption of Industry 4.0 will increase the company's rate of patent application activity, given the wide variation in patent application activity across industries. To attain a consistent level, the annual patent submission count was divided by the company's five-year moving average of patent submissions from 2011 to 2017.

Vol: 14 **No:** 4 **Year:** 2022 **ISSN**: 2146-0744 (Online) (**pp.** 174-196) **Doi:** 10.34109/ijebeg. 202214208

H3: Lean manufacturing practices mediate the relationship between industry 4.0 adoption and manufacturing performance.

3. RESEARCH METHODOLOGY

3.1 Research Database

This study employs causal analysis to investigate the impact of various factors on manufacturing performance. This study collected and analyzed data quantitatively, disseminating questionnaires as a data collection instrument. Industry 4.0 adoption (X1) and lean manufacturing practices (X2) constitute the exogenous constructs. The endogenous construct is production output (Y). The pattern of the path coefficient explains the relationship between exogenous and endogenous variables in this study, as it has both direct and indirect effects. On a five-point Likert scale, responses to the survey ranged from "completely disagree" (1) to "completely agree" (5). The researcher discussed the study's objectives and some manufacturing terminology with the participants. The questions posed in this survey are based on those asked in previous studies. According to research from 2020 by Chauhan et al., the adoption of Industry 4.0 was measured using six distinct indicators. The dimensions of lean manufacturing practices are divided into four segments: Supplier Factors, Customer Factors, Process Factors and Control, and Human Factors, each with three indicators (Neumann et al., 2021). Each of the dimensions of manufacturing performance consists of three indicators: Quality Performance, Production Flexibility, and Operation Cost.

3.2 Measures

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to obtain a comprehensive view of the entire model to determine the effect of the variables in this study (Hair & Alamer, 2022). PLS employs a mixed-model evaluation strategy to ensure its findings' validity and dependability. This strategy involves evaluating the prediction model in conjunction with the measurement model. Constructs' convergent and discriminant facts can be demonstrated by assessing measurement models.

3.3 Sample, Respondent Profile and Biases

The population of this research consists of employees from 35 manufacturing companies in the province of North Sumatra. Because not all employees can respond to the questionnaire based on the actual conditions, purposeful sampling is selected as the sampling technique. Workers on the production floor of a palm oil mill, from the loading ramp station to the kernel station, are the subjects of this investigation. The participants comprise production managers, manufacturing engineers, production supervisors, and PPIC managers.

INTERNATIONAL JOURNAL OF eBUSINESS and eGOVERNMENT STUDIES
Vol: 14 **No:** 4 **Year:** 2022 **ISSN**: 2146-0744 (Online) (**pp.** 174-196) **Doi:** 10.34109/ijebeg. 202214208

There are 135 participants in this study, most male (91%) and of varying ages. Participants included forty production supervisors, thirty-eight PPIC managers, thirty-seven manufacturing engineers, and twenty production managers.

Figure 1 illustrates the characteristics of the participants.

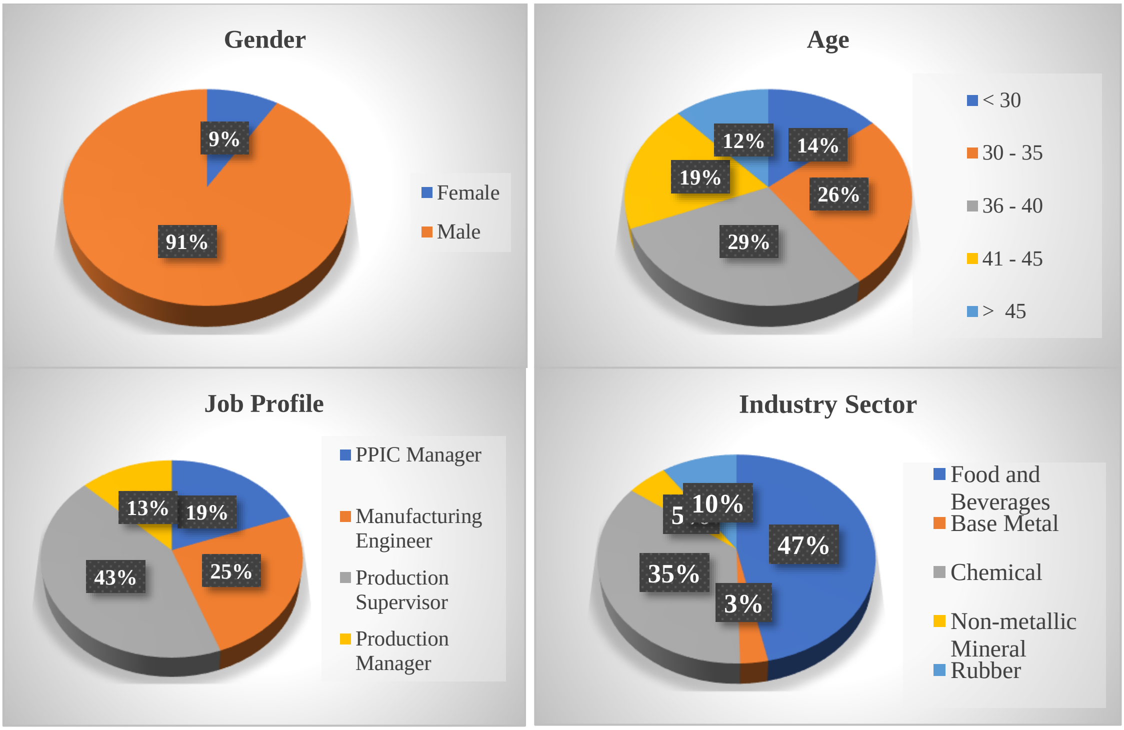


Figure 2. Characteristics of the Participant

4. ANALYSIS AND FINDINGS OF THE STUDY

A structural equation modeling–partial least square (SEM–PLS) analysis is performed on the data to investigate its relationships. We will conduct a battery of measurement model experiments on the measurement scales we will use at the outset of this investigation. This will allow us to ascertain the reliability and validity of our measurement scales.

4.1 Convergent Validity

The value of each indicator's factor loading component determines the convergent validity of the measurement model. According to Hair and Alamer (2022), the loading values of manufacturing performance indicators must exceed 0.70, and their p-values must be less than 0.05. This is because the adoption of Industry 4.0, lean manufacturing practices, and manufacturing performance are reflective. Table 2 demonstrates that the loading factor values for each construct indicator satisfy the validity criteria.

Vol: 14 **No:** 4 **Year:** 2022 **ISSN**: 2146-0744 (Online) (**pp.** 174-196) **Doi:** 10.34109/ijebeg. 202214208

Table 2. Convergent Validity

Constructs	Indicator	Outer Loading Factor
Industry 4.0 Adoption	IN1	0.810
	IN2	0.879
	IN3	0.841
	IN4	0.817
	IN5	0.883
	IN6	0.819
Lean Manufacturing Practices	SF1	0.909
	SF2	0.872
	SF3	0.918
	CF1	0.843
	CF2	0.872
	CF3	0.875
	PF1	0.855
	PF2	0.936
	PF3	0.883
	CHF1	0.921
	CHF2	0.937
	CHF3	0.799
Manufacturing Performance	QP1	0.940
	QP2	0.941
	QP3	0.924
	PRF1	0.803
	PRF2	0.891
	PRF3	0.873
	OC1	0.870
	OC2	0.862
	OC3	0.777

Source: SmartPLS Result (2021)

4.2 Discriminant Validity

The concept of discriminant validity, which can be expressed as a cross-loading factor value, is predominantly based on the principle that different measures of different constructs should not have a strong correlation. Using discriminant validity, one can determine if a construct has a sufficient discriminant by comparing the loading value on the intended construct to the other values; the loading value on the intended construct must be greater than the different values. As a general rule, it is suggested that the value of each construct be more significant than 0.5. Table 2's results indicate that the cross-loading value for each construct is more significant than 0.5. This demonstrates that the

INTERNATIONAL JOURNAL OF eBUSINESS and eGOVERNMENT STUDIES
Vol: 14 **No:** 4 **Year:** 2022 **ISSN**: 2146-0744 (Online) (**pp.** 174-196) **Doi:** 10.34109/ijebeg. 202214208

manifest variables adequately explain the latent variables and that all of the items used in this study have the potential to be considered valid.

Table 3. Discriminant Validity

	CF	**CHF**	**I4**	**LM**	**MP**	**OC**	**PF**	**PRF**	**QP**	**SF**
CF1	**0.839**	0.583	0.558	0.745	0.636	0.549	0.729	0.564	0.618	0.618
CF2	**0.864**	0.725	0.681	0.848	0.788	0.719	0.809	0.666	0.764	0.753
CF3	**0.861**	0.714	0.512	0.788	0.654	0.594	0.656	0.49	0.692	0.705
CHF1	0.633	**0.853**	0.525	0.748	0.687	0.636	0.658	0.504	0.725	0.645
CHF2	0.636	**0.886**	0.541	0.766	0.678	0.605	0.662	0.572	0.67	0.673
CHF3	0.747	**0.817**	0.552	0.806	0.686	0.574	0.712	0.595	0.695	0.729
IN1	0.564	0.545	**0.844**	0.601	0.562	0.487	0.579	0.56	0.492	0.548
IN2	0.539	0.416	**0.856**	0.516	0.584	0.539	0.499	0.558	0.504	0.464
IN3	0.539	0.456	**0.828**	0.533	0.514	0.437	0.523	0.503	0.465	0.466
IN4	0.607	0.527	**0.78**	0.634	0.739	0.694	0.623	0.724	0.611	0.601
IN5	0.612	0.54	**0.853**	0.604	0.643	0.564	0.552	0.548	0.639	0.54
IN6	0.49	0.612	**0.752**	0.59	0.57	0.528	0.527	0.443	0.579	0.57
OC1	0.652	0.552	0.539	0.629	0.775	**0.856**	0.586	0.601	0.67	0.55
OC2	0.612	0.72	0.502	0.735	0.769	**0.818**	0.682	0.568	0.714	0.727
OC3	0.506	0.445	0.594	0.517	0.706	**0.755**	0.503	0.633	0.559	0.467
PF1	0.773	0.635	0.6	0.792	0.679	**0.572**	0.873	0.646	0.633	0.668
PF2	0.832	0.71	0.671	0.862	0.8	**0.698**	0.881	0.686	0.794	0.782
PF3	0.519	0.651	0.405	0.711	0.61	**0.552**	0.744	0.429	0.67	0.745
PRF1	0.53	0.479	0.614	0.56	0.729	**0.641**	0.548	0.846	0.522	0.525
PRF2	0.605	0.542	0.581	0.616	0.717	**0.619**	0.626	0.835	0.518	0.518
PRF3	0.572	0.632	0.55	0.646	0.795	**0.614**	0.625	0.852	0.706	0.576
QP1	0.705	0.674	0.569	0.781	0.819	**0.694**	0.747	0.621	0.906	0.783
QP2	0.803	0.733	0.7	0.815	0.85	**0.747**	0.755	0.681	0.881	0.742
QP3	0.587	0.723	0.473	0.727	0.715	**0.638**	0.676	0.488	0.808	0.727
SF1	0.728	0.658	0.624	0.816	0.729	**0.659**	0.799	0.589	0.736	0.846
SF2	0.791	0.735	0.599	0.829	0.706	**0.614**	0.708	0.55	0.751	0.854
SF3	0.531	0.645	0.43	0.733	0.648	**0.555**	0.716	0.485	0.714	0.844

Source: SmartPLS Result (2021)

4.3 Reliability Test

A measuring device is considered highly reliable if it can provide accurate and consistent information about the measured construct. Cronbach's Alpha and Composite Reliability are two methodologies that can be employed in PLS-SEM to analyze construct reliability. Composite Reliability and Cronbach's Alpha are considered valid methods

Vol: 14 **No:** 4 **Year:** 2022 **ISSN**: 2146-0744 (Online) (**pp.** 174-196) **Doi:** 10.34109/ijebeg. 202214208

for determining reliability; a constructed value is deemed reliable if either of these methods yields a value greater than 0.70.

Table 4. Reliability Test

Constructs	**Cronbach's Alpha**	**Composite Reliability**
Industry 4.0 Adoption	0.918	0.936
Lean Manufacturing Practices	0.963	0.967
Supplier Factors	0.882	0.927
Customer Factors	0.829	0.898
Process Factors	0.871	0.921
Control and Human Factors	0.863	0.917
Manufacturing Performance	0.951	0.959
Quality Performance	0.928	0.954
Production Flexibility	0.818	0.892
Operations Cost	0.786	0.875

Source: SmartPLS Result (2021)

4.4 R Square

The coefficient of determination (R2) is a statistical measure that can determine how shifts in Industry 4.0 and lean manufacturing practices can account for variations in manufacturing performance variables. Purwanto et al. (2021) define a robust model with an R-squared value of 0.67, a medium model of 0.33, and a weak model of 0.19. When assessing the capacity of a structural model to explain the variance, the R2 value for endogenous latent constructs is typically the preferred metric. Table 5 displays the R2 value associated with this analysis.

Table 5. R Square

Item	**R Square**	**R Square Adjusted**
Manufacturing Performance	0.802	0.799

Source: SmartPLS Result (2021)

4.5 Q^2 Predictive Relevance

R-squared size and predictive sample reuse, which is the synthesis of cross-validation and fitting functions with predictions from observed variables and estimates of construct parameter values, can be used to evaluate the performance of the PLS model. It is possible to combine predictive sample reuse with R-squared size. If Q2 is more significant than zero, the model can be used to make accurate predictions; if Q2 equals zero, the model cannot be used to make accurate predictions. The strength of a model can be determined, according to Purwanto (2021), by evaluating the Q2 predictive relevance values, which range from 0.02 to 0.15 to 0.35. If Q2 is more significant than

Vol: 14 **No:** 4 **Year:** 2022 **ISSN**: 2146-0744 (Online) (**pp.** 174-196) **Doi:** 10.34109/ijebeg. 202214208

zero, then the model can be used to make predictions; if it is less than zero, it lacks predictive value. Table 6 exhibits Q2's numerical value.

Table 6. Q2 Predictive Relevance

Item	SSO	SSE	Q2=(1-SSE/SSO)
Manufacturing Performance	1215	660.495	0.456

Source: SmartPLS Result (2021)

4.6 Hypotheses Testing Results

A bootstrapping procedure is required to determine whether the effect between variables is significant. The initial sample is utilized for resampling using the bootstrap procedure. The initial sample size should always be greater than the number of bootstrap samples, which is why 5,000 are recommended. The resampling bootstrap method employs two-tailed t-values of 1.65 (at a significance level of 10%), 1.96 (at a significance level of 5%), and 2.58 (at a significance level of 1%) to assess the results of repeated sampling. When the value is positive, the impact is favorable, but when the value is negative, the effect is unfavorable. When the value is positive, the result is positive. Path coefficients can be used to determine the degree of association between two variables. If the t-count value (t-statistic) is greater than the t-table at the 5% significance level (Juwaini et al.,2022), which is 1.96, the bootstrapping method used in this study can be used to approve the research hypothesis. It is also evident from the p-values, which have a statistically significant impact when they fall below the error rate. The primary objective of the preliminary sample was to determine the nature and direction of the variable's influence.

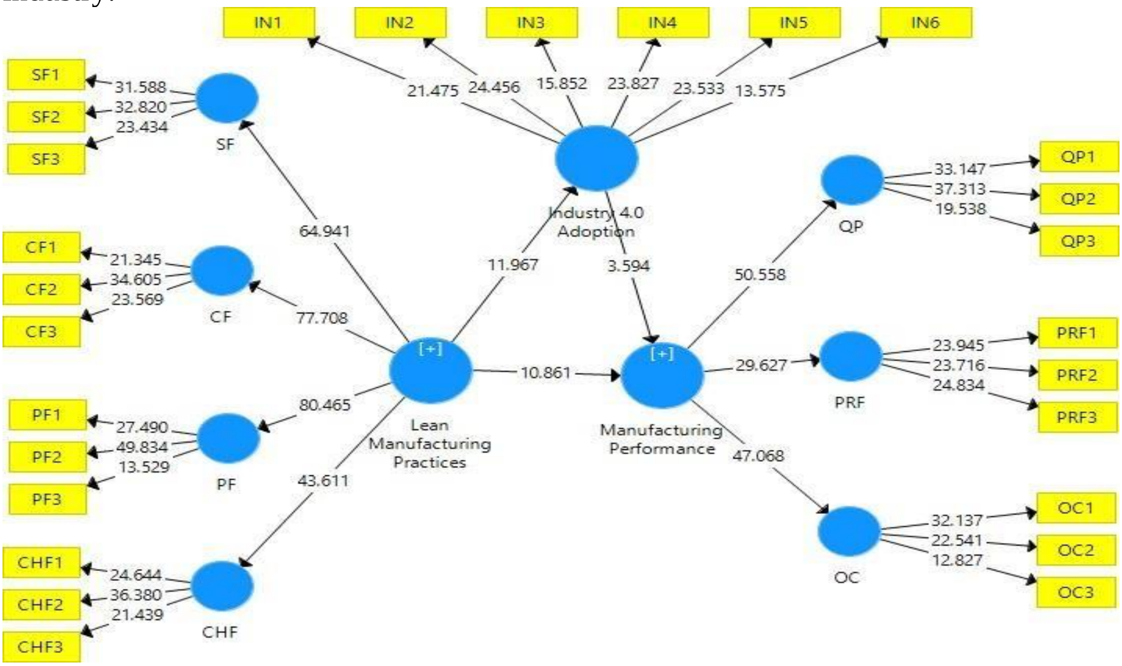
Table 7. Result of Hypothesis Testing

	Original Sample (O)	T Statistics (|O/STDEV|)	P Values	Supported?
Industry 4.0 Adoption -> Manufacturing Performance	0.237	3.594	0.00	Yes
Lean Manufacturing Practices -> Manufacturing Performance	0.711	10.861	0.00	Yes
Lean Manufacturing Practices -> Industry 4.0 Adoption -> Manufacturing Performance	0.169	3.224	0.001	Yes

Source: Smart PLS Result (2021)

Figure 2 depicts the t-statistic value for each variable to illustrate how implementing Industry 4.0 and lean manufacturing practices increases production output. This result is directly attributable to the implementation of these practices. There is consensus that poor manufacturing practices have the most significant impact of the three. The pervasive implementation of lean manufacturing practices has directly contributed to a 71.1% improvement in the manufacturing industry's overall performance.

industry.



Source: SmartPLS Result (2021)
Figure 3. Full Research Model

Based on the previous response, it can be concluded that there is a positive regression result (with a coefficient value of 0.237) between the implementation of Industry 4.0 and the manufacturing output. The discovery mentioned above is consistent with the resource-based theory, which posits that firms with unique and valuable resources and capabilities are more likely to sustain a competitive advantage and outperform their competitors. Integrating sophisticated technologies within Industry 4.0 may provide a valuable resource and power for boosting production yield. A positive regression coefficient of 0.711 indicates a significant relationship between lean manufacturing practices and manufacturing performance, as determined by the present study. This finding is consistent with the resource-based theory principles. By implementing lean manufacturing practices, businesses can increase their operational efficiency by reducing inefficiencies and increasing output. In accordance with the principles of resource-based theory, the results of the regression analysis indicate a positive relationship (coefficient of.169) between the implementation of lean manufacturing

Vol: 14 **No:** 4 **Year:** 2022 **ISSN**: 2146-0744 (Online) (**pp.** 174-196) **Doi:** 10.34109/ijebeg. 202214208

practices and the adoption of Industry 4.0. There is a statistically significant relationship between the two variables, as shown by the results. This finding suggests that businesses with complementary resources and capabilities may have an advantage when competing successfully with other businesses. By incorporating technologies from Industry 4.0, the benefits of lean manufacturing practices could be increased when applied in this context.

5. CONCLUSION

This study investigates the impact of employees' perceptions of Industry 4.0 adoption and lean manufacturing practices on manufacturing performance in North Sumatra Province manufacturing firms. Several authors' initial expectations regarding the relationship between Industry 4.0 adoption and poor manufacturing practices and manufacturing performance were not met by the findings of this study. (Mofolasayo et al., 2022) Both industry 4.0 adoption and lean manufacturing practices aspire to increase the manufacturing system's responsiveness and efficiency while decreasing production waste. Effective production processes can increase company productivity, thereby enhancing manufacturing performance. The likelihood of implementing Industry 4.0 significantly increases in organizations adopting lean production.

6. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

The results of the data analysis indicate that lean manufacturing practices significantly impact the manufacturing performance of North Sumatra's manufacturing companies. Industry 4.0 is a relatively new technology, and most manufacturing companies in North Sumatra are in the process of achieving full-fledged deployment, so industry 4.0 adoption has a limited impact, indicating that several companies have not been able to adopt the technology. Consequently, the respondents' perspectives in their questionnaires may not be solely based on their practical experience with the technology. Therefore, the simultaneous implementation of the two variables has been appropriately synchronized and has had the most significant effect on manufacturing performance. Because lean manufacturing practices are the foundation for Industry 4.0, businesses must be able to implement industrial technology version 4.0. By executing it simultaneously, the performance of the manufacturing company in the province of North Sumatra is expected to improve.

REFERENCES

Abbas, J., Aman, J., Nurunnabi, M., & Bano, S. (2019). The impact of social media on learning behavior for sustainable education: Evidence of students from selected universities in Pakistan. *Sustainability, 11*(6), 1683. doi: https://doi.org/10.3390/su11061683

Afonso, T., Alves, A., Carneiro, P., & Vieira, A. (2021). Simulation pulled by the need to reduce wastes and human effort in an intralogistics project, *International*

Journal of Industrial Engineering and Management, *12*(4), 274 -285. doi: http://doi.org/10.24867/IJIEM-2021-4-294

Agrawal, T. K., Angelis, J., Khilji, W. A., Kalaiarasan, R., & Wiktorsson, M. (2023). Demonstration of a blockchain-based framework using smart contracts for supply chain collaboration. *International Journal of Production Research*, *61*(5), 1497-1516. doi: https://doi.org/10.1080/00207543.2022.2039413

Agyabeng-Mensah, Y., Afum, E., Agnikpe, C., Cai, J., Ahenkorah, E., & Dacosta, E. (2021). Exploring the mediating influences of total quality management and just in time between green supply chain practices and performance. *Journal of Manufacturing Technology Management*, *32*(1), 156-175. doi: https://doi.org/10.1108/JMTM-03-2020-0086

Amaro, P., Alves, A. C., & Sousa, R. M. (2019). Lean thinking: a transversal and global management philosophy to achieve sustainability benefits. *Lean Engineering for Global Development*, 1-31. doi: https://doi.org/10.1007/978-3-030-13515-7_1

Bakke, M., & Claudio, D. (2023). Efficiency realization and capacity increase: implementing lean six sigma in a growing startup. *Small Enterprise Research*, 1-16. doi: https://doi.org/10.1080/13215906.2023.2200746

Bi, Z. (2021). *Practical Guide to Digital Manufacturing: First-Time-Right for Design of Products, Machines, Processes and System Integration*. Springer Nature. Retrieved from https://books.google.ae/books?hl

Byrne, B., McDermott, O., & Noonan, J. (2021). Applying lean six sigma methodology to a pharmaceutical manufacturing facility: A case study. *Processes*, *9*(3), 550. doi: https://doi.org/10.3390/pr9030550

Chanana, N. (2021). Employee engagement practices during COVID-19 lockdown. *Journal of Public Affairs*, *21*(4), e2508. doi: https://doi.org/10.1002/pa.2508

Chari, A., Niedenzu, D., Despeisse, M., Machado, C. G., Azevedo, J. D., Boavida-Dias, R., & Johansson, B. (2022). Dynamic capabilities for circular manufacturing supply chains—Exploring the role of Industry 4.0 and resilience. *Business Strategy and the Environment*, *31*(5), 2500-2517. doi: https://doi.org/10.1002/bse.3040

Ciano, M. P., Dallasega, P., Orzes, G., & Rossi, T. (2021). One-to-one relationships between Industry 4.0 technologies and Lean Production techniques: a multiple case study. *International Journal of Production Research*, *59*(5), 1386-1410. doi: https://doi.org/10.1080/00207543.2020.1821119

Ciliberto, C., Szopik-Depczyńska, K., Tarczyńska-Łuniewska, M., Ruggieri, A., & Ioppolo, G. (2021). Enabling the Circular Economy transition: A sustainable lean manufacturing recipe for Industry 4.0. *Business Strategy and the Environment*, *30*(7), 3255-3272. doi: https://doi.org/10.1002/bse.2801

Cohen, M. A., & Kouvelis, P. (2021). Revisit of AAA excellence of global value chains: Robustness, resilience, and realignment. *Production and Operations Management*, *30*(3), 633-643. doi: https://doi.org/10.1111/poms.13305

D'Orazio, L., Messina, R., & Schiraldi, M. M. (2020). Industry 4.0 and world class manufacturing integration: 100 technologies for a WCM-I4. 0 matrix. *Applied Sciences*, *10*(14), 4942. doi: https://doi.org/10.3390/app10144942

Dashtdar, M., Najafi, M., & Esmaeilbeig, M. (2021). Reducing LMP and resolving the congestion of the lines based on placement and optimal size of DG in the power network using the GA-GSF algorithm. *Electrical Engineering*, *103*, 1279-1306. doi: https://doi.org/10.1007/s00202-020-01142-z

De Giovanni, P., & Cariola, A. (2021). Process innovation through industry 4.0 technologies, lean practices and green supply chains. *Research in Transportation Economics*, *90*, 100869. doi: https://doi.org/10.1016/j.retrec.2020.100869

Debnath, B., Shakur, M. S., Bari, A. M., & Karmaker, C. L. (2023). A Bayesian Best–Worst approach for assessing the critical success factors in sustainable lean manufacturing. *Decision Analytics Journal*, *6*, 100157. doi: https://doi.org/10.1016/j.dajour.2022.100157

Delic, M., & Eyers, D. R. (2020). The effect of additive manufacturing adoption on supply chain flexibility and performance: An empirical analysis from the automotive industry. *International Journal of Production Economics*, *228*, 107689. doi: https://doi.org/10.1016/j.ijpe.2020.107689

Denicolai, S., Zucchella, A., & Magnani, G. (2021). Internationalization, digitalization, and sustainability: Are SMEs ready? A survey on synergies and substituting effects among growth paths. *Technological Forecasting and Social Change*, *166*, 120650. doi: https://doi.org/10.1016/j.techfore.2021.120650

Deshmukh, M., Gangele, A., Gope, D. K., & Dewangan, S. (2022). Study and implementation of lean manufacturing strategies: A literature review. *Materials Today: Proceedings*, *62*(3), 1489-1495. doi: https://doi.org/10.1016/j.matpr.2022.02.155

Distelhorst, G., & McGahan, A. (2022). Socially irresponsible employment in emerging-market manufacturers. *Organization Science*, *33*(6), 2135-2158. doi: https://doi.org/10.1287/orsc.2021.1526

Ezzeldin, A. I., Mohamed, T. A., & Abdallah, K. S. (2022). Improving the productivity of an assembly production line utilising lean tools and simulation: a case study. *International Journal of Six Sigma and Competitive Advantage*, *14*(2), 227-246. doi: https://doi.org/10.1504/IJSSCA.2022.124977

Fan, F., & Zhang, X. (2021). Transformation effect of resource-based cities based on PSM-DID model: An empirical analysis from China. *Environmental Impact Assessment Review*, *91*, 106648. doi: https://doi.org/10.1016/j.eiar.2021.106648

Frederico, G. F., Kumar, V., Garza-Reyes, J. A., Kumar, A., & Agrawal, R. (2021). Impact of I4. 0 technologies and their interoperability on performance: future pathways for supply chain resilience post-COVID-19. *The International Journal* *of Logistics Management*, (ahead-of-print). doi: https://doi.org/10.1108/IJLM-03-2021-0181

Gayer, B. D., Saurin, T. A., & Anzanello, M. (2022). The nature and role of informal resilience practices in the performance of lean production systems. *Journal of Manufacturing Technology Management*, *33*(6), 1080-1101. doi: https://doi.org/10.1108/JMTM-12-2021-0489

Hahn, G. J. (2020). Industry 4.0: a supply chain innovation perspective. *International Journal of Production Research*, *58*(5), 1425-1441. doi: https://doi.org/10.1080/00207543.2019.1641642

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3), 100027. doi: https://doi.org/10.1016/j.rmal.2022.100027

Hallioui, A., Herrou, B., Santos, R. S., Katina, P. F., & Egbue, O. (2022). Systems-based approach to contemporary business management: An enabler of business sustainability in a context of industry 4.0, circular economy, competitiveness and diverse stakeholders. *Journal of Cleaner Production*, *373*, 133819. doi: https://doi.org/10.1016/j.jclepro.2022.133819

Hangler, M. (2020). *Socio-economic consequences of an industry: How palm oil production affects Indonesias locals/written by Magdalena Hangler* (Doctoral dissertation, Universität Linz). Retrieved from https://epub.jku.at/obvulihs/content/titleinfo/5271701

Hao, Z., Liu, C., & Goh, M. (2021). Determining the effects of lean production and servitization of manufacturing on sustainable performance. *Sustainable Production and Consumption*, *25*, 374-389. doi: https://doi.org/10.1016/j.spc.2020.11.018

Jan, Z., Ahamed, F., Mayer, W., Patel, N., Grossmann, G., Stumptner, M., & Kuusk, A. (2022). Artificial Intelligence for Industry 4.0: Systematic Review of Applications, Challenges, and Opportunities. *Expert Systems with Applications*, *216*, 119456. doi: https://doi.org/10.1016/j.eswa.2022.119456

Januszek, S. (2022). *Implementing Lean Production: A Behavioral Perspective* (Doctoral dissertation, ETH Zurich), 1-157. Retrieved from https://www.research-collection.ethz.ch/handle/20.500.11850/597088

Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2021). Substantial capabilities of robotics in enhancing industry 4.0 implementation. *Cognitive Robotics*, *1*, 58-75. doi: https://doi.org/10.1016/j.cogr.2021.06.001

Juwaini, A., Chidir, G., Novitasari, D., Iskandar, J., Hutagalung, D., Pramono, T., ... & Purwanto, A. (2022). The role of customer e-trust, customer e-service quality and customer e-satisfaction on customer e-loyalty. *International Journal of Data and Network Science*, *6*(2), 477-486. doi: http://dx.doi.org/10.5267/j.ijdns.2021.12.006

Kramer, A., & Kramer, K. Z. (2020). The potential impact of the Covid-19 pandemic on occupational status, work from home, and occupational mobility. *Journal of Vocational Behavior*, *119*, 103442. doi: https://doi.org/10.1016/j.jvb.2020.103442

MacDuffie, J. P., & Helper, S. (1997). Creating lean suppliers: diffusing lean production through the supply chain. *California Management Review*, *39*(4), 118-151. doi: https://doi.org/10.2307/41165913

Madhani, P. M. (2020). Lean Six Sigma deployment in retail industry: enhancing competitive advantages. *The IUP Journal of Business Strategy*, *17*(3), 25-45. doi: https://dx.doi.org/10.2139/ssrn.4002472

Mareta, F., Ulhaq, A., Resfitasari, E., Febriani, I., & Elisah, S. (2022, February). Effect of Debt to Equity Ratio, Current Ratio, Total Assets Turnover, Earning Per Share, Price Earning-Ratio, Sales Growth, and Net Profit Margin on Return on Equity. In *International Conference on Economics, Management and Accounting (ICEMAC 2021)*, 417-426. Atlantis Press. doi: https://doi.org/10.2991/aebmr.k.220204.047

Mofolasayo, A., Young, S., Martinez, P., & Ahmad, R. (2022). How to adapt lean practices in SMEs to support Industry 4.0 in manufacturing. *Procedia Computer Science*, *200*, 934-943. doi: https://doi.org/10.1016/j.procs.2022.01.291

Morgan, J., Halton, M., Qiao, Y., & Breslin, J. G. (2021). Industry 4.0 smart reconfigurable manufacturing machines. *Journal of Manufacturing Systems*, *59*, 481-506. doi: https://doi.org/10.1016/j.jmsy.2021.03.001

Na, E., Jung, Y., & Kim, S. (2023). How do care service managers and workers perceive care robot adoption in elderly care facilities?. *Technological Forecasting and Social Change*, *187*, 122250. doi: https://doi.org/10.1016/j.techfore.2022.122250

Nardo, M., Forino, D., & Murino, T. (2020). The evolution of man–machine interaction: The role of human in Industry 4.0 paradigm. *Production & Manufacturing Research*, *8*(1), 20-34. doi: https://doi.org/10.1080/21693277.2020.1737592

Neumann, W. P., Winkelhaus, S., Grosse, E. H., & Glock, C. H. (2021). Industry 4.0 and the human factor–A systems framework and analysis methodology for successful development. *International Journal of Production Economics*, *233*, 107992. doi: https://doi.org/10.1016/j.ijpe.2020.107992

Nishal, M. (2023). Analysing Roles of I4. 0 Technologies in the Lean-Green Paradigm. In *Lean Thinking in Industry 4.0 and Services for Society*, 167-193. IGI Global. doi: https://doi.org/10.4018/978-1-6684-5606-4.ch009

Ozkan-Ozen, Y. D., Kazancoglu, Y., & Mangla, S. K. (2020). Synchronized barriers for circular supply chains in industry 3.5/industry 4.0 transition for sustainable resource management. *Resources, Conservation and Recycling*, *161*, 104986. doi: https://doi.org/10.1016/j.resconrec.2020.104986

Purwanto, A. (2021). Partial least squares structural squation modeling (PLS-SEM) analysis for social and management research: a literature review. *Journal of*

Industrial Engineering & Management Research, *10*. Retrieved from https://ssrn.com/abstract=3982764

Purwanto, A., Fahmi, K., Irwansyah, I., Hadinegoro, R., Rochmad, I., Syahril, S., & Sulastri, E. (2022). The role of green innovation and green supply chain management on the sustainability of the performance of SMEs. *Journal of Future Sustainability*, *2*(2), 49-52. doi: http://dx.doi.org/10.5267/j.jfs.2022.9.003

Rai, R., Tiwari, M. K., Ivanov, D., & Dolgui, A. (2021). Machine learning in manufacturing and industry 4.0 applications. *International Journal of Production Research*, *59*(16), 4773-4778. doi: https://doi.org/10.1080/00207543.2021.1956675

Rathi, R., Kaswan, M. S., Garza-Reyes, J. A., Antony, J., & Cross, J. (2022). Green Lean Six Sigma for improving manufacturing sustainability: Framework development and validation. *Journal of Cleaner Production*, *345*, 131130. doi: https://doi.org/10.1016/j.jclepro.2022.131130

Rossini, M., Powell, D. J., & Kundu, K. (2023). Lean supply chain management and Industry 4.0: A systematic literature review. *International Journal of Lean Six Sigma*, *14*(2), 253-276. doi: https://doi.org/10.1108/IJLSS-05-2021-0092

Sartal, A., Llach, J., & León-Mateos, F. (2022). Do technologies really affect that much? Exploring the potential of several industry 4.0 technologies in today's lean manufacturing shop floors. *Operational Research*, *22*(5), 6075-6106. doi: https://doi.org/10.1007/s12351-022-00732-y

Shenshinov, Y., & Al-Ali, A. (2020). The tools of increasing efficiency of human resource in the lean production environment: Conceptual study. *International Journal of Core Engineering & Management*, *6*(7), 1-18. Retrieved from https://www.researchgate.net/profile/Abdulsattar-Al-Ali-2/publication/369356379

Shou, W., Wang, J., Wu, P., & Wang, X. (2020). Value adding and non-value adding activities in turnaround maintenance process: classification, validation, and benefits. *Production Planning & Control*, *31*(1), 60-77. doi: https://doi.org/10.1080/09537287.2019.1629038

Teixeira, J. E., & Tavares-Lehmann, A. T. C. (2022). Industry 4.0 in the European union: Policies and national strategies. *Technological Forecasting and Social Change*, *180*, 121664. doi: https://doi.org/10.1016/j.techfore.2022.121664

Tortorella, G. L., Giglio, R., & Van Dun, D. H. (2019). Industry 4.0 adoption as a moderator of the impact of lean production practices on operational performance improvement. *International Journal of Operations & Production Management*, *39*(6/7/8), 860-886. doi: https://doi.org/10.1108/IJOPM-01-2019-0005

Tortorella, G. L., Pradhan, N., Macias de Anda, E., Trevino Martinez, S., Sawhney, R., & Kumar, M. (2020). Designing lean value streams in the fourth industrial revolution era: proposition of technology-integrated guidelines. *International*

Journal of Production Research, *58*(16), 5020-5033. doi: https://doi.org/10.1080/00207543.2020.1743893

Tortorella, G., Sawhney, R., Jurburg, D., de Paula, I. C., Tlapa, D., & Thurer, M. (2021). Towards the proposition of a lean automation framework: Integrating industry 4.0 into lean production. *Journal of Manufacturing Technology Management*, *32*(3), 593-620. doi: https://doi.org/10.1108/JMTM-01-2019-0032

Tovar, E., & Arana, P. (2021). Financial return on equity (froe): Case of Colombian Industrial Companies. *Academy of Accounting and Financial Studies Journal*, *25*(1), 1-6. Retrieved from https://www.proquest.com/openview/fc32e409b8ff4663f4d68f309acd1eed/1?pq-origsite=gscholar&cbl=29414

Valamede, L. S., & Akkari, A. C. S. (2020). Lean 4.0: A new holistic approach for the integration of lean manufacturing tools and digital technologies. *International Journal of Mathematical*, *Engineering and Management Sciences*, *5*(5), 851. doi: https://doi.org/10.33889/IJMEMS.2020.5.5.066

Yadav, G., Luthra, S., Jakhar, S. K., Mangla, S. K., & Rai, D. P. (2020). A framework to overcome sustainable supply chain challenges through solution measures of industry 4.0 and circular economy: An automotive case. *Journal of Cleaner Production*, *254*, 120112. doi: https://doi.org/10.1016/j.jclepro.2020.120112

Yamamoto, K., Milstead, M., & LIoyd, R. (2019). A review of the development of lean manufacturing and related lean practices: The case of Toyota Production System and managerial thinking. *International Management Review*, *15*(2), 21-90. Retrieved from https://www.researchgate.net/profile/Robert-Lloyd-13/publication/340449306