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Lean Manufacturing and Industry 4.0: Unveiling Trends, Applications, and Global Impacts in Manufacturing Through Comprehensive Literature Review

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ABSTRACT

The integration of Lean Manufacturing (LM) and Industry 4.0 (I4.0), also known as Lean Manufacturing 4.0 or Smart Factory, is increasingly adopted by manufacturers for their effectiveness in reducing losses and improving efficiency. Despite their established benefits, there is a notable gap in comprehensive analyses regarding the integration of I4.0's Manufacturing Execution System (MES) and Total Productive Maintenance's Overall Equipment Effectiveness (OEE) within lean practices. Therefore, the purpose of this paper is to provide a comprehensive literature review offering thorough insights into the trends, applications, and impacts of Lean Manufacturing 4.0. Utilizing a systematic literature review, this research initially assesses 250 papers for bibliometric trends, narrowing down to 44 papers for content analysis. The bibliometric analysis reveals trends in Lean Manufacturing 4.0 publications, including historical series, publications across countries, highly cited articles and types of papers. Noteworthy findings from the content analysis are the frequent connection between LM's Process Mapping and I4.0's MES, as well as the frequent association of I4.0's Internet of Things with LM's OEE. The OEE-I4.0 integration is predominantly characterized by enhanced OEE and real-time data utilization, while MES-Lean integration showcases documented impacts on production efficiency, resource management, and continuous and operational system improvement. This study highlights the importance of adopting relevant Lean Manufacturing 4.0 practices for manufacturers and scholars. The importance of Lean Manufacturing 4.0 practices and the understanding of connections between OEE and I4.0, as well as MES and LM, are addressed in this study, emphasizing the imperative for businesses to adopt Lean Manufacturing 4.0.

Keywords: Overall Equipment Effectiveness(OEE);ManufacturingExecutionSystem(MES);InternetofThings (IoT), Lean Manufacturing 4.0; Smart Factory.

INTRODUCTION

INDUSTRY 4.0 – MES

The historical context of industrial revolutions provides a backdrop for understanding the transformative journey of manufacturing, as depicted in Figure 1. Rather than producing items by hand, industries turned to machinery, leading to the Industrial Revolution of the 18th century (Dhibar, Maji et al. 2023). Starting with the integration of steam engines in 1782, marking the onset of Industry 1.0, with innovations in transportation, such as railroads and steamboats, improved water power efficiency and broadened steam power usage, while machine tools and water canals were also developed during this era (Shah, Hussain Madni et al. 2024). Industry 2.0 then introduced electrical power, assembly lines, and conveyor belts, altering manufacturing methodologies (Rahigude, Khwairakpam et al. 2022). Building on this, the arrival of electronics in 1954 played another crucial role, where the third industrial revolution brought computer-controlled automation into the manufacturing sector. This was subsequently replaced by the digital transformation of the fourth industrial revolution, where devices autonomously communicate throughout the value chain, representing the most significant shift in technology and labor markets (Szabó-Szentgróti, Végvári et al. 2021). Each phase in this historical progression not only represents a chronological step forward but also reflects a notable transformation in manufacturing processes (Karjagi Nigappa alias Shridhar and Selvakumar 2016).

The influence of I4.0 technologies on manufacturers has been substantial, with notable enhancements observed in production processes, operational performance optimization, and improved product development, along with refined supply chain planning (Zheng, Ardolino et al. 2021).

One of the foundational I4.0 technologies, the Manufacturing Execution System (MES), employs advanced equipment such as sensors and IoT devices, combined with sophisticated software, to gather, store, and analyze production data (Pusztai, Nagy et al. 2023). Some studies also indicate that modern MES should handle real-time data from the shop floor, manage manufacturing activities, and analyze data efficiently (Ahakonye, Zainudin et al. 2024). Figure 2 highlights the seamless integration of physical components, connectivity, and software applications within the MES framework.

The manufacturing industry chain typically includes supply, processing, transportation, and sales, each producing significant amounts of production data (Feng and Yu 2023, Liu, Yu et al. 2024). Relying solely on manual labor or paper-based systems imposes a heavy workload on the team to manage data and increases the risk of errors, (Jantaro and Badir 2024) which could be mitigated by implementing an MES. A study also revealed that Small and Medium Enterprises (SMEs) prefer flexible systems that are easy to customize, technically straightforward, functionally robust, integrative, and affordable, with Jakarta-based retailers particularly needing such systems due to the dynamic nature of customer habits (Hermawan, Yuliani et al. 2019), another reason businesses opt for MES or Enterprise Resource Planning (ERP). This integration of MES contributes significantly to the data-driven efficiency and optimization central to the principles of I4.0.

LEAN MANUFACTURING – OEE

Lean Manufacturing (LM) practices have become a preferred choice for organizations aiming to identify and eliminate inefficiencies. For some businesses, especially SMEs, adopting LM is necessary to the extent that it becomes crucial for staying competitive in the market (Bugvi, Hameed et al. 2021). This is because these practices significantly impact manufacturers by maximizing production efficiency while minimizing delays and redundancy (Breen, Trepp et al. 2020). The Toyota Production System, developed by Taiichi Ohno, emphasizes the elimination of unnecessary and repetitive movements as a cornerstone of LM practices (Ohno and Bodek 2019). LM offers organizations a choice not only to reduce production costs and eliminate waste but also to optimize space utilization, facilitate Just-In-Time (JIT) production, and improve information communication (Abu, Gholami et al. 2021).

Organizations have a range of LM tools at their disposal, including well-researched areas like Kanban, quality control, Kaizen, and JIT. Among these, 5S holds significance in research discussions as it goes beyond spatial organization, serving as a complementary tool alongside others in the LM toolkit (Abu, Gholami et al. 2019). Additionally, a case study conducted at a manufacturing SME in Pakistan demonstrated that applying VSM to identify waste and propose improvements resulted in a reduced processing time per unit by approximately 19% and a shortened production lead time for 100 units by about 21% (Bugvi, Hameed et al. 2021).

Seiichi Nakajima, a pioneer in Total Productive Maintenance (TPM), introduced Overall Equipment Effectiveness (OEE) as a quantitative tool to assess the performance of production systems, making it one of the most valuable methods in the industrial sector for evaluating the performance of individual machines or entire production lines (Kustiyawan, Roestan et al. 2023). OEE, a fundamental metric within the realm of LM practices, plays a crucial role in mitigating productivity loss in machinery and equipment. Its widespread application across diverse sectors aims to eliminate productivity losses incurred by machinery and equipment systematically (Brodny and Tutak 2019).

OEE improves industry performance by decreasing equipment downtime (Rathi, Sahu et al. 2023). To achieve this, OEE delves into a multifaceted evaluation, encompassing three key components: availability, performance, and quality. Firstly, it measures equipment availability by considering factors such as unplanned downtimes and planned stoppages. Secondly, OEE evaluates performance by evaluating the speed and efficiency of equipment during actual production compared to its maximum potential. Lastly, the quality component of OEE focuses on the ratio of good-quality products produced to the total output (Abd Rahman, Mohamad et al. 2020, Bhade and Hegde 2020, Haddad, Shaheen et al. 2021). As organizations increasingly prioritize efficiency and continuous improvement, OEE stands out as a valuable instrument in the pursuit of excellence within LM methodologies and TPM implementations (Brodny and Tutak 2019).

LEAN MANUFACTURING 4.0 – SMART FACTORY

The evolving relationship between LM principles and I4.0 signifies a dynamic synergy between traditional efficiency-focused LM methodologies and the transformative technologies of I4.0. Lean Manufacturing 4.0, also known as Smart Factory practices, has become a prominent trend in recent years, driven by enterprises seeking greater flexibility, efficiency, and sustainability (Bianchini, Savini et al. 2024). While LM principles emphasize waste reduction, I4.0 introduces digitalization, connectivity, and automation. This integration aims to create a more interconnected, intelligent, and data-driven manufacturing framework, where smart technologies enhance LM implementation communication (Abu, Gholami et al. 2021, Zheng, Ardolino et al. 2021). A study even suggests that relying solely on I4.0 may not deliver the anticipated success, making LM essential as a foundational step before implementing I4.0 technologies (Ijaz, Ismail et al. 2023). Figure 3 visually underscores the convergence of I4.0 and LM, underscoring the pivotal roles played by automation and connectivity in this integration.

I4.0 technologies not only facilitate and enable but also exert a significant impact on OEE (Ghouat, Benhadou et al. 2022). However, while the interactions of Lean Manufacturing 4.0 are acknowledged, comprehensive analyses specifically addressing the integration of I4.0 specifically MES with LM principles are yet to be fully explored (Perico, Arica et al. 2019). Past studies have indicated that the outcomes of Lean Manufacturing 4.0 implementation often lack specificity, and the benefits are sometimes challenging to quantify through conventional quantitative metrics (Ejsmont, Gladysz et al. 2020). Addressing these challenges requires a nuanced understanding of the synergies between LM and I4.0, emphasizing the need for research to provide more concrete evidence of the effectiveness of integrative approaches.

Acknowledging the potential of integrating I4.0 technologies and LM principles in addressing modern production challenges, the article sets out to answer the research question: "What is the most commonly paired LM practices and I4.0 technologies with MES and OEE, and what is their status of deployment in the manufacturing industry?". The structure of the article unfolds as follows: Section 2 elucidates the Methodology of Systematic Literature Review, covering descriptive findings and content analysis. Section 3 delves into the results and discussions of bibliometric analysis, highlighting publication trends. Section 4 centers on the main findings and discussion, focusing primarily on the content analysis of OEE and MES applications and their impacts. Finally, Section 5 outlines the conclusion, and limitations, and offers future research recommendations arising from this study.

METHODOLOGY

The research utilized a Systematic Literature Review (SLR) comprising bibliometric and content analysis. The systematic literature review involves three main criteria which are identification, screening, and inclusion (Xiao and Watson 2019, Ching, Ghobakhloo et al. 2022). Scopus is the chosen database for literature analysis due to its comprehensive coverage, encompassing over 60% more records than the Web of Science Core Collection, and its inclusion of in-press articles (Ejsmont, Gladysz et al. 2020). Figure 4 illustrates the flowchart depicting the research methodology.

The initial step in the SLR process is identifying relevant keywords related to Lean Manufacturing 4.0, such as "Lean Production" and "Industry 4.0," along with interchangeable terms like "Lean Manufacturing," "Lean Practices," and "Fourth Industrial Revolution." Subsequently, utilizing Scopus, the search strategy is developed based on specific inclusion criteria: (1) Documents retrieved are limited up to December 2022; (2) The first document published for the keyword is included regardless of date and year; (3) Documents retrieved are restricted to English language; (4) No limitations on document type or source type to ensure comprehensive inclusion of all relevant documents. The screening process yielded the recognition of 250 documents within the Scopus database. The information extracted from Scopus will be employed for bibliometric analysis, wherein graphs will be generated using Microsoft Excel to illustrate patterns in annual publications, scientific document types, geographical distribution of papers, and highly cited articles.

To attain the research objective, a two-phase selection process is implemented. In the initial phase, documents failing to meet research requirements are excluded based on a review of the title and abstract, specifically targeting document types other than articles, conference articles, or review articles. Additionally, articles offering general explanations or focusing extensively on technical definitions of the topic, as well as those omitting mentions of manufacturing, are eliminated, as they do not contribute significantly to addressing the research objective.

The second phase involves a thorough reading of the full paper to further refine the selection. In addition to the previously stated exclusion criteria, articles concentrating solely on one technology (either LM or I4.0) and those not applicable to the manufacturing business are discarded. Consequently, after these reading phases, a total of 44 papers are deemed suitable for performing content analysis. The content of these papers is meticulously examined and tabulated to identify common applications of OEE with I4.0 technologies and their impacts, as well as common applications of MES with LM principles and their impacts.

RESULTS AND DISCUSSIONS

DOCUMENT TYPES IN SCIENTIFIC LITERATURE

The predominant document type in the selected papers spanning the 8 years from 2015 is conference papers, constituting 50% of the total documents. It is followed by articles at 36% and reviews at 4%. This indicates a prevalence of practical papers over theoretical ones based on document types. Other document types, including conference reviews, book chapters, and books, collectively account for 10% of the total retrieved documents.

Notably, there are no publications under the document types of data paper, editorial, or short survey on this specific topic. The keywords and number of articles based on the document types are illustrated in Table 1.

TABLE 1. Keyword search and document type.

Keyword Search	Article	Conference Paper	Review paper	Others	Total
Lean production	44	82	1	1	128
Lean manufacturing	37	39	0	4	80
Lean practices	9	3	0	0	12
Industry 4.0	69	84	6	4	163
Fourth industrial revolution	2	3	0	0	5
Keywords combination	89	125	10	26	250

HISTORICAL SERIES

The surge in interest surrounding the Lean Manufacturing 4.0 topic is evident from the years 2015 to 2022, as depicted in Figure 5. The earliest selected paper was published in 2015, marking the beginning of the trend. Despite only one publication in 2015, the overall number of publications steadily increased over the subsequent years. The graph illustrates this upward trajectory, with a rise of 3 publications in 2016, 10 publications in 2017, 25 publications in 2018, 44 publications in 2019, 60 publications in 2020, 83 publications in 2021, and 24 publications in 2022. The peak in publications occurred in 2021, reaching 83, indicating a significant increase of 38.3% compared to the previous year. However, the growth rate experienced a decline in 2022, with only 22 publications.

It is crucial to consider the broader context of the decline, particularly the impact of the Covid-19 pandemic in 2019. The outbreak had substantial repercussions on businesses, leading to the closure of approximately 142,000 companies in Morocco, with over 90% being SMEs and very small companies (Farissi, Driouach et al. 2021). Similarly, micro-businesses in Malaysia also faced significant challenges due to the pandemic's economic decline (Muhamad, Zahid et al. 2023). The most prevalent barriers to I4.0 integration were high implementation costs, technological incompatibility, and extended learning curves (Macias-Aguayo, Garcia-Castro et al. 2022).

Considering these challenges, it becomes apparent that given the current circumstances, manufacturing organizations might prioritize navigating through immediate crises, adapting to new norms such as enhanced hygiene and physical distancing, rather than investing heavily in I4.0 technologies, which are presently perceived as having high costs and efforts.

PUBLICATIONS ACROSS COUNTRIES

Figure 6 illustrates the top 12 countries with the highest publications in this domain. Out of a total of 60 contributing nations, these leading 12 countries collectively account for 88% of the overall publications. Italy leads with the highest number of papers at 43, followed by Brazil with 34, the United Kingdom with 20, India with 18, and Portugal with 16 papers. Notably, European countries dominate the field of Lean Manufacturing 4.0, constituting 7 out of the top 12 countries with the highest publications. As a study suggests, in the European manufacturing sector, lean flow, lean work organization, and lean human resource management are positively correlated with the adoption of digital technologies (von Haartman, Bengtsson et al. 2021), indicating that companies with these established Lean practices are likely to be more advanced in their use of digital technologies.

This trend may be attributed to the heightened interest in the Lean Manufacturing 4.0 concept among developed nations compared to their developing or emerging counterparts. For example, findings from a study indicate that in Italian factories, the emphasis is more on digitalization and interconnection rather than solely on automation, leading to increased management control and decreased workers' autonomy (Cirillo, Rinaldini et al. 2021).

In the context of developing countries, Malaysia stands out as one of the four developing nations with substantial contributions in this field. It secures the 12th position overall with 8 papers, following the Russian Federation with 10 papers. One study highlights that, as a developing country, India is focusing on the integration of TPM and I4.0 to guide professionals in combining I4.0 technologies with productive maintenance systems (Sudhir, D et al. 2023).

HIGHLY CITED ARTICLES

Table 2 presents the top 10 highly cited articles in this field obtained from Scopus. A paper delves into research activities regarding I4.0's enablers for LM, which holds the highest number of citations at 473 times (Sanders, Elangeswaran et al. 2016). In this work, the authors discuss challenges in LM implementation and propose solutions from I4.0, introducing the LI4.0 framework. Additionally, the paper suggests that German SMEs can effectively implement I4.0 through a lean shop-floor approach.

TABLE 2. Top 10 Highly Cited Articles

Year of Publish	Title and Author	Cites
2016	Industry 4.0 implies lean manufacturing: Research activities in Industry 4.0 function as enablers for lean manufacturing (Sanders, Elangeswaran et al. 2016)	473
2018	The link between Industry 4.0 and lean manufacturing: Mapping current research and establishing a research agenda (Buer, Strandhagen et al. 2018)	403
2015	Lean Automation enabled by Industry 4.0 Technologies (Kolberg and Zühlke 2015)	374
2018	Implementation of Industry 4.0 and lean production in Brazilian manufacturing companies (Tortorella and Fettermann 2018)	341
2017	Towards Lean Production in Industry 4.0 (Mrugalska and Wyrwicka 2017)	290
2017	Industry 4.0 Impacts on Lean Production Systems (Wagner, Herrmann et al. 2017)	235
2020	Industry 4.0 and lean manufacturing practices for sustainable organizational performance in Indian manufacturing companies (Kamble, Gunasekaran et al. 2020)	219
2017	Towards a lean automation interface for workstations (Kolberg, Knobloch et al. 2017).	153
2019	Industry 4.0 adoption as a moderator of the impact of lean production practices on operational performance improvement (Tortorella, Giglio et al. 2019)	147

OEE-I4.0 INTEGRATION – COMMON PAIRINGS

The applications of I4.0 technologies in conjunction with OEE within the manufacturing sector are illustrated in Figure 7. Notably, the most frequently combined I4.0 technology with OEE is the Internet of Things (IoT), constituting 34%. This is trailed by Cyber-Physical Systems (CPS) at 25%, Artificial Intelligence (AI), and Simulation and Modelling (S&M), each at 13%, and Cloud Computing (CC) at 9%, while Industrial Robots (IR) and Additive Manufacturing (AM) contribute 3% each.

With IoT emerging as the most frequently paired technology with OEE at 34%, it underscores industry recognition of IoT's pivotal role in optimizing machinery efficiency and providing real-time insights. IoT itself optimizes the execution of daily tasks and advances communication between individuals (Alphonse, Abinaya et al. 2023). This connectivity can seamlessly integrate into MES and ERP systems, offering a comprehensive view of production operations and fostering data-driven decision-making across departments.

The second most paired technology with OEE, which is CPS at 25%, involves linking physical machines with digital systems. This creates a feedback loop for advanced control and automation, particularly beneficial in a smart factory setting where CPS can facilitate adaptive manufacturing processes responsive to changing demands or unforeseen disruptions. The reason it is the second most commonly paired with OEE may be due to the necessity for unwanted signals or disruptions, which can potentially compromise the effectiveness of the monitoring system in the CPS (Wen 2024).

Considering OEE-AI integration, the cost-effective and scalable nature of cloud computing facilitates the implementation of AI applications. This approach allows manufacturers to leverage AI capabilities without substantial upfront investments in hardware infrastructure, making OEE improvements accessible to organizations of varying sizes. For instance, a study used AI techniques to develop models that assess the effectiveness of lean maintenance implementation by evaluating how maintenance practices improve OEE (Antosz, Paśko et al. 2020).

Next, S&M, as observed in OEE-S&M pairings, presents a potent toolset for manufacturers to analyze, optimize, and strategically plan production processes, thereby contributing to an enhanced OEE. OEE and S&M techniques can be employed to accurately model and optimize production systems, improving OEE by addressing various inefficiencies and synchronizing work-in-process (Kampa 2023).

In the context of IR, renowned for its high-speed and repetitive task capabilities, the integration of OEE-IR signifies the automation of specific manufacturing processes. This, in turn, can significantly elevate production speed, minimize cycle times, and enhance OEE overall. IR is commonly used in the food manufacturing industry but faces significant cyber-attack risks due to treating cybersecurity as a technical rather than a business risk, resulting in its lower prioritization (Alqudhaibi, Krishna et al. 2024). The low pairings of IR with OEE may also be due to the cost, as it is estimated that the cost of purchasing the robot accounts for only about 50% of the total investment in a robotic workstation (Singh, Goyat et al. 2024). Another reason might be the necessity of precise planning and scheduling of the robot's tasks for optimal performance (Barosz, Gołda et al. 2020).

Like IR, there are not many studies on integrating LM principles into AM. The reason is that AM is mainly used in small-scale production, where only 63% of industries employ it for prototyping and 21% for producing complex items (Prashar, Vasudev et al. 2023). Additionally, AM primarily focuses more on integrating reinforced composites into 3D printing applications than integrating LM principles, due to the challenges associated with the materials, such as ensuring material compatibility, determining optimal processing parameters, managing cost and availability, and considering environmental impact (Khalid, Radzuan et al. 2022).

MES-LEAN INTEGRATION – COMMON PAIRINGS

The common applications of LM practices in conjunction with MES in the manufacturing sector are illustrated in Figure 8. The most frequently paired LM practices with MES include Process Mapping at 21%, followed by OEE and JIT at 16%. Kanban and Jidoka stand at 11%, while Waste Identification and Elimination (WI&E), Kaizen, Value Stream Mapping (VSM), Total Productive Maintenance (TPM), and Visual Management (VM) each contribute 5%.

Process mapping focuses on detailing each step within a process, providing a detailed view of activities and their links to each other (Memari, Panjehfouladgaran et al. 2024). When MES is combined with process mapping, this integration enables manufacturers to visualize and comprehend the real-time flow of processes, a critical element for monitoring and optimizing production activities.

Ranking second in common pairings, the integration of MES with JIT practices supports efficient order fulfillment. MES systems dynamically adjust production schedules in response to incoming orders, ensuring precise manufacturing and timely delivery, thereby minimizing lead times, and enhancing customer satisfaction.

Also ranking second, the pairing of OEE and MES leverages the integration and seamless interaction of smart devices and technologies to create a strong connection between physical systems, such as machinery, and their digital counterparts like software and data analytics (Singh, Goyat et al. 2024). Another study indicates that the MES provides access to reports that generate machine efficiency, OEE data, and personnel efficiency metrics (Temel, Ayaz et al. 2023).

The MES-Kanban integration, ranking third in common pairings, fosters improved communication and collaboration across different departments involved in the production process. This integration ensures seamless sharing of information on Kanban signals, work orders, and inventory levels, promoting a synchronized approach to production. This may be due to the Kanban system streamlining the production scheduling and part identification, making it easier for operators to follow the schedule and locate missing parts (Konrad, Sommer et al. 2023), which can be further enhanced by the capabilities of MES.

Similarly, MES-Jidoka, also ranked third, aligns with Jidoka's goal of minimizing waste by detecting defects early in the production process. MES integration contributes to waste reduction by providing tools for proactive quality management, reducing the need for costly rework, and ensuring the production line advances only high-quality products. This is because by integrating human and machine capabilities more effectively, manufacturers can enhance their ability to design products, manage manufacturing engineering, and perform maintenance, repair, and overhaul tasks more efficiently (Villalba-Diez and Ordieres-Meré 2021).

Ranked fourth in common pairings, integrating MES with WI&E processes offers a comprehensive view of resource utilization. WI&E is examining the current state of the process to identify areas needing improvement (Klimecka-Tatar and Obrecht 2024). MES-WI&E allows manufacturers to automatically identify inefficiencies, optimize resource allocation, reduce excess inventory, and minimize waste in the form of unused materials or finished goods.

Similarly, MES integration with Kaizen initiatives, also ranking fourth, aids in documenting changes and improvements. It supports knowledge management by capturing and preserving information about successful practices, ensuring continuous improvement. The integration of procedural data through advanced technologies creates a man-machine relationship, where employees, having access to detailed data, become more critical and capable of identifying and implementing solutions to improve production line performance (Torre, Leo et al. 2023).

MES-VSM is another fourth-ranking pairing, that ensures the enforcement and monitoring of standardized work practices. This contributes to consistency and stability in manufacturing processes. Similar to a study that proposed enriching VSM with I4.0 information, such as capturing, measuring, communicating and connecting, data processing, and controlling, this approach aligns closely with the core capabilities of MES (Magnus 2023).

Additionally, MES provides insights into the causes of downtime, whether due to equipment failures or other factors. Integration with TPM is also the fourth common pairing and supports the identification of root causes and the implementation of preventive measures, thereby reducing overall downtime and enhancing equipment efficiency. Lastly, MES integration with VM, also ranking fourth, ensures that visual indicators on boards are based on real-time data. This facilitates quick issue identification and resolution, minimizing downtime and improving overall efficiency.

OEE-I4.0 INTEGRATION – IMPACTS OF IMPLEMENTATION

The results of OEE-I4.0 have been systematically categorized into five distinct groups, as illustrated in Table 3. Among the nine publications examining the impact of OEE-I4.0 integration, enhanced OEE emerges as a recurring theme. Following closely is the utilization of real-time data, documented in six papers. Moreover, cost identification and reduction are reported in five papers as an outcome of OEE-I4.0 implementation. Decision support resulting from OEE-I4.0 is documented in five papers, and production optimization is recorded in four papers.

Numerous studies have documented multiple positive outcomes resulting from integration efforts, such as Ayala, J.G.C., and J.H.A. Alcantara, 2021, Dol, S. and R. Bhinge., 2018, and Canizo, M., et al., 2019. These diverse applications underscore the breadth of positive impacts achievable through integration approaches in various manufacturing contexts.

In summary, OEE-I4.0 emerges as a crucial catalyst for innovation, driving continuous improvement through real-time data utilization and the integration of advanced technologies like AI, big data analytics, and IoT. This technological ecosystem forms the foundation for I4.0-driven advancements, enhancing global competitiveness by ensuring efficient product delivery and swift responsiveness to market demands. The streamlined decision support systems enable agile decision-making, adapting quickly to dynamic market conditions. Moreover, OEE-I4.0's impact on cost reduction, resource optimization, and energy efficiency aligns with sustainability goals, reflecting a commitment to environmentally responsible practices.

MES-LEAN INTEGRATION – IMPACTS OF IMPLEMENTATION

The impacts of MES-Lean have been classified into six distinct categories as shown in Table 4. Examining different integration strategies, a total of six papers have documented positive outcomes in the categories of production efficiency and resource management. In the realm of integrated production activities, a collective total of three papers have made contributions. Other than that, three papers in total have documented positive impacts in the automation and mobile support category. A single paper integrated MES-

JIT, while a separate paper integrated MES-Kanban, and both investigations produced outcomes associated with visibility, traceability, and forecasting. A total of six papers recorded continuous improvement and operational system enhancement as impacts of MES-Lean integration.

The effective integration of MES-Lean systems can revolutionize manufacturing, making it more adaptable to dynamic market demands. In the I4.0 era, incorporating emerging technologies like artificial intelligence and machine learning could enhance the already positive outcomes of MES-Lean implementations. For manufacturing decision-makers, a phased MES-Lean approach is recommended, beginning with pilot projects, and gradually expanding to ensure smooth transitions. Prioritizing training initiatives acknowledges the human element and empowers employees to fully utilize MES-Lean system capabilities. The resulting reduced carbon footprint not only aligns with environmental sustainability goals but also positions manufacturing companies as responsible entities. In a world increasingly focused on environmental concerns, such practices are becoming a crucial differentiator in the industry.

TABLE 3. Impacts of OEE-I4.0 Integration – Description and Sources

Impacts of the Implementation	Description and Sources	I4.0 Technologies Paired with OEE						
		IoT	CPS	CC	AI	S&M	IR	AM
Enhanced OEE	External sensor setup is used to evaluate and improve OEE by automatically detecting changeovers (Miller, Borysenko et al. 2021).	✓						
	IoT is used in an assembly manufacturing line to evaluate and improve OEE by providing real-time monitoring (Ayala and Alcantara 2021).	✓						
	IoT is used to evaluate and improve the OEE of machines in rubber encapsulation factories by sorting out the production flow (Krishnaraj, Gomathi Prabha et al. 2021).	✓						
	Using CPS to monitor factory processes and enable decision-making processes for corrective actions to improve OEE and productivity (Dol and Bhinge 2018).		✓					
	Using CPS for real-time monitoring and analysis of industrial press machines to improve OEE (Canizo, Conde et al. 2019).		✓					
	Using cloud computing to observe processes to reduce losses and improve OEE, quality, and profits (Harris 2021).			✓				
	To track production, identify and minimize losses in a production process, and improve OEE (Hassan and Abdul-Kader 2020).					✓		
	To evaluate the system's performance before implementing the optimization idea and modifying the real system (Yazdi, Azizi et al. 2019).					✓		
	To prove that the increase in total lead time for parts delivery will result in a lower OEE, thus helping in optimizing OEE by changing the decision-making for order allocation (Antônio Mendonça, da Piedade Francisco et al. 2022).							✓
Real-time data utilization	IoT is used in an assembly manufacturing line to evaluate and improve OEE by providing real-time monitoring (Ayala and Alcantara 2021).	✓						
	Real data was collected from the factory shop floor to improve the production process by using OEE (Król and Czarnecki 2021).	✓						
	Low-cost IoT (Raspberry Pi) to measure OEE in real-time to enable accurate OEE (Herrero, Sanguesa et al. 2021).	✓						
	Data was collected from the CNC machine to identify the cause of downtime in the process to aid the decision-making process and provide remote condition monitoring (Siddhartha, Chavan et al. 2021).	✓						
	Using IoT for assembly lines for engineers to get real-time information from the machines and self-diagnostic functions (Markov and Vitliemov 2022).	✓			✓			
	Using CPS for real-time monitoring and analysis of industrial press machines to improve OEE (Canizo, Conde et al. 2019).		✓					

continue ...

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Cost Identification and Reduction	Combines IoT, CPS, and CC for the creation of a new tool for maintenance activities scheduling to identify the costs (Caterino, Fera et al. 2019).	✓	✓	✓				
	Using CPS to reduce carbon footprint and energy costs while ensuring production goals are met (Nota, Nota et al. 2020).		✓					
	Using vertical integration where cloud data and other components are used for optimizing resource utilization and eliminating wastes to reduce the consumption of energy, water, electricity, and transportation (Jena, Mishra et al. 2020).		✓					
	Using machine learning-based applications to identify potential savings (Carvalho, Cosgrove et al. 2018).				✓			
Decision support	Used for internal interoperability, external interoperability, and time-sensitive Key Performance Indicators which are useful for the decision-making process (Fenza, Gallo et al. 2020).		✓					
	Using CPS to monitor factory processes and enable decision-making processes for corrective actions to improve OEE and productivity (Dol and Bhinge 2018).		✓					
	Using cloud computing to solve problems while implementing just-in-time and OEE principles to increase profit to an ideal value (Dziurzanski, Swan et al. 2018).			✓				
	To help choose the best method to optimize the production using simulation (Caterino, Greco et al. 2020).					✓		
	To support the decision-making process for the improvements to be easily adopted to improve production processes using data simulation (Abd Rahman, Mohamad et al. 2020).					✓		
Production Optimization	Combines IoT (sensors) and Big data analytics (software) to gather and analyze large volumes of data to optimize production, including lead time, product cost, and shop floor productive capacity (Garcia-Garcia, Coulthard et al. 2021).	✓						
	IIoT uses low-cost sensors to enable predictive maintenance to improve OEE (Strauß, Schmitz et al. 2019).	✓			✓			
	Identifying the machines' operational parameters using SCADA (Brodny and Tutak 2019).				✓			
	Using industrial robots for material handling uses sensors to increase the accuracy of robot programs (Yazdi, Azizi et al. 2018).						✓	

Notes: Internet of Things (IoT); Cyber-physical systems (CPS); Cloud Computing (CC); Artificial Intelligence (AI); Simulation and Modelling (S&M); IR (Industrial Robots); AM (Additive Manufacturing).

TABLE 4. Impacts of MES-Lean Integration - Description and Sources

Impacts of the Implementation	Description and Sources	Lean Manufacturing Practices Paired with MES									
		PM	OEE	JIT	Kanban	Jidoka	WI&E	Kaizen	VSM	TPM	VM
Production Efficiency and Resource Management	Improved production management, increased production efficiency, and the capacity of resource allocation (Zeng, Hao et al. 2019).	✓									
	Reduced the production cycle time and number of workers, and increased the production balance rate (Song and Zhou 2021).	✓									
	Optimized activity in enterprise, to increase their efficiency by reducing repair costs, reducing information working time, and reducing the number of defects (Makarov, Frolov et al. 2019).		✓								

continue ...

... cont.

	Achieved better production management goals, simultaneous scheduling, better efficiency, process optimization, and closed-loop management (Yuan, Chen et al. 2020).			✓							
	Evaluated the production strategies, to identify and reduce the performance losses (Barni, Pietraroia et al. 2020).									✓	
	Reduced the degree of uncertainty and flexibly made informed management decisions (Vozhakov 2021).			✓							
Continuous improvement and operational system enhancement	Shorten the assembly cycle, reduce material inventory, cut back the number of products in process, and upgrade workshop management level (Yang and Ren 2013).				✓						
	Monitored and improved production processes and shift from a central decision-making process to a decentralized one (Theuer, Gronau et al. 2013).					✓					
	Improved the shop floor data collection to support the decision-making process (D'Antonio, Bedolla et al. 2016).						✓				
	Processed the factory information on a device level and MES level for workers to do Kaizen activities (Kimura, Tezuka et al. 2008).							✓			
	Evaluated the production strategies, to identify and reduce the performance losses (Barni, Pietraroia et al. 2020).									✓	
	Optimized the process scheduling by gathering and visualization information (Müller, Vette-Steinkamp et al. 2018).										✓
Integrated Production Activities	Improved management of production activities, integrated data, and synchronized production tasks and materials, oriented by demand (Guirro, Asato et al. 2020).	✓									
	Provided real-time information to be used for forecasting to smooth demands in production (Chai, Zhou et al. 2008).				✓						
	Identified the problems in operational system and production based on real-time data, prioritizing wastes to eliminate, and forecasting the impacts of different proposed improvements on the future system's performance (Cortes, Daaboul et al. 2016).								✓		
Automation and Mobile support	Enabled mobile support and import of working time and downtime of machines (Simon 2018).		✓								
	Automated production line to prevent deviations from target control charts, to help process robustness and control by operators (Gendre, Waridel et al. 2016).		✓								
	Automated Quality management on the MES level to reduce the production cost and delivery time using MES (Cupek, Erdogan et al. 2015).					✓					
Visibility, traceability, and forecasting	Enabled shop floor visibility and traceability to facilitate JIT implementation and mass customization (Dai, Zhong et al. 2012).			✓							
	Provided real-time information to be used for forecasting to smooth demands in production (Chai, Zhou et al. 2008).				✓						
Cost and Environmental Impact	Reduced cost and carbon footprint (Perino-Gallice, Masson et al. 2019).	✓									

Notes: PM (Process Mapping); Just-in-Time (JIT); WI&E (Waste Identification & Elimination); VSM (Value Stream Mapping); TPM (Total Productive Maintenance); VM (Visual Management).

CONCLUSIONS

Using a systematic literature review, this study has extensively examined Lean Manufacturing 4.0, focusing on trends, applications, and impacts in manufacturing industries. Key conclusions from the study include:

1. Practical papers, especially conference papers, surpass theoretical contributions, highlighting a need for more diverse research despite the high number of contributions.
2. Interest in Lean Manufacturing 4.0 has grown since 2015, but a recent decline in 2022 publications raises concerns, potentially related to perceived costs and technological adoption challenges.
3. Developed countries, led by Italy, contribute significantly to this topic, while even developing countries like Malaysia rank high, indicating global relevance irrespective of industrialization and income levels.
4. The most cited paper by Sanders et al. addresses the challenges of LM implementation and advocates applying I4.0 technologies with an LM approach to SMEs, emphasizing positive impacts.
5. OEE-I4.0 integration is extensively studied, with OEE paired with IoT being the most researched, followed by other combinations like CPS, CC, AI, S&M, IR, and AM.
6. MES paired with Process Mapping is the most examined MES-Lean integration, followed by other integration such as OEE, JIT, Kanban, Jidoka, WI&E, VSM, TPM, and VM.
7. The most documented impact of OEE-I4.0 implementation is enhanced OEE, followed by real-time data utilization, while the least common impact is production optimization.
8. The most documented impact of MES-Lean implementation is production efficiency and resource management, while the least common impact is cost and environmental impact.

While this study effectively addressed the research question, acknowledging its limitations provides valuable insights for future investigations. One constraint is associated with the search term criteria used in the study's inclusion criteria, as it may not encompass all relevant literature in the database. This limitation arises from the potential existence of alternative keywords used by authors, leading to the oversight of certain papers in the search process. Another limitation pertains to the exclusive use of Scopus as the sole database for bibliometric analysis. To enhance the comprehensiveness of comparisons, it is recommended that future studies explore additional databases, such as WOS.

In this study, I4.0 technologies were specifically focused on MES, while LM practices were confined to OEE. To broaden the scope of future research, consideration should be given to exploring the practicality of other I4.0 technologies and lean practices within the manufacturing context. Furthermore, subsequent studies should investigate the integration of Lean Manufacturing 4.0 to validate results, particularly in the context of manufacturing SMEs, where numerous research opportunities exist.

The paper also offers practical implications; the outcomes of this literature review elucidate the impacts and appropriateness of Lean Manufacturing 4.0 integration in manufacturing businesses. As a result, manufacturing companies can utilize this research to discern and evaluate the most suitable Lean Manufacturing 4.0 integration for their operations, along with its potential consequences. The findings are equally relevant for academics, providing a foundation for further studies in this area based on the presented information from the current bibliometric and content analysis.

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DECLARATION OF COMPETING INTEREST

None.

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