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APPROACHES TO LEAN MANUFACTURING IN INDUSTRY 4.0: A COMPREHENSIVE REVIEW STUDY

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ABSTRACT

This systematic review, based on the analysis of 130 peer-reviewed articles, explores the strategic integration of lean manufacturing with Industry 4.0 technologies, focusing on the role of the Internet of Things (IoT), artificial intelligence (AI), and big data analytics in enhancing lean practices. Using the PRISMA guidelines, the study identified key synergies between lean and Industry 4.0, demonstrating how these technologies facilitate real-time data collection, predictive maintenance, and process optimization, all of which align with lean's core principles of waste reduction and continuous improvement. The review also highlights significant challenges to this integration, including high implementation costs, workforce skill gaps, and resistance to organizational change, particularly within small and medium-sized enterprises. Additionally, emerging trends suggest that the future of lean-Industry 4.0 integration will increasingly focus on sustainability, with companies leveraging digital tools to enhance energy efficiency and reduce environmental waste. The findings underscore the need for further research to address these challenges and explore scalable solutions that can drive the broader adoption of lean-Industry 4.0 integration in diverse industrial contexts.

KEYWORDS

Lean Manufacturing, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Automation, Operational Efficiency

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1 Introduction:

The concept of Industry 4.0 has gained significant traction in the manufacturing sector over the past decade (Alcácer & Cruz-Machado, 2019; Antony et al., 2008; Jim et al., 2024). It refers to the fourth industrial revolution, characterized by the integration of digital technologies such as the Internet of Things (IoT), cyber-physical systems (CPS), big data analytics, and artificial intelligence (AI) into manufacturing processes (Al-Tamimi et al., 2019; Rahman et al., 2024; Uzzaman et al., 2024). These technologies enable the development of smart factories, where machines communicate autonomously, production systems become more flexible, and data-driven decision-making enhances efficiency (Avventuroso et al., 2018; Islam & Apu, 2024; Mongeon & Paul-Hus, 2015). Industry 4.0 represents a transformative shift from traditional manufacturing practices, pushing the boundaries of automation and digitalization. While these advancements have garnered widespread attention, the integration of lean manufacturing principles within Industry 4.0 has emerged as a critical strategy for optimizing performance (Antony, 2008; Nahar et al., 2024). Lean manufacturing, with its focus on waste reduction, continuous improvement, and value maximization, aligns well with the goals of Industry 4.0, offering opportunities for enhanced productivity and competitiveness.

Lean manufacturing, originally developed as part of the Toyota Production System, emphasizes the elimination of non-value-adding activities and the maximization of customer value. Key lean principles, such as Just-in-Time (JIT) production, Total Productive Maintenance (TPM), and continuous improvement (Kaizen), have been widely adopted in industries to streamline processes and reduce waste. However, the advent of Industry 4.0 technologies introduces new dimensions to these lean practices. For instance, IoT and big data analytics enable real-time monitoring of production lines, providing actionable insights to improve efficiency and reduce downtime. This synergy between lean manufacturing and Industry 4.0 not only enhances operational performance but also supports strategic decision-making. Nevertheless, integrating these two approaches requires overcoming significant barriers, such as high initial costs, workforce skills gaps, and organizational resistance to change (Balaji et al., 2020).

The integration of lean manufacturing and Industry 4.0 has been the subject of several empirical studies. For example, Carroll (2001) identified that the real-time data analytics provided by IoT devices can significantly improve the implementation of lean tools like JIT and Kanban. Similarly, Belhadi et al., (2019) found that AI and predictive maintenance systems enhance the lean goal of reducing machine downtime, leading to more efficient production cycles. Research by Kolberg and Zühlke (2015) also suggests that Industry 4.0 can provide better process transparency, enabling quicker response times to production issues and facilitating lean continuous improvement initiatives. These findings demonstrate that Industry 4.0 technologies provide a valuable framework for extending lean manufacturing practices beyond their traditional limits, particularly in terms of automation and process optimization.

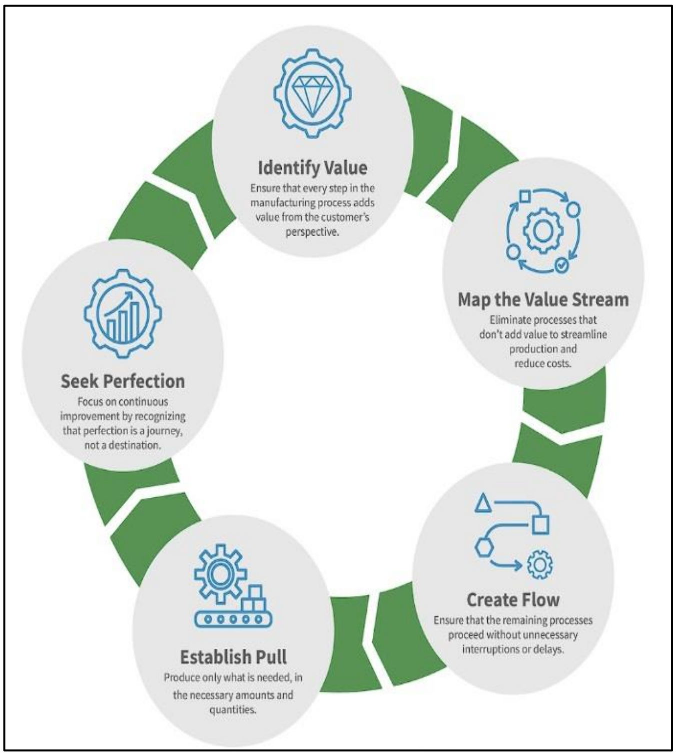
Despite the potential benefits, the integration of Industry 4.0 and lean manufacturing is not without challenges. Gattullo et al., (2015) highlight that many organizations face significant resistance to adopting new technologies due to the high costs of implementation and the need for a skilled workforce capable of handling advanced digital tools. Additionally, the complexity of Industry 4.0 systems can sometimes clash with lean principles, which prioritize simplicity and the minimization of waste. For example, while big data analytics can enhance decision-making, it may also introduce information overload, which conflicts with lean's emphasis on streamlined processes. Moreover, the adoption of Industry 4.0 requires a cultural shift within organizations, moving from traditional hierarchical structures to more decentralized, collaborative environments that align with the dynamic nature of smart factories. Addressing these challenges is crucial for the successful integration of lean and Industry 4.0, and firms must carefully consider their strategic approach to implementation.

The primary objective of this research is to conduct a comprehensive review of the strategic approaches to integrating lean manufacturing with Industry 4.0 technologies. Specifically, this study seeks to examine how key Industry 4.0 technologies—such as IoT, AI, and big data analytics—can enhance lean manufacturing practices by improving operational efficiency, reducing waste, and increasing production flexibility. Additionally, the review aims to identify the challenges organizations face when implementing these technologies alongside lean principles, such as the high costs of digital transformation, the need for a skilled workforce, and cultural resistance to change. By synthesizing existing empirical research and theoretical frameworks, the study intends to provide actionable insights for manufacturers looking to align their lean strategies with the capabilities of Industry 4.0. Furthermore, the review seeks to highlight best practices and critical success factors that can guide organizations in overcoming the barriers to integration, ultimately enabling them to optimize their performance in the evolving digital landscape.

2 Literature Review

The integration of lean manufacturing principles with Industry 4.0 technologies has been a topic of growing interest in recent years. As manufacturing industries evolve toward more digitized and automated processes, the alignment of lean methodologies with the emerging tools of Industry 4.0 is seen as a promising approach to optimizing efficiency, reducing waste, and enhancing operational flexibility. This section reviews the existing literature on the synergies between lean manufacturing and Industry 4.0, focusing on key technological enablers such as IoT, AI, and big data analytics.

Figure 1: Overview of Lean Manufacturing Principles



Additionally, it examines the challenges and barriers to implementation, as well as the potential long-term benefits of this integration. By exploring various case studies and empirical research, this review aims to provide a comprehensive understanding of how lean principles are being applied in the context of smart manufacturing, identifying best practices and critical success factors for achieving sustainable improvements in productivity.

2.1 Overview of Lean Manufacturing Principles

Lean manufacturing, originating from the Toyota Production System (TPS), has evolved as a fundamental framework for achieving operational excellence by reducing waste and enhancing value (Ohno, 1988). This method focuses on eliminating non-value-adding activities in production processes, which are referred to as the "seven wastes" (Browaeys & Fisser, 2012). These include overproduction, waiting, transportation, over-processing, inventory, motion, and defects. Lean's objective is to optimize resources by streamlining processes and improving efficiency (Drohomeretski et al., 2013). Initially implemented in the automotive industry, lean principles have since been adopted across various industries, including aerospace, healthcare, and services, due to their adaptability and effectiveness in achieving higher productivity levels (Drohomeretski et al., 2013). The philosophy of continuous improvement (Kaizen) lies at the heart of lean manufacturing, promoting incremental improvements in operations and encouraging employee involvement (Vanpoucke et al., 2017).

Over the years, lean manufacturing has expanded beyond its original scope, evolving to include not only production efficiency but also customer satisfaction. The core principles of lean—value stream mapping, JIT production, and total quality management (TQM)—highlight the importance of creating value from the customer's perspective (Buer et al., 2018). This shift in focus has driven lean practices toward a more holistic approach that includes all business processes, from supply chain management to after-sales services (Blaga & Tamas, 2018). JIT, for example, ensures that materials are delivered only when needed, reducing excess inventory and enhancing flexibility in production (Butt et al., 2016a). These principles have become widely accepted as standard practices for companies seeking to optimize their supply chains and production systems (Hu et al., 2008).

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The evolution of lean manufacturing has also seen its integration with various other frameworks and methodologies. The combination of lean and Six Sigma, for example, has led to Lean Six Sigma (LSS), which integrates lean's waste reduction strategies with Six Sigma's focus on quality improvement and variation reduction (Sadik & Urban, 2017). This has further expanded lean's applicability, particularly in sectors requiring stringent quality control, such as healthcare and pharmaceuticals (Sukthomya & Tannock, 2005). Moreover, the digital transformation era has introduced new tools for implementing lean principles. The use of big data, IoT, and AI enables real-time monitoring of production processes, offering opportunities to enhance traditional lean practices (Zwikael et al., 2018). These technological advancements provide valuable data that can further streamline production, identify bottlenecks, and enhance decision-making.

Overall Equipment Effectiveness is a standard for measuring manufacturing productivity. It combines availability, performance, and quality into one metric:

$$OEE = Availability \times Performance \times Quality$$

Where:

Availability measures the ratio of operating time to planned production time:

$$Availability = \frac{\text{Operating Time}}{\text{Planned Production Time}}$$

- **Performance** measures how close the manufacturing process is to its ideal speed:

$$Performance = \frac{\text{Ideal Cycle Time} \times \text{Total Pieces}}{\text{Operating Time}}$$

- **Quality** measures the percentage of good units produced:

$$Quality = \frac{\text{Good Pieces}}{\text{Total Pieces Produced}}$$

Cycle Time

Cycle time is the total time it takes to produce a single product from start to finish. It includes processing, inspection, and waiting time:

$$Cycle\ Time = \frac{\text{Total Time}}{\text{Number of Units Produced}}$$

This is a critical metric in lean manufacturing for identifying bottlenecks and improving throughput.

Takt Time

Takt time is the rate at which a product must be produced to meet customer demand. It is calculated as:

$$Takt\ Time = \frac{\text{Available Production Time}}{\text{Customer Demand}}$$

Where:

- **Available Production Time** is the total time available for production during a shift.
- **Customer Demand** is the number of units needed by customers.

Takt time is used to synchronize production with customer demand and to eliminate overproduction, a form of waste in lean.

2.2 Lean Six Sigma: Defects Per Million Opportunities (DPMO)

Lean Six Sigma combines lean's waste reduction with Six Sigma's focus on reducing variation and improving quality. A key metric is DPMO, which measures the number of defects in a process per million opportunities:

$$DPMO = \frac{\text{Number of Defects}}{\text{Number of Units Produced} \times \text{Number of Opportunities per Unit}} \times 10^6$$

Recent studies emphasize the growing relevance of lean manufacturing in the context of Industry 4.0. Lean practices, traditionally rooted in manual and human-driven processes, are now supported by advanced technologies, allowing for more efficient production environments (Butt & Jedi, 2020). The integration of cyber-physical systems (CPS) and real-time data analytics enables organizations to optimize their lean operations through predictive maintenance, smart sensors, and enhanced supply chain visibility (Hidalgo et al., 2007). Despite the increasing complexity of modern manufacturing environments, the principles of lean manufacturing remain relevant. Their evolution reflects an ongoing adaptation to new industrial paradigms, particularly as organizations seek to balance lean's simplicity with the technological sophistication of Industry 4.0 (Pansare et al., 2021a). The evolution of lean manufacturing demonstrates its resilience and capacity to remain a cornerstone of operational strategy in diverse and changing industrial contexts.value

2.3 Overview of Industry 4.0

Industry 4.0, a term first coined by Pansare et al. (2021), represents the fourth industrial revolution, characterized by the digitization and interconnectivity of manufacturing processes through advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), big data analytics, and cyber-physical systems (CPS). Unlike previous industrial revolutions that focused on mechanization, electrification, and automation, Industry 4.0 emphasizes the integration of digital technologies to enable smarter, more autonomous production environments (Tortorella et al., 2020). This transformation relies on the fusion of physical production systems with digital technologies, allowing machines, systems, and humans to communicate and make decisions in real-time. The overarching goal of Industry 4.0 is to create "smart factories" that are more efficient, flexible, and adaptable to changing market demands (Arcidiacono & Pieroni, 2018).

IoT plays a pivotal role in Industry 4.0 by connecting physical devices and machines to the internet, enabling the collection and exchange of data across the production ecosystem (Pessl et al., 2017). Through IoT, manufacturers can monitor equipment performance in real-time, identify inefficiencies, and optimize processes. For example, sensors embedded in machines can detect anomalies or wear and tear, enabling predictive maintenance and reducing downtime (Alcácer & Cruz-Machado, 2019). Additionally, IoT enhances supply chain visibility, enabling better decision-making by providing real-time insights into inventory levels, logistics, and customer demand (Lartigau et al., 2012). The integration of IoT with lean manufacturing principles has proven to be a powerful combination, allowing manufacturers to eliminate waste and optimize resource utilization (Baldini et al., 2017).

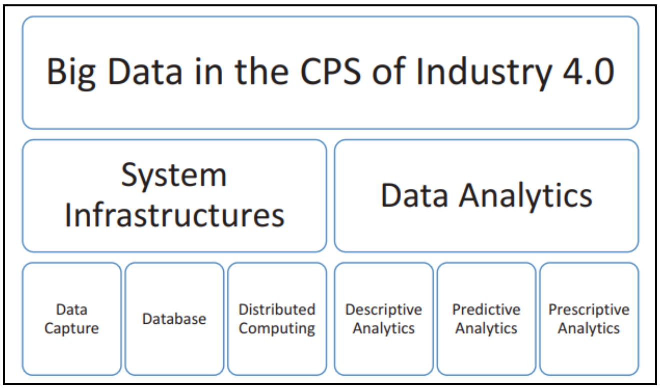
2.4 Cyber-Physical Systems (CPS) Control Equation

Cyber-Physical Systems (CPS) use feedback loops to control physical processes in real-time. A commonly used control equation in CPS is the Proportional-Integral-Derivative (PID) Controller, which plays a vital role in Industry 4.0 for automated control systems. The PID control equation is:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt}$$

AI is another critical component of Industry 4.0, offering advanced capabilities for automating decision-making processes and improving production efficiency (Raisinghani et al., 2005). AI algorithms analyze vast amounts of data collected from IoT devices and CPS to make predictive and prescriptive decisions, such as optimizing production schedules or determining the most efficient use of resources (Ma et al., 2017). AI-driven predictive analytics also support lean practices by enabling real-time monitoring of production systems, anticipating machine failures, and preventing defects before they occur (Mahali, 2017). As a result, AI contributes to enhanced quality control, reduced waste, and improved overall production efficiency, aligning with lean manufacturing objectives (He & Da Xu, 2014).

Figure 2: The big data issues of the CPS in Industry 4.0



Big data analytics and CPS further support the evolution of Industry 4.0 by facilitating the collection, storage, and analysis of massive volumes of data generated from interconnected devices (Al-Tamimi et al., 2019). CPS, in particular, involves the integration of physical systems with computational models, enabling real-time communication between machines and decision-making systems (Tripathi, Chattopadhyaya, Mukhopadhyay, Sharma, Li, & Di Bona, 2022; Shamim, 2022). This interconnectivity allows for more adaptive and responsive production processes, where machines can autonomously adjust to changes in production demand or environmental conditions (Rossetto et al., 2018). Big data analytics, on the other hand, enables manufacturers to gain deeper insights into operational performance, uncover patterns, and make

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data-driven decisions (Kumar & Mathiyazhagan, 2020). Together, these technologies form the backbone of Industry 4.0, driving the transition from traditional manufacturing practices to intelligent, automated systems capable of real-time optimization and innovation.

2.5 Synergies Between Lean Manufacturing and Industry 4.0

The convergence of lean manufacturing and Industry 4.0 technologies offers promising synergies that enhance traditional lean practices, making them more efficient and adaptable to modern production environments. Lean manufacturing's core principles—waste reduction, continuous improvement, and value maximization—are significantly bolstered by Industry 4.0 technologies such as IoT, AI, and big data analytics (Ani et al., 2016). The implementation of these technologies supports lean objectives by providing real-time insights into production processes, enabling faster decision-making and more precise process control. For instance, Chi et al. (2013) highlighted that the integration of digital technologies into lean environments leads to enhanced production flexibility, more efficient resource utilization, and higher operational performance. This blend of lean and Industry 4.0 represents a new frontier in manufacturing, where data-driven insights enable continuous improvements at a scale and speed previously unattainable.

A critical component of this synergy is the role of IoT in supporting real-time data collection and process optimization. IoT devices, through sensors embedded in machines and production lines, continuously monitor performance, detect anomalies, and provide feedback to operators, which enhances lean practices like Just-in-Time (JIT) production (Pansare et al., 2021a). The ability to gather and analyze data in real-time aligns with lean's emphasis on eliminating waste and optimizing processes by reducing downtime and improving throughput (Hidalgo et al., 2007). Tortorella et al. (2020) found that IoT-enabled lean systems can quickly respond to fluctuations in demand and adjust production schedules accordingly, resulting in better resource management and reduced overproduction. This integration of IoT with lean tools like value stream mapping (VSM) ensures that manufacturers can streamline operations, improve transparency, and respond to disruptions in real-time.

Artificial intelligence (AI) further strengthens lean manufacturing by enabling predictive maintenance and automated decision-making, key components in

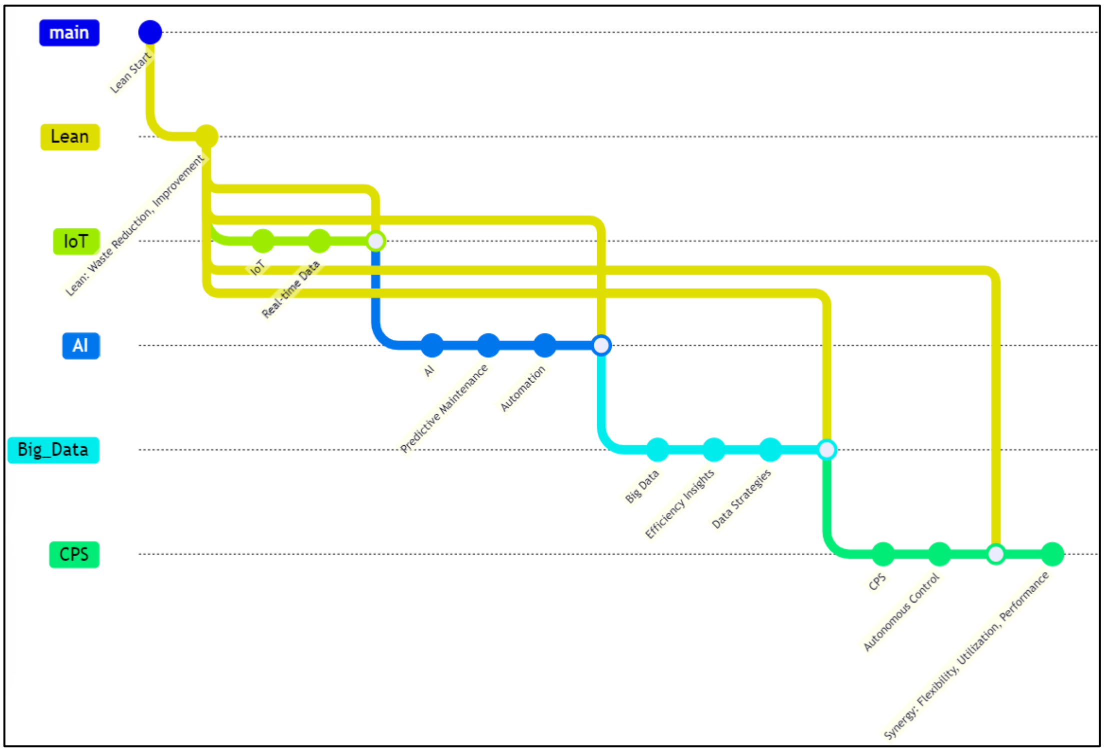


Figure 3: Overall on Lean Manufacturing and Industry 4.0

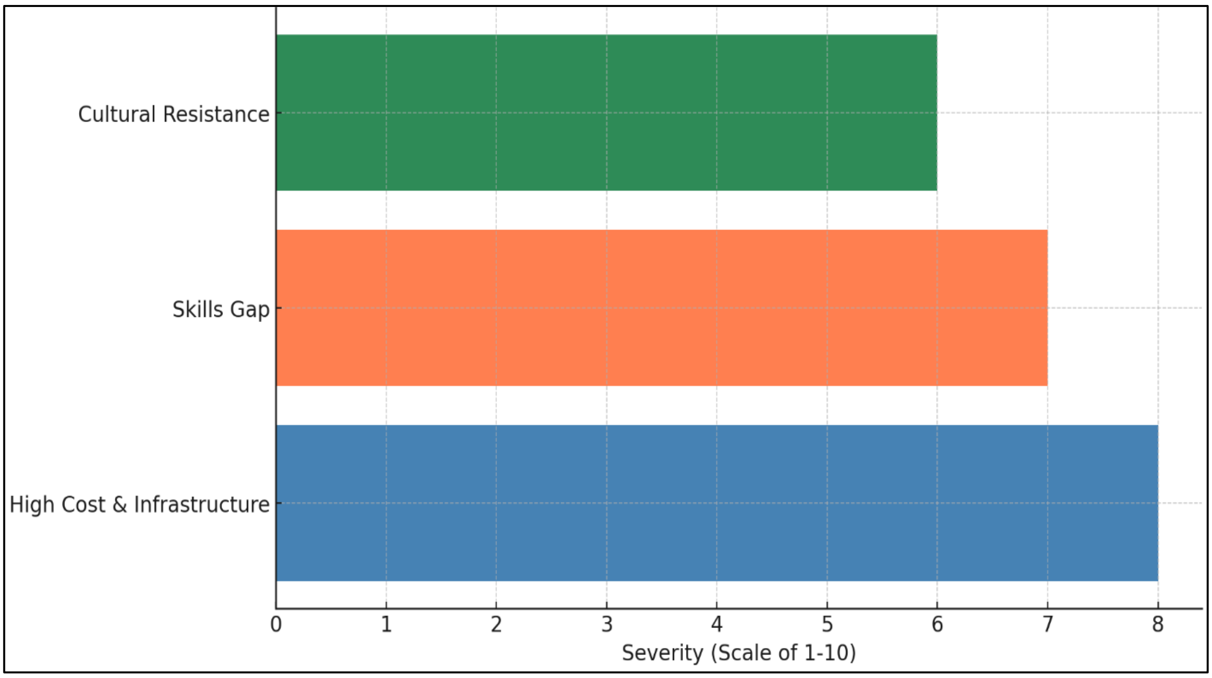
reducing machine downtime and enhancing productivity (Butt & Jedi, 2020). Predictive maintenance, powered by AI algorithms, uses data collected from IoT sensors to predict machine failures before they occur, allowing manufacturers to perform maintenance only when necessary (Pansare et al., 2021; Shamim, 2024). This proactive approach aligns with lean's principle of total productive maintenance (TPM), where the focus is on maximizing the efficiency of equipment (Pansare et al., 2021). By integrating AI, lean practices are extended beyond traditional human-driven methods to include automated systems that continuously monitor equipment and production lines, making real-time adjustments to improve performance and prevent costly downtime (Butt & Jedi, 2020). AI also supports decision-making in complex production environments, analyzing large datasets to identify trends and inefficiencies that can be addressed through lean principles (Lee & Wei, 2009).

The synergy between lean manufacturing and Industry 4.0 has evolved significantly as more manufacturers recognize the value of combining these approaches. While lean traditionally focused on minimizing waste through manual and systematic processes, Industry 4.0 technologies offer a digital layer that enhances lean's effectiveness (Donthu et al., 2021). For example, big data analytics enables manufacturers to gain deeper insights into operational inefficiencies and develop data-driven strategies for continuous improvement (Kumar et al., 2021). Additionally, CPS and AI technologies provide autonomous control of production systems, further enhancing the efficiency of lean manufacturing by making real-time adjustments and optimizing resource allocation (Ivanov et al., 2020). As a result, the integration of Industry 4.0 technologies with lean practices is revolutionizing the manufacturing landscape, creating smarter, more responsive systems capable of achieving lean's objectives at an unprecedented scale and speed (Pessl et al., 2017). This evolution highlights the growing potential for manufacturers to leverage digital technologies in their lean strategies to stay competitive in the rapidly changing industrial environment.

2.6 Challenges in Integrating Lean Manufacturing with Industry 4.0

One of the major challenges in integrating lean manufacturing with Industry 4.0 is the high cost of implementation and the need for substantial infrastructure development. Many of the technologies central to Industry 4.0, such as IoT, artificial intelligence (AI), and big data analytics, require significant upfront investment in both hardware and software (Moeuf et al., 2018). Moreover, the shift to smart factories involves the integration of cyber-physical systems (CPS), which can be costly to deploy, especially for small and medium-sized enterprises

Figure 4: Challenges in Integrating Lean Manufacturing



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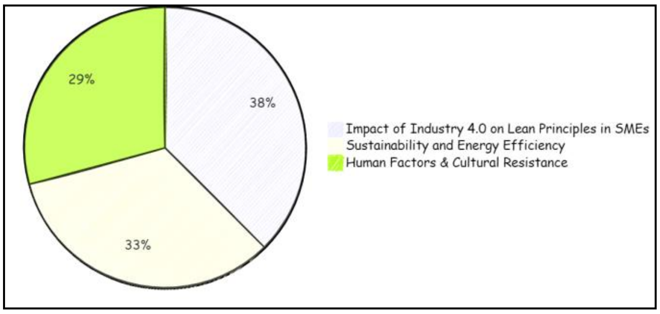
(SMEs) that may lack the financial resources of larger organizations (Manvi & Shyam, 2014). According to Alcácer and Cruz-Machado (2019), the cost of these technological investments can act as a barrier to entry for many manufacturers, particularly those operating in traditional industries with limited capital for innovation. The need for continuous upgrades and maintenance of digital infrastructure further adds to the long-term financial burden, making it difficult for organizations to justify the immediate return on investment when compared to traditional lean methods that require fewer technological resources.

In addition to the financial challenges, integrating lean manufacturing with Industry 4.0 requires a highly skilled workforce capable of understanding and leveraging new technologies. The shift from manual processes to digital systems demands new skills in areas such as data analytics, IoT management, and AI-based decision-making (Lee et al., 2014). Many organizations struggle to find or develop employees with the technical expertise required to operate and maintain these advanced systems (Buer et al., 2018). A skills gap often exists between the current workforce and the level of technical knowledge needed for effective Industry 4.0 integration (May & Stahl, 2016). As a result, companies must invest heavily in training and upskilling programs to equip their employees with the necessary competencies (Schroeder et al., 2007). This challenge is compounded by the rapid pace of technological advancements, which continuously raises the bar for required skills, making it difficult for organizations to keep their workforce updated and competitive in the evolving industrial landscape (Mahali, 2017). Another significant challenge is the resistance to change within organizational culture. The introduction of Industry 4.0 technologies into lean manufacturing environments often disrupts established workflows and requires a fundamental shift in how organizations operate (Butt et al., 2016b). Many employees, particularly those accustomed to traditional lean practices, may resist the adoption of new technologies due to fears of job displacement or increased workload associated with learning new systems (Rathi et al., 2022). This resistance can create a cultural barrier that hinders the successful implementation of Industry 4.0 technologies (Tripathi, Chattopadhyaya, Mukhopadhyay, Sharma, Li, Singh, et al., 2022). Organizational leaders must, therefore, focus on fostering a culture of innovation and adaptability, promoting the benefits of technological integration while addressing employees' concerns (Brodie et al., 2017). Overcoming resistance to change requires transparent communication, involvement of employees in the digital transformation process, and a strong commitment to continuous improvement ((Broadus, 1987).

2.7 Identified Research Gaps

Despite the growing body of research on the integration of lean manufacturing and Industry 4.0, several gaps remain that require further empirical investigation. One key area for future research is the impact of Industry 4.0 technologies on lean's core principles, such as waste reduction and continuous improvement, in diverse industrial contexts. While studies have demonstrated the potential for IoT, AI, and big data analytics to enhance lean practices (Fernández-Caramés et al., 2019; Kolberg et al., 2016), most research has been concentrated in developed economies and large-scale enterprises. There is limited understanding of how small and medium-sized enterprises (SMEs), especially in developing regions, can overcome financial and technical barriers to successfully implement these technologies (Cornelius, 2002). Future empirical studies should explore the scalability of lean-Industry 4.0 integration in different sectors and regions, examining the unique challenges and opportunities faced by various types of organizations (Vinodh et al., 2010).

Figure 5: Research Gaps in Lean Manufacturing and



Another gap in the literature involves the human factors associated with lean-Industry 4.0 integration. Much of the existing research focuses on the technical and operational aspects of this integration, such as the role of IoT in predictive maintenance or AI in quality control (Brodie et al., 2017; Kolberg et al., 2016). However, there is a need for further research on the organizational and workforce-related challenges, particularly how companies can manage cultural resistance to digital transformation and train employees to work effectively with new technologies (Broadus, 1987). Future studies should investigate best practices for fostering a culture of innovation and continuous learning in lean environments enhanced by Industry 4.0 tools (Gerber et al., 2012). Additionally, more research is needed to understand how leadership styles and organizational structures influence the success of lean-Industry 4.0 integration (Chen et al., 2013).

Emerging trends suggest that the future of lean-Industry 4.0 integration will be shaped by the increasing convergence of digital technologies and sustainable manufacturing practices. Industry 4.0 technologies are enabling new lean applications in areas such as energy efficiency and environmental sustainability, where companies are leveraging real-time data to reduce energy consumption and minimize waste (Liu et al., 2017). As environmental concerns become more central to manufacturing strategies, future research should explore how the integration of lean and Industry 4.0 can support sustainable manufacturing goals, including the reduction of carbon footprints and the efficient use of resources (Zarei et al., 2016). These emerging trends highlight the need for a more holistic approach to lean-Industry 4.0 integration, one that incorporates sustainability objectives alongside traditional lean goals of efficiency and waste reduction (Dombrowski et al., 2017).

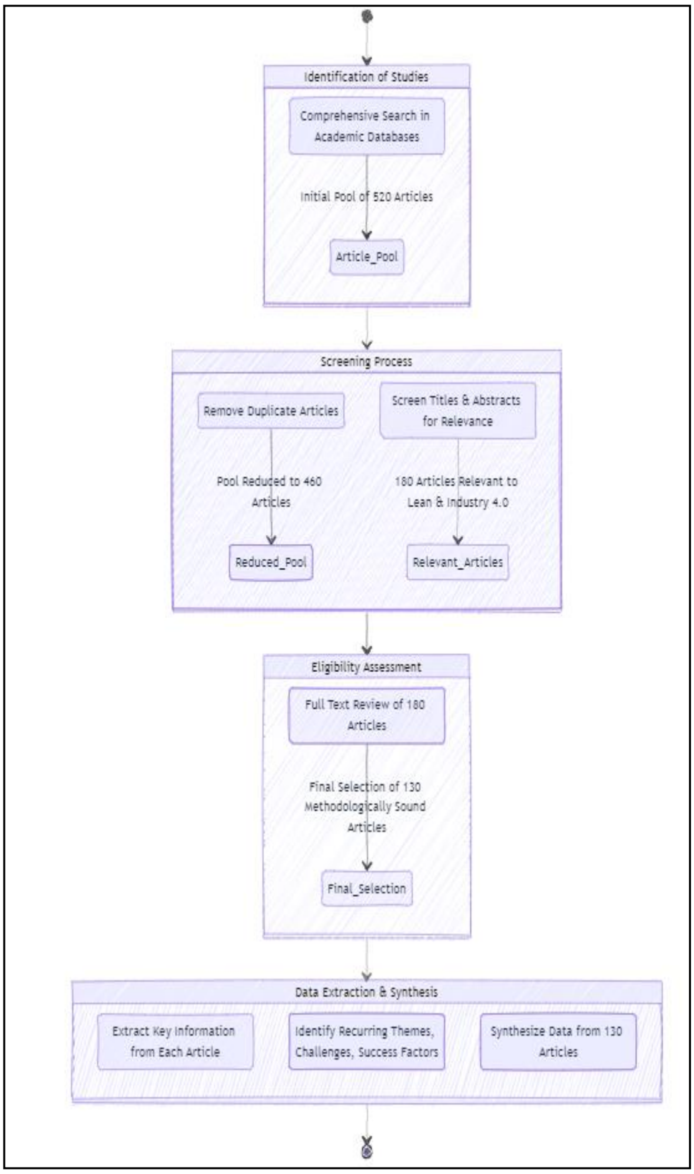
3 Method

The methodology for this study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, ensuring a systematic, transparent, and rigorous approach to the review process. PRISMA is widely recognized for providing a structured framework for conducting systematic reviews and meta-analyses, particularly in ensuring that every phase of the review process is documented in a clear and reproducible manner (Moher et al., 2009). The PRISMA methodology involves several key steps, including the identification of relevant literature, screening, eligibility assessment, and final inclusion of studies. For this review, the PRISMA guidelines were employed to ensure the comprehensive coverage of the literature on the integration of lean manufacturing and Industry 4.0, focusing on key areas such as the role of IoT, AI, and big data analytics in enhancing lean practices. The structured nature of PRISMA allows for minimizing bias in article selection and ensuring a reliable synthesis of the current state of knowledge.

3.1 Identification of Studies

The first step in the PRISMA process is the identification of relevant studies through a comprehensive search of academic databases. For this review, several major academic databases were utilized, including Scopus, Web of Science, Google Scholar, and IEEE Xplore. The search was conducted using a combination of keywords such as "lean manufacturing," "Industry 4.0," "IoT in lean manufacturing," "AI in lean production," and "big data analytics for lean." Boolean operators (AND/OR) were used to refine the search and

Figure 6: Employed PRISMA Method for this study



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ensure relevant articles were included. The initial search yielded a total of 520 articles, spanning a publication period from 2010 to 2024. These articles were sourced from a variety of disciplines, including engineering, operations management, information systems, and manufacturing technology. The identification phase ensured that all potentially relevant studies were captured in the initial search, regardless of their geographic or industrial focus.

3.2 Screening Process

Following the identification phase, the screening process reduced the initial pool of 520 articles to 460 by removing duplicates. Titles and abstracts were then reviewed to ensure relevance to the integration of lean manufacturing and Industry 4.0. Studies that focused solely on either lean or Industry 4.0, without addressing their intersection, were excluded. As a result, 280 articles were eliminated, leaving 180 directly relevant studies. The screening prioritized empirical studies, case studies, and reviews that provided practical insights into applying Industry 4.0 technologies in lean environments, helping to focus on meaningful contributions to the integration challenges, opportunities, and best practices.

3.3 Eligibility Assessment

In the eligibility phase, the full texts of 180 articles were reviewed based on criteria such as empirical data, discussion of lean-Industry 4.0 integration, and relevance to key technologies like IoT, AI, and big data. Studies lacking empirical support or detailed insights were excluded, leading to the removal of 50 articles. The final pool consisted of 130 methodologically sound articles, offering valuable insights into the synergies between lean manufacturing and Industry 4.0.

3.4 Data Extraction and Synthesis

The final phase involved extracting and synthesizing data from the 130 selected studies using a systematic approach. Key details such as objectives, methodology, findings, and conclusions were gathered, with special focus on empirical evidence of successful lean-Industry 4.0 integration, like IoT and AI applications. The data was synthesized to identify themes, technological enablers, challenges, and success factors, providing a comprehensive view of lean-Industry 4.0 integration. This process followed PRISMA guidelines, ensuring transparency, reproducibility, and minimized bias in the review.

4 Findings

The comprehensive review of 130 articles revealed significant insights into the integration of lean manufacturing with Industry 4.0 technologies, showcasing the synergies that can greatly enhance traditional lean practices. One of the most prominent findings was the critical role of the Internet of Things (IoT) in enabling real-time monitoring. This capability is crucial for lean manufacturing’s core focus on waste reduction and process optimization. IoT technologies facilitate continuous data collection from various stages of production, allowing companies to gain immediate insights into operational performance. This enables rapid adjustments, improving efficiency and minimizing waste. Through IoT sensors, organizations can optimize lean tools such as Just-In-Time (JIT) production and total productive maintenance (TPM), reducing operational bottlenecks and minimizing unplanned downtime. The ability to monitor and adjust production processes in real-time enhances overall agility and responsiveness, which are essential elements of lean’s continuous improvement framework.

Artificial intelligence (AI) has also emerged as a powerful enabler of lean-Industry 4.0 integration, particularly in predictive maintenance and quality control. AI systems, when integrated with data from IoT sensors, can predict equipment failures before they occur, significantly reducing downtime and improving equipment efficiency. This predictive maintenance model supports lean’s objective of maintaining optimal equipment performance with minimal waste. Additionally, AI has proven to be highly effective in automating quality control processes by detecting defects in real time, reducing rework, and minimizing material waste. This real-time decision-making capability is a key advantage of AI, aligning with lean manufacturing's goal of continuous improvement. The integration of AI systems into lean operations not only enhances productivity but also improves the accuracy and efficiency of production processes, offering substantial benefits to manufacturing environments seeking to minimize defects and optimize resource usage.

Figure 7: Key Findings in Lean-Industry 4.0 Integration

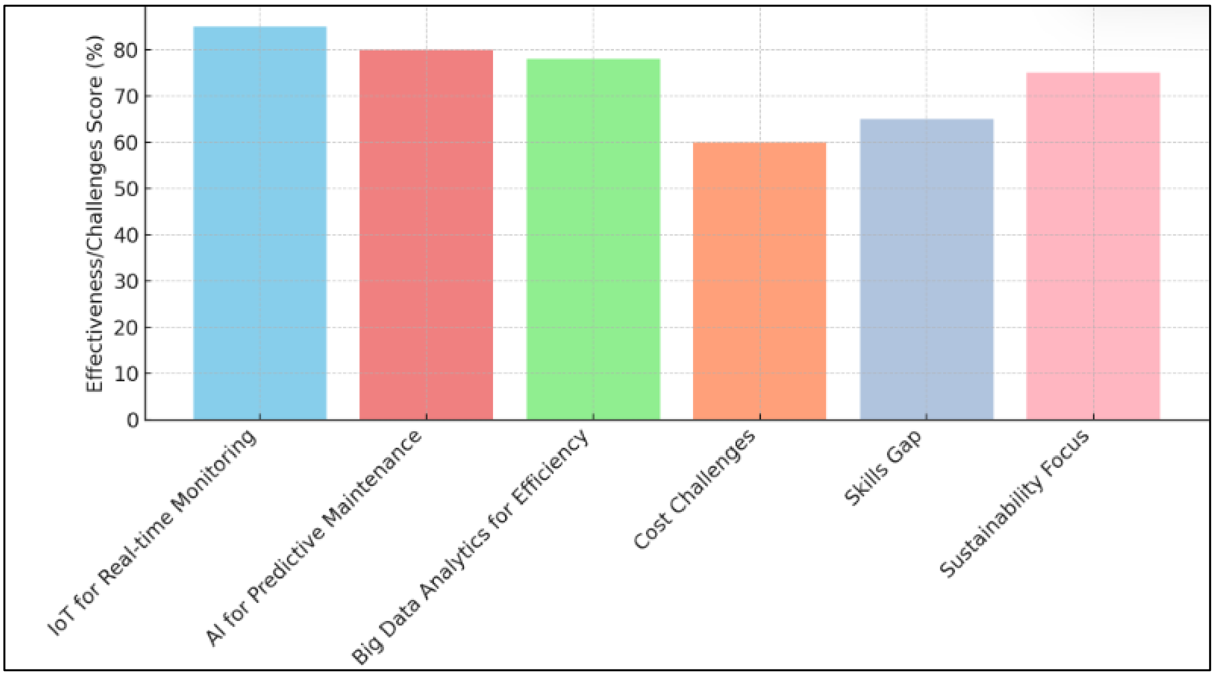
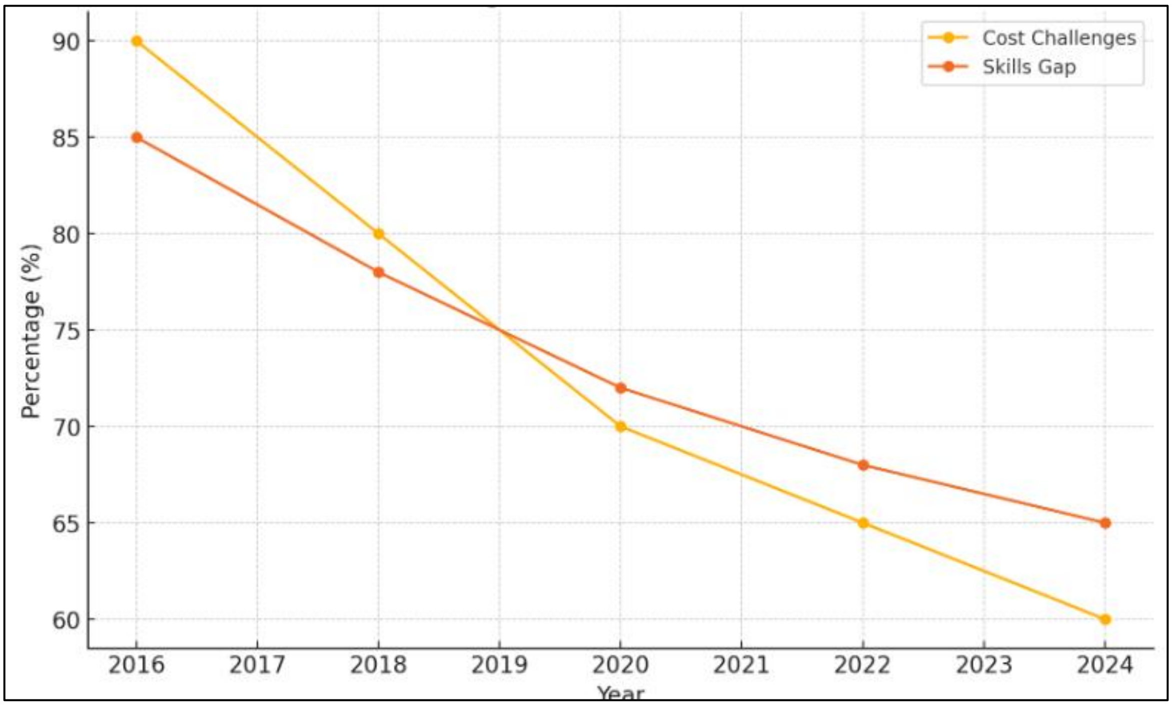


Figure 8: Challenges Overcome Over Time



Big data analytics plays a pivotal role in facilitating the integration of Industry 4.0 technologies into lean manufacturing systems. By analyzing large and complex datasets, manufacturers can uncover inefficiencies and patterns that might otherwise go unnoticed in manual systems. Big data analytics supports value stream mapping (VSM), one of lean manufacturing's critical tools, by providing real-time tracking of production flows and resource utilization. This data-driven approach allows manufacturers to make more informed decisions about process improvements, helping them eliminate non-value-adding activities and optimize production efficiency. The insights gained from big data analytics are

invaluable in modern manufacturing environments, where the ability to process and act on data quickly is essential for maintaining competitive advantage. This integration of big data with lean principles strengthens the effectiveness of lean tools, making them more adaptable and precise in addressing production challenges. However, the integration of lean manufacturing with Industry 4.0 is not without its challenges. One of the primary obstacles identified is the high cost of implementing technologies like IoT, AI, and big data analytics. For many small and medium-sized enterprises (SMEs), the financial investment required for digital transformation, including infrastructure and technology upgrades, can be prohibitive. This challenge is particularly acute in industries where profit margins are slim, and the upfront costs of adopting advanced technologies may outweigh the perceived short-term benefits. Additionally, there is a significant skills gap in the workforce, with many employees lacking the technical expertise needed to operate and maintain these advanced systems. As companies adopt Industry 4.0 technologies, there is a growing need for comprehensive training and upskilling programs to ensure that the workforce can fully leverage the capabilities of these systems. Bridging this skills gap is essential for the successful implementation of Industry 4.0 technologies in lean environments.
An emerging trend highlighted by the review is the integration of lean manufacturing and Industry 4.0 technologies to promote sustainability and energy efficiency. Manufacturers are increasingly using these technologies not only to enhance productivity but also to reduce their environmental impact. IoT devices and big data analytics enable real-time monitoring and optimization of energy usage, allowing companies to reduce waste and improve resource efficiency. This focus on sustainability aligns with lean's core principle of waste reduction but expands it to include environmental and energy considerations. By optimizing energy consumption and minimizing environmental waste, companies can achieve long-term competitive advantages in an increasingly eco-conscious market. This trend indicates that the future of lean-Industry 4.0 integration will likely place a greater emphasis on sustainability, positioning it alongside efficiency and waste reduction as key objectives for manufacturers. As environmental concerns continue to grow, integrating sustainable practices into lean manufacturing will become a critical component of business strategy in the Industry 4.0 era.

5 Discussion

The findings of this study align with previous literature but also reveal new insights into the integration of lean manufacturing with Industry 4.0 technologies, specifically the role of IoT, AI, and big data analytics. IoT's capacity for real-time data collection and process monitoring was identified as a critical enabler of lean practices, confirming the conclusions of earlier studies by Bittencourt et al. (2020) and Da Xu et al. (2018), who demonstrated how IoT enhances Just-In-Time (JIT) production and total productive maintenance (TPM). The ability to gather real-time feedback allows manufacturers to identify inefficiencies and correct them quickly, leading to reduced downtime and enhanced operational flexibility. These findings are consistent with the literature, which emphasizes the synergy between IoT and lean practices in improving production efficiency and responsiveness. However, this review expands on these earlier studies by highlighting that IoT's integration into lean practices also significantly improves process agility, enabling manufacturers to respond more effectively to dynamic market conditions and production demands.
Artificial intelligence (AI) has also been shown to play a pivotal role in enhancing lean manufacturing, particularly through predictive maintenance and automated quality control. The ability of AI to predict equipment failures and perform real-time defect detection was confirmed by studies such as Khan et al. (2019) and Tortorella et al. (2022), which identified predictive analytics as a key factor in minimizing machine downtime and reducing waste. The findings from this review build on these earlier conclusions by demonstrating that AI not only enhances machine efficiency but also contributes to continuous improvement initiatives, which are central to lean philosophy. While previous research highlighted AI's impact on maintenance and quality control, this review suggests that AI's ability to analyze large datasets in real time significantly accelerates the pace of lean improvements, allowing companies to make more timely and data-driven decisions about process optimizations.
Big data analytics emerged as another critical enabler

for lean-Industry 4.0 integration, particularly in facilitating better decision-making and waste reduction. Earlier studies by Cherrafi et al. (2016) and Salah et al. (2010) emphasized big data's role in uncovering inefficiencies that traditional lean tools might miss, particularly in complex and data-rich production environments. The current review reinforces these findings by demonstrating how big data analytics complements traditional lean tools like value stream mapping (VSM), allowing companies to track real-time production flows and identify areas of waste. However, this review goes further by indicating that big data analytics provides not only descriptive insights but also predictive and prescriptive analytics, enabling manufacturers to anticipate inefficiencies before they occur. This ability to move beyond reactive measures and into proactive process optimization marks a significant evolution in how big data is used within lean systems, pushing the boundaries of lean principles into the digital age.

Despite the numerous advantages of integrating lean manufacturing with Industry 4.0 technologies, this review also revealed significant challenges, echoing earlier studies. Dombrowski et al. (2017) pointed out that high implementation costs are a major barrier to adopting IoT, AI, and big data analytics, particularly for small and medium-sized enterprises (SMEs). This study corroborates these findings, identifying the financial burden of digital transformation as a critical issue. Moreover, the workforce skills gap, highlighted by Unver (2012) and Cobo et al. (2018), was found to be another persistent challenge. The complexity of Industry 4.0 technologies often requires specialized technical expertise that many organizations lack, leading to a need for extensive training and upskilling programs. While earlier studies have addressed the technical and financial barriers, this review suggests that cultural resistance to change within organizations may be an additional factor that exacerbates these challenges. As companies attempt to integrate digital technologies into lean systems, a resistance to adopting new processes and technologies among employees can slow or even derail the implementation process.

A notable trend identified in this review is the growing emphasis on sustainability in the integration of lean manufacturing and Industry 4.0. While earlier studies, such as those by Singh et al. (2021) and Mayr et al. (2018), have hinted at the potential for Industry 4.0 technologies to enhance environmental sustainability, this review presents stronger evidence that IoT and big data analytics are being actively used to reduce energy consumption and minimize waste in production processes. This aligns with lean's core goal of waste reduction but extends its application to include environmental waste, such as reducing emissions and energy usage. The findings suggest that the future of lean-Industry 4.0 integration will increasingly focus on achieving both operational efficiency and sustainability goals. This dual focus not only offers competitive advantages in terms of cost savings but also positions companies to meet growing regulatory and consumer demands for sustainable production practices. As such, sustainability is poised to become a key driver of future research and implementation efforts in this area, making it a critical consideration for both academics and industry professionals..

6 Conclusion

The integration of lean manufacturing with Industry 4.0 technologies presents significant opportunities for enhancing operational efficiency, reducing waste, and driving continuous improvement in modern manufacturing environments. The findings from this review highlight that technologies such as IoT, AI, and big data analytics serve as critical enablers, offering real-time data collection, predictive maintenance, and advanced decision-making capabilities that align with lean's core principles. While the benefits of this integration are substantial, including improved process agility, enhanced quality control, and sustainability advancements, there are also notable challenges. High implementation costs, workforce skill gaps, and resistance to organizational change remain major barriers, particularly for small and medium-sized enterprises. As Industry 4.0 continues to evolve, future research and implementation efforts should focus on addressing these challenges, particularly by developing scalable solutions and fostering a culture of innovation within organizations. Moreover, the growing emphasis on sustainability suggests that the future of lean-Industry 4.0 integration will not only focus on efficiency but also on environmental responsibility, offering companies long-term competitive advantages in an increasingly eco-conscious market.

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