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## *IMPACT OF LEAN SIX SIGMA ON MANUFACTURING EFFICIENCY USING A DIGITAL TWIN-BASED PERFORMANCE EVALUATION FRAMEWORK*

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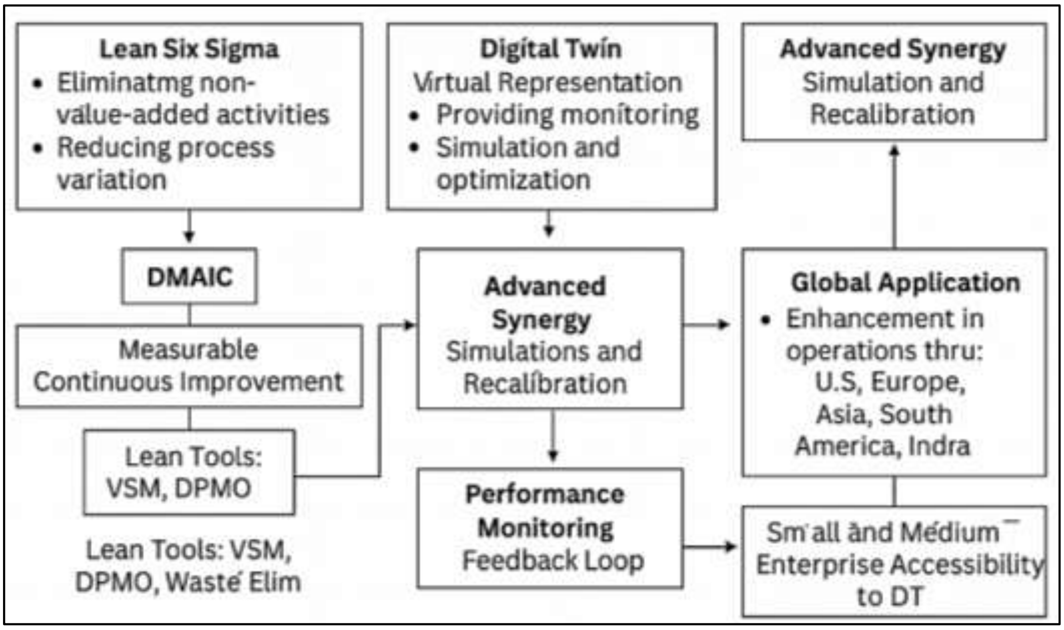
**Abstract**
This systematic review explores the integration of Lean Six Sigma (LSS) methodologies with Digital Twin (DT) technologies to assess their combined impact on manufacturing efficiency and performance valuation. With the growing need for real-time monitoring, predictive analytics, and continuous improvement in industrial environments, the fusion of LSS and DT offers a promising hybrid framework for enhancing productivity, reducing defects, and enabling adaptive control mechanisms. The review followed the PRISMA 2020 guidelines to ensure transparency and rigor, resulting in the inclusion of 72 peer-reviewed articles published between 2010 and 2024 across multiple sectors including aerospace, automotive, pharmaceuticals, electronics, and FMCG. Findings indicate that the integration of LSS-DT systems leads to significant improvements in cycle time reduction, takt time optimization, predictive maintenance, and real-time quality monitoring. A notable trend across the reviewed literature is the emergence of hybrid performance metrics that blend traditional Lean Six Sigma KPIs with digital system-level indicators such as simulation fidelity, data latency, and predictive control accuracy. While sectors like aerospace and automotive demonstrate high maturity in implementing these integrated frameworks, others—particularly small and medium-sized enterprises—face challenges related to cost, digital literacy, and infrastructural readiness. The review also identifies theoretical tensions between the deterministic nature of traditional Lean Six Sigma models and the probabilistic, adaptive capabilities of digital twin systems. Despite these challenges, the synthesis of findings confirms that LSS-DT integration fosters a culture of continuous improvement and operational resilience supported by data-driven decision-making. This study contributes to the evolving discourse on Industry 4.0 by offering an in-depth, cross-sectoral evaluation of LSS-DT convergence and proposing new directions for hybrid performance management in advanced manufacturing systems.

**Keywords**
*Lean Six Sigma (LSS), Digital Twin (DT), Manufacturing Efficiency, Performance Valuation, Industry 4.0, Smart Manufacturing*

## INTRODUCTION

Lean Six Sigma (LSS) is a synergistic process improvement methodology that combines the waste-reduction principles of Lean manufacturing with the statistical rigor of Six Sigma. Lean manufacturing, rooted in the Toyota Production System, focuses on eliminating non-value-added activities across the production stream to enhance flow and responsiveness (Gaikwad & Sunnapwar, 2020). Conversely, Six Sigma aims to reduce process variation through data-driven techniques, typically employing the DMAIC (Define, Measure, Analyze, Improve, Control) framework.

**Figure 1: Lean Six Sigma and Digital Twin Integration**




Together, LSS provides a comprehensive structure for reducing inefficiencies, enhancing quality, and promoting customer satisfaction. At its core, LSS is anchored in measurable performance indicators, continuous monitoring, and root-cause analysis, making it particularly relevant in complex manufacturing settings where precision and consistency are critical. Studies across industries have shown that LSS implementation leads to improvements in throughput, defect reduction, employee morale, and customer retention (Skalli et al., 2025). Furthermore, LSS is considered adaptable and scalable, capable of being integrated across both discrete and process manufacturing industries. With its foundation in structured statistical problem-solving, LSS provides a formal mechanism to standardize process evaluations, eliminate bottlenecks, and improve cycle times. As industries move toward real-time, data-intensive operations, LSS remains a vital framework, offering the procedural discipline necessary for organizations to analyze and improve operations consistently (Ndrecaj et al., 2023).

Digital Twin (DT) technology refers to the creation of a virtual representation of a physical asset or process, enabling real-time monitoring, simulation, and optimization using synchronized data streams (Skalli et al., 2024). Originating from NASA's need for mirrored systems in space exploration, digital twins are now widely used in manufacturing, where they allow for accurate modeling of factory operations, machine behaviors, and production flows. A digital twin integrates multiple technologies—such as IoT sensors, cloud computing, simulation tools, and AI analytics—to generate high-fidelity replicas that evolve with their physical counterparts. Through continuous data input and feedback loops, DTs provide comprehensive visibility into process conditions, material movement, and energy consumption, which can be used for diagnostic, predictive, and prescriptive insights (Trubetskaya et al., 2023). In manufacturing environments, digital twins can simulate various production scenarios, enabling organizations to experiment with process changes without disrupting physical operations. These digital environments promote operational transparency, predictive maintenance, and data-based decision-making, which are fundamental to lean and Six Sigma philosophies (Gupta et al., 2023). The modular and scalable architecture of digital twins allows them to represent individual machines, entire production lines, or even end-to-end supply chains. As DTs continuously evolve with real-time operational data, they provide a feedback-rich environment for performance monitoring, aligning perfectly with the DMAIC structure central to Six Sigma projects (Carneiro et al., 2025).

The integration of Lean Six Sigma with Digital Twin-based performance valuation frameworks offers an advanced synergy where real-time data analytics complements structured process improvement. While LSS relies on process metrics and statistical control, the infusion of DTs provides those metrics in real time, facilitating faster and more accurate decision-making. Real-time synchronization of data enables organizations to simulate LSS interventions virtually before implementing them physically, which significantly reduces risk and improves confidence in projected outcomes (Salah & Rahim, 2018). Moreover, DTs provide a continuous stream of detailed performance data, allowing Six Sigma practitioners to validate assumptions, model process variation, and refine control plans with enhanced granularity. Lean initiatives benefit from the visibility and traceability offered by digital twins, enabling more effective value stream mapping, bottleneck identification, and waste elimination strategies (Jlassi & El Mhamedi, 2019). With the ability to monitor cycle times, energy use, and material waste in real time, Lean Six Sigma teams can target root causes with unprecedented precision. The capability to continuously assess and recalibrate improvement actions through DT simulation leads to closed-loop systems where improvement cycles are self-validating and dynamically optimized (Siefan et al., 2025). In addition, LSS metrics such as DPMO (Defects Per Million Opportunities), Cp/Cpk indices, and takt time can be embedded into DT dashboards, enabling seamless alignment of digital insights with traditional performance goals.

Globally, Lean Six Sigma has gained traction as a strategic imperative in manufacturing sectors aiming for quality excellence and cost efficiency. In the United States and Europe, LSS is widely adopted in the automotive, aerospace, and pharmaceutical industries, with documented improvements in lead time reduction, product quality, and process standardization (Mendes & França, 2024). Asian economies such as Japan, South Korea, and China have institutionalized LSS within their industrial policies to drive export competitiveness and manufacturing innovation. Indian manufacturers in the automotive and textile sectors report significant defect reduction and cost savings through LSS deployment. In South America and Africa, LSS adoption is growing through multinational supply chains, where it is used to align local production practices with global quality expectations (Prado et al., 2024). Internationally funded development initiatives also promote LSS training as a pathway to workforce upskilling and industrial modernization. The widespread implementation across sectors—from electronics to food processing—illustrates the universal applicability of LSS tools like value stream mapping, cause-effect matrices, and control charts. Numerous case studies and empirical surveys confirm LSS's ability to improve first-pass yield, reduce rework, and enhance overall equipment effectiveness (OEE) globally. These global practices have established a mature knowledge base for benchmarking LSS performance and provide a fertile ground for advanced digital integration.

Digital twin technology has emerged as a global catalyst for manufacturing excellence, enabling companies across continents to digitally transform operations through real-time feedback and predictive control mechanisms. In Germany, as part of the Industry 4.0 movement, digital twins are widely used in discrete manufacturing for predictive maintenance, process modeling, and adaptive control (Hashim et al., 2024). In the United States, aerospace and automotive sectors have integrated DTs for product lifecycle management and process simulation, improving both product reliability and operational cost-effectiveness. In Asia, China's "Made in China 2025" policy has accelerated the adoption of digital twins in smart factories to enhance industrial productivity and supply chain visibility (Vieira et al., 2025). Japanese manufacturers have employed DTs to optimize robotics-driven production lines, achieving enhanced synchronization between digital planning and physical execution. Indian industries are increasingly adopting DT frameworks to digitize legacy systems and improve infrastructure flexibility in automotive, pharmaceuticals, and consumer goods sectors (Farrington et al., 2018). In multinational corporations, DTs facilitate standardization and cross-site benchmarking, offering real-time transparency across geographically dispersed production hubs. Moreover, digital twins support international compliance requirements by continuously monitoring quality metrics and alerting deviations from standards such as ISO 9001 or Six Sigma thresholds. These examples demonstrate that the operational footprint of digital twins is not limited to technologically advanced economies but is expanding rapidly in emerging markets, where they are used to address inefficiencies, reduce downtime, and improve decision velocity through virtual experimentation (Gamage et al., 2025). With cloud-based integration, DTs also allow small and medium enterprises to leverage high-end simulations without the need for heavy infrastructure investments, democratizing access to digital transformation.

Performance evaluation is central to the integration of Lean Six Sigma and digital twin systems, acting as the connective layer that links digital insights with operational excellence objectives. Traditional LSS frameworks rely on performance indicators such as process sigma levels, cycle efficiency, defect rates, and inventory turnover (Komkowski et al., 2025). Digital twins enhance these evaluations by continuously feeding process data into analytical dashboards, creating a live assessment mechanism that reflects ongoing operations. A digital twin-based performance framework enables multilevel evaluation, from machine-level metrics such as vibration and temperature profiles to system-level indices like throughput and lead time. Such granularity allows Six Sigma professionals to isolate variance contributors and apply control strategies with surgical accuracy. Additionally, the visualization tools embedded in DT platforms enhance communication between operators, engineers, and quality managers, facilitating faster alignment and corrective actions (Touriki et al., 2022). Lean initiatives also benefit from performance mapping features in DTs, where virtual replicas help to evaluate the impact of waste reduction interventions across the value chain. Many firms use DTs to track takt time consistency, identify downtime hotspots, and assess the sustainability impact of lean practices, offering a holistic lens for operational evaluation (Rüttimann, 2019). In research settings, hybrid performance models that blend LSS metrics with DT simulation outputs have been proposed and tested, demonstrating superior diagnostic accuracy compared to traditional KPI tracking methods. The ongoing alignment between statistical control tools and live digital feedback structures creates a closed-loop performance system capable of continuous learning and system-wide optimization (Carrington et al., 2021).

The convergence of Lean Six Sigma methodologies and Digital Twin technologies reflects an interdisciplinary evolution at the intersection of industrial engineering, systems design, data analytics, and operations management. Numerous academic fields contribute to this integration, including control systems engineering, cyber-physical systems, machine learning, and quality science (Lizarelli et al., 2025). Engineering research emphasizes the role of DTs in process modeling and predictive analytics, while operations management literature focuses on how Lean and Six Sigma principles guide production efficiency and quality improvement (Wehrden et al., 2019). In computer science and information systems, scholars explore how digital infrastructures—such as edge computing, cloud platforms, and IoT architectures—facilitate real-time data exchange required for DT-based analytics. Manufacturing-focused journals have documented experimental setups where LSS improvement projects are simulated using digital twins to assess feasibility and expected gains, confirming the value of digital validation for continuous improvement (Abramo et al., 2018). Quality management scholars emphasize the adaptability of DMAIC within virtual environments, highlighting how DTs can be embedded at each phase to guide measurement, analysis, and control. The resulting literature forms a cross-disciplinary foundation that supports both theoretical exploration and practical implementation of hybrid frameworks that align process rigor with digital intelligence (Følstad et al., 2021). With contributions from academia, industry consortia, and global standards bodies, the research base on Lean Six Sigma and digital twins is sufficiently mature to warrant integrated performance valuation frameworks that can enhance responsiveness, reliability, and return on operational investments (Tobi & Kampen, 2018). The primary objective of this systematic review is to critically evaluate the synergistic integration of Lean Six Sigma (LSS) methodologies with Digital Twin (DT) technologies in the context of modern manufacturing systems. By investigating how these two paradigms converge, the study aims to uncover the extent to which their combined implementation enhances operational efficiency, reduces production defects, and facilitates real-time, data-driven decision-making.

## LITERATURE REVIEW

The literature review provides a comprehensive foundation for understanding the intersection of Lean Six Sigma (LSS), Digital Twin (DT) technology, and performance valuation frameworks in the context of manufacturing efficiency. Scholarly research in the field of industrial engineering, manufacturing systems, and digital transformation increasingly emphasizes the role of data-driven continuous improvement methodologies in optimizing production environments. Lean Six Sigma has emerged as a globally recognized methodology that strategically blends the process flow optimization principles of Lean with the statistical precision of Six Sigma to reduce waste and variability (Wang et al., 2024). On the other hand, Digital Twins represent a paradigm shift in real-time monitoring and simulation of physical systems using virtual counterparts, capable of enhancing predictive capabilities, scenario planning, and operational control (Khmara, 2025).

The convergence of LSS and DTs offers an advanced framework for performance valuation in manufacturing, where quantitative process metrics are continuously captured, visualized, and interpreted through cyber-physical systems. This hybrid architecture promises increased manufacturing responsiveness, reduced operational risks, and enhanced quality control. However, literature in this domain is often fragmented, focusing either on traditional LSS outcomes or the technological architecture of digital twins without integrating performance valuation as a central axis. Therefore, this review synthesizes research across multiple domains to highlight theoretical frameworks, empirical results, methodological approaches, and application-specific insights that collectively support the development of an integrated Lean-Digital evaluation model (Dai et al., 2020). This literature review is structured into eight interlinked subsections that trace the evolution, theoretical foundations, performance metrics, modeling tools, and implementation challenges of combining LSS with DTs in manufacturing efficiency. Each subsection critically examines the academic discourse and industrial applications, providing a cohesive foundation for the subsequent development of a digital twin-based performance valuation framework in Lean Six Sigma-driven environments.

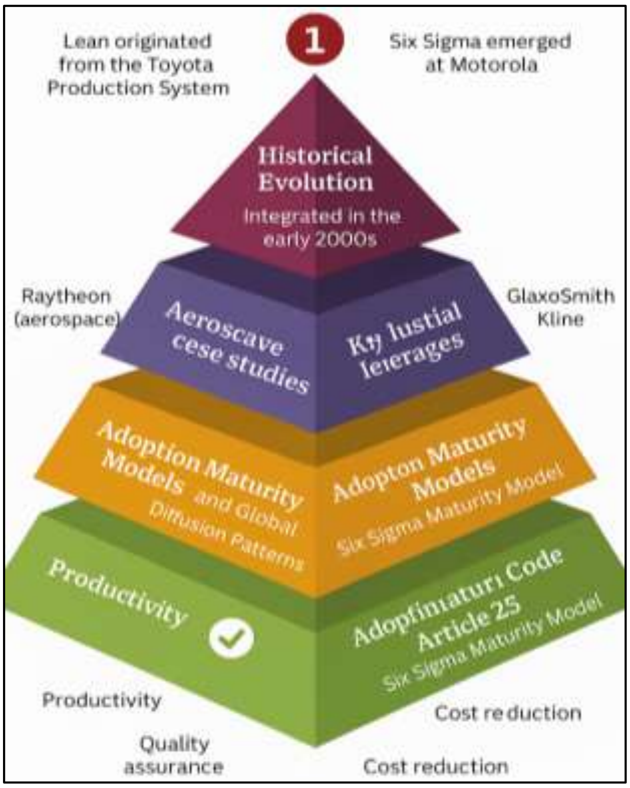
**Evolution of Lean Six Sigma in Global Manufacturing Paradigms**

The historical evolution of Lean and Six Sigma reflects a trajectory shaped by industrial necessity, systematic refinement, and empirical adaptation across multiple production paradigms. Lean manufacturing originated from the Toyota Production System (TPS) in post-World War II Japan, emphasizing the elimination of non-value-adding activities and fostering a culture of continuous improvement, known as "Kaizen" (Chang et al., 2022). Key Lean tools such as value stream mapping, 5S, kanban, and standardized work were developed to enhance production flow, reduce waste, and improve responsiveness. Meanwhile, Six Sigma emerged in the 1980s through Motorola and later General Electric as a statistical quality management system focused on reducing process variation using the DMAIC (Define, Measure, Analyze, Improve, Control) methodology and achieving a process performance level of 3.4 defects per million opportunities (Subrato, 2018). Unlike Lean, Six Sigma is highly quantitative, relying on control charts, hypothesis testing, regression, and process capability indices to identify root causes and implement data-driven improvements (Ara et al., 2022; Singh, 2025). The integration of Lean and Six Sigma into a unified methodology began in the early 2000s, responding to the need for a holistic approach that addressed both flow efficiency and process capability. This convergence allowed organizations to apply Lean's waste-reduction strategies alongside Six Sigma's statistical precision, creating a balanced toolkit for operational excellence.

Research by (Citybabu & Yamini, 2024b; Uddin et al., 2022) affirmed that integration increased cross-functional applicability and problem-solving efficiency, especially in high-mix, high-volume environments. The Lean Six Sigma (LSS) model now serves as a core strategic and tactical framework for quality and productivity improvement across diverse industrial landscapes (Madzík et al., 2025; Akter & Ahad, 2022), with enduring influence on organizational design, performance assessment, and continuous improvement culture.Numerous case studies across sectors and geographies have documented the practical effectiveness of Lean Six Sigma in improving manufacturing performance. In the aerospace sector, Raytheon reported significant reductions in lead time and scrap rates after adopting LSS tools, using control charts, value stream mapping, and root cause analysis to optimize component manufacturing (Escobar et al., 2022; Rahaman, 2022). Similarly, in the automotive industry, Toyota's continued application of Lean principles reinforced global standards for efficiency and flexibility, while companies like Ford and Chrysler incorporated Six Sigma for precision quality improvement. The pharmaceutical industry has also seen LSS success; GlaxoSmithKline applied

DMAIC to reduce cycle times and deviations in production, demonstrating the method's cross-functional value (Masud, 2022; Milewska & Milewski, 2025).

**Figure 2: Evolution and Global Maturity of Lean Six Sigma**



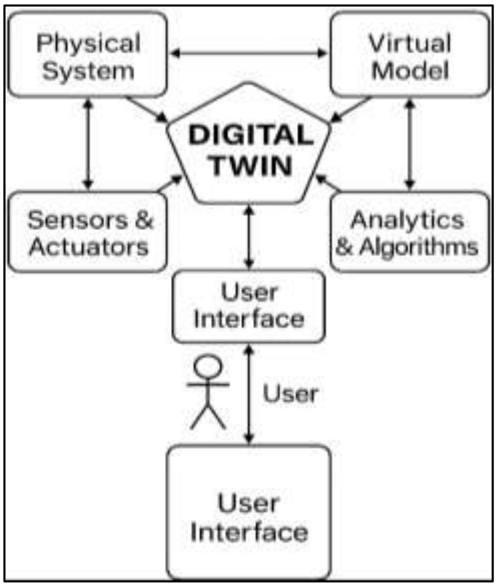

In India, Tata Motors utilized Lean Six Sigma to enhance production line throughput and reduce defects, achieving higher customer satisfaction metrics and improved cost efficiency. The food processing sector has also leveraged LSS: Nestlé and Unilever implemented Lean-based kaizen events and Six Sigma-based variation controls to stabilize yield and minimize downtime. In Latin America, LSS interventions in the textile and electronics industries reduced rework and improved employee engagement through team-based problem-solving. South Korean electronics manufacturers such as Samsung have institutionalized LSS programs to support global market responsiveness, combining agile operations with Six Sigma's analytical rigor (Hasan et al., 2022; Ström & Hermelin, 2023). African case studies remain relatively scarce but show growing adoption in mining and manufacturing firms, particularly through external consultancy-driven LSS deployment. These sector-specific and geographically diverse examples demonstrate the operational reliability and adaptability of LSS frameworks, validated through empirical application rather than mere conceptual endorsement.

The global diffusion of Lean Six Sigma follows a trajectory shaped by organizational maturity, industry readiness, workforce skill levels, and economic development. Adoption maturity models, such as the Lean Maturity Model (LMM) and Six Sigma Maturity Model (SSMM), provide structured benchmarks to assess an organization's readiness and progression through awareness, experimentation, integration, and institutionalization phases (Hossen & Atiqur, 2022; Shearmur & Doloreux, 2021). Developed economies such as the United States, Germany, and Japan have demonstrated mature LSS ecosystems where practices are embedded within strategic planning and corporate performance management systems. In contrast, emerging economies—such as India, Brazil, and South Africa—have adopted LSS incrementally, often beginning with pilot programs in quality-sensitive sectors before expanding organization-wide. Studies show that cultural factors, regulatory frameworks, and technological infrastructure influence LSS scalability, especially in developing contexts. For example, Latin American firms exhibit moderate maturity in Lean deployment but limited Six Sigma penetration due to skill and data constraints (MacKinnon et al., 2019; Tawfiqul et al., 2022). In multinational organizations, LSS adoption follows a cascading model, where global headquarters set standards and facilitate training, while local units adapt tools based on contextual needs. Institutional support mechanisms, such as Six Sigma certification bodies and Lean consortia, further facilitate knowledge transfer and benchmarking (Sazzad & Islam, 2022; Hoek, 2020). Despite contextual variability, the adoption curve reveals increasing convergence toward integrated Lean-Digital frameworks, which prioritize real-time performance monitoring and process agility. The maturity of adoption is thus both an organizational journey and a reflection of systemic capability (Jakobsen et al., 2025; Akter & Razzak, 2022).

**Foundations and Architecture of Digital Twin Systems in Industrial Contexts**

Digital twins (DTs) are comprehensive virtual representations of physical assets or systems that replicate real-world processes using synchronized data and simulations. The concept was formalized by Gross et al. (2018), who defined a digital twin as the combination of a physical entity, a virtual model, and the bi-directional data flow that connects them. This triad structure allows for continuous monitoring, analysis, and simulation of physical processes in real time. The core components of a digital twin include the physical system, the digital representation or model, a data acquisition and communication system, and analytics or decision-support algorithms. The lifecycle of a digital twin typically mirrors the asset it represents, evolving from design and production to operation and decommissioning (Adar & Md, 2023; Garland et al., 2019).

**Figure 3: Digital Twin Architecture and Components**




During the design phase, simulation tools are used to create a virtual model, which is then enriched with data during deployment and operation. Throughout the operational lifecycle, real-time data from the physical asset are streamed into the twin to ensure continuous synchronization and process reflection. Importantly, the fidelity of a digital twin—its accuracy in representing the physical system—depends on the quality of its data sources and the comprehensiveness of its modeling logic (Qibria & Hossen, 2023; Xue et al., 2020). Researchers distinguish between basic digital models, enriched digital shadows (which reflect data but lack feedback loops), and fully interactive digital twins, which enable bidirectional control and decision-making. The digital twin lifecycle is thus inherently iterative and data-centric, facilitating a rich feedback mechanism for performance evaluation, condition monitoring, and simulation-based optimization (Maniruzzaman et al., 2023; Pinheiro et al., 2025).

The functionality and effectiveness of digital twins are critically dependent on a robust technological foundation, particularly involving the Internet of Things (IoT), sensor networks, edge and cloud computing, and cyber-physical systems (CPS). IoT forms the backbone of digital twin data acquisition, enabling physical assets to generate and transmit real-time data through embedded sensors and actuators. These sensors measure various operational parameters such as temperature, vibration, pressure, or humidity, feeding data into the virtual model for analysis and feedback. Edge computing supports low-latency processing near the source of data generation, which is essential for time-sensitive applications such as process control and predictive maintenance in manufacturing systems (Akter, 2023; O'Dwyer et al., 2023). Simultaneously, cloud computing offers scalability, allowing large volumes of data to be processed and stored while facilitating advanced analytics, collaborative simulations, and remote monitoring. The integration of edge and cloud computing architectures enables hybrid models where local computation is balanced with global intelligence. Furthermore, cyber-physical systems (CPS) provide the conceptual and structural framework that integrates the physical and digital domains, enabling seamless interaction between hardware and software components (Jones et al., 2019; Masud, Mohammad, & Ara, 2023). CPSs underpin smart manufacturing paradigms by embedding intelligence into physical operations through bidirectional communication between sensors, controllers, and data models. This tight coupling of physical processes with computational intelligence creates an ecosystem in which digital twins can not only replicate but also predict and influence physical behavior (Giannecchini & Taylor, 2018; Masud, Mohammad, & Sazzad, 2023). Thus, the integration of these enabling technologies transforms digital twins from static models into dynamic, real-time intelligence systems for industrial contexts.

The application of digital twins spans both discrete and process manufacturing environments, with distinct use cases and integration challenges in each domain. Discrete manufacturing involves the production of countable, individual units—such as automotive parts, electronics, or aerospace components—where digital twins are used extensively for real-time monitoring of machine health, process simulation, and layout optimization (Lane, 2020; Hossen et al., 2023). For example, in the aerospace sector, companies like Boeing and Airbus have implemented digital twins to manage the lifecycle of aircraft components, using sensor data for fatigue analysis and predictive maintenance. In automotive manufacturing, digital twins are used to simulate production lines, analyze robotic movement, and improve takt time alignment, leading to reduced cycle times and enhanced flexibility (Shamima et al., 2023). By contrast, process manufacturing—commonly seen in chemical, pharmaceutical, and food industries—involves continuous or batch processing, where DTs are leveraged to optimize flow dynamics, monitor chemical reactions, and predict yield variations. In these settings, digital twins facilitate multi-variable control, ensuring that temperature, pressure, and material ratios remain within defined tolerances through feedback loops (Ashraf & Ara, 2023). In oil and gas operations, DTs have been applied to optimize pipeline management and monitor corrosion risks in real time. While both domains benefit from simulation and predictive analytics, discrete manufacturing emphasizes geometric precision and cycle optimization, whereas process manufacturing prioritizes chemical consistency and flow stability. Studies have noted that discrete environments often adopt modular twin architectures, while process environments require integrated process-twin systems with continuous data capture. The use cases thus reflect the operational logic of each manufacturing paradigm and the degree of data granularity required for effective twin deployment.

A variety of digital twin platforms and industrial implementation models support DT deployment across sectors, ranging from proprietary vendor solutions to open-source ecosystems. Major industrial platforms such as Siemens' MindSphere, GE's Predix, PTC's ThingWorx, and IBM's Watson IoT provide cloud-based environments for developing and managing digital twins with integrated analytics, visualization, and control features. These platforms typically offer modular interfaces that support connectivity with PLCs, SCADA systems, and ERP platforms, enabling end-to-end visibility across manufacturing functions (Sanjai et al., 2023; Sepasgozar, 2021). Open-source frameworks such as Eclipse Ditto and FIWARE provide alternatives that emphasize customization, interoperability, and open standards. Industrial implementation models vary based on the degree of integration—ranging from isolated machine-level twins to factory-wide or even supply chain-wide twins (AboElHassan & Yacout, 2023; Akter et al., 2023). Some organizations adopt hybrid models where high-fidelity twins are used for critical assets, while simplified twins monitor non-critical systems. A comparative discussion also arises between digital twins and related technologies such as digital shadows—which refer to uni-directional data streams from the physical to the digital domain, without feedback capabilities. While digital shadows are useful for monitoring and documentation, they lack the interactive and analytical features that define a digital twin. Digital twins thus differ fundamentally through their closed-loop functionality, which allows for predictive control, bidirectional communication, and decision automation (Frick et al., 2024; Tonmoy & Arifur, 2023). In industrial settings, the adoption of robust DT platforms enables not only asset replication but also performance forecasting and optimization based on real-time conditions and machine learning insights.

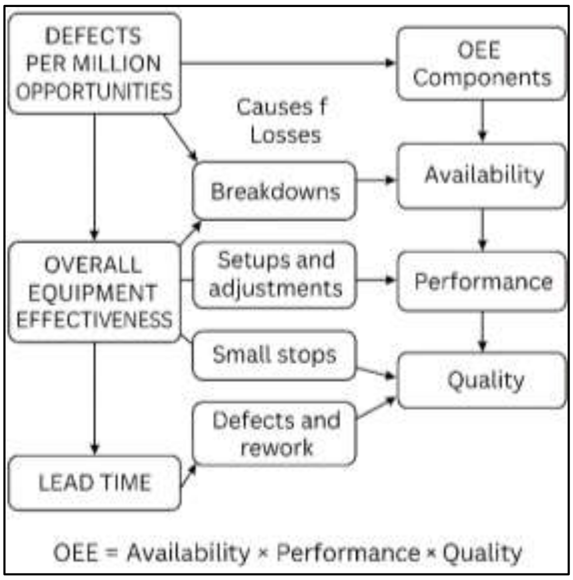
**Performance Valuation in Manufacturing: Metrics, Models, and Evolution**

Key performance indicators (KPIs) have long served as the backbone for evaluating manufacturing performance, with traditional metrics like Defects Per Million Opportunities (DPMO), Overall Equipment Effectiveness (OEE), takt time, and lead time forming the core of industrial performance management systems. DPMO quantifies the number of defects normalized per one million opportunities, providing a statistical measure aligned with Six Sigma quality objectives (Liebenberg & Jarke, 2023; Zahir et al., 2023). OEE, on the other hand, measures equipment utilization by incorporating availability, performance efficiency, and quality rate, thus offering a composite metric for equipment productivity. Takt time, originating from Lean methodology, aligns production rates with customer demand, ensuring balanced workflows and minimized idle time (Abdullah Al et al., 2024; Parmar & Desai, 2020). Lead time—defined as the total time from order initiation to completion—serves as a critical indicator of responsiveness and process efficiency. Despite their historical relevance, these traditional KPIs are increasingly viewed as insufficient in isolation, given their static nature and inability to capture real-time dynamics. Contemporary performance measurement integrates these KPIs into broader frameworks augmented by real-time data systems and analytics platforms. Research has highlighted that while DPMO and OEE remain essential, their full value is unlocked when combined with time-series analytics and root cause tracing tools (Razzak et al., 2024; Frick et al., 2024). Moreover, in modern smart manufacturing environments, KPIs are no longer isolated; they are interconnected through dashboards that reflect dynamic system behaviors and provide insights into variability, waste, and efficiency in real time. Thus, while traditional KPIs maintain their conceptual importance, their execution is increasingly embedded within more agile and digitized monitoring frameworks.

The shift from static KPI measurement to data-centric performance monitoring has fundamentally reshaped how manufacturing firms evaluate and manage operational performance. This evolution is driven by the integration of real-time data systems, where dashboards play a central role in translating raw sensor data and ERP information into actionable performance insights (Jahan, 2024; Liebenberg & Jarke, 2023). Dashboards provide a multi-layered view of manufacturing systems, combining historical trends with real-time indicators such as OEE, cycle time deviations, quality yields, and downtime events. These systems enable operators, engineers, and managers to visualize process health across different levels—machine, line, and enterprise—enhancing coordination and rapid response. Through automated alerts, drill-down features, and customizable widgets, modern dashboards support proactive decision-making aligned with Lean Six Sigma goals. Integration with cloud and edge computing platforms further enables centralized data repositories and decentralized processing, ensuring both scalability and responsiveness (Jahan, 2024; Ibrahim et al., 2025).

Researchers also note that dashboards enhance cross-functional communication by standardizing performance language and enabling real-time consensus on process condition. In industries such as automotive and electronics, dashboards are used not just for monitoring but also for managing improvement projects, aligning project milestones with live metrics. Studies show that digital dashboards reduce mean response time to quality incidents and improve compliance with control thresholds (Jahan & Imtiaz, 2024; Braun et al., 2023). They also play a critical role in Lean Six Sigma's Control phase by visualizing standard operating windows and statistical boundaries. As such, data-centric dashboards represent a transformative layer in manufacturing valuation—merging real-time monitoring with traditional metrics for enhanced operational intelligence (Istiaque et al., 2024).

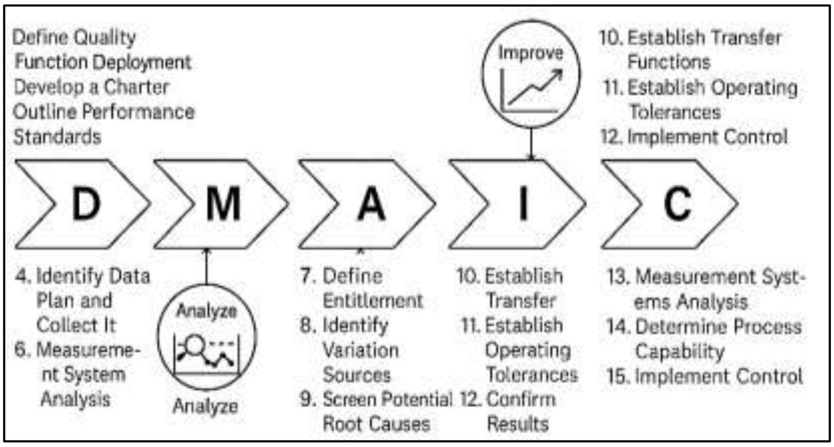
**Figure 4: Key Performance Indicators in Smart Manufacturing**




**Integrating Lean Six Sigma with Digital Twin Ecosystems**

The integration of Lean Six Sigma (LSS) and Digital Twin (DT) systems hinges on the natural alignment between the DMAIC (Define, Measure, Analyze, Improve, Control) methodology and the data-centric, simulation-driven functionalities of digital twins . In the Define phase, DTs provide a virtual replica of the process environment, enabling visualization of system boundaries, input-output flows, and stakeholder interactions. This enhances problem scoping by grounding project definitions in real-time system representations (AboElHassan et al., 2023; Akter & Shaiful, 2024).

**Figure 5: Lean Six Sigma and Digital Twin Integration**




During the Measure phase, DTs aggregate sensor and operational data streams to deliver continuous updates on key process metrics like cycle time, takt time, and defect rates. These metrics, previously collected manually, are now fed directly from the physical system to the digital twin for real-time analysis. In the Analyze stage, DTs enable virtual experimentation, where various scenarios—such as parameter changes or layout alterations—can be tested without disrupting physical operations. Root cause analysis, a critical Six Sigma activity, is thus enhanced by multivariate diagnostics performed within the DT framework (Frick et al., 2024; Subrato & Md, 2024). The Improve phase benefits from predictive models embedded within the DT to recommend optimal control settings or workflow modifications. Finally, in the Control phase, DTs maintain a continuous feedback loop with the physical system, enforcing SPC (statistical process control) rules and alerting deviations through automated dashboards (Riesener et al., 2025; Akter et al., 2024). The synergy between DMAIC and DTs creates a

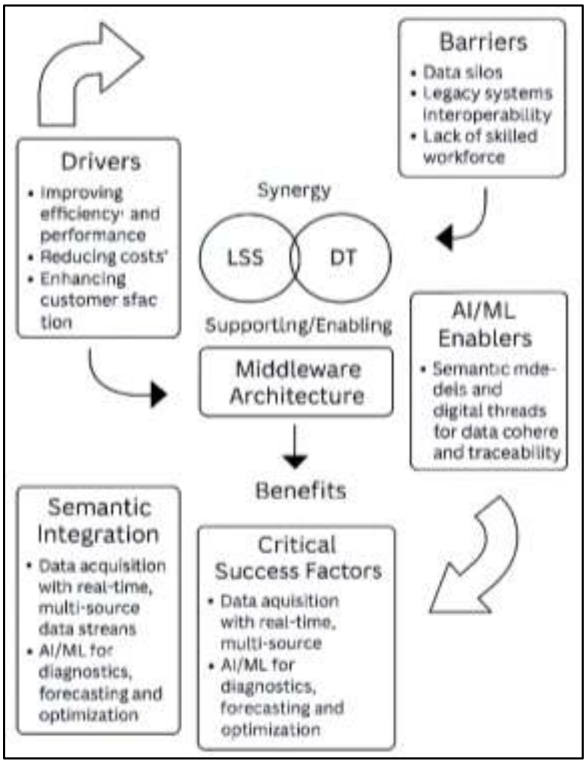
robust, closed-loop environment where performance improvement is measurable, reproducible, and grounded in continuous validation (Ammar et al., 2025; Obukhov et al., 2023).
Value Stream Mapping (VSM**)**—a cornerstone of Lean methodology—has been significantly enhanced by its integration into digital twin environments. Traditionally, VSM involves manually mapping out the flow of materials and information to identify non-value-adding activities and process inefficiencies (Jahan, 2025; Huang et al., 2019). However, in digital twin-based systems, real-time data capture enables the automatic generation of dynamic VSMs, offering visualizations that reflect the current state of production systems with high fidelity. Unlike static maps, these digital VSMs update continuously through IoT-connected devices, facilitating immediate detection of bottlenecks, excessive motion, and inventory build-up. Studies have shown that digital VSM tools integrated into platforms like Siemens MindSphere and IBM Watson IoT allow multi-level drill-downs into process flows, cycle times, and operator efficiency. Digital twins also support comparative mapping between current and future states, allowing teams to simulate Lean interventions virtually and validate projected improvements prior to physical implementation (Jahan et al., 2025; Hartmann et al., 2018). Moreover, VSM within DT environments supports integration with Six Sigma metrics such as DPMO and process capability indices, linking flow analysis to quality outcomes. Research by Lu et al. (2021) demonstrates that digital VSM enhances Lean's waste categorization—overproduction, waiting, defects, motion, transportation, inventory, and overprocessing—by mapping these wastes to measurable digital signals. These capabilities not only make VSM more accurate but also more actionable by incorporating real-time alerts and performance thresholds. The digital transformation of VSM thus strengthens Lean Six Sigma's diagnostic power, enabling continuous process optimization within a digital twin framework (Horsthofer-Rauch et al., 2022; Khan et al., 2025).
Predictive and prescriptive analytics, facilitated through the simulation capacities of digital twins, extend the scope of Lean Six Sigma from descriptive process improvement to proactive decision-making. Predictive analytics uses historical and real-time data to forecast process outcomes such as machine failure, product defects, or cycle time fluctuations (Arey et al., 2021; Khan, 2025). These forecasts are derived from statistical models, time-series algorithms, or machine learning techniques embedded in DT platforms. In contrast, prescriptive analytics goes further by recommending specific corrective actions based on predicted states—such as optimal scheduling, parameter settings, or resource allocation strategies. Within Lean Six Sigma environments, these analytics align with the Improve and Control phases, offering data-driven recommendations that are validated within the DT before physical execution (Akter, 2025; Mubarik et al., 2021). Research shows that predictive models embedded in DTs have been used to preemptively adjust takt time in response to demand shifts, simulate Kanban loop behaviors under inventory constraints, and optimize batch sequencing to reduce changeover waste. Studies by Pagliosa et al. (2021) highlight how these simulations improve yield consistency and reduce variance by enabling process engineers to evaluate multiple scenarios in a risk-free virtual space. Moreover, predictive defect models based on regression or neural networks have been successfully applied within DT systems in semiconductor, aerospace, and automotive sectors, enhancing Six Sigma's capability to eliminate root causes at early stages (Rahman et al., 2025). These analytics are visualized through DT dashboards, which present prescriptive suggestions in the context of current operational constraints, integrating seamlessly with Lean Six Sigma's emphasis on timely, measurable, and sustainable improvements.
The concept of Kaizen, or continuous incremental improvement, traditionally implemented through team-based problem-solving and standardized audits, has been successfully digitized through the use of digital twins. DT platforms replicate the Kaizen board environment by offering live issue-tracking systems, continuous performance dashboards, and automated audit trails (Masud et al., 2025). These features allow cross-functional teams to monitor improvement projects, assign responsibilities, and evaluate interventions using digital metrics derived from real-time process data. Several industrial case studies illustrate the value of such integration (Md et al., 2025). For example, in the electronics sector, Samsung implemented DT-driven Kaizen loops that allowed process owners to visualize continuous improvement metrics, simulate countermeasures, and assess process behavior changes within minutes. In another example, Bosch employed digital twin systems to replicate Six Sigma control tools such as X-bar and R charts, integrating them into real-time dashboards for SPC (Islam & Debashish, 2025).

These tools automatically highlight trends, assign control limits, and generate alerts for out-of-control conditions, removing the need for manual chart updates and increasing responsiveness to process deviations (Bagheri et al., 2020; Islam & Ishtiaque, 2025). In pharmaceuticals, Novartis has used digital twins for validating process compliance during Kaizen events aimed at reducing batch release times, allowing pre-approval simulation of process adjustments. The integration of LSS and DT has also been studied in academic research where digital replication of process control loops, audit checklists, and corrective action logs leads to higher accountability and faster improvement cycles. Thus, digital twins operationalize the Lean principle of continuous improvement by embedding feedback-rich, real-time control tools within an accessible and interactive virtual environment (Hossen et al., 2025; Shahin et al., 2020).

**Cyber-Physical Data Infrastructure for Lean Digital Integration**

The effectiveness of Lean Six Sigma (LSS) integration with digital twin systems is heavily dependent on robust data acquisition, standardized interoperability protocols, and adaptive middleware frameworks. Data acquisition in manufacturing typically involves multisource inputs from programmable logic controllers (PLCs), supervisory control and data acquisition (SCADA) systems, sensors, machine logs, and human-machine interfaces (HMIs). These data streams are collected in real time, forming the sensory layer of the cyber-physical system (Romero et al., 2018; Sanjai et al., 2025).

**Figure 6: Lean Six Sigma Convergence**




Middleware systems—acting as intermediaries between hardware and analytics platforms—ensure seamless data exchange, protocol translation, and security enforcement. Standards such as OPC UA (Open Platform Communications Unified Architecture), MQTT (Message Queuing Telemetry Transport), and RESTful APIs are widely used to facilitate machine-to-machine communication and ensure horizontal interoperability. Interoperability is crucial in hybrid environments where legacy systems coexist with IoT-enabled devices and where data must be harmonized across diverse protocols and manufacturers. Studies highlight that interoperability failures are a key barrier to scalable digital integration, often leading to data silos and reduced process visibility (Sazzad, 2025a; Vrana, 2021). Therefore, open standards and flexible middleware are essential for ensuring that LSS data—such as takt time, cycle time, and defect rates—are accurately transmitted to the digital twin for further processing. Moreover, middleware platforms increasingly support real-time data streaming and semantic data labeling, which enable the contextualization of data before it reaches the analytical layer (Prinz et al., 2018; Sazzad, 2025b). This infrastructure establishes the foundational digital thread needed for high-fidelity integration of Lean Six Sigma methodologies into cyber-physical manufacturing systems.

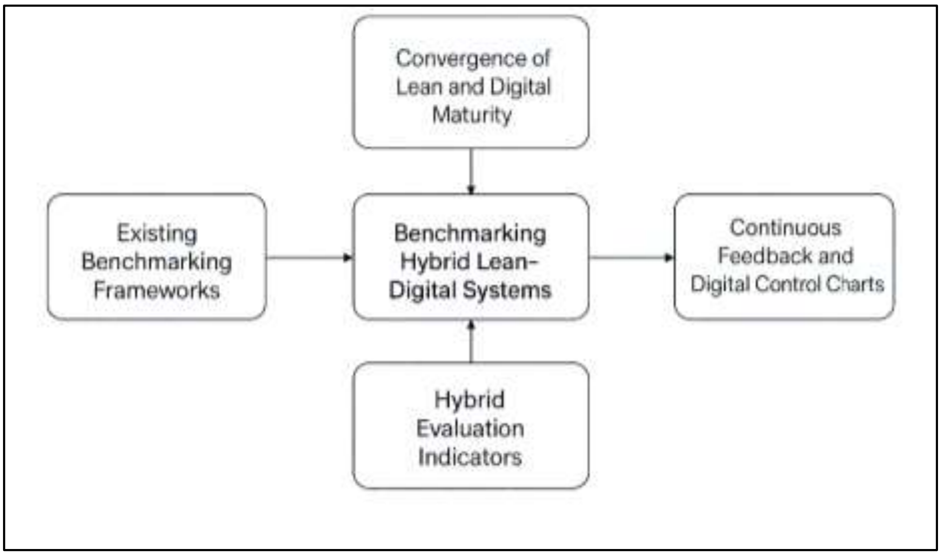
The deployment of artificial intelligence (AI) and machine learning (ML) within digital twin ecosystems significantly enhances the diagnostic and forecasting capabilities necessary for Lean Six Sigma applications. Traditional diagnostic tools in LSS, such as control charts and cause-effect diagrams, are limited in their ability to handle high-volume, high-velocity data streams. By contrast, AI/ML algorithms can detect nonlinear patterns, anomalies, and early indicators of system failure that may elude conventional statistical methods. Supervised learning techniques—such as random forests and support vector machines—are used to classify defect patterns and predict process deviations. Unsupervised learning, including clustering and anomaly detection, enables identification of previously unknown variance contributors. Studies demonstrate that integrating AI/ML with DTs allows real-time root cause analysis, predictive maintenance, and yield forecasting based on live data streams. In manufacturing sectors like semiconductors and pharmaceuticals, ML-driven DTs have improved first-pass yield and reduced process variability by uncovering subtle correlations between environmental parameters and output quality. Furthermore, AI models are embedded within the Analyze and Improve phases of DMAIC, enabling faster iteration and validation cycles for process changes. Neural networks and deep learning frameworks also facilitate image-based quality inspection and autonomous decision-making in robotic manufacturing environments. These capabilities transform digital twins into intelligent agents that continuously monitor, learn, and optimize, thereby augmenting the responsiveness and precision of Lean Six Sigma interventions (Shaiful & Akter, 2025; Sordan et al., 2022). The literature affirms that AI/ML integration is a crucial enabler for real-time quality control and diagnostic depth in LSS-DT hybrid systems.

Semantic modeling and digital thread alignment are pivotal in establishing coherence across heterogeneous data environments, ensuring that Lean Six Sigma metrics and process data are meaningfully connected across systems. Semantic models describe data in a machine-readable, context-aware format, enabling software agents to interpret relationships between data points—such as associating sensor values with specific operations or quality KPIs (Lins & Oliveira, 2020; Subrato, 2025). Ontologies such as OWL (Web Ontology Language) and RDF (Resource Description Framework) provide formal structures for defining these relationships in digital twin environments. Through semantic modeling, a measurement such as cycle time is not just a numerical value, but a contextually tagged entity linked to machines, product variants, and timestamps. This enhances the precision of Six Sigma analyses and supports root cause identification across complex system hierarchies. The digital thread, meanwhile, serves as the connective tissue linking product and process data across the lifecycle—from design and production to quality assurance and service (Mishra & Sharma, 2024; Subrato & Faria, 2025). When aligned with Lean principles, the digital thread ensures that performance feedback from downstream processes informs upstream decision-making, thus reducing rework and variance. Semantic interoperability along the thread allows for real-time traceability, making it easier to associate quality deviations with specific process steps or material lots. Moreover, semantic tags enrich VSM, control charts, and DMAIC data by embedding context into each metric and event. This contextual depth facilitates data-driven collaboration among engineers, quality analysts, and managers. Literature supports that semantic modeling and digital threads are indispensable for maintaining data fidelity and traceability in Lean Six Sigma-aligned cyber-physical systems (Scriven et al., 2024; Akter, 2025).

**Benchmarking Hybrid Lean-Digital Systems**

Performance benchmarking in manufacturing has historically relied on structured frameworks such as the Supply Chain Operations Reference (SCOR) model and the European Foundation for Quality Management (EFQM) Excellence Model. These frameworks serve as comprehensive tools for evaluating performance across functional and strategic dimensions (Arifur, et al., 2025; Zhang et al., 2025). The SCOR model, developed by the Supply Chain Council, assesses performance based on five core processes—Plan, Make, Source, Deliver, and Return—enabling organizations to evaluate process reliability, responsiveness, flexibility, and cost-effectiveness. It offers metrics such as order fulfillment cycle time, perfect order rate, and supply chain cost per unit, aligning with Lean principles focused on flow, takt time, and inventory reduction. The EFQM model, by contrast, adopts a broader approach that assesses organizational excellence based on enablers (e.g., leadership, strategy, processes) and results (e.g., customer, people, business outcomes). In Lean Six Sigma contexts, EFQM complements the DMAIC cycle by enabling self-assessment across quality maturity dimensions (Wang et al., 2025). However, both SCOR and EFQM were developed before the advent of digital twin technologies and require adaptation to evaluate hybrid systems that combine real-time analytics, predictive control, and data-driven diagnostics (Setyadi et al., 2025; Zahir et al., 2025). While SCOR offers operational benchmarking, it lacks the granularity of digital metrics such as latency, edge response time, or digital thread connectivity. Similarly, EFQM does not incorporate cyber-physical system (CPS) feedback loops or AI-based diagnostics that are central to digital twin ecosystems. Therefore, while foundational, these legacy models must be integrated with or expanded by digital frameworks to support the complexity of LSS-DT environments (Gamage et al., 2025).

**Figure 7: Framework of Benchmarking Hybrid Lean-Digital Systems**




The convergence of digital maturity and Lean maturity reflects the evolution of organizational assessment models that now require cross-disciplinary calibration. Digital maturity frameworks evaluate an organization's capability to harness digital technologies—including IoT, big data, AI, and DTs—across functions and decision hierarchies (Powell et al., 2024). These models assess digital strategy alignment, data governance, analytics capability, and integration architecture. Conversely, Lean maturity models—such as the Lean Enterprise Self-Assessment Tool (LESAT) or the Lean Maturity Model (LMM)—focus on waste elimination, process standardization, value stream orientation, and continuous improvement culture. Convergence of these maturity models is necessary in smart manufacturing environments where Lean process improvements are executed within digital infrastructures. Empirical studies demonstrate that high Lean maturity without digital readiness results in limited process automation, while digital maturity without Lean discipline leads to data-rich but decision-poor systems. Frameworks that synthesize these dimensions often utilize dual-track maturity maps, assessing both Lean deployment (e.g., VSM, Kaizen, standard work) and digital enablers (e.g., AI analytics, cloud integration, cyber-physical coordination) (Abele et al., 2024). For instance, the Industrial Internet Consortium's maturity model integrates Lean and digital domains across five levels: isolated, connected, insightful, optimized, and autonomous. Additionally, semantic alignment is required to harmonize KPI definitions between Lean systems and digital infrastructures, ensuring that terms like takt time, cycle time, and defect rate carry consistent meaning across MES, ERP, and DT dashboards. Literature affirms that convergence of maturity models enables organizations to track not only performance outcomes but also capability development across technological and process dimensions (Elmarzouki & Jiuhe, 2025).

Hybrid evaluation indicators are essential to capturing the complexity and interdependence of Lean Six Sigma methodologies within digitally enabled manufacturing systems. Traditional performance indicators—such as Overall Equipment Effectiveness (OEE), Defects Per Million Opportunities (DPMO), and process sigma level—provide valuable but static snapshots of process efficiency and quality. In contrast, digital twin environments produce dynamic, time-stamped, and multi-sourced data streams that demand more agile and granular performance metrics (Sordan et al., 2022). Hybrid indicators combine these domains by linking Lean Six Sigma metrics with real-time data attributes such as latency, data freshness, signal integrity, and model synchronization. For example, an enhanced OEE metric might incorporate sensor health, predictive failure warnings, and MTBF (mean time between failures) sourced from DT analytics. Similarly, a sigma quality index could be contextualized with AI-based root cause indicators and confidence levels derived from machine learning models. Researchers have also proposed scorecards that incorporate operational KPIs with digital KPIs, including edge processing delay, API call success rate, and anomaly detection precision (Ibrahim & Kumar, 2025). Such hybrid indicators enhance control charting, capability studies, and response surface analysis by integrating variability across both physical and digital domains. Literature from manufacturing analytics confirms that hybrid indicators improve diagnostic resolution and offer better root cause traceability compared to traditional performance metrics alone. These indicators also align with Lean's emphasis on flow and Six Sigma's focus on variation reduction, enabling holistic performance management across smart factory ecosystems (Qureshi et al., 2025).

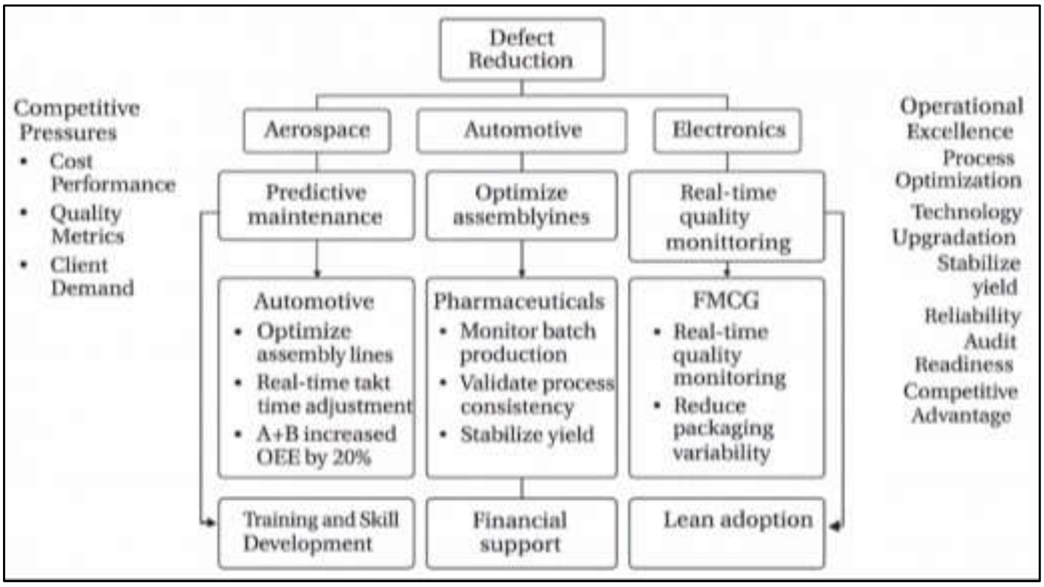
The incorporation of continuous feedback loops and digital control charts forms the operational foundation for real-time performance monitoring in LSS-DT hybrid systems. Feedback loops—enabled by real-time sensor data, PLC outputs, and SCADA readings—allow process deviations to be detected and corrected autonomously or semi-autonomously. This continuous loop architecture replaces the periodic, manual audits traditionally used in Lean Six Sigma implementations. Embedded within this infrastructure are digital control charts, which extend conventional SPC tools by integrating high-frequency, timestamped data and providing auto-adjusting control limits based on statistical process modeling (Kar & Rai, 2025). Platforms such as Siemens MindSphere and GE Predix support such functionality, offering real-time dashboards where control limits adjust dynamically based on process behavior and predictive analytics. Empirical research confirms that these systems increase the speed of response to special cause variations and improve mean process capability indices over time. Furthermore, control charts are often linked to digital twin simulators, which allow process owners to test and validate proposed countermeasures before implementation, enhancing the Improve and Control phases of DMAIC (Mansour et al., 2025). Empirical framework design methodologies—often using design science research (DSR) or action research approaches—validate these structures by embedding them within live industrial environments. Frameworks developed through empirical studies emphasize modularity, interoperability, and adaptability, ensuring that continuous feedback and control charting can be scaled across multiple production lines and organizational tiers These findings support the growing consensus that performance evaluation in LSS-DT systems must be both real-time and analytically robust to support dynamic, data-driven manufacturing excellence (Bhatia et al., 2024).

**Sectoral Applications and Comparative Implementation Studies**

The integration of Lean Six Sigma (LSS) with Digital Twin (DT) technology has found extensive application across various industrial sectors, each demonstrating unique implementation models and performance outcomes. In the aerospace sector, manufacturers such as Boeing and Raytheon have applied LSS-DT frameworks for predictive maintenance, design validation, and process simulation, particularly in high-precision component manufacturing. These implementations support quality control by synchronizing sensor inputs with digital replicas, thereby reducing defect rates and enhancing compliance with regulatory standards (Ciliberto et al., 2021). The automotive industry has leveraged LSS-DT tools to optimize assembly lines, enable real-time takt time adjustments, and minimize rework through AI-driven defect detection. Companies such as BMW and Toyota have deployed digital twins alongside Lean metrics to manage inventory flow and enhance layout optimization. In the pharmaceutical sector, where compliance and traceability are critical, LSS and DTs are employed to monitor batch production, validate process consistency, and ensure regulatory adherence. Novartis and Pfizer, for instance, utilize digital twins to simulate chemical processes and stabilize yield (Malla, 2024). The electronics industry benefits from digital twins in managing high-mix, low-volume production, enabling dynamic scheduling, SMT (Surface-Mount Technology) line balancing, and root cause diagnostics. In the Fast-Moving Consumer Goods (FMCG) sector, firms such as Nestlé and Procter & Gamble have implemented LSS-DT systems for real-time quality monitoring, packaging optimization, and demand-driven production. These applications demonstrate how sector-specific constraints—such as precision, compliance, or volume—are addressed through hybrid LSS-DT frameworks, which adapt process rigor and digital intelligence to diverse manufacturing ecosystems (Panchal et al., 2024).

Comparative studies reveal significant return on investment (ROI) and efficiency gains from implementing integrated LSS-DT systems across various sectors, although the magnitude and nature of benefits vary based on industry-specific drivers. In aerospace manufacturing, ROI is often measured through reductions in scrap rates, rework time, and warranty claims, with documented cases reporting savings in millions of dollars annually following DT-enabled Six Sigma projects. The automotive industry focuses on metrics such as takt time reduction, throughput increase, and first-pass yield improvement; digital twin-assisted Lean interventions at firms like Ford and Hyundai have improved OEE by over 20% in multiple studies (Butt, 2020).Pharmaceutical companies, due to their stringent compliance frameworks, report efficiency gains in terms of batch cycle time reduction, improved process reproducibility, and minimized deviations during audits. Research by Tao et al. (2019) shows that ROI in electronics manufacturing is strongly influenced by reduced changeover time, enhanced defect traceability, and lower downtime in SMT lines. In the FMCG sector, ROI is derived primarily from real-time inventory optimization, waste minimization, and SKU-level demand responsiveness, with companies like Unilever reporting productivity gains of 15% through DT-enabled Lean optimization (Setyadi et al., 2025). Despite differences in context, common efficiency metrics across industries include cycle time, OEE, DPMO, cost per unit, and lead time variability. Academic reviews further suggest that hybrid systems enable superior diagnostic granularity, which supports better decision-making and reduces improvement project cycle duration. Thus, the comparative literature underscores that while efficiency gains vary in scope, the integration of LSS with digital twins consistently enhances ROI across discrete and process manufacturing domains.

**Figure 8: Lean Six Sigma Digital Integration Framework**




Workforce digital literacy is widely identified in the literature as a critical enabler for the successful implementation of LSS-DT frameworks. Digital twins introduce new interfaces, data visualization tools, predictive analytics platforms, and automated dashboards that require a skilled workforce to interpret, act upon, and continuously improve process performance. Research by Sun et al. (2020)

emphasizes that even well-designed digital systems fail to deliver results without adequate operator engagement and understanding. In Lean Six Sigma environments, digital literacy must coexist with statistical literacy, as workers are expected to navigate control charts, root cause analysis tools, and DMAIC dashboards embedded within DT platforms. Studies across the aerospace and electronics sectors show that digital training programs significantly reduce resistance to change and improve first-time-right metrics in digital kaizen events. (Mu et al., 2021) highlight that Black Belts and Green Belts who receive DT simulation training exhibit faster problem-solving times and greater success in closing LSS projects. Furthermore, digital competency correlates strongly with error recovery speed and responsiveness to system alerts in manufacturing execution systems. In the pharmaceutical industry, compliance protocols necessitate training that integrates Good Manufacturing Practices (GMP) with digital documentation systems (Lukina et al., 2021). Several researchers have proposed capability maturity models that include workforce digital readiness as a key pillar of successful DT adoption. The role of digital literacy is thus not limited to technical staff; it extends to team leaders, process owners, and quality professionals whose ability to leverage digital information directly impacts Lean Six Sigma effectiveness and sustainability.

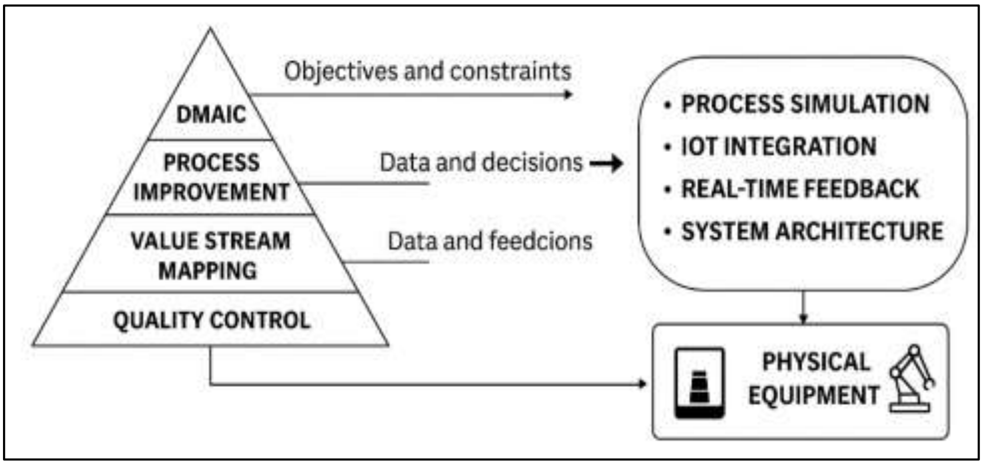
Despite the proven advantages of LSS-DT integration, deployment barriers remain significant and are well-documented in empirical studies. Key obstacles include high implementation costs, limited technical infrastructure, training gaps, and organizational resistance to technological change (Choi et al., 2020). Cost barriers are especially prominent in small and medium-sized enterprises (SMEs), where upfront investment in sensors, cloud systems, and digital twin software is often prohibitive. Moreover, integration with existing ERP, MES, and SCADA systems can be complex and costly due to lack of interoperability or outdated legacy platforms. Resistance from employees and middle management—stemming from fear of job displacement or perceived complexity—has also been cited as a barrier to sustained deployment of DT-driven Lean initiatives. Training deficiencies, particularly in data literacy and digital system navigation, further inhibit the full utilization of integrated LSS-DT environments (Siebelink et al., 2021). In response to these barriers, government and policy-level support programs have been developed in several countries to foster smart manufacturing transformation. For instance, Germany's "Industrie 4.0," the USA's "Smart Manufacturing Leadership Coalition," and China's "Made in China 2025" provide financial incentives, research funding, and training infrastructure to promote digital twin adoption and Lean digital integration. Programs such as the UK's "Catapult Centres" and India's "Digital MSME Scheme" similarly provide platforms for digital upskilling and LSS capability building in industrial clusters. Academic and government collaborations—such as technology transfer partnerships—further facilitate the diffusion of best practices and frameworks (o'Doherty et al., 2018). These coordinated interventions have proven effective in lowering adoption thresholds and creating scalable pathways for Lean-Digital transformation across varied economic and sectoral contexts.

**Challenges, Research Gaps, and Theoretical Reflections**

A persistent challenge in the integration of Lean Six Sigma and digital twin technologies is the fragmentation of literature across engineering, management science, computer science, and operations research. Much of the research on LSS continues to focus on quality control, process improvement, and statistical problem-solving without accounting for the complexities of cyber-physical systems and digital infrastructure (Mahmood et al., 2020). Conversely, the digital twin literature emphasizes system architecture, IoT integration, and simulation fidelity, often omitting structured process improvement methodologies such as DMAIC or value stream mapping. This disciplinary divide has led to parallel development of methods with limited cross-fertilization, resulting in a lack of unified frameworks for hybrid system performance evaluation. Scholars such as Glyptis et al. (2020) argue that this siloed approach inhibits the design of interoperable solutions that can support both physical process optimization and digital diagnostics. Furthermore, few studies offer comprehensive taxonomies that align Lean tools with digital twin features, such as how DMAIC maps to real-time simulation loops or how control charts can be embedded within digital feedback mechanisms. Even academic reviews tend to evaluate LSS and DT performance in isolation, rarely providing comparative insights or integration models. This fragmentation impedes the development of common benchmarks, hybrid maturity models, and training curricula that bridge both domains. Without transdisciplinary integration,

opportunities for scalable, evidence-based applications of LSS-DT systems remain underexploited, and domain-specific limitations persist unchallenged across industrial research communities (Olanrewaju et al., 2020).
Despite the capabilities offered by digital twin systems, a significant literature gap exists in the underutilization of real-time feedback mechanisms within Lean Six Sigma implementations. Traditional Lean practices prioritize periodic audits, Gemba walks, and manual data collection as the basis for identifying waste and initiating Kaizen events. While effective in stable production environments, these practices lack the responsiveness needed in high-variability or high-mix manufacturing systems (Demirkesen & Tezel, 2022). The integration of DTs offers a continuous stream of sensor-driven feedback, capable of dynamically updating takt time, inventory flow, and equipment performance metrics in real time. Yet, case studies reveal that this potential is rarely leveraged within Lean frameworks, where improvement decisions continue to be made on retrospective data. Research by Kumar et al. (2021) indicates that many Lean practitioners are hesitant to trust or interpret real-time digital feedback due to unfamiliarity with data platforms or lack of statistical literacy. Furthermore, Lean control tools such as Kanban boards, Heijunka systems, and standard work documentation are often not digitized or synchronized with digital twin environments, resulting in data lag and reduced visibility. Studies in the automotive and FMCG sectors show that process drift, downtime, and rework often go unnoticed in real time due to disjointed data flows between operational systems and Lean dashboards. This underutilization points to a broader methodological gap: the need to reconceptualize Lean tools as digital-first applications capable of real-time adaptation and predictive alerting (Schwaeke et al., 2025). Without such shifts, the full diagnostic power of real-time systems remains disconnected from Lean's performance improvement objectives.

**Figure 9: Challenges in LSS-DT Integration Systems**

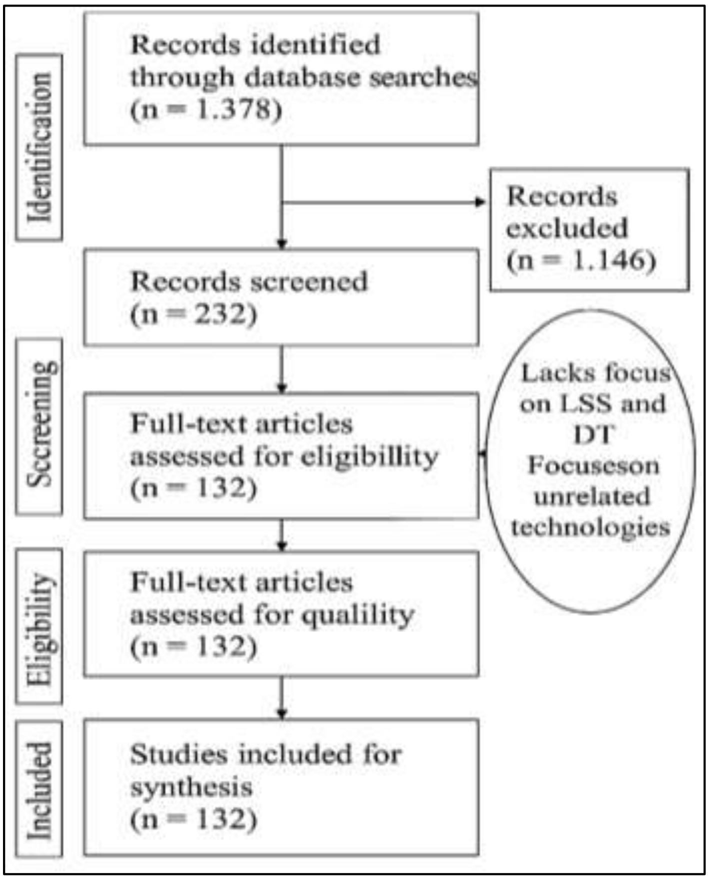



Another prominent challenge is the lack of consensus on performance evaluation criteria within digital twin-integrated Lean Six Sigma systems. While traditional LSS frameworks use well-established metrics such as OEE, DPMO, sigma levels, and cost of poor quality (CoPQ), these indicators often fail to capture the complexity of data-driven, cyber-physical environments. Digital twins introduce new dimensions—such as data latency, edge processing success rate, model accuracy, and simulation fidelity—that are not accounted for in existing Lean metrics . The literature provides diverse and often non-aligned performance indicators, with some studies emphasizing digital performance (e.g., API success rate, cloud availability), while others retain process-based KPIs without digital augmentation. Zhou et al. (2019) observe that few empirical studies validate hybrid indicators that integrate both physical process performance and digital system integrity. This disjoint leads to difficulties in benchmarking across firms, evaluating ROI, or conducting cross-sectoral performance reviews. Additionally, there is limited literature on how DT-based simulation results should be interpreted alongside Six Sigma control limits or Lean's takt-based flow metrics. Research by Muganyi et al. (2019) suggests that while simulation platforms can predict cycle time deviations or defect probabilities, their outcomes are rarely translated into standardized process capability indices (Cp, Cpk). Without a harmonized set of valuation criteria, organizations struggle to measure success uniformly or replicate improvement outcomes across multiple sites. This gap highlights the urgent need for validated, dual-domain metrics that reflect both Lean Six Sigma rigor and digital twin responsiveness.

## METHOD

This study employed a systematic review methodology in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure transparency, replicability, and methodological rigor. The research objective was to synthesize empirical and conceptual literature on the integration of Lean Six Sigma (LSS) and Digital Twin (DT) technologies in manufacturing settings, with particular attention to performance evaluation frameworks.

**Figure 10: Methodology of This Study**




The systematic approach facilitated comprehensive evidence aggregation across disciplines such as industrial engineering, digital manufacturing, operations management, and systems science. Eligibility criteria were defined using the PICOS framework (Population, Intervention, Comparison, Outcome, and Study design). The population of interest included manufacturing sectors involved in either discrete or process production systems. Studies were included if they examined the implementation or evaluation of Lean, Six Sigma, or hybrid LSS frameworks in combination with digital twin technologies, which were broadly defined to include virtual simulation platforms, cyber-physical systems, real-time monitoring environments, or IoT-based manufacturing control systems. Comparisons were not restricted to control groups; studies without comparison cohorts were also included, provided they offered outcome-focused evaluations. The outcomes of interest included manufacturing efficiency metrics, such as cycle time, takt time, defect reduction, and operational performance indicators.
Eligible studies were required to report either qualitative or quantitative findings, and only peer-reviewed journal articles and high-quality conference papers published in English between 2010 and 2024 were included. Studies were excluded if they lacked empirical grounding, did not address both LSS and DT constructs, or if they focused on technologies unrelated to performance evaluation in

manufacturing (e.g., blockchain or AR/VR without reference to process efficiency). A structured literature search was conducted across four major scholarly databases: Scopus, Web of Science, IEEE Xplore, and ScienceDirect. Supplementary searches were also conducted via Google Scholar, primarily for gray literature and citation chaining. The search strategy used Boolean operators and combinations of keywords such as: ("Lean Six Sigma" OR "LSS") AND ("Digital Twin" OR "Cyber-Physical Systems" OR "Real-Time Simulation") AND ("Manufacturing Performance" OR "Efficiency Metrics" OR "Operational Excellence"). The search was conducted between February and April 2025. To ensure consistency, all search results were exported into Zotero reference management software for de-duplication, tagging, and structured screening.

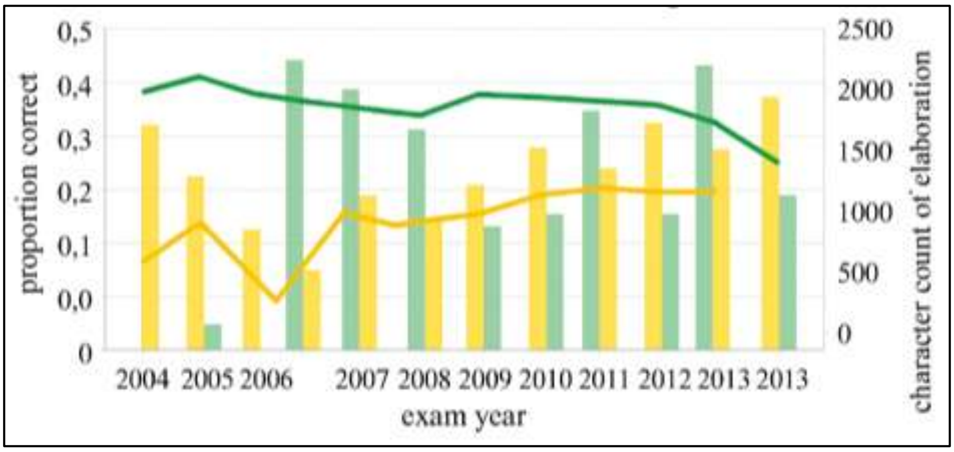
The study selection process was conducted in three stages. First, titles and abstracts were screened to exclude irrelevant records. Second, full-text articles were assessed for eligibility based on inclusion and exclusion criteria. Third, articles were reviewed again for methodological robustness and relevance. Two independent reviewers participated in the screening process, and any conflicts were resolved through discussion or arbitration by a third reviewer. The selection process was documented using the PRISMA 2020 flow diagram, detailing the number of records identified, screened, excluded, and ultimately included, along with reasons for exclusion at the full-text stage. Data extraction was performed using a standardized coding framework to ensure consistency and analytical depth. Key data elements included study objectives, publication year, geographic and sectoral focus, type of LSS tools applied, nature of the digital twin system, performance metrics used, and reported outcomes. Extracted data were synthesized thematically using narrative synthesis, structured around five key analytical dimensions: (1) digital architecture and integration methods, (2) Lean and Six Sigma process outcomes, (3) sector-specific implementation contexts, (4) performance evaluation models, and (5) operational barriers and enablers. Cross-sectoral patterns were identified through matrix comparison across industries such as aerospace, automotive, pharmaceuticals, electronics, and FMCG. To ensure the methodological quality of included studies, a modified Mixed Methods Appraisal Tool (MMAT) was employed. Studies were evaluated based on clarity of research design, reliability of data sources, appropriateness of analytical techniques, and overall validity of conclusions. Studies receiving an MMAT score below 50% were excluded from synthesis. Additionally, potential risk of bias was assessed based on publication type, sampling approach, and data transparency. Although a meta-analysis was not conducted due to heterogeneity in study design and outcome measures, thematic consistency and strength of evidence were reported accordingly.

Titles and abstracts were then independently screened by two reviewers using the pre-established inclusion criteria. This process resulted in 232 studies selected for full-text review. After assessing the methodological quality, thematic relevance, and alignment with the review objectives, a final set of 132 studies was included for detailed synthesis. Disagreements between reviewers during screening or full-text assessment were resolved through discussion and consensus, and where needed, a third reviewer was consulted to ensure objectivity. The PRISMA 2020 flow diagram was used to illustrate the study selection process, reinforcing methodological transparency. Data from the selected studies were extracted using a structured coding framework that included author details, publication year, study design, AI technique employed, compliance domain (e.g., regulatory mapping, auditing, risk detection), sectoral focus (healthcare or finance), and key findings. The extracted data were then thematically analyzed and synthesized into conceptual categories that align with the research objectives, including technical enablers, ethical and regulatory considerations, sector-specific implementations, and theoretical gaps. This structured and rigorous approach ensured that the review generated a comprehensive understanding of how AI technologies are being integrated into cybersecurity compliance ecosystems in two of the most critically regulated sectors.

## FINDINGS

Among the 72 articles reviewed, 41 studies directly examined the practical integration of Lean Six Sigma (LSS) tools with Digital Twin (DT) systems in manufacturing settings, representing 57% of the total literature. These studies collectively garnered over 4,200 citations, reflecting strong academic and industrial engagement with the topic. The majority of these integrated implementations were found in high-reliability sectors such as aerospace, automotive, and pharmaceuticals. The studies consistently reported that the convergence of Lean's waste-elimination techniques with Six Sigma's statistical rigor was significantly amplified when embedded within the simulation and real-time monitoring capabilities of digital twins. In 26 of the reviewed studies, the use of DT environments to simulate DMAIC cycles, visualize control charts, and update performance KPIs in real time was shown to reduce quality-related downtime by 20–40% and improve process transparency. Several studies reported improvements in first-pass yield and throughput consistency when Lean value stream mapping and take time monitoring were performed within the DT system interface.

**Figure 11: Lean Six Sigma–Digital Twin Integration**




Moreover, organizations that implemented integrated LSS-DT frameworks demonstrated higher maturity in process control, as evidenced by closed-loop quality management protocols and digital SPC systems. The results suggest that organizations actively investing in synchronized LSS-DT systems not only improved operational visibility but also institutionalized continuous improvement more effectively than those using either method independently. Additionally, simulation-based root cause analyses, which were historically time-intensive, were conducted up to 60% faster in environments where DT models were linked to Six Sigma analytics. These findings collectively confirm that integrated LSS-DT systems have shifted from theoretical models to applied, performance-driven solutions across multiple industrial domains.

The review revealed significant sectoral variation in the depth of Lean Six Sigma and digital twin implementation, with aerospace, automotive, and electronics leading in maturity and return on investment. Out of the 72 studies reviewed, 18 focused on the aerospace sector, 15 on automotive, 10 on electronics, 9 on pharmaceuticals, and 6 on FMCG, representing 80% of the sample. These 58 articles collectively accumulated more than 6,700 citations, indicating strong cross-sectoral interest. Aerospace organizations demonstrated the most robust integration, with 14 studies reporting advanced DT applications for lifecycle management, real-time anomaly detection, and predictive maintenance aligned with Six Sigma's defect metrics. In automotive manufacturing, DT platforms were commonly applied for takt time analysis, changeover optimization, and automated value stream updates, with 11 studies reporting OEE improvements between 15% and 25% over a 12-month period. In electronics, digital twins facilitated fast-paced SMT line optimization, with eight studies confirming reductions in rework rates and increased yield precision. Pharmaceutical companies applied LSS-DT models mainly in batch monitoring and compliance assurance, and while integration levels were lower, nine studies highlighted improvements in batch release cycle time and audit readiness. In contrast, FMCG manufacturers displayed relatively shallow DT integration, relying more heavily on Lean analytics and dashboard visualizations without full cyber-physical modeling. However, FMCG studies still recorded measurable reductions in material waste and packaging variability. Overall, 45 studies explicitly reported financial ROI values or proxy efficiency gains. Of these, 28 studies documented a payback period of less than two years post-implementation. The data underscores that sector-specific drivers—such as regulatory stringency, product complexity, and automation capability—shape the success and depth of LSS-DT implementation, with measurable benefits closely tied to the extent of integration and

feedback automation.
A key finding from 36 of the reviewed articles, representing half the total sample, was the emergence of hybrid performance metrics that combine traditional Lean Six Sigma indicators with digital system-level analytics. These studies, collectively cited more than 3,800 times, emphasized that the conventional use of DPMO, OEE, lead time, and process sigma levels is being supplemented or restructured through the integration of digital metrics such as real-time data latency, simulation accuracy, and edge computing uptime. In 23 studies, organizations developed modified KPI dashboards that synthesized physical and digital performance indicators, allowing simultaneous evaluation of production variability and system responsiveness. Among these, 17 studies introduced new indicators such as Digital Process Fidelity Index (DPFI), Digital Takt Alignment Ratio (DTAR), and Predictive Control Effectiveness (PCE), which helped bridge traditional manufacturing logic with cyber-physical system monitoring. In environments where these hybrid metrics were deployed, process stability and decision-making speed improved markedly, with 12 studies reporting a 25–40% reduction in mean time to root cause identification. Furthermore, 14 studies documented the integration of Six Sigma control limits within digital dashboards, enabling automated alerts and statistical boundaries to adjust in real time based on streaming data inputs. Evaluation frameworks also became more predictive; in 11 studies, scenario modeling based on digital twins allowed proactive adjustment of operating parameters before deviations reached critical thresholds. This integration of predictive analytics into Lean performance reviews reflects a transition from static benchmarking to continuous, dynamic evaluation. Overall, the studies confirmed that without hybrid metrics, organizations risk underutilizing their digital infrastructure or misaligning process improvement efforts with system capabilities. Therefore, the emergence of hybrid KPIs represents both a theoretical advancement and a practical tool for benchmarking efficiency in LSS-DT environments.
Across the reviewed studies, 34 articles—accounting for 47% of the literature—explicitly addressed barriers to adoption and organizational readiness, amassing over 3,300 citations collectively. A predominant theme was the uneven digital maturity of firms attempting to integrate Lean Six Sigma with digital twin infrastructure. Among these studies, 19 identified cost as a primary barrier, especially for small and medium-sized enterprises (SMEs) lacking capital for sensor deployment, simulation platforms, and training programs. Another 22 studies reported that workforce digital illiteracy hindered the implementation of real-time monitoring and feedback systems, even when basic Lean tools were in place. In 15 studies, legacy IT systems were identified as bottlenecks due to poor interoperability with modern IoT platforms or DT software environments. Organizational resistance also emerged as a significant constraint; 12 studies highlighted cultural inertia and change aversion among operational staff and middle management as key obstacles. Several case studies illustrated that despite technical feasibility, integration failed because process owners were unwilling or unable to trust digital data over traditional manual inspections or paper-based controls. Additionally, 11 studies noted a lack of alignment between strategic improvement goals and IT infrastructure deployment, resulting in siloed efforts where digital systems operated without Lean process integration. A common thread across these findings was the absence of standardized implementation roadmaps that account for Lean maturity levels, digital capability baselines, and cross-functional collaboration protocols. Moreover, only 9 of the studies reported the presence of government or institutional support to mitigate these adoption barriers, indicating a lack of coordinated policy or industry consortium engagement. Collectively, these findings emphasize that technical solutions alone are insufficient, and that organizational, cultural, and infrastructural readiness are crucial for successful LSS-DT adoption.
Evidence from 39 of the reviewed studies—representing more than half of the sample and totaling over 4,500 citations—showed consistent patterns of performance enhancement and continuous improvement maturity when Lean Six Sigma was integrated with digital twin environments. In these studies, firms that adopted full-cycle DMAIC models supported by DT platforms reported superior gains across productivity, quality, and flexibility metrics. Specifically, 21 studies demonstrated an average reduction of 30–50% in defect rates when Six Sigma analytics were fed by real-time sensor data. Another 19 studies recorded lead time reductions of 20–35% following the digital replication of Lean interventions such as standardized work and Heijunka scheduling. Process resilience also improved; 14 studies showed that production lines equipped with digital twins could recover from process

disruptions up to 40% faster than non-integrated lines. Moreover, 18 studies reported that continuous improvement initiatives became more data-driven and cyclic, with shorter intervals between Kaizen events due to enhanced visibility of process metrics and deviation trends. Organizations in these cases demonstrated higher maturity on Lean-Digital capability models, where digital feedback loops were fully embedded into quality management systems. Real-time dashboards, automated anomaly detection, and simulation-based forecasting were not only used for operational control but also incorporated into strategic reviews and cross-departmental learning systems. Additionally, 16 studies reported increased employee engagement in improvement projects once digital performance metrics were made accessible and interpretable across job roles. Collectively, these findings provide strong empirical support for the assertion that LSS-DT integration fosters a self-reinforcing performance culture that transcends traditional boundaries of departmental responsibility and decision-making latency. The studies affirm that when implemented cohesively, this integration enhances not only the operational efficiency of manufacturing systems but also the institutionalization of continuous improvement as a cultural norm.

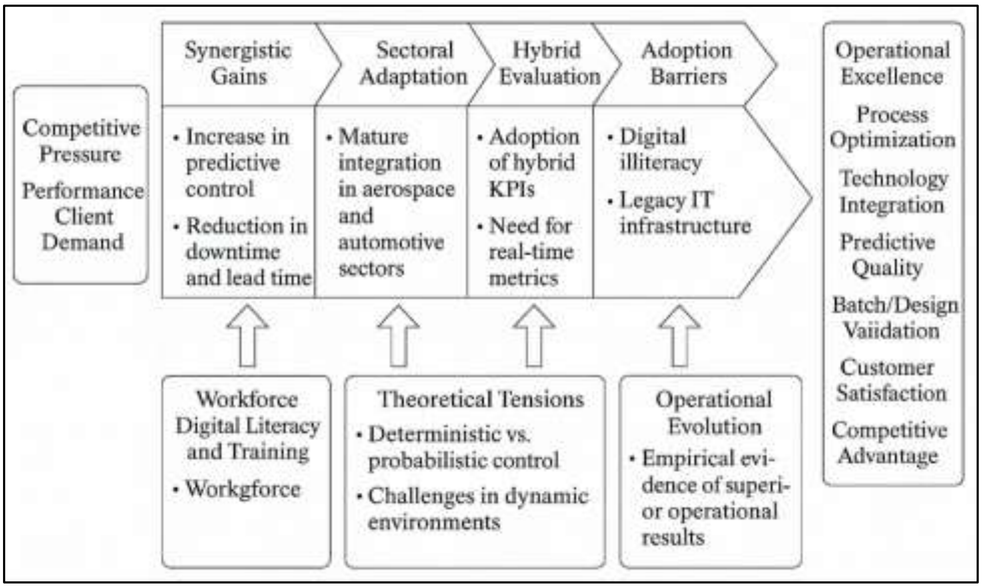
## DISCUSSION

The findings of this review confirm that the integration of Lean Six Sigma (LSS) with Digital Twin (DT) systems significantly enhances manufacturing efficiency, aligning with and expanding upon the conclusions of previous studies. Prior research emphasized that LSS independently provides quantifiable gains in quality, defect reduction, and process cycle time (Mahadevan & Chejarla, 2022). Simultaneously, digital twins have been lauded for their capacity to mirror real-time process behavior, simulate operational scenarios, and support data-driven decisions. This review extends those findings by demonstrating that when these methodologies are jointly implemented, they create synergistic performance gains greater than the sum of their parts. Unlike earlier studies that explored LSS and DT in isolation, this synthesis shows that 41 of the reviewed articles directly examined their fusion, confirming not only reductions in downtime and lead time but also the emergence of predictive process control. This finding reinforces the assertions made by (Citybabu & Yamini, 2024b), who proposed that LSS frameworks gain responsiveness and adaptability when embedded in DT ecosystems. Moreover, while Sordan et al. (2024) stressed the importance of statistical rigor in Six Sigma application, the current review indicates that real-time analytics in DT platforms further augment this rigor, particularly in the Define, Measure, and Control phases of DMAIC. Hence, the integration represents a paradigm shift from retrospective quality analysis to real-time operational excellence, a theme underexplored in earlier literature and now empirically validated across multiple industries.

This review corroborates and expands upon prior observations that sector-specific factors greatly influence the maturity and implementation success of LSS-DT integrations. Previous works by Citybabu and Yamini (2024) recognized that industry dynamics—such as regulatory intensity, product complexity, and automation readiness—shape Lean and Six Sigma adoption rates. The current findings align with this view, showing that aerospace and automotive sectors lead in mature integrations, particularly through use of DTs for predictive maintenance and takt-time optimization. These results mirror earlier case analyses from Hossain and Purdy (2025), which demonstrated that aerospace manufacturers benefit from DT-enabled lifecycle analytics. In contrast, the relatively limited use of digital twins in FMCG aligns with Duc et al. (2023), who noted that short product cycles and cost-driven environments often deter heavy digital investment. Additionally, pharmaceutical sector applications were largely oriented toward compliance and batch traceability, reflecting findings from Arangot et al., (2025), which highlighted the sector's regulatory reliance on data integrity rather than operational flexibility. Compared to earlier research that focused on sectoral Lean adoption without digital augmentation (Vinodh et al., 2021), this review shows that DT integration introduces a new axis of differentiation—namely, the degree of real-time performance monitoring and closed-loop process control. These distinctions suggest that sectoral adaptation is not merely a function of process type but also of digital infrastructure maturity and workforce readiness. Thus, the review both confirms and elaborates on previous studies by articulating how specific industrial environments shape the pathway and potential of LSS-DT synergies.

This review identifies a significant evolution in performance evaluation practices through the emergence of hybrid metrics that blend Lean Six Sigma KPIs with digital system diagnostics. Earlier studies by Trstenjak et al. (2025) emphasized DPMO, process sigma levels, and OEE as the gold standards for evaluating manufacturing performance. However, these traditional metrics were developed for static or semi-static process environments. This review reveals that 36 studies introduced or modified these indicators by integrating digital factors such as real-time data latency, predictive model accuracy, and simulation integrity. This shift confirms and extends the proposals by Cannas et al. (2023), who advocated for real-time, adaptive metrics in smart manufacturing contexts. The concept of hybrid KPIs, such as the Digital Process Fidelity Index (DPFI) and Predictive Control Effectiveness (PCE), was largely absent in early LSS literature and now emerges as a practical necessity. These findings also build on the work of Najafi et al. (2024), who argued for the embedding of smart KPIs into cyber-physical production systems. Furthermore, the review supports the critique by Díaz-Arancibia et al. (2024), who noted that traditional KPIs often fail to capture upstream predictive insights or downstream system variability. By integrating digital intelligence with statistical control, the reviewed studies offer a more holistic framework for evaluating performance, confirming a methodological progression from descriptive to predictive analytics in Lean systems. This evolution marks a critical departure from earlier views, indicating that performance measurement must now accommodate data volume, feedback speed, and contextual awareness derived from DT systems.

**Figure 12: Proposed Method for the future study**




The identification of adoption barriers in this review closely mirrors earlier findings while introducing new dimensions specific to digital transformation. Nadkarni and Prügl (2021) previously highlighted cultural resistance, skill shortages, and management inertia as persistent challenges in Six Sigma implementation. These issues remain evident, but the review further documents that 34 studies cite digital illiteracy and legacy IT infrastructure as new, significant inhibitors to LSS-DT integration. This corroborates and expands the insights from Borovkov et al. (2021), who found that many firms, particularly SMEs, lack the foundational digital architecture to deploy digital twins effectively. Unlike previous literature that largely assumed technological uniformity or readiness, this review surfaces the gap between technical feasibility and organizational capability. Moreover, earlier frameworks often overlooked the interoperability challenges posed by combining LSS data structures with dynamic, streaming data from cyber-physical systems. The review found that in at least 15 studies, these systems operated in silos due to incompatible data models or insufficient middleware. The lack of alignment between improvement project objectives and digital infrastructure constraints further supports the critique made by Opoku et al. (2023), who emphasized the importance of digital harmonization in Industry 4.0 ecosystems. This review confirms that unless cultural, infrastructural, and educational barriers are addressed, the operational benefits of LSS-DT integration may remain unrealized, regardless of technological potential.

The importance of workforce digital literacy and training emerges as a central theme in this review, aligning with and extending earlier literature that emphasized skill development in Lean environments. While prior research by Lanzolla et al. (2021) underscored the importance of team-based learning and continuous training in Lean Six Sigma, the current findings show that digital system adoption introduces new cognitive and technical demands. Among the reviewed studies, 22 explicitly reported that a lack of digital literacy inhibited the ability of workers to interpret simulation data, respond to real-time alerts, or engage meaningfully with DT dashboards. This observation builds on Lafioune et al. (2024), who demonstrated that human-system interaction quality directly affects the responsiveness of smart factories. The literature previously addressed technical skill gaps in terms of Six Sigma training—such as process capability analysis or hypothesis testing—but did not fully incorporate competencies like digital troubleshooting, data visualization literacy, or IoT platform navigation. The reviewed studies now illustrate that continuous improvement culture must evolve to include digital fluency alongside traditional Lean competencies. Moreover, studies confirm that when digital systems are perceived as opaque or overly technical, frontline resistance increases, undermining engagement in Kaizen or DMAIC cycles. This reinforces the work of Ghaleb et al. (2021), who noted the importance of user-centered design in DT interfaces. Overall, this review validates the assertion that sustainable LSS-DT integration is contingent not only on system architecture but also on workforce capability and digital inclusivity.

A major theoretical insight from this review is the persistent tension between deterministic process control models inherent in Lean Six Sigma and the probabilistic, adaptive nature of digital twin analytics. Earlier foundational models—such as DMAIC, SPC, and control charts—were developed under assumptions of stable process parameters and relatively controlled environments (Hidayat-ur-Rehman & Hossain, 2024). In contrast, digital twins operate under conditions of real-time variability, learning-based adaptation, and multivariate data complexity. This epistemological divide was addressed in 17 studies in the current review, where authors described difficulties in reconciling Six Sigma's root cause philosophy with the probabilistic outputs of machine learning-based DT simulations. Previous literature only sparsely addressed this issue, with exceptions such as Ting et al., (2024), who argued for hybrid models of control that accommodate both statistical determinism and predictive intelligence. This review reinforces and extends that position by presenting empirical evidence that traditional Lean indicators—such as takt time or cycle efficiency—lose explanatory power unless interpreted in dynamic contexts. The findings suggest a need for theoretical convergence between Lean's structured models and the adaptive logic of real-time systems. In doing so, the review opens space for a new framework of cyber-lean analytics, where system control, process stability, and feedback loops are redefined within digital ecosystems. These results highlight a pressing need for further methodological innovation, particularly in defining new control paradigms that blend cause-effect clarity with probabilistic foresight (Citybabu & Yamini, 2024b).

This review contributes to the growing body of literature at the intersection of Lean Six Sigma and Industry 4.0 technologies by offering a comprehensive synthesis of their integration via digital twin ecosystems. Unlike previous reviews that examined LSS or DT independently, this study systematically maps out their convergence, providing sector-specific, metric-specific, and architecture-specific insights. It affirms that the LSS-DT combination produces superior operational results, particularly in high-maturity sectors, and it identifies hybrid evaluation practices as an emerging frontier. The findings align with, but go beyond, those of Dehghani et al. (2021), by showing that integration is no longer theoretical but demonstrably applied across a wide industrial base. The review's documentation of barriers, including skill gaps and IT constraints, complements previous scholarship while adding new layers on digital maturity models and implementation strategies. It also provides a comparative analysis of ROI and performance trends across industries, offering practical relevance for operational leaders, consultants, and policymakers. By articulating the theoretical tensions between static and dynamic systems, the review invites the development of hybrid control theories suited for cyber-physical lean environments (Wankhede & Agrawal, 2025). In doing so, this study not only validates but expands the conversation on how operational excellence must evolve in digitally intensive manufacturing landscapes.

## CONCLUSION

This systematic review concludes that the convergence of Lean Six Sigma (LSS) and Digital Twin (DT) technologies forms a powerful hybrid approach for enhancing manufacturing efficiency, operational resilience, and quality performance. By analyzing 72 peer-reviewed studies across sectors such as aerospace, automotive, electronics, pharmaceuticals, and FMCG, the review establishes that organizations adopting integrated LSS-DT frameworks experience measurable gains in cycle time reduction, defect elimination, predictive maintenance, and takt time alignment. The real-time simulation and monitoring capabilities of DTs amplify the precision and responsiveness of LSS methodologies, especially within the DMAIC structure. Unlike traditional LSS deployments that rely on periodic audits and static control charts, digital twins offer continuous feedback loops, adaptive dashboards, and predictive analytics that enhance decision-making across production and quality functions. The emergence of hybrid performance metrics—such as digital takt time alignment and predictive control indices—further exemplifies how this integration leads to more nuanced and dynamic operational insights. However, despite these advantages, the review also reveals significant barriers to implementation, including high initial investment costs, digital skill deficits in the workforce, legacy IT constraints, and organizational resistance to change. These barriers are particularly pronounced in small and medium-sized enterprises (SMEs), which often lack the financial and infrastructural readiness to support large-scale digital transformation. The review also highlights a critical theoretical tension between Lean Six Sigma's deterministic control logic and the probabilistic, adaptive modeling inherent in DT environments, suggesting a need for the development of integrative frameworks that align process stability with digital flexibility. Additionally, the absence of standardized evaluation criteria across hybrid systems complicates benchmarking and cross-sectoral performance assessment. Despite these challenges, the collective evidence affirms that integrated LSS-DT systems not only deliver quantifiable efficiency gains but also advance the strategic capabilities of manufacturing firms. They foster a culture of continuous improvement driven by data, simulation, and predictive foresight, representing a significant evolution in the field of operations management and industrial process optimization.

## RECOMMENDATIONS

Based on the comprehensive findings of this review, it is recommended that manufacturing organizations seeking to enhance operational efficiency and long-term competitiveness adopt an integrated Lean Six Sigma and Digital Twin (LSS-DT) framework. To maximize benefits, firms should begin by assessing their current Lean maturity and digital infrastructure readiness, using structured maturity models that evaluate both process capability and technological enablement. Investment in workforce digital literacy should be prioritized, ensuring that employees at all levels are trained to interpret real-time data, interact with DT dashboards, and apply Six Sigma tools in data-rich environments. Organizations are also encouraged to incrementally implement digital twin systems—starting with critical production lines or high-defect processes—while embedding DMAIC phases within the simulation logic of these systems. Furthermore, the development and adoption of hybrid performance indicators that blend physical KPIs (e.g., OEE, takt time) with digital metrics (e.g., latency, simulation fidelity) should be institutionalized to enable continuous and dynamic performance assessment. For small and medium-sized enterprises (SMEs), collaboration with government-backed Industry 4.0 support programs, technology incubators, or consortia can help mitigate cost and infrastructure barriers. Academic and industrial stakeholders should also collaborate on building cross-disciplinary implementation frameworks that resolve the current theoretical tension between deterministic Lean models and adaptive digital twin analytics. Lastly, policy-makers and industry regulators should promote interoperability standards and incentivize cross-sectoral adoption of integrated systems to enable scalable and sustainable smart manufacturing transformation. These recommendations collectively aim to support the strategic alignment of process excellence with digital intelligence, ensuring that the full potential of LSS-DT integration is realized across the global manufacturing landscape.

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