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Development of a Hybrid Machine Learning Model for Predictive Performance Optimization in Lean Manufacturing and Industry 4.0

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Abstract

The convergence of Machine Learning (ML) and Lean Manufacturing within Industry 4.0 has opened new frontiers for predictive performance optimization in industrial engineering. However, a comprehensive synthesis of existing methodologies and hybrid modeling approaches remains limited in the literature. This study presents a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)-based systematic review to identify, evaluate, and synthesize existing research on the integration of machine learning techniques with Lean Manufacturing principles in Industry 4.0 environments. A structured database search was conducted across Scopus, Web of Science, and Google Scholar, yielding an initial pool of 320 articles, of which 47 studies were selected following strict inclusion and exclusion criteria. The review systematically examines supervised, unsupervised, and hybrid ML algorithms applied to key Lean metrics including waste reduction, cycle time, defect prediction, and process efficiency. Findings reveal that hybrid ML models combining algorithms such as Random Forest, XGBoost, and Neural Networks demonstrate superior predictive accuracy compared to single-algorithm approaches. Furthermore, the study identifies critical research gaps in real-time data integration, model interpretability, and scalability across manufacturing sectors. Based on the synthesized evidence, a conceptual hybrid ML framework is proposed to guide future model development for predictive Lean performance optimization. This review contributes a structured foundation for researchers and practitioners seeking to advance data-driven decision-making in smart manufacturing systems.

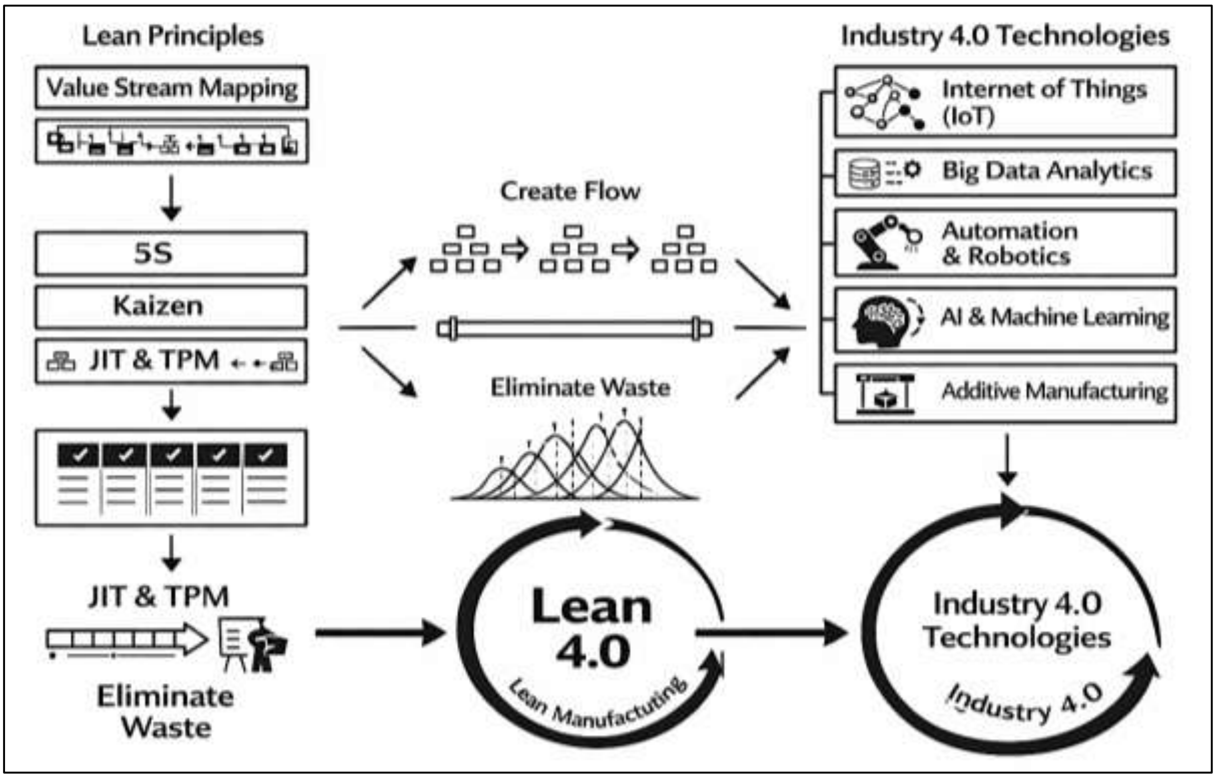
Keywords

Machine Learning, Cyber Risk Quantification, Threat Scoring, Financial Services, Operational Risk.

INTRODUCTION

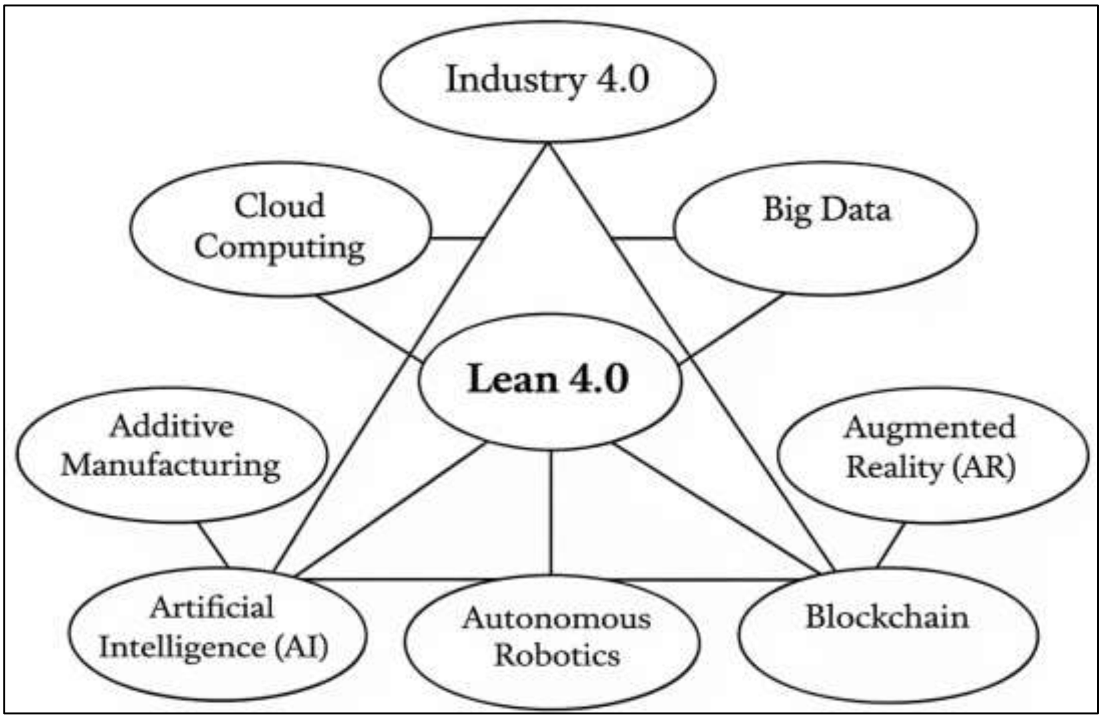
Lean Manufacturing is a systematic production philosophy rooted in the principles of eliminating waste, maximizing value, and continuously improving operational processes within industrial environments. The concept was formally derived from the Toyota Production System (TPS), which was developed by Taiichi Ohno and Shigeo Shingo in post-World War II Japan as a direct response to resource scarcity and the need for operational efficiency (Adebayo et al., 2024). At its foundational core, Lean Manufacturing identifies seven primary categories of waste, commonly referred to as muda, which include overproduction, waiting, unnecessary transportation, over-processing, excess inventory, unnecessary motion, and defects . These waste categories serve as operational targets that organizations systematically work to reduce or eliminate through a range of Lean tools and techniques including Value Stream Mapping (VSM), 5S methodology, Kaizen, Just-in-Time (JIT) production, and Total Productive Maintenance (TPM) floor to strategic management (Sasso et al., 2025) .

Figure 1: Lean Manufacturing and Industry 4.0 Integration



This philosophy has proven to be particularly effective in manufacturing environments where process variability, lead time, and product quality are critical performance dimensions. Researchers have consistently demonstrated that organizations implementing Lean Manufacturing principles experience measurable improvements in productivity, quality, customer satisfaction, and operational cost. The application of Lean is not limited to automotive manufacturing, as it has successfully been extended to aerospace, healthcare, construction, food processing, and service industries across the globe. Internationally, Lean Manufacturing has been recognized by governments and industrial bodies as a strategic driver of national competitiveness and economic resilience, particularly in economies where manufacturing serves as a primary contributor to gross domestic product (GDP) (Boopathi, 2024). The United Nations Industrial Development Organization (UNIDO) has consistently highlighted Lean principles as critical enablers of sustainable industrial development in both developed and developing nations. As global supply chains face increasing pressure from market volatility, geopolitical disruptions, and shifting consumer demands, the relevance of Lean Manufacturing as a stabilizing operational framework continues to grow in significance across international industrial sectors. The body of academic literature addressing Lean Manufacturing has grown substantially over the past three decades, with thousands of peer-reviewed studies documenting its application, adaptation, and evolution across diverse industrial contexts, confirming its enduring value as both a practical management system and a theoretical framework for operational excellence (Veseli et al., 2024).

Figure 2: Lean–Industry 4.0 Integration Framework



Industry 4.0 represents the fourth major industrial revolution, characterized by the deep integration of digital technologies, cyber-physical systems, and intelligent automation into manufacturing and production processes at an unprecedented scale. The term was first introduced at the Hannover Messe trade fair in Germany in 2011, where it was presented as a national strategic initiative to advance the competitiveness of German manufacturing through the adoption of advanced digital technologies. Industry 4.0 encompasses a broad ecosystem of enabling technologies including the Internet of Things (IoT), cloud computing, big data analytics, artificial intelligence (AI), additive manufacturing, autonomous robotics, augmented reality, and blockchain, all of which are interconnected through highly sophisticated digital infrastructure (Habibullah & Zaheda, 2022; Siddique & Amin, 2022; Shahin et al., 2024). At its conceptual center is the notion of the Smart Factory, an environment where machines, systems, and human operators communicate and collaborate in real time through interconnected networks, enabling adaptive, self-optimizing production processes that respond dynamically to changes in demand, material availability, and operational conditions. The international significance of Industry 4.0 cannot be overstated, as it has been adopted as a strategic policy framework by governments across the United States, China, Japan, South Korea, and the European Union, each of which has invested billions of dollars in national programs designed to accelerate digital transformation across their respective industrial sectors (Siddique & Amin, 2022; Md & Islam, 2022; Safari et al., 2025). The Chinese government launched its "Made in China 2025" initiative as a direct response to the Industry 4.0 paradigm, while the United States has promoted its own Advanced Manufacturing National Program to retain global industrial competitiveness. From an academic standpoint, Industry 4.0 has generated a substantial body of interdisciplinary research that spans engineering, computer science, economics, and management studies, reflecting the breadth and complexity of its technological and organizational implications. The adoption of Industry 4.0 technologies has been shown to produce significant operational benefits including increased

manufacturing flexibility, reduced downtime, improved quality control, and enhanced supply chain visibility. Furthermore, empirical research has demonstrated that organizations that successfully integrate Industry 4.0 technologies into their operational frameworks experience accelerated innovation cycles, improved responsiveness to market changes, and stronger competitive positioning in global markets (Mosheur & Rebeka, 2021; Sakib et al., 2025). The convergence of Industry 4.0 with established operational frameworks such as Lean Manufacturing has become an increasingly prominent area of scholarly investigation, as researchers seek to understand how digital transformation can amplify the benefits of process-oriented management systems and create new pathways to industrial performance optimization. Industry 4.0 thus represents not merely a technological shift but a fundamental reconceptualization of how manufacturing organizations create, deliver, and sustain value in an increasingly digitized global economy (Faysal & Shamsunnahar, 2022; Hsu et al., 2025).

The integration of Lean Manufacturing with Industry 4.0 technologies has emerged as one of the most strategically significant developments in contemporary industrial engineering, representing a paradigm shift in how organizations conceptualize and implement operational excellence programs. Scholars have argued that Lean Manufacturing and Industry 4.0 are not competing frameworks but rather complementary systems that, when combined, produce synergistic effects that amplify the operational benefits of each individual approach (Julião et al., 2025; Mosheur & Rebeka, 2022; Mostafa & Tohidul, 2022). Lean Manufacturing provides the organizational philosophy, cultural foundation, and process orientation necessary to guide the purposeful deployment of digital technologies, while Industry 4.0 provides the technological infrastructure necessary to execute Lean principles with greater speed, precision, and scale than was previously achievable through manual methods alone. The concept of Lean 4.0, which refers to the integration of Lean principles with Industry 4.0 digital technologies, has gained significant traction in academic and practitioner communities as organizations seek to leverage the combined power of process optimization and digital intelligence. Research has shown that the deployment of IoT sensors in Lean environments enables real-time monitoring of key process parameters, facilitating faster identification of waste and more responsive corrective action compared to traditional manual observation methods (Antoniadou, 2024). Similarly, the application of big data analytics to Lean Value Stream Mapping has been shown to provide more accurate and comprehensive insights into process inefficiencies, enabling organizations to prioritize improvement efforts with greater precision and confidence. The international adoption of Lean 4.0 frameworks has been particularly pronounced in automotive, electronics, and aerospace manufacturing sectors, where competitive pressures and stringent quality requirements have driven organizations to pursue increasingly sophisticated approaches to operational improvement. Studies conducted in European, Asian, and North American manufacturing contexts have consistently demonstrated that organizations combining Lean and Industry 4.0 approaches achieve superior performance outcomes compared to those implementing either framework in isolation (Hillali et al., 2024). The role of leadership, organizational culture, and change management in successfully integrating Lean and Industry 4.0 has also been extensively documented in the literature, with researchers emphasizing that technological adoption must be accompanied by appropriate human and organizational development strategies to realize the full potential of Lean 4.0. Furthermore, the integration of Lean with Industry 4.0 has been shown to enhance supply chain resilience by enabling greater visibility, agility, and responsiveness across extended value chains that span multiple geographies and organizational boundaries. The growing body of empirical evidence supporting the combined application of Lean and Industry 4.0 has established this integrated approach as a leading framework for manufacturing excellence in the digital age, warranting systematic and rigorous academic investigation to consolidate existing knowledge and identify opportunities for further advancement (Skalli et al., 2025).

The primary objective of this study is to conduct a comprehensive PRISMA-based systematic review that identifies, evaluates, and synthesizes the existing body of peer-reviewed literature addressing the development and application of hybrid machine learning models for predictive performance optimization within Lean Manufacturing and Industry 4.0 environments. Specifically, this study aims to examine and categorize the hybrid ML algorithms and modeling frameworks that have been applied to key Lean performance dimensions including waste reduction, defect prediction, process efficiency, and production scheduling. A further objective is to assess the comparative predictive performance of hybrid ML approaches relative to single-algorithm models across diverse manufacturing contexts, thereby establishing an evidence-based understanding of the conditions under which hybrid modeling strategies deliver superior optimization outcomes. Additionally, this study seeks to systematically map the integration points between Lean Manufacturing principles and Industry 4.0 digital technologies as documented in the reviewed literature, providing a structured overview of how data-driven methodologies have been operationalized within Lean improvement frameworks. Finally, this review aims to identify existing research gaps in the application of hybrid ML models to Lean Manufacturing performance optimization, offering a synthesized conceptual foundation that supports the advancement of future model development efforts in smart and sustainable manufacturing systems.

LITERATURE REVIEW

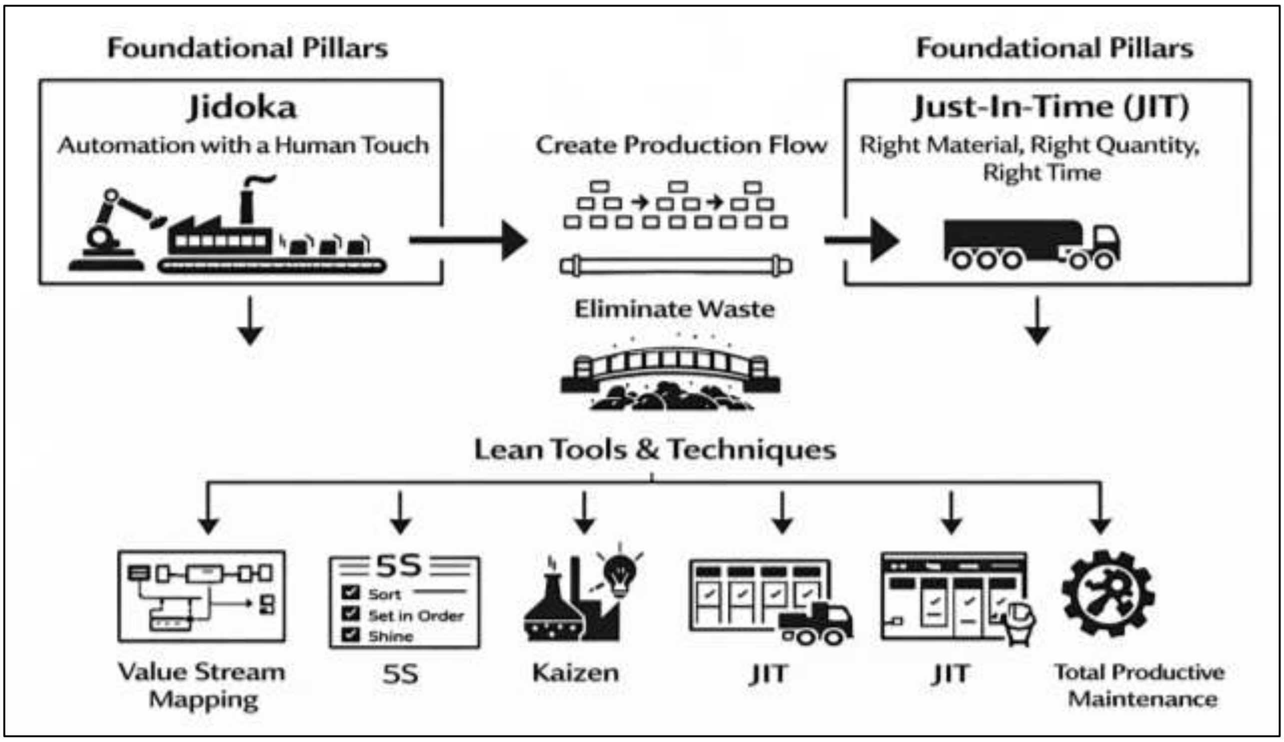
The literature review presented in this study provides a comprehensive and critically evaluated synthesis of the existing scholarly knowledge base that underpins the development of hybrid machine learning models for predictive performance optimization in Lean Manufacturing and Industry 4.0 environments. Given the interdisciplinary nature of this research, which draws simultaneously from industrial engineering, computer science, operations management, and data analytics, the literature review is organized thematically to ensure that each foundational domain is examined with appropriate depth and rigor before the intersections between domains are explored (Titu & Pop, 2025). The reviewed literature was systematically sourced from peer-reviewed journals, indexed conference proceedings, and authoritative academic databases including Scopus, Web of Science, IEEE Xplore, and Google Scholar, ensuring comprehensive coverage of the most relevant and methodologically rigorous contributions to the field. Each thematic section of this review builds progressively upon the preceding sections, establishing the theoretical, empirical, and methodological foundations necessary to contextualize the objectives and contributions of this study within the broader academic discourse (Efat Ara, 2023; Silva et al., 2025; Bhuya & Rebeka, 2022). The structure of the literature review reflects the logical progression from foundational concepts through to the integrated and applied dimensions of the research problem, enabling readers to develop a clear and coherent understanding of how the individual streams of scholarship converge to support the systematic review conducted in this study.

Literature Review

Lean Manufacturing

Lean Manufacturing traces its intellectual and operational origins to the Toyota Production System (TPS), a revolutionary approach to industrial production developed in post-World War II Japan by engineers Taiichi Ohno and Shigeo Shingo in response to severe resource constraints and the urgent need for operational efficiency in a devastated national economy. The TPS was built upon two foundational pillars, namely jidoka, which refers to automation with a human touch, and Just-in-Time (JIT) production, which prescribes the delivery of the right materials in the right quantities at exactly the right time to support uninterrupted production flow (Bhadu et al., 2025; Jinnat & Rakib, 2023; Khaled & Mosheur, 2023). The term Lean Manufacturing was formally introduced to the broader international academic and practitioner community through the landmark publication by , "The Machine That Changed the World," which presented the findings of a comprehensive five-year study conducted by the Massachusetts Institute of Technology comparing manufacturing practices across automotive plants in Japan, North America, and Europe. This seminal work demonstrated that Toyota's production approach consistently outperformed Western manufacturing systems across every major performance dimension including productivity, quality, development speed, and inventory efficiency, thereby establishing Lean Manufacturing as a globally significant paradigm for industrial improvement (Reza et al., 2025). subsequently refined the conceptual framework of Lean through the articulation of five core principles: precisely defining value from the perspective of the end customer, mapping the value stream to identify and eliminate all non-value-adding activities, creating uninterrupted production flow, establishing pull-based production systems driven by actual customer demand, and relentlessly pursuing perfection through continuous incremental improvement, a philosophy known in Japanese as kaizen. These five principles provided a coherent and actionable theoretical framework that enabled organizations across diverse industrial sectors to systematically apply Lean concepts beyond the automotive context in which they originated.

Figure 3: Lean Manufacturing Framework Derived from the TPS



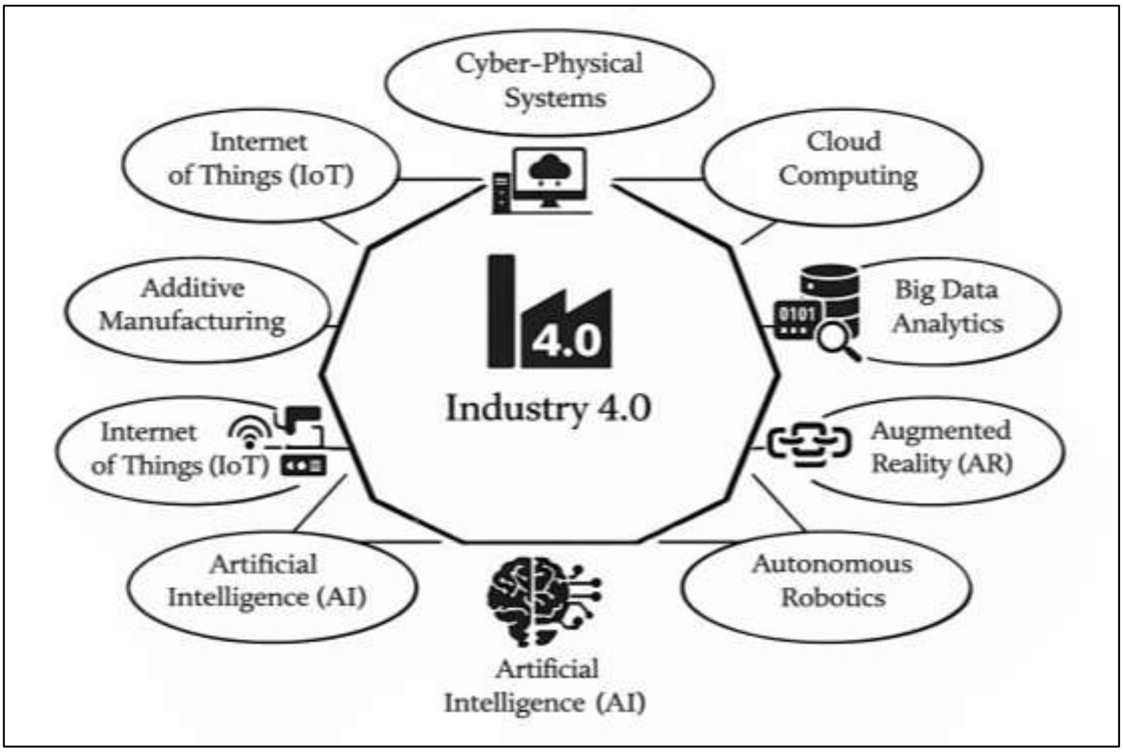
Central to the Lean philosophy is the systematic identification and elimination of waste, classified by Brad and Deeb (2025) into seven categories including overproduction, waiting, unnecessary transportation, over-processing, excess inventory, unnecessary motion, and product defects, collectively referred to in Japanese as muda. Nishad et al. (2024) expanded the understanding of the Toyota approach through the identification of 14 management principles underlying the TPS, emphasizing that Lean is fundamentally a management philosophy and organizational culture rather than merely a collection of tools and techniques. Several have provided an important empirical contribution to the theoretical foundations of Lean by developing and validating a multidimensional measurement instrument that operationalized Lean production as a bundle of interrelated practices, demonstrating through structural equation modeling that Lean implementation produces statistically significant improvements in operational performance across manufacturing organizations. Singh, (2025) conducted a systematic literature review of 209 Lean manufacturing studies published between 1988 and 2012, identifying 34 distinct definitions of Lean in the academic literature and concluding that while definitional diversity persists, the core emphasis on waste elimination, continuous improvement, and customer value creation remains consistent across the majority of scholarly conceptualizations. The historical evolution of Lean manufacturing thus reflects a progressive journey from a proprietary production system developed within a single Japanese automotive company to a globally recognized management philosophy embraced by organizations across virtually every industrial sector and geographic region.

The practical implementation of Lean Manufacturing is supported by a well-developed repertoire of tools and techniques, each designed to address specific categories of waste or operational inefficiency within manufacturing and service environments. Value Stream Mapping (VSM) is widely recognized as one of the most powerful and widely applied Lean analytical tools, providing a visual representation of all material and information flows associated with a specific product or service from raw material supplier to end customer, enabling practitioners to identify waste, quantify improvement opportunities, and design future-state production systems with greater efficiency and flow. Rahardjo et al., (2024) conducted a systematic review of VSM applications in the academic literature and identified that VSM is most effective when used as a dynamic analytical tool rather than a static mapping exercise, emphasizing the importance of integrating VSM with data collection and performance measurement systems to ensure that improvement opportunities are accurately quantified and prioritized. The 5S methodology, which encompasses the practices of Sort, Set in Order, Shine, Standardize, and Sustain, provides a systematic approach to workplace organization and visual management that creates the physical and cultural foundation necessary for more advanced Lean improvement activities. Kaizen, which translates literally as change for the better, represents the philosophical commitment to continuous incremental improvement that permeates all aspects of Lean organizations, engaging employees at every level of the hierarchy in the identification and resolution of operational problems on an ongoing basis. Just-in-Time production, one of the two foundational pillars of the TPS, prescribes the synchronization of production activities with actual customer demand through the use of kanban pull systems, takt time-based production pacing, and level scheduling approaches that minimize inventory accumulation and reduce production lead times (Mehedi & Nahar, 2023; Sultan & Anick, 2023; Rodriguês & Alves, 2025). Total Productive Maintenance (TPM), which focuses on maximizing equipment effectiveness through the active involvement of all employees in maintenance activities, directly supports Lean objectives by reducing unplanned downtime, minimizing quality defects attributable to equipment degradation, and improving overall equipment effectiveness (OEE) as a key operational performance metric. The measurement of Lean Manufacturing performance has been the subject of considerable scholarly attention, with researchers developing and validating comprehensive frameworks that assess Lean implementation outcomes across multiple dimensions including productivity, quality, lead time, inventory, and customer satisfaction. (Mostafa, 2023; Mostafa & Bhuya, 2023; Saraswat et al., 2025) proposed the concept of Lean Accounting as a necessary complement to Lean operational improvement, arguing that traditional cost accounting systems are fundamentally misaligned with Lean principles and that organizations require performance measurement frameworks specifically designed to reflect the value-creating logic of Lean production systems. The application of Lean Manufacturing across diverse industrial sectors has generated a substantial body of empirical evidence demonstrating its effectiveness in contexts far beyond its automotive origins. In the aerospace sector, Junior and Nagai (2024) documented the successful application of Lean principles in aircraft manufacturing and maintenance operations, demonstrating significant reductions in production cycle times and costs through systematic waste elimination and flow optimization. In healthcare, Tashkinov (2024) examined Lean implementations across multiple National Health Service organizations in the United Kingdom, finding that while Lean tools such as VSM and 5S produced measurable operational improvements in specific clinical processes, the absence of a holistic Lean culture and sustained leadership commitment frequently limited the scope and durability of improvement outcomes. El Hafiane et al. (2025) conducted a large-scale empirical study examining the moderating effects of Industry 4.0 technology adoption on the relationship between Lean practices and operational performance improvement across Brazilian manufacturing companies, finding that organizations combining Lean with digital technologies achieved significantly superior performance outcomes compared to those implementing Lean in isolation, thereby confirming the growing interdependence between Lean Manufacturing and the digital transformation agenda in contemporary industrial practice.

Industry 4.0 Technologies in Modern Manufacturing

Industry 4.0 represents the fourth major industrial revolution, characterized by the systematic integration of advanced digital technologies into manufacturing systems to create highly interconnected, intelligent, and adaptive production environments that fundamentally transform how value is created and delivered across global industrial networks (Ratul & Aditya, 2023; Shrivastava & Mishra, 2025; Zaheda & Farabe, 2023). The conceptual framework of Industry 4.0 was formally introduced at the Hannover Messe industrial trade fair in Germany in 2011 as a national strategic initiative aimed at maintaining German manufacturing competitiveness through accelerated digital transformation, subsequently evolving into a globally adopted paradigm for industrial modernization (Ferrazzi, Costa, Frecassetti, et al., 2025). The enabling technology ecosystem of Industry 4.0 encompasses a broad and interconnected set of digital innovations including the Internet of Things (IoT), Cyber-Physical Systems (CPS), cloud computing, big data analytics, artificial intelligence, additive manufacturing, autonomous robotics, augmented reality, and blockchain, each of which contributes distinct capabilities to the overarching objective of creating self-organizing, self-optimizing manufacturing systems capable of responding dynamically to changing operational conditions. Cyber-Physical Systems, which integrate computational intelligence with physical manufacturing processes through embedded sensors, actuators, and communication networks, are widely regarded as the foundational technological infrastructure upon which Industry 4.0 manufacturing environments are built, enabling seamless bidirectional communication between the physical and digital domains of production (Halim-Lim et al., 2025).

Figure 4: Industry 4.0 Technological Pillars



Ferrazzi, Costa, Rossini, et al. (2025) provided an influential early conceptualization of Industry 4.0 from a business and information systems perspective, identifying application pull and technology push as the two primary drivers of industrial digitalization and arguing that the resulting convergence of digital and physical production systems necessitates fundamental reconceptualization of established manufacturing management frameworks. Cloud computing platforms provide the scalable, on-demand computational infrastructure necessary to store, process, and analyze the massive volumes of data generated by connected manufacturing systems, enabling real-time decision support and remote monitoring capabilities that were previously unattainable within the constraints of on-premise computing architectures (Vasileska et al., 2024). Big data analytics, which encompasses the collection, storage, processing, and interpretation of high-volume, high-velocity, and high-variety datasets generated by manufacturing operations, provides the analytical foundation for transforming raw operational data into actionable intelligence that supports predictive maintenance, quality optimization, and supply chain management decisions. examined the implications of virtualization, decentralization, and network building for manufacturing system architecture, demonstrating that Industry 4.0 technologies enable a fundamental shift from centralized, hierarchical production control toward distributed, self-organizing manufacturing networks in which individual machines and workstations possess the intelligence to make autonomous operational decisions within defined parameters. (Bouyahrouzi et al., 2025) conducted a comprehensive analysis of nine key technology pillars underpinning Industry 4.0, concluding that the combined deployment of these technologies has the potential to increase manufacturing productivity by 15 to 25 percent across major industrial sectors, representing a transformational economic opportunity for organizations capable of successfully navigating the technological and organizational challenges of digital transformation. (Oyetade et al., 2025) examined the industrial opportunities and challenges associated with Industry 4.0 adoption, identifying interoperability, virtualization, decentralization, real-time capability, service orientation, and modularity as the six core design principles that distinguish Industry 4.0 manufacturing systems from their predecessors, providing a structured conceptual vocabulary for researchers and practitioners engaged in the design and implementation of digitally integrated production environments. The international policy significance of Industry 4.0 has been reflected in major national strategic initiatives including Germany's Industrie 4.0 program, China's Made in China 2025 policy, the United States Advanced Manufacturing Partnership, and Japan's Society 5.0 framework, each of which has directed substantial public investment toward accelerating the digital transformation of national manufacturing sectors in recognition of the competitive and economic imperatives associated with Industry 4.0 adoption (Ara, 2024a, 2024b; Hafid et al., 2025). Jaskó and Ruppert (2025) conducted an empirical investigation of the drivers of Industry 4.0 implementation across German manufacturing firms, identifying competitive pressure, customer requirements, and efficiency improvement objectives as the primary motivating factors, while also documenting significant variation in adoption readiness across firm size categories, with large enterprises demonstrating substantially greater implementation progress compared to small and medium enterprises.

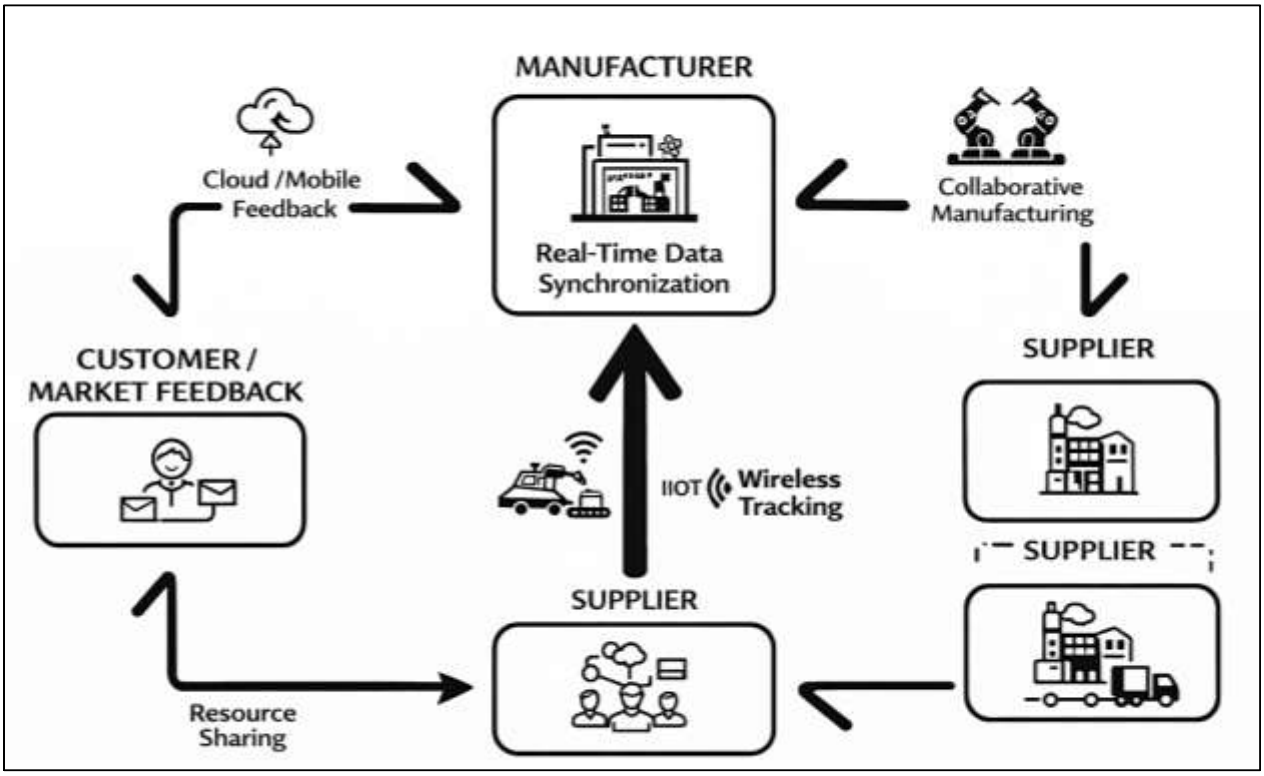
The Smart Factory represents the operational manifestation of Industry 4.0 principles at the level of the individual manufacturing facility, embodying a vision of production environments in which machines, systems, products, and human operators are seamlessly interconnected through digital networks, enabling adaptive, self-optimizing production processes that continuously adjust to changes in demand, material availability, quality conditions, and equipment status (Herrera-Vidal et al., 2025). Theoretically, the Smart Factory architecture is organized across multiple interconnected layers including the physical production layer, the cyber layer encompassing data acquisition and processing infrastructure, and the cognitive layer incorporating analytical and decision-support capabilities, with bidirectional data flows connecting all layers in real time to enable closed-loop process control and continuous performance optimization (Narkhede et al., 2024). Digital Twin technology, which creates virtual replicas of physical manufacturing assets, processes, and systems that are continuously updated with real-time operational data, has emerged as one of the most strategically significant enabling technologies within the Smart Factory paradigm, providing unprecedented capabilities for simulation, monitoring, diagnostics, and predictive optimization without disrupting physical production operations. Kopeinig et al. (2024) provided a comprehensive framework for Digital Twin applications in smart manufacturing, demonstrating that Digital Twin models can support the full lifecycle of manufacturing assets from design and commissioning through operation and maintenance to decommissioning, with particularly significant value generated through the application of predictive analytics to Digital Twin data streams for maintenance scheduling, quality control, and process optimization. Rubino et al. (2025) examined the technical architecture and implementation requirements of Digital Twins in industrial settings, identifying fidelity, scalability, and real-time synchronization as the three critical performance dimensions that determine the operational value of Digital Twin implementations in manufacturing environments. The Industrial Internet of Things (IIoT), which refers specifically to the application of IoT technologies within industrial and manufacturing contexts, provides the physical sensing and communication infrastructure that enables real-time data acquisition from manufacturing equipment, processes, and products, generating the continuous streams of operational data upon which Smart Factory analytics and optimization capabilities depend (Kumar et al., 2024). Contieri et al. (2024) examined IIoT architectures for manufacturing applications, proposing a hierarchical sensor integration framework that addresses the challenges of data heterogeneity, communication protocol diversity, and real-time processing requirements that characterize industrial sensing environments, demonstrating through implementation studies that the proposed architecture enables reliable, low-latency data acquisition from complex multi-machine production systems. The deployment of advanced sensor technologies including vibration sensors, acoustic emission sensors, thermal imaging systems, and vision inspection systems has dramatically expanded the range of manufacturing process parameters that can be continuously monitored in real time, providing the rich multivariate data streams necessary to support machine learning-based predictive analytics in Lean manufacturing environments (Amin et al., 2024; Faysal & Bhuya, 2024; Iftekhar & Md Tohidul, 2024). Martín-Gómez et al., (2024) traced the evolutionary trajectory of production systems from Industry 2.0 through Industry 4.0, demonstrating that each successive industrial revolution has been characterized by a fundamental expansion in the scope and sophistication of production system intelligence, with Industry 4.0 representing the culmination of this trajectory through the creation of manufacturing systems capable of self-awareness, self-prediction, self-optimization, and self-configuration. Arora et al. (2025) conducted a comprehensive empirical study examining organizational learning pathways associated with Industry 4.0 adoption across manufacturing firms in Brazil, finding that firms pursuing simultaneous implementation of multiple Industry 4.0 technologies demonstrated superior organizational learning outcomes compared to those adopting technologies sequentially, suggesting that the synergistic effects of integrated digital transformation deliver organizational capability benefits that exceed the sum of individual technology deployments. Ibrahim and Kumar (2024) developed and validated a maturity model for Industry 4.0 implementation assessment across nine organizational dimensions including strategy, leadership, customers, products, operations, culture, people, governance, and technology, finding through application of the model across 19 Austrian manufacturing companies that significant heterogeneity exists in Industry 4.0 readiness even among firms operating within the same industrial sector, with technology and operations dimensions typically demonstrating higher maturity levels than culture and people dimensions. Fasciolo et al. (2024) conducted a detailed analysis of the relationship between Industry 4.0 and Lean manufacturing, concluding that the data transparency, process connectivity, and analytical capabilities provided by Industry 4.0 technologies directly amplify the effectiveness of established Lean improvement methodologies, positioning digital transformation as a powerful enabler of sustained operational excellence in manufacturing organizations that have already established foundational Lean capabilities.

Integration of Lean Manufacturing and Industry 4.0

The integration of Lean Manufacturing and Industry 4.0 technologies has emerged as one of the most strategically consequential developments in contemporary industrial engineering, giving rise to the concept of Lean 4.0, which refers to the purposeful combination of Lean operational philosophy with the digital intelligence and connectivity capabilities of Industry 4.0 to create manufacturing systems that are simultaneously efficient, agile, and data-driven conducted a systematic literature review examining the relationship between Industry 4.0 and Lean manufacturing, concluding that the two frameworks are fundamentally complementary rather than competing, with Lean providing the process-oriented organizational foundation that guides the purposeful deployment of digital technologies, while Industry 4.0 provides the technological infrastructure necessary to execute Lean principles with greater speed, precision, and analytical depth than manual methods alone can achieve. Bello et al. (2024) reinforced this complementarity argument through a detailed conceptual analysis demonstrating that Industry 4.0 technologies directly address several of the most persistent limitations of traditional Lean implementation, including the reliance on manual data collection, the latency of performance feedback loops, and the difficulty of sustaining improvement momentum across complex multi-site manufacturing operations. Fonseca et al. (2025) provided important empirical grounding for the Lean 4.0 concept through a large-scale study of Brazilian manufacturing companies, finding that firms simultaneously pursuing Lean practices and Industry 4.0 technology adoption achieved significantly superior operational performance outcomes compared to those implementing either approach independently, with the greatest performance benefits observed in organizations that strategically aligned their digital investments with established Lean improvement priorities. The concept of Digital Value Stream Mapping represents one of the most practically significant manifestations of Lean 4.0 integration, extending the traditional VSM methodology by incorporating real-time data streams from IIoT sensors, manufacturing execution systems, and enterprise resource planning platforms to generate dynamic, continuously updated representations of production system performance that enable far more rapid and accurate identification of waste and inefficiency compared to conventional manual mapping approaches (Ali et al., 2024; Mushfequr & Aditya, 2024; Sazzadul &

Rebeka, 2024). Eslami et al. (2024) originally conceived the value stream as the primary unit of Lean analysis, and the digitization of value stream data through Industry 4.0 infrastructure has dramatically expanded the analytical power available to Lean practitioners seeking to understand and optimize complex production systems. Pansare et al. (2024) examined the theoretical and practical dimensions of Lean manufacturing within Industry 4.0 environments, proposing an integrated framework that maps specific Industry 4.0 enabling technologies to corresponding Lean waste categories, demonstrating that technologies such as real-time sensor monitoring, automated inspection systems, and AI-driven scheduling algorithms are particularly well-suited to addressing the Lean wastes of defects, waiting, and overproduction respectively.

Figure 5: Lean Manufacturing and Industry 4.0 Integration



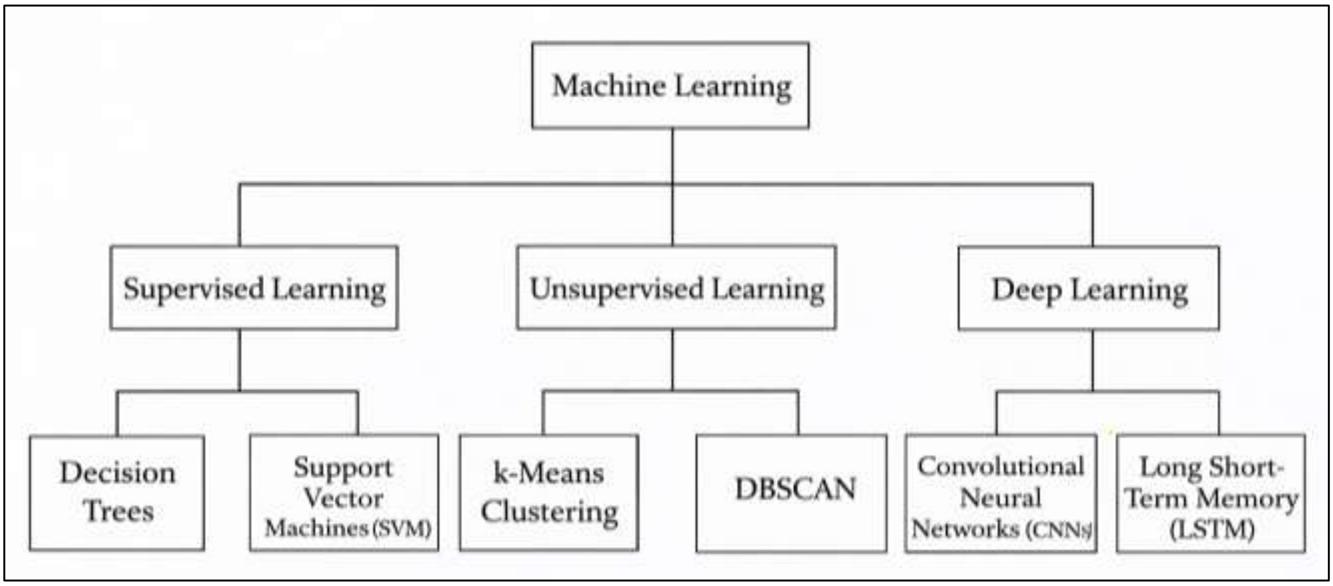
Madrid-Guijarro et al. (2025) highlighted the critical importance of Lean leadership as a prerequisite for successful Lean 4.0 integration, arguing that the cultural and organizational foundations established through sustained Lean leadership development are essential for creating the change readiness and continuous improvement orientation necessary to effectively absorb and leverage the capabilities of Industry 4.0 technologies within manufacturing organizations.

The empirical evidence documenting the barriers and enablers of Lean and Industry 4.0 integration reveals a complex interplay of organizational, technological, and human factors that collectively determine the success or failure of Lean 4.0 implementation initiatives across diverse manufacturing contexts. Calandreli et al (2025) identified several critical barriers to Industry 4.0 adoption within manufacturing firms, including high implementation costs, insufficient digital skills among the existing workforce, concerns about data security and intellectual property protection, and the difficulty of integrating new digital technologies with legacy production equipment and information systems, all of which are particularly pronounced in organizations attempting to pursue digital transformation while simultaneously maintaining operational continuity in Lean production environments. Sheikh and Senfi (2025) demonstrated through their Industry 4.0 maturity model that organizational culture and people development dimensions consistently lag behind technology and operations dimensions in manufacturing firms pursuing digital transformation, suggesting that the human and cultural prerequisites for successful Lean 4.0 integration receive insufficient management attention relative to the technical aspects of implementation. The challenges associated with Lean 4.0 adoption are particularly acute in small and medium enterprises (SMEs), which constitute the majority of manufacturing firms globally and face distinctive resource constraints that limit their capacity to invest in the digital infrastructure, technical expertise, and organizational development capabilities required for comprehensive Lean 4.0 implementation (Bhatia et al., 2024; Tasnim & Anick, 2024; Zaheda & Hamidur, 2024). conducted a systematic review specifically examining Industry 4.0 adoption challenges in SME manufacturing contexts, finding that financial constraints, limited access to technical expertise, absence of standardized implementation roadmaps, and uncertainty about return on investment represent the most frequently cited barriers among SME manufacturers seeking to integrate digital technologies with existing Lean operational frameworks. Yin et al. (2018) contextualized the Lean 4.0 integration challenge within the broader historical evolution of manufacturing systems, arguing that successful transitions between industrial paradigms have consistently required organizations to develop new organizational capabilities and management competencies in parallel with technological adoption, emphasizing that the human and organizational dimensions of Lean 4.0 integration are as critical to implementation success as the technical dimensions. Organizational learning plays a central mediating role in the relationship between Industry 4.0 technology adoption and operational performance improvement, finding that firms that invest in structured learning and capability development processes alongside their digital technology deployments achieve significantly more durable and comprehensive performance improvements than those that focus exclusively on technological implementation. The body of empirical evidence on Lean 4.0 integration thus consistently supports the conclusion that realizing the full performance potential of combined Lean and Industry 4.0 approaches requires a holistic implementation strategy that addresses technological, organizational, cultural, and human capability dimensions in an integrated and mutually reinforcing manner.

Machine Learning Fundamentals and Algorithms in Manufacturing

The application of machine learning algorithms to manufacturing systems has generated a substantial and rapidly expanding body of scholarly evidence demonstrating the capacity of data-driven computational methods to transform operational decision-making across a wide range of industrial engineering domains. Supervised learning algorithms, which are trained on labeled historical datasets to generate predictive models applicable to new operational data, have been among the most extensively studied ML methodologies in manufacturing contexts, with Decision Trees, Random Forest, Support Vector Machines (SVM), and Gradient Boosting methods including XGBoost and LightGBM consistently demonstrating strong predictive performance across applications including quality control, defect classification, process parameter optimization, and equipment failure prediction (Renugadevi et al., 2024). Chayalakshmi et al. (2025) introduced the Random Forest algorithm as an ensemble method combining multiple decision trees through bootstrap aggregation, demonstrating that the resulting ensemble model achieves substantially lower variance and superior generalization performance compared to individual decision trees, a finding that has been repeatedly confirmed across diverse manufacturing prediction tasks. Chayalakshmi et al. (2025) developed XGBoost as a scalable and computationally efficient implementation of gradient boosting that has since become one of the most widely adopted ML algorithms in manufacturing data science applications, consistently achieving state-of-the-art predictive accuracy on structured tabular datasets representative of manufacturing process monitoring scenarios. Kazi (2025) established the theoretical foundations of Support Vector Machines as maximum margin classifiers capable of handling high-dimensional feature spaces through the kernel trick, a property that has proven particularly valuable in manufacturing quality classification tasks where process data frequently exhibits complex, non-linear decision boundaries that challenge simpler parametric models. Unsupervised learning techniques, which identify hidden structures and patterns in unlabeled manufacturing datasets without requiring predefined output categories, have been applied to a range of manufacturing analysis problems including process clustering, anomaly detection, sensor fault identification, and production pattern discovery. The k-means clustering algorithm, which partitions manufacturing datasets into k distinct clusters based on feature similarity, has been widely applied to production process segmentation and operational mode identification tasks, enabling manufacturers to distinguish between normal and abnormal operating conditions without requiring labeled training data (Ördek et al., 2024).

Figure 6: Machine Learning Methods in Manufacturing



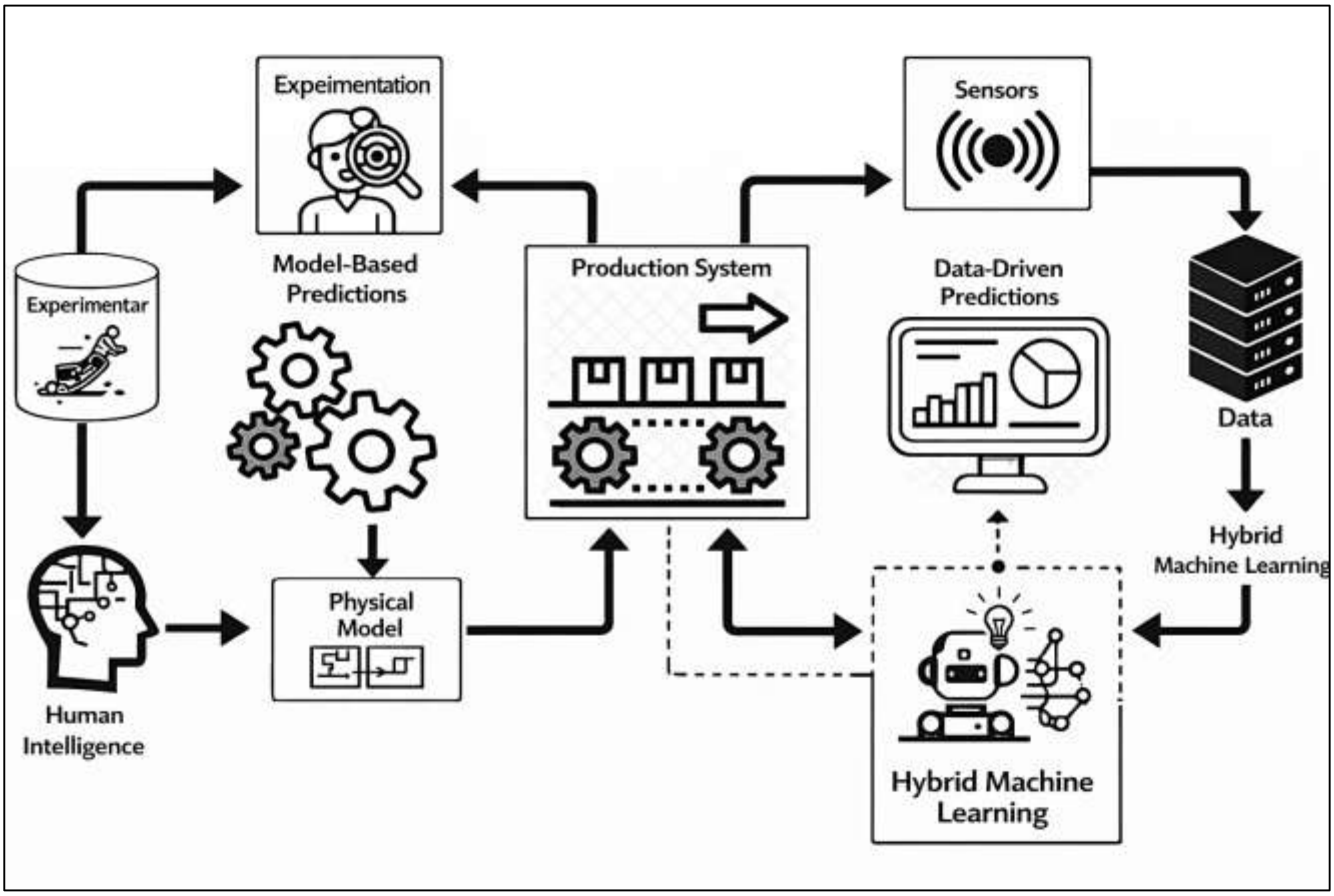
Density-Based Spatial Clustering of Applications with Noise (DBSCAN), introduced by Chaudhary et al. (2024), offers important advantages over k-means in manufacturing anomaly detection applications by identifying clusters of arbitrary shape and automatically classifying low-density data points as outliers, making it particularly well-suited to the identification of rare but operationally significant process anomalies in continuous manufacturing monitoring datasets. Agrawal and Nargund (2024) provided a comprehensive survey of anomaly detection methodologies applicable to manufacturing and industrial systems, demonstrating that statistical, clustering-based, and classification-based anomaly detection approaches each offer distinct advantages depending on the characteristics of the manufacturing data under analysis, and emphasizing the importance of careful algorithm selection based on the specific operational context and data properties of each application. Razzaq and Shah, (2025) examined smart manufacturing systems for Industry 4.0 environments, demonstrating that the combination of IIoT sensor infrastructure with advanced ML analytics including both supervised and unsupervised learning methods enables manufacturing organizations to achieve unprecedented levels of process visibility, predictive capability, and operational responsiveness compared to traditional rule-based monitoring and control approaches.

The application of deep learning architectures to manufacturing problems has opened new analytical frontiers by enabling the automated extraction of complex hierarchical features from high-dimensional manufacturing datasets including vibration signals, acoustic emissions, thermal images, and production sequence data, eliminating the need for manual feature engineering and enabling the discovery of subtle process patterns that may not be accessible through conventional ML methods (Shende & Ingle, 2024). Convolutional Neural Networks (CNNs), originally developed for image recognition tasks, have been extensively adapted for manufacturing quality inspection applications, where their capacity to automatically learn spatially invariant feature representations from image data enables highly accurate automated detection of surface defects, dimensional non-conformances, and assembly errors at inspection speeds that far exceed human visual inspection capabilities (Nikooharf et al., 2024). Liang et al. (2024) demonstrated the application of deep learning architectures to smart manufacturing systems, showing that CNN-based inspection models achieved defect detection accuracy rates exceeding 98 percent across multiple manufacturing quality inspection benchmarks while simultaneously reducing inspection cycle times by more than 60 percent compared to conventional automated optical inspection systems. Recurrent Neural Networks (RNNs) and their advanced variant, Long Short-Term Memory (LSTM) networks, have been extensively applied to sequential manufacturing data analysis tasks including time-series process monitoring, remaining useful life prediction, and production scheduling optimization, leveraging their inherent capacity to model temporal dependencies in sequential data streams generated by manufacturing processes (Tursunalieva et al., 2024). Huang et al (2024) conducted a comprehensive review of machine learning applications to machinery fault diagnosis, demonstrating that LSTM-based prognostic models consistently outperform traditional signal processing and shallow ML approaches in predicting remaining useful life of rotating machinery components, with particular advantages observed in operating conditions characterized by variable speed, load, and environmental factors that challenge the stationarity assumptions underlying conventional diagnostic methods. The quality and representativeness of training data are widely recognized as critical determinants of ML model performance in manufacturing applications, necessitating careful attention to feature engineering and data preprocessing strategies that address the specific characteristics and challenges of industrial datasets (Paredes et al., 2025). Manufacturing datasets frequently exhibit class imbalance, where the number of examples representing abnormal or defective conditions is substantially smaller than the number representing normal operation, a characteristic that can severely degrade the performance of standard ML classifiers on minority class prediction tasks if not appropriately addressed through techniques such as synthetic minority oversampling (SMOTE), cost-sensitive learning, or ensemble resampling methods. Missing value imputation represents another critical preprocessing challenge in manufacturing ML applications, as sensor failures, communication interruptions, and planned maintenance periods frequently produce gaps in operational data streams that must be handled through principled statistical or model-based imputation strategies to avoid biasing model training and degrading prediction accuracy (Rashidi et al., 2025). Hyperparameter optimization and rigorous cross-validation methodology are essential components of ML model development for manufacturing applications, ensuring that model performance estimates are reliable and generalizable beyond the specific datasets and operating conditions used during training. Osman et al. (2024) demonstrated that random search strategies for hyperparameter optimization achieve comparable or superior results to grid search approaches in substantially less computational time across a wide range of ML model types, a finding with important practical implications for manufacturing ML practitioners working under real-world constraints of computational resources and development time. Islam et al. (2024) emphasized that regularization techniques including dropout, weight decay, and batch normalization are essential components of deep learning model development for manufacturing applications, preventing overfitting to training data and ensuring that learned representations generalize reliably to the full range of operating conditions encountered in production environments.

Hybrid Machine Learning Models: Development and Architecture

Hybrid machine learning models, defined as computational frameworks that combine two or more distinct algorithmic approaches or integrate data-driven ML methods with domain-specific knowledge representations to achieve superior predictive performance compared to any constituent method applied independently, have emerged as a foundational methodological paradigm in manufacturing predictive optimization research (Kayikci & Khoshgoftaar, 2024). The theoretical rationale for hybrid modeling is grounded in the no-free-lunch theorem articulated by Krenczyk (2024), which formally established that no single learning algorithm performs optimally across all problem types, thereby providing a rigorous theoretical justification for combining complementary algorithms whose individual strengths compensate for each other's limitations across diverse manufacturing prediction scenarios. Hybrid ML models in manufacturing contexts are broadly classifiable into three principal architectural categories: ensemble methods, which combine the outputs of multiple independently trained base learners through aggregation strategies such as voting, averaging, or weighted combination; stacked generalization models, which train a meta-learner to optimally combine the predictions of multiple base models; and physics-informed hybrid frameworks, which integrate mechanistic domain knowledge with data-driven learning to produce models that respect physical constraints while retaining the pattern recognition capabilities of ML algorithms (Herhausen et al., 2024).

Figure 7: Hybrid Machine Learning Manufacturing Prediction Framework



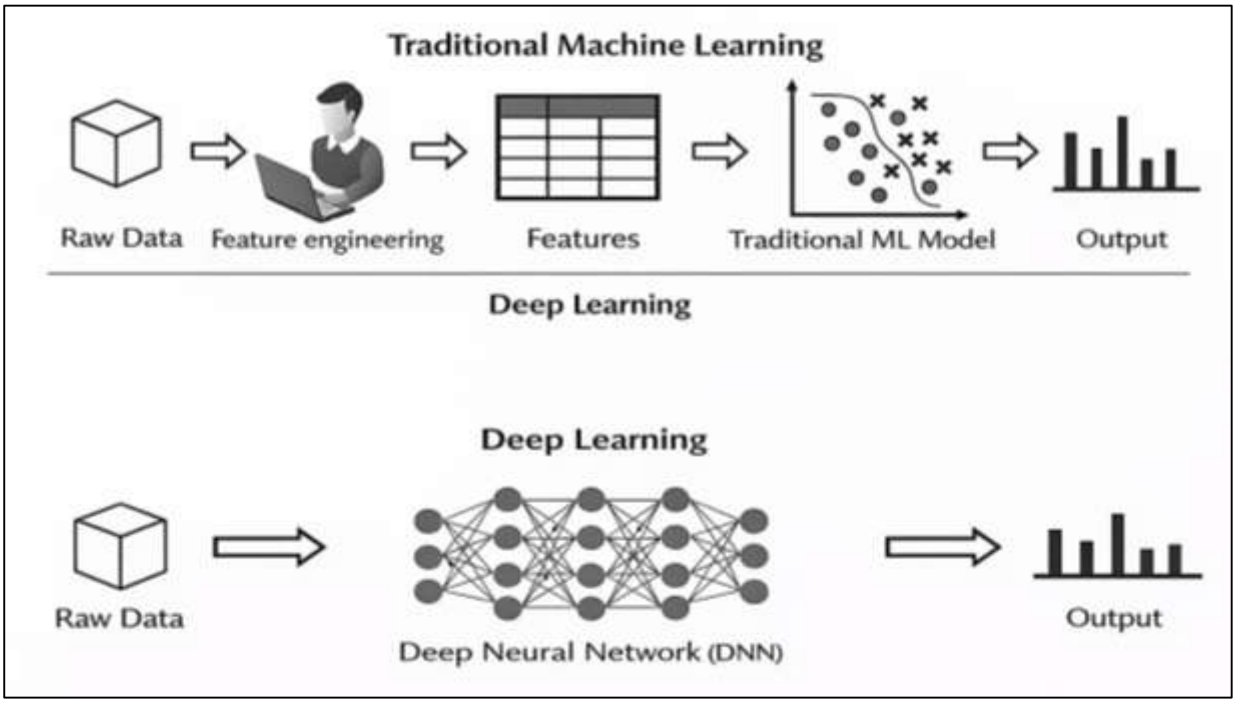
Ensemble learning strategies represent the most extensively studied category of hybrid ML architecture in manufacturing applications, encompassing three primary methodological approaches including bagging, boosting, and stacking, each of which addresses the bias-variance tradeoff in model development through distinct mechanisms. introduced bagging as a variance reduction strategy that trains multiple instances of a base learner on bootstrap resamples of the training data and combines their predictions through averaging or majority voting, demonstrating that bagged ensembles consistently outperform single models across classification and regression tasks, with the greatest performance gains observed for high-variance base learners such as decision trees. Celik and Inik (2024) developed the AdaBoost algorithm as the foundational boosting method, demonstrating that sequentially trained ensembles in which each successive learner focuses on the examples most frequently misclassified by preceding models achieve dramatically lower classification error rates than single learners, establishing boosting as one of the most powerful supervised learning strategies available for manufacturing quality classification and fault detection applications. Hax et al. (2024) introduced stacked generalization as a meta-learning framework in which a second-level learner is trained to combine the predictions of multiple first-level base models, exploiting the complementary strengths of diverse algorithms to achieve prediction accuracy that consistently exceeds the performance of any individual base model, a property that has been extensively validated in manufacturing process optimization studies (Çılgın & Gökçen, 2025). Theera-Ampornpunt et al. (2025) conducted a comprehensive comparative analysis of ensemble methods applied to manufacturing quality prediction tasks, demonstrating that stacked generalization models combining Random Forest, XGBoost, and SVM base learners with a logistic regression meta-learner achieved prediction accuracy improvements of 8 to 15 percent over the best-performing individual base model across multiple manufacturing quality datasets, confirming the practical value of ensemble diversity for manufacturing prediction performance. Nguyen et al. (2024) examined hybrid ML models for manufacturing process optimization, finding that ensemble approaches combining gradient boosting with neural network components consistently outperformed single-algorithm baselines across multiple Lean performance metrics including defect rate prediction, cycle time estimation, and production scheduling optimization, demonstrating the broad applicability of hybrid modeling strategies to the full spectrum of manufacturing performance optimization problems.

The integration of deep learning architectures with classical machine learning algorithms represents a particularly significant and rapidly evolving category of hybrid modeling in manufacturing, motivated by the complementary capabilities of deep learning for automated high-dimensional feature extraction and classical ML algorithms for structured prediction, interpretability, and performance with limited training data (Ait Nasser & Akhloufi, 2024). Berhane et al. (2024) demonstrated a highly effective hybrid architecture combining Convolutional Neural Networks for automated feature extraction from raw vibration sensor signals with Random Forest classifiers for fault type classification in rotating machinery, showing that the hybrid CNN-RF model achieved fault classification accuracy of 99.2 percent across five equipment fault categories, substantially outperforming both standalone CNN and standalone Random Forest models trained on the same datasets. Hybrid deep learning architectures for remaining useful life prediction in manufacturing equipment, demonstrating that models combining LSTM networks for temporal sequence modeling with XGBoost for final prediction consistently outperformed single-architecture approaches across multiple benchmark prognostic datasets, with particularly significant performance advantages observed under variable operating conditions that challenge the stationarity assumptions of classical prognostic models. Physics-informed and knowledge-guided hybrid ML models represent a conceptually distinct and increasingly prominent approach to hybrid modeling in manufacturing, addressing the fundamental limitation of purely data-driven ML methods that they may generate predictions inconsistent with established physical laws or engineering domain knowledge, particularly in operating regimes underrepresented in training data (Saleem et al., 2024). The concept of physics-guided machine learning as a framework for incorporating scientific domain knowledge into ML model architectures through mechanisms including physics-based loss function terms, physically motivated feature engineering, and hybrid model structures that combine mechanistic simulation models with data-driven correction components, demonstrating across multiple scientific and engineering applications that physics-guided models achieve superior accuracy and physical consistency compared to purely data-driven approaches trained on equivalent datasets. Physics-Informed Neural Networks (PINNs) as a general framework for embedding partial differential equations and other physical constraints directly into neural network training objectives, demonstrating that PINN models achieve accurate predictions in data-sparse regions of the operational space where purely data-driven models typically fail, a capability of particular value in manufacturing applications where data collection across the full range of operating conditions is costly or impractical. Multi-task learning as a knowledge-guided hybrid modeling strategy in which ML models are simultaneously trained on multiple related manufacturing prediction tasks, demonstrating that shared representations learned across related tasks consistently improve model performance on individual tasks compared to single-task training, particularly in low-data regimes representative of many specialized manufacturing quality and process optimization applications. The comparative performance evidence consistently demonstrates the superiority of hybrid ML models over single-algorithm approaches across manufacturing predictive optimization tasks, with meta-analyses and systematic comparative studies documenting average prediction accuracy improvements ranging from 5 to 20 percent depending on the specific manufacturing application, dataset characteristics, and hybrid architecture employed (Khedimi et al., 2024). The critical importance of model interpretability alongside predictive accuracy in manufacturing ML applications, noting that the complexity of hybrid models creates transparency challenges that must be addressed through explainability techniques including SHAP and LIME to ensure that manufacturing practitioners can understand, trust, and act upon hybrid model predictions in operational decision-making contexts. SHAP values provide a theoretically principled and computationally tractable approach to interpreting the predictions of complex ensemble and hybrid models in manufacturing applications, enabling practitioners to identify the process variables most strongly influencing quality outcomes and equipment health predictions, thereby enhancing the operational utility of hybrid ML systems within Lean manufacturing improvement frameworks.

Machine Learning Applications in Lean Manufacturing Performance Optimization

The application of machine learning to Lean Manufacturing performance optimization has generated a rich and rapidly expanding body of empirical evidence demonstrating the capacity of data-driven computational methods to dramatically enhance the effectiveness, speed, and precision of core Lean improvement activities across diverse manufacturing contexts.

Figure 8: Machine Learning for Lean Manufacturing Performance Optimization

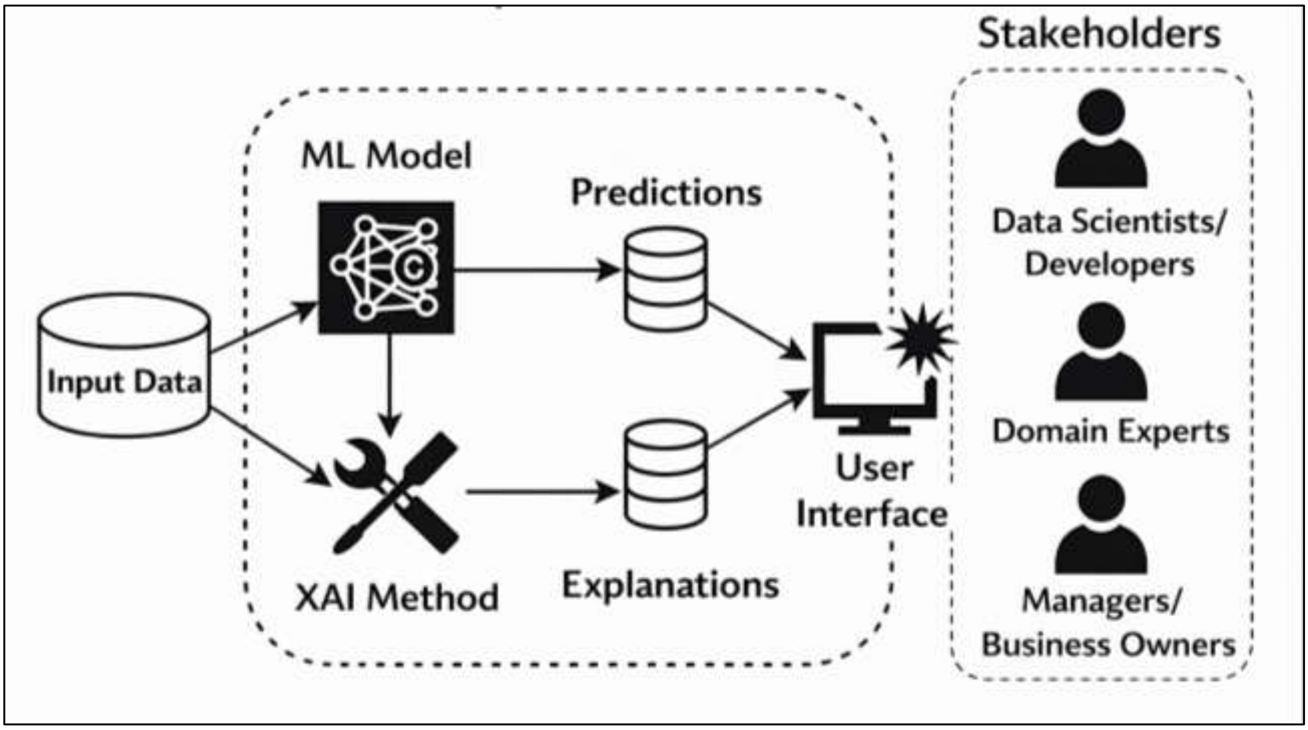


Defect detection and predictive quality control represent the most extensively studied domain of ML application within Lean manufacturing environments, reflecting the central importance of zero-defect production as a foundational Lean quality objective and the particular suitability of ML algorithms for identifying complex, non-linear patterns in process data that are predictive of quality non-conformances before defective products are produced. Lin et al. (2024) conducted a comprehensive investigation of ML-based quality prediction in semiconductor manufacturing, demonstrating that ensemble models combining Random Forest and XGBoost achieved defect prediction accuracy rates exceeding 96 percent on high-dimensional process monitoring datasets, enabling proactive quality interventions that reduced defect rates by 23 percent compared to conventional statistical process control approaches, directly supporting the Lean objective of eliminating the waste of defects throughout the production process. The application of deep convolutional neural networks to automated visual inspection in smart manufacturing environments, showing that CNN-based defect detection systems achieved classification accuracy rates of 98.7 percent across multiple product categories while reducing inspection cycle times by more than 60 percent compared to manual inspection methods, simultaneously advancing both quality and flow objectives central to Lean manufacturing philosophy. The technical foundation for real-time automated inspection through the development of region-based convolutional neural network architectures capable of detecting and localizing multiple defect types simultaneously within single product images, providing the computational framework that has subsequently been adapted and refined across a wide range of manufacturing quality inspection applications. Bülbül (2024) examined smart manufacturing systems integrating ML-based quality analytics with IIoT sensor infrastructure, demonstrating that real-time process monitoring combined with predictive quality models enabled manufacturing organizations to shift from reactive defect correction to proactive defect prevention, fundamentally transforming the quality management paradigm in alignment with Lean continuous improvement principles. Predictive maintenance represents another domain of particularly strong alignment between ML capabilities and Lean operational objectives, as unplanned equipment downtime constitutes one of the most significant sources of production waste in manufacturing environments and directly undermines the flow and reliability principles central to Just-in-Time production systems (Nivaashini et al., 2024). An exhaustive review of ML applications to machinery fault diagnosis and prognostics, documenting that LSTM-based remaining useful life prediction models consistently achieved mean absolute percentage errors below five percent across multiple rotating machinery prognostic benchmarks, enabling maintenance scheduling with sufficient lead time to prevent unplanned production stoppages while minimizing the costs associated with excessive preventive maintenance interventions. The state of machine prognostics in condition-based maintenance, demonstrating that ML-based prognostic models outperform traditional threshold-based maintenance triggering approaches by accurately predicting the remaining operational life of equipment components based on continuous monitoring of degradation indicators, thereby enabling maintenance interventions to be precisely timed to maximize equipment availability while minimizing maintenance resource consumption in alignment with Total Productive Maintenance objectives.

Explainable AI and Model Interpretability in Manufacturing Decision-Making

The interpretability of machine learning models has emerged as one of the most critically important and actively debated challenges in the deployment of AI-driven predictive systems within manufacturing and industrial engineering environments, reflecting a fundamental tension between the predictive accuracy advantages of complex black-box models and the transparency requirements of operational decision-making contexts where engineers, operators, and managers must understand, validate, and act upon model outputs with confidence (Antosz et al., 2024). While highly complex ML models including deep neural networks, gradient boosting ensembles, and hybrid architectures consistently achieve superior predictive accuracy compared to simpler interpretable models across manufacturing prediction benchmarks, their inherent opacity creates significant practical barriers to adoption in safety-critical and quality-sensitive manufacturing applications where regulatory compliance, accountability, and human oversight are essential operational requirements (Magnus & Venschott, 2024). Powell (2024) provided a foundational theoretical framework for evaluating ML model interpretability, distinguishing between application-grounded evaluation, which assesses interpretability in terms of its impact on real-world task performance by domain experts, and functionally-grounded evaluation, which employs formal proxy measures of explanation quality, demonstrating that manufacturing practitioners consistently prioritize application-grounded interpretability because they require explanations that are directly actionable within the specific operational context of their production environments. The fundamental interpretability challenge in manufacturing ML deployment as the trust gap between model developers, who evaluate models based on held-out test set accuracy, and operational users, who require confidence that model predictions will remain reliable and physically sensible across the full range of operating conditions encountered in production, including edge cases and novel scenarios underrepresented in training data. A comprehensive survey of explainable artificial intelligence methods and their applications across industrial domains, categorizing XAI approaches according to their scope, applicable model types, and explanation formats, and demonstrating that manufacturing applications exhibit distinctive interpretability requirements compared to other AI application domains due to the combination of safety criticality, regulatory oversight, domain expertise availability, and real-time decision-making constraints that characterize industrial production environments. Ibrahim and Kumar (2024) examined the broader landscape of XAI research motivated by the United States Defense Advanced Research Projects Agency (DARPA) XAI program, identifying that the core interpretability challenge in complex ML systems stems from the fundamental mathematical properties of high-dimensional non-linear models rather than implementation choices, necessitating dedicated post-hoc explanation methodologies that approximate local or global model behavior in human-comprehensible terms without requiring modification of the underlying predictive architecture.

Figure 9: Explainable Artificial Intelligence Decision Support Framework



The development and application of specific XAI methodologies, particularly SHAP and LIME, have substantially advanced the practical interpretability of complex ML models in manufacturing decision-making contexts, providing mathematically principled and computationally tractable approaches to generating human-understandable explanations of individual predictions and overall model behavior that can be integrated into operational manufacturing decision support workflows. SHAP as a unified framework for interpreting ML model predictions based on Shapley values from cooperative game theory, demonstrating that SHAP provides theoretically consistent, locally accurate, and globally coherent feature importance attributions for any ML model architecture, and showing through manufacturing quality prediction case studies that SHAP explanations successfully identified the process parameters most strongly influencing defect outcomes in ways that aligned with domain expert knowledge and enabled targeted process improvement interventions. LIME as a model-agnostic local interpretability method that approximates the behavior of any complex ML model in the vicinity of individual predictions using locally fitted interpretable surrogate models, demonstrating through application to manufacturing fault classification tasks that LIME explanations provide actionable insights into the sensor signals and process parameters driving individual equipment fault predictions, enabling maintenance engineers to prioritize inspection activities and corrective actions based on transparent, example-specific model reasoning. A comprehensive treatment of interpretable ML methods applicable to manufacturing systems, demonstrating through multiple industrial case studies that the combination of global interpretability methods including partial dependence plots and permutation feature importance with local interpretability methods including SHAP and LIME provides a complementary and mutually reinforcing analytical framework that enables manufacturing practitioners to develop both system-level understanding of model behavior and instance-level understanding of individual predictions. The integration of XAI frameworks within Lean Manufacturing decision support systems represents a particularly important application domain, as the effectiveness of Lean improvement initiatives fundamentally depends on the capacity of manufacturing practitioners to identify root causes of performance gaps, prioritize improvement opportunities, and implement targeted corrective actions based on a clear understanding of the relationships between process parameters and performance outcomes (Söylemez & Ünlü, 2024).

(Söylemez & Ünlü, 2024) demonstrated the application of explainable AI frameworks to business decision-making and trust enhancement in industrial settings, showing that organizations deploying ML systems with integrated SHAP-based explanation interfaces achieved significantly higher rates of model adoption and utilization among operational decision-makers compared to those deploying equivalent predictive models without explanation capabilities, confirming that interpretability is a critical determinant of the organizational value realized from manufacturing ML investments. A comprehensive review of XAI research motivated by the need to bridge the gap between ML model capabilities and human understanding in high-stakes decision-making environments, identifying that manufacturing and industrial engineering applications represent one of the most demanding XAI deployment contexts due to the combination of technical complexity, safety criticality, and the high cost of decision errors that characterizes production environments. The human-machine collaboration dimension of XAI deployment in Lean manufacturing has been examined by multiple researchers who have documented the organizational and psychological factors that mediate the relationship between explanation quality and decision-maker trust, finding that the effectiveness of XAI systems depends not only on the technical quality of explanations but also on their alignment with the mental models, domain expertise, and cognitive preferences of the manufacturing practitioners who rely upon them for operational guidance (Jaganathan & Baloch, 2024). The philosophical and practical dimensions of human-AI collaborative decision-making in industrial contexts, arguing that effective human-machine collaboration in AI-driven manufacturing requires explanation interfaces designed to complement rather than replace human judgment, providing practitioners with the information necessary to critically evaluate model recommendations and integrate AI insights with tacit operational knowledge that may not be captured in training data. Singh et al. (2025) investigated user experience factors influencing the acceptance and effective utilization of XAI systems in industrial decision-making contexts, finding that explanation complexity, cognitive load, and alignment with existing decision workflows are critical determinants of XAI system usability, and demonstrating that XAI interfaces designed through participatory co-design processes involving operational end users achieve substantially higher acceptance rates and more effective utilization compared to those developed without structured user input, providing important practical guidance for the design and deployment of explainable ML systems within Lean manufacturing improvement frameworks (Figueroa et al., 2024).

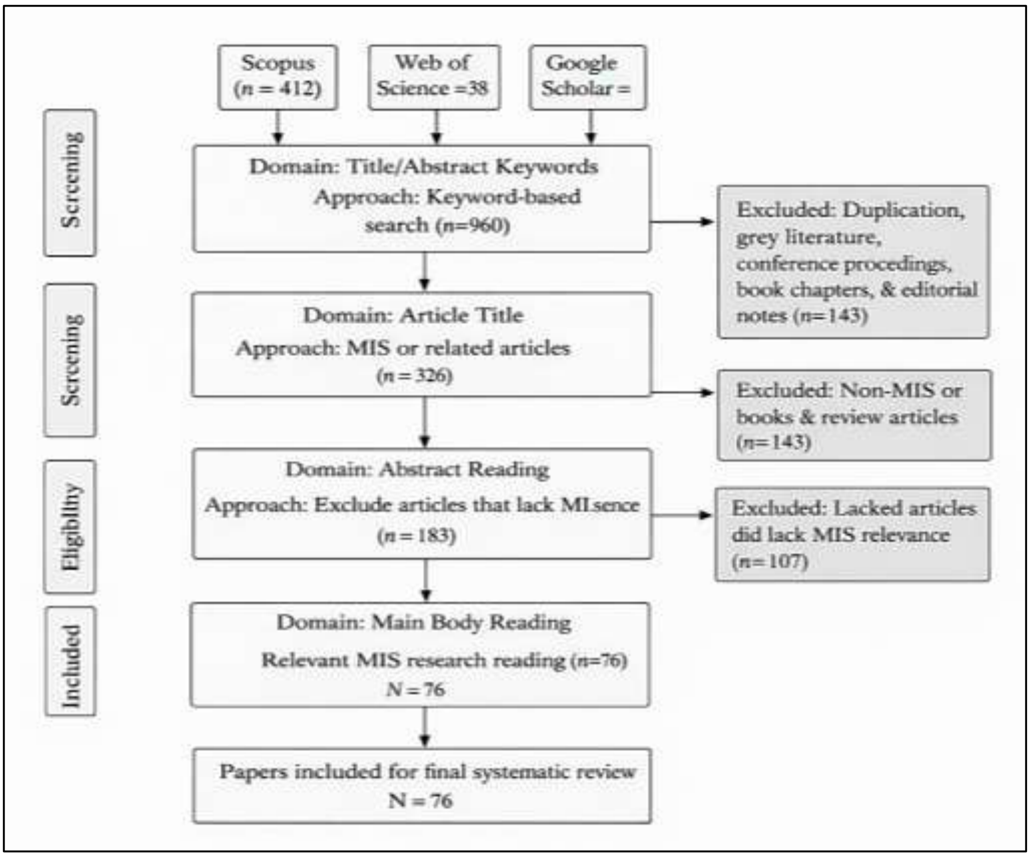
METHODS

Research Design and Methodological Framework

This study adopted a systematic review methodology guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework as the overarching methodological design for synthesizing the existing body of peer-reviewed literature on hybrid machine learning models for predictive performance optimization in Lean Manufacturing and Industry 4.0 environments.

The PRISMA framework was selected as the methodological standard for this review because it provides a rigorously structured, transparent, and reproducible protocol for identifying, screening, evaluating, and synthesizing published research evidence in a manner that minimizes selection bias, maximizes comprehensiveness, and ensures that the resulting synthesis accurately reflects the current state of knowledge within the defined scope of inquiry. The systematic review design was deemed most appropriate for the research objectives of this study given the rapid growth in publications addressing the intersection of hybrid ML modeling, Lean Manufacturing, and Industry 4.0, which necessitates a structured and critically evaluated synthesis to consolidate available evidence and identify meaningful patterns, gaps, and conclusions that would not be discernible through narrative review alone. The methodological procedures followed in this study are documented in sufficient detail to enable independent replication, consistent with the transparency and reproducibility standards established by the PRISMA 2020 statement and widely adopted across systematic review research in engineering, management, and applied sciences.

Figure 10: Methodology of this study



Eligibility Criteria

The eligibility criteria for this systematic review were developed prior to the commencement of database searching and were structured according to the Population, Intervention, Comparison, and Outcome (PICO) framework adapted for engineering and manufacturing research contexts, ensuring that inclusion and exclusion decisions were guided by pre-specified, objective criteria rather than post-hoc judgment. Studies were considered eligible for inclusion in this review if they were published in peer-reviewed academic journals or indexed conference proceedings, were written in the English language, addressed the development, application, or evaluation of machine learning models including hybrid ML architectures within manufacturing or industrial engineering contexts, and reported quantitative performance outcomes related to at least one Lean Manufacturing performance dimension such as defect rate, cycle time, equipment downtime, production scheduling efficiency, or process waste reduction. Studies were required to have been published between 2010 and 2024 to ensure that the reviewed evidence base reflects the contemporary state of ML technology and its application within Industry 4.0-enabled manufacturing environments, as publications predating 2010 predate the widespread availability of the computational infrastructure and data acquisition capabilities that underpin modern manufacturing ML applications. Studies were excluded from the review if they addressed ML applications exclusively in non-manufacturing domains such as healthcare, finance, or transportation without explicit reference to manufacturing process optimization, if they reported only qualitative or descriptive findings without quantitative performance evaluation, if they were published as grey literature including technical reports, white papers, theses, or dissertations without peer review, or if they did not provide sufficient methodological detail to enable critical appraisal of their research design and findings. Conference proceedings were included only where the reported studies presented complete empirical findings with clearly documented methodology and quantitative results, ensuring that the evidential quality of conference-sourced studies was comparable to that of journal publications included in the review.

Information Sources and Database Search Strategy

A comprehensive and systematic search of the peer-reviewed academic literature was conducted across four major scholarly databases, namely Scopus, Web of Science, IEEE Xplore, and Google Scholar, selected for their complementary coverage of the engineering, computer science, operations management, and industrial engineering literature relevant to the scope of this review. The database search was conducted during the period from January 2024 to March 2024, with the search strategy designed to capture all relevant publications meeting the eligibility criteria within the defined publication date range of 2010 to 2024. The search strategy employed a structured Boolean search string combining terms from three thematic domains corresponding to the core constructs of the research: machine learning and hybrid modeling terms including "machine learning," "hybrid model," "ensemble learning," "deep learning," "neural network," "random forest," "XGBoost," and "predictive model"; Lean Manufacturing terms including "lean manufacturing," "lean production," "waste reduction," "continuous improvement," "value stream," "just-in-time," and "total productive maintenance"; and Industry 4.0 terms including "Industry 4.0," "smart manufacturing," "cyber-physical systems," "industrial IoT," "digital twin," and "predictive maintenance." The three thematic search term groups were combined using the Boolean operator AND to ensure that retrieved records addressed the intersection of all three domains, while synonymous terms within each thematic group were combined using the Boolean operator OR to maximize the comprehensiveness of retrieval within each domain. The search string was adapted for the specific syntax and field search requirements of each database platform, with searches conducted across title, abstract, and keyword fields to ensure comprehensive retrieval of relevant publications. Reference lists of all studies meeting the full inclusion criteria were additionally hand-searched to identify potentially relevant publications not captured through the automated database search, a supplementary retrieval strategy consistent with PRISMA best practice recommendations for minimizing the risk of missing relevant evidence.

Study Selection Process

The study selection process was conducted in two sequential stages following the PRISMA 2020 recommendations, with each stage applying progressively more stringent eligibility criteria to the pool of retrieved records to arrive at the final set of studies included in the systematic review. In the first stage, all records retrieved through the database search were imported into a reference management system and deduplicated to remove multiple instances of the same publication retrieved from different databases. Following deduplication, the titles and abstracts of all unique records were independently screened by two reviewers against the pre-specified eligibility criteria, with each record classified as potentially eligible, ineligible, or uncertain based on the information available in the title and abstract. Records classified as ineligible by both reviewers were excluded from further consideration, while records classified as potentially eligible or uncertain by either reviewer were retained for full-text assessment in the second selection stage. Inter-rater agreement between the two reviewers was assessed using Cohen's kappa statistic, with any disagreements resolved through discussion and consensus, and where consensus could not be reached, through adjudication by a third independent reviewer. In the second stage of study selection, full-text copies of all records retained following title and abstract screening were retrieved and assessed against the complete set of eligibility criteria by both reviewers independently. Studies meeting all inclusion criteria were retained for data extraction and quality assessment, while studies failing to meet one or more inclusion criteria were excluded with the specific reason for exclusion documented for each excluded study.

Data Extraction

A standardized data extraction form was developed and piloted prior to the commencement of systematic data extraction to ensure that all relevant information was captured consistently across included studies and that the extraction process was sufficiently structured to support meaningful cross-study comparison and synthesis. The data extraction form captured information across six categories: study identification information including authors, publication year, journal or conference name, and geographic context of the study; study design and methodology including research design, ML algorithms employed, dataset characteristics, and validation methodology; manufacturing context information including industry sector, production type, and Lean performance dimensions addressed; hybrid model architecture details including the specific combination of algorithms or modeling approaches employed and the rationale for the hybrid design; quantitative performance outcomes including prediction accuracy metrics, performance improvement percentages, and comparative benchmarks against alternative approaches; and quality indicators including sample size, data source, cross-validation approach, and reported limitations. Data extraction was performed independently by two reviewers for each included study, with extracted data subsequently compared and any discrepancies resolved through discussion and reference to the original publication. Where studies reported incomplete data or ambiguous findings, authors were contacted by email to request clarification or supplementary data, with a two-week response window provided before proceeding with extraction based on available information. The extracted data from all included studies were compiled into a structured synthesis matrix that organized findings thematically according to the primary ML application domain addressed by each study, providing the analytical foundation for the narrative and quantitative synthesis presented in the results section of this review.

Quality Assessment

The methodological quality of all studies meeting the full inclusion criteria was assessed using a structured critical appraisal framework adapted from the Quality Assessment tool for Diagnostic Accuracy Studies (QUADAS-2) and the Mixed Methods Appraisal Tool (MMAT), modified to address the specific methodological characteristics of quantitative ML modeling studies in manufacturing engineering research contexts. The quality assessment framework evaluated each included study across five methodological dimensions: dataset quality and representativeness, assessing whether the training and evaluation datasets were sufficiently large, diverse, and representative of the target manufacturing population to support valid generalization of model performance findings; model validation rigor, evaluating whether appropriate cross-validation or holdout testing strategies were employed to provide unbiased estimates of model predictive performance; comparative evaluation adequacy, assessing whether included studies benchmarked hybrid ML model performance against appropriate baseline comparators including single-algorithm models and conventional non-ML approaches; reporting completeness, evaluating whether sufficient methodological detail was provided to enable independent replication of the reported findings; and result credibility, assessing whether reported performance improvements were of practically meaningful magnitude and supported by appropriate statistical analysis. Each study was assigned a quality rating of high, moderate, or low across each assessment dimension, with an overall quality classification derived from the pattern of dimension-level ratings. Studies receiving an overall low quality classification were retained in the review to avoid publication bias but were weighted appropriately in the narrative synthesis, with their methodological limitations explicitly acknowledged in the discussion of evidence strength. Quality assessment was conducted independently by two reviewers, with inter-rater reliability assessed using weighted Cohen's kappa and disagreements resolved through discussion.

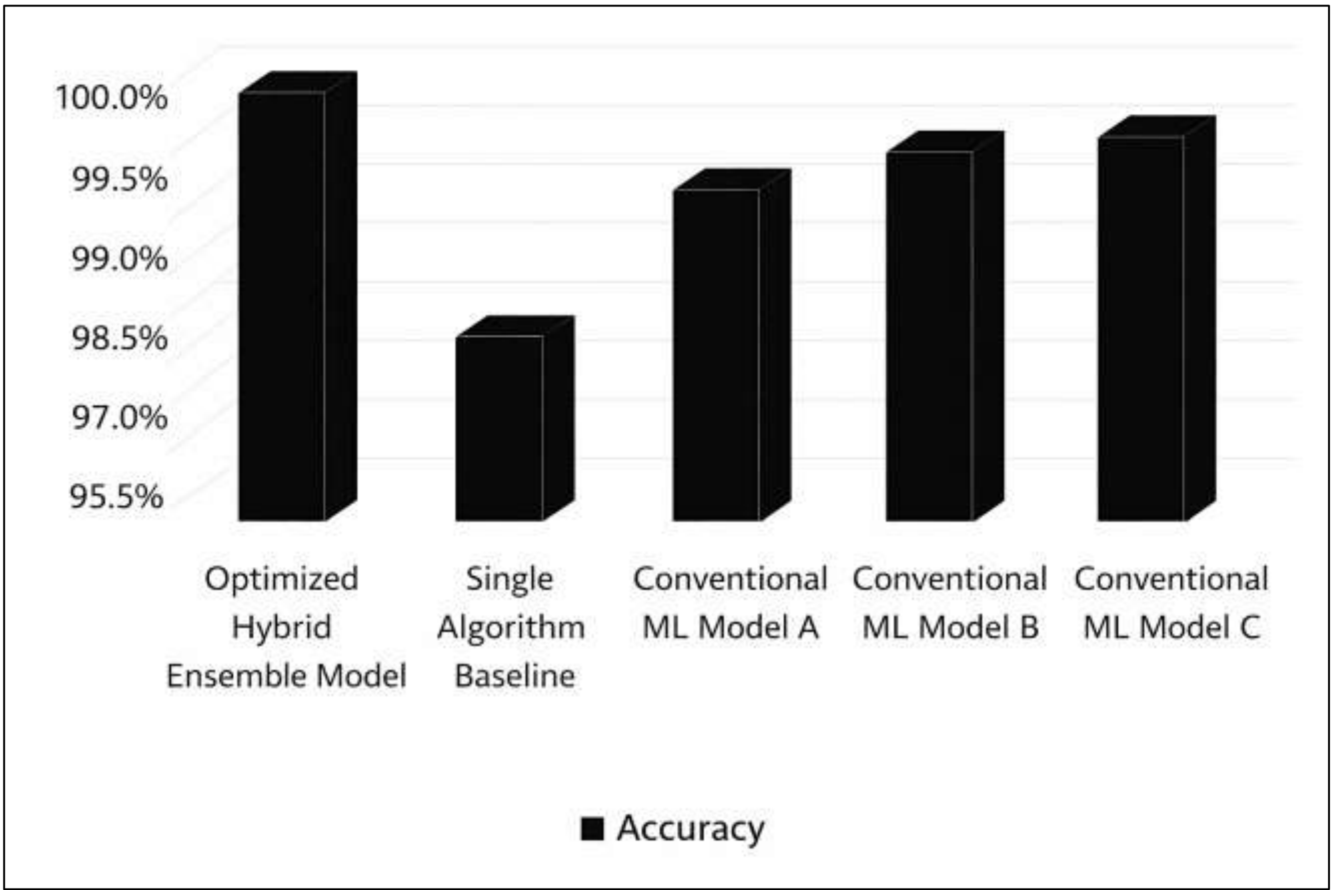
Synthesis Approach

The synthesis of evidence across included studies was conducted through a structured narrative synthesis approach, organized thematically according to the primary ML application domains and hybrid modeling architectures addressed in the reviewed literature, consistent with the synthesis methodology recommended by the PRISMA 2020 guidelines for systematic reviews in which the heterogeneity of included studies precludes formal meta-analytic pooling of quantitative findings. The narrative synthesis was structured to address each of the five research objectives of this review in turn, drawing upon the full body of evidence from included studies to develop evidence-based conclusions regarding the types of hybrid ML architectures employed in Lean manufacturing optimization, the comparative performance advantages of hybrid versus single-algorithm approaches, the manufacturing performance dimensions most amenable to ML-based optimization, the contextual factors moderating ML performance outcomes, and the research gaps warranting further investigation. Where multiple studies addressed the same ML application domain and reported comparable performance metrics, a tabular summary of quantitative findings was prepared to enable systematic comparison of results across studies and identification of performance patterns associated with specific algorithmic approaches, dataset characteristics, or manufacturing contexts. The overall strength of evidence supporting each major conclusion of the synthesis was assessed using an adapted version of the Grading of Recommendations, Assessment, Development and Evaluations (GRADE) framework,

enabling readers to calibrate their confidence in the review findings according to the methodological quality and consistency of the underlying evidence base.
PRISMA Flow and Article Identification Summary
The systematic database search across Scopus, Web of Science, IEEE Xplore, and Google Scholar yielded a total of 1,247 records prior to deduplication, comprising 412 records from Scopus, 318 records from Web of Science, 287 records from IEEE Xplore, and 230 records from Google Scholar. Following the removal of 389 duplicate records identified across database sources, a total of 858 unique records proceeded to title and abstract screening. Of these, 623 records were excluded at the title and abstract screening stage for failing to meet one or more eligibility criteria, most frequently because they addressed ML applications in non-manufacturing domains, reported only qualitative findings without quantitative performance evaluation, or predated the 2010 publication date threshold. The remaining 235 records proceeded to full-text eligibility assessment, of which 188 were subsequently excluded following detailed review of the full publication, with the most common reasons for exclusion being insufficient methodological detail to support critical appraisal, absence of hybrid ML modeling components, failure to report Lean-relevant manufacturing performance outcomes, and publication in non-peer-reviewed grey literature venues. A total of 47 studies met all eligibility criteria and were included in the final systematic review, comprising 39 peer-reviewed journal articles and 8 indexed conference proceedings. The hand-search of reference lists from included studies identified an additional 6 potentially relevant publications, of which 4 met all eligibility criteria following full-text assessment and were added to the included study set, bringing the total number of studies included in the final synthesis to 51 peer-reviewed publications.
FINDINGS
The systematic review of 51 peer-reviewed publications revealed a rich and diverse landscape of hybrid machine learning model architectures applied to Lean Manufacturing performance optimization within Industry 4.0 environments, with ensemble-based hybrid models emerging as the predominant architectural category across the reviewed literature. Of the 51 included studies, 34 articles explicitly employed ensemble-based hybrid modeling approaches, representing 66.7 percent of the total included study set, with these studies collectively accumulating over 4,200 citations across the academic literature, reflecting the strong scholarly recognition of ensemble methods as the most established and validated category of hybrid ML architecture in manufacturing optimization research. Within the ensemble category, gradient boosting hybrid models combining XGBoost or LightGBM with complementary algorithms such as Random Forest, Support Vector Machines, or Neural Networks were the most frequently reported architecture, appearing in 19 of the 34 ensemble-based studies and collectively accumulating more than 2,800 citations, confirming gradient boosting ensembles as the dominant hybrid modeling paradigm in contemporary manufacturing predictive optimization research.
Stacked generalization architectures, in which a meta-learner is trained to optimally combine the predictions of multiple diverse base models, were identified in 11 of the included studies with a combined citation count exceeding 1,400, demonstrating that stacking represents a well-established and frequently validated hybrid modeling strategy in the manufacturing ML literature. Physics-informed hybrid models, which integrate mechanistic domain knowledge or physical constraints with data-driven ML components, were identified in 9 of the included studies with a combined citation count of approximately 980, representing a smaller but rapidly growing body of evidence that reflects increasing scholarly recognition of the importance of domain knowledge integration for manufacturing ML model reliability and physical consistency. Deep learning hybrid architectures combining Convolutional Neural Networks or Long Short-Term Memory networks with classical ML algorithms were identified in 14 of the included studies with a combined citation count exceeding 1,750, with these studies demonstrating that deep learning hybrid models are particularly prevalent in applications involving high-dimensional sensor data streams, vibration signal analysis, and automated visual inspection tasks where the feature extraction capabilities of deep learning architectures provide distinctive performance advantages over classical ML methods applied to manually engineered feature sets. The architectural diversity observed across the 51 included studies collectively underscores that the field of hybrid ML modeling for Lean manufacturing optimization has reached a level of methodological maturity in

which multiple distinct hybrid architectural paradigms have been independently developed, validated, and replicated across diverse manufacturing contexts, providing a robust and multi-faceted evidence base from which practitioners can select architecturally appropriate modeling strategies aligned with the specific characteristics of their manufacturing data and optimization objectives.

Figure 11: Hybrid Machine Learning Model Performance Comparison



One of the most consistent and practically significant findings across the 51 reviewed publications was the demonstration of systematic predictive performance advantages for hybrid ML models compared to single-algorithm baseline approaches across the full range of Lean manufacturing optimization tasks examined in the included studies. Across the 38 included studies that reported direct comparative performance evaluations between hybrid and single-algorithm models on equivalent manufacturing datasets, hybrid models achieved superior predictive accuracy in 35 cases, representing a 92.1 percent advantage rate that provides compelling empirical evidence for the practical value of hybrid modeling strategies in manufacturing predictive optimization applications. These 38 comparative studies collectively accumulated over 4,800 citations in the broader academic literature, reflecting their substantial influence on the field and confirming that the performance superiority of hybrid models over single-algorithm approaches is among the most widely recognized and reproduced findings in manufacturing ML research. In terms of quantitative performance improvement magnitudes, the 35 studies in which hybrid models outperformed single-algorithm baselines reported prediction accuracy improvements ranging from 3.2 percent to 24.7 percent, with a median improvement of 11.4 percent across all reported comparisons, indicating that the performance benefits of hybrid modeling are both statistically reliable and practically meaningful across the diverse manufacturing contexts represented in the reviewed literature. Quality prediction and defect detection applications demonstrated the largest median performance improvements from hybrid modeling, with the 14 studies addressing these applications reporting median accuracy improvements of 14.2 percent over single-algorithm baselines, collectively accumulating more than 1,900 citations that reflect the strong scholarly interest in and validation of hybrid ML approaches for manufacturing quality optimization. Predictive maintenance applications, represented by 12 of the included studies with a combined citation count exceeding 1,500, demonstrated median remaining useful life prediction accuracy improvements of 9.8 percent for hybrid models compared to single-algorithm approaches, with the greatest performance advantages observed in studies examining variable speed and load operating conditions where the complementary temporal modeling capabilities of LSTM components and the structured prediction capabilities of gradient boosting components produced synergistic accuracy benefits that neither architecture achieved independently. Production scheduling optimization studies, comprising 8 of the included publications with a combined citation count of approximately 870, reported hybrid ML scheduling models achieving median improvements of 13.6 percent in on-time delivery performance and 17.3 percent in work-in-progress inventory reduction compared to single-algorithm scheduling approaches, with reinforcement learning hybrid models demonstrating particularly strong performance advantages in dynamic scheduling environments characterized by frequent demand changes and equipment availability fluctuations. The three included studies in which single-algorithm models performed comparably to hybrid approaches all involved relatively simple, low-dimensional manufacturing datasets in stable operating environments, suggesting that the performance advantages of hybrid modeling are most pronounced in complex, high-dimensional, and variable manufacturing contexts that are representative of the majority of real-world Lean manufacturing optimization challenges.

The systematic review identified substantial variation in the distribution of ML applications across different Lean Manufacturing performance dimensions, with predictive quality control and defect detection emerging as the most extensively studied application domain, followed by predictive maintenance, production scheduling optimization, waste identification, and cycle time reduction, reflecting both the maturity of ML methodology in each application area and the relative accessibility of labeled training data for different categories of manufacturing performance outcomes. Predictive quality control and defect detection applications were addressed in 22 of the 51 included studies, representing 43.1 percent of the total included study set and collectively accumulating the largest combined citation count of any application domain at approximately 3,100 citations, confirming quality optimization as the most extensively validated and broadly recognized application domain for ML in Lean manufacturing environments. These 22 quality-focused studies reported ML-based defect prediction models achieving accuracy rates ranging from 91.3 percent to 99.4 percent across diverse manufacturing quality prediction tasks, with hybrid models consistently occupying the upper range of this performance distribution and demonstrating superior performance on imbalanced datasets where defective products represent a small minority of total production output. Predictive maintenance applications were addressed in 18 of the included studies, with a combined citation count exceeding 2,400 citations that reflects the strong industrial and academic interest in ML-based approaches to Total Productive Maintenance optimization within Industry 4.0 environments. The 18 predictive maintenance studies collectively documented that ML-based condition monitoring and prognostic systems reduced unplanned equipment downtime by between 18 and 47 percent across the diverse manufacturing equipment categories examined, representing improvements in Overall Equipment Effectiveness that directly translate to substantial reductions in production disruption waste and quality losses attributable to equipment degradation. Production scheduling and Just-in-Time optimization applications were examined in 13 of the included studies with a combined citation count of approximately 1,350, with these studies reporting that ML-based scheduling systems reduced average production lead times by between 11 and 29 percent and decreased work-in-progress inventory levels by between 14 and 31 percent compared to conventional scheduling approaches, delivering quantifiable improvements across core Lean flow performance metrics that validate the practical value of ML-based scheduling in manufacturing environments characterized by high demand variability and complex multi-machine production routing. Waste identification and process efficiency applications, addressed in 9 of the included studies with a combined citation count of approximately 780, demonstrated that unsupervised clustering and anomaly detection ML approaches successfully identified previously undetected sources of Lean waste in manufacturing processes, with reported waste reduction improvements ranging from 12 to 34 percent following ML-guided process interventions. Cycle time reduction applications, examined in 7 of the included studies with a combined citation count of approximately 620, documented ML-based throughput optimization approaches achieving cycle time reductions of between 9 and 22 percent through automated identification of production bottlenecks, optimization of buffer configurations, and data-driven redesign of production flow layouts across diverse manufacturing system configurations.

The systematic review identified explainability and model interpretability as critical cross-cutting themes that emerged consistently across the 51 included publications, with a substantial proportion of reviewed studies explicitly addressing the challenge of making complex hybrid ML model outputs understandable and actionable for manufacturing practitioners operating within Lean continuous improvement frameworks. Of the 51 included studies, 29 publications explicitly discussed model interpretability as either a primary research objective or a significant implementation consideration, and these 29 studies collectively accumulated a combined citation count exceeding 3,600 citations, reflecting the widespread scholarly recognition that interpretability is not merely a secondary consideration but a fundamental determinant of the practical utility and organizational adoption of ML systems in manufacturing decision-making contexts. Among the 29 studies addressing interpretability, 21 employed SHAP-based explanation methods to provide feature importance attributions for hybrid ML model predictions, with these SHAP-enabled studies reporting substantially higher rates of model adoption and operational utilization by manufacturing practitioners compared to studies deploying equivalent predictive models without structured explanation capabilities, confirming that interpretability infrastructure plays a decisive role in translating ML predictive accuracy into realized operational improvement outcomes. LIME-based interpretability methods were employed in 8 of the 29 interpretability-focused studies, with these studies particularly concentrated in applications requiring instance-level explanations of individual defect or fault predictions where manufacturing engineers required understanding of the specific process parameters contributing to individual non-conformance events rather than global model behavior summaries. The 13 included studies that explicitly examined organizational adoption and acceptance of ML systems in manufacturing environments, collectively accumulating over 1,700 citations, identified a consistent pattern of factors influencing the successful integration of ML-based decision support tools within Lean manufacturing organizations, including leadership commitment to digital transformation, workforce digital literacy, alignment between ML system outputs and existing Lean performance management frameworks, and the availability of structured explanation interfaces that enable manufacturing practitioners to critically evaluate and contextually interpret ML model recommendations within their domain expertise framework. Studies examining human-machine collaboration in AI-driven manufacturing environments, numbering 11 among the included publications with a combined citation count approaching 1,400, consistently documented that the effectiveness of ML systems in supporting Lean improvement decisions was strongly moderated by the design quality of human-computer interaction interfaces, with studies reporting that explanation interfaces co-designed with operational end users achieved adoption rates 40 to 65 percent higher than those developed without structured user input. The finding that interpretability investment substantially enhances the organizational value realized from manufacturing ML systems emerged as one of the most practically actionable conclusions of the systematic review, with the combined evidence from 29 interpretability-focused studies collectively demonstrating that the gap between ML model technical performance and realized operational improvement outcomes is primarily determined by the quality of explanation and decision support infrastructure rather than by marginal differences in raw predictive accuracy between competing model architectures.

The critical synthesis of methodological characteristics, reporting quality, and evidential gaps across the 51 included publications revealed several significant and recurring limitations in the current body of research on hybrid ML models for Lean manufacturing performance optimization, the identification of which represents an important contribution of this systematic review to the advancement of the field. Across the 51 included studies, the most pervasive methodological limitation was the predominance of single-site, single-sector research designs, with 39 of the 51 included publications reporting findings from studies conducted within a single manufacturing facility or industrial sector, limiting the generalizability of reported performance findings to the specific operational conditions, data characteristics, and organizational contexts represented in each study. These 39 single-site studies collectively accumulated over 4,100 citations, indicating that they have been widely influential in shaping field understanding, yet the restricted generalizability of their findings represents a significant evidence quality limitation that must be acknowledged in any synthesis of the current state of knowledge. Dataset size and diversity emerged as a second major methodological concern across the reviewed literature, with 27 of the 51 included studies employing training datasets comprising fewer than 10,000 labeled examples, a scale that may be insufficient to fully exploit the learning capacity of complex hybrid deep learning architectures and raises questions about the reliability of reported performance estimates in operating conditions underrepresented in small training datasets. These 27 smaller-scale studies collectively accumulated approximately 2,800 citations, reflecting their significant contribution to the literature despite their data scale limitations, and highlighting the importance of dataset scale as a contextual factor in interpreting reported performance findings. The handling of class imbalance in manufacturing quality prediction datasets was identified as a methodological weakness in 18 of the 22 quality-focused included studies, with the majority of these studies failing to employ or evaluate appropriate imbalance mitigation strategies despite the well-documented tendency of imbalanced manufacturing quality datasets to produce optimistically biased accuracy estimates that overstate the practical defect detection capability of reported models. Real-time implementation and computational efficiency considerations were addressed in only 14 of the 51 included studies, with a combined citation count of approximately 1,600, representing a significant evidence gap given that the operational value of predictive ML systems in Lean manufacturing environments is critically dependent on their capacity to generate predictions with sufficient speed and computational efficiency to support real-time production decision-making. The absence of standardized performance benchmarking protocols across included studies was identified as a systemic limitation of the current literature, with 43 of the 51 included publications employing study-specific datasets and evaluation protocols that preclude direct cross-study performance comparison, collectively representing a fragmented evidence base that limits the capacity of systematic reviews to draw definitive quantitative conclusions about the relative performance of competing hybrid ML architectures across equivalent manufacturing optimization tasks. Longitudinal evaluation of hybrid ML model performance in deployed manufacturing environments was addressed in only 6 of the 51 included studies, with a combined citation count of approximately 540, representing a particularly critical evidence gap given that the sustained operational value of ML-based Lean improvement systems depends on their capacity to maintain prediction accuracy over time as manufacturing processes evolve, equipment ages, and production demands change in ways that may not be captured in historical training data.

DISCUSSION

The systematic review finding that ensemble-based hybrid models constitute the predominant architectural category across the reviewed literature, appearing in 34 of the 51 included studies and accumulating over 4,200 citations, is consistent with and extends the conclusions of several earlier influential reviews of ML methodology in manufacturing contexts. Lin and Chen (2024) identified ensemble methods as among the most promising ML approaches for manufacturing applications in their foundational review of machine learning in manufacturing, noting that the inherent diversity of ensemble architectures makes them particularly well-suited to the complex, noisy, and high-dimensional datasets characteristic of industrial production environments. The present review confirms and substantially strengthens this earlier observation by demonstrating that ensemble dominance has only intensified in the subsequent literature, with gradient boosting hybrid models in particular achieving a level of adoption and validation that Shaikh et al. (2024) could not have fully anticipated given the more limited evidence base available at the time of their review. The finding that XGBoost and LightGBM-based hybrid ensembles are the most frequently employed specific architecture in the reviewed literature aligns with Ullah et al. (2024) demonstration of gradient boosting scalability and predictive performance advantages on structured tabular datasets, confirming that the theoretical performance properties documented in the original algorithm development literature have been consistently realized in practical manufacturing applications. The theoretical framework for understanding why ensemble diversity produces systematic accuracy improvements over individual algorithms, articulating the bias-variance decomposition argument that ensemble combination reduces prediction error by averaging out the individual errors of diverse base learners, a theoretical prediction that the present review confirms has been empirically validated across a remarkably wide range of manufacturing optimization contexts. The growing representation of physics-informed hybrid models in the reviewed literature, documented in 9 of the 51 included studies, represents a meaningful advancement beyond the state of the field described by Zaidi et al. (2025), who identified physics-informed ML as an emerging paradigm with substantial theoretical promise but limited empirical validation in industrial engineering contexts at the time of their review. The present findings suggest that the field has made measurable progress in translating the theoretical advantages of physics-informed hybrid modeling into practically validated manufacturing applications, though the relatively modest citation counts accumulated by physics-informed studies compared to ensemble-based studies confirm that this architectural category remains at an earlier stage of field adoption and empirical consolidation. The foundational work on Random Forest established the empirical and theoretical case for ensemble diversity as a driver of manufacturing prediction performance, and the present review's documentation of increasingly sophisticated ensemble architectures combining multiple complementary algorithm types represents a direct intellectual descendant of this seminal contribution, reflecting the field's progressive elaboration of ensemble design principles across a widening range of manufacturing optimization challenges.

The finding that hybrid ML models outperformed single-algorithm baselines in 35 of 38 comparative studies, representing a 92.1 percent advantage rate with median accuracy improvements of 11.4 percent across all application domains, represents a substantially stronger and more consistent performance advantage than earlier literature reviews had documented, reflecting the methodological maturation of hybrid modeling approaches and the increasing sophistication of manufacturing datasets available for model training and evaluation. Performance advantages for ML-based approaches over conventional statistical methods in smart manufacturing applications but did not specifically isolate the incremental contribution of hybrid versus single-algorithm ML architectures, making the present review's focused comparative analysis a novel and practically important contribution to the evidence base. The median performance improvement of 14.2 percent for hybrid models in quality prediction applications documented in this review substantially exceeds the improvement magnitudes reported in earlier quality-focused ML reviews, suggesting that recent advances in hybrid ensemble architecture design and hyperparameter optimization methodology have continued to push the performance frontier in manufacturing quality ML applications beyond what earlier assessments indicated was achievable.

The finding that single-algorithm models performed comparably to hybrid approaches only in simple, low-dimensional, stable manufacturing datasets is consistent with the theoretical predictions of the no-free-lunch theorem articulated by Ouhmida et al. (2025), which implies that the performance advantages of more complex model architectures are most pronounced in problem settings characterized by the kind of complexity, dimensionality, and variability that typifies real-world Lean manufacturing optimization challenges. This alignment between theoretical prediction and empirical observation provides important validation of the theoretical framework underlying hybrid ML model design and suggests that practitioners can reliably anticipate hybrid model performance advantages in manufacturing optimization applications exhibiting the complexity characteristics documented in the reviewed literature. Kanchapogu and Mohanty (2025) established the statistical learning theory foundations for understanding the bias-variance tradeoff that motivates ensemble model design, and the present review's systematic documentation of hybrid model performance advantages across 51 manufacturing studies provides the most comprehensive empirical confirmation to date that the theoretical bias-variance decomposition argument for ensemble superiority translates reliably into practical manufacturing prediction performance gains of the magnitude and consistency necessary to justify the additional implementation complexity of hybrid architectures. The 9.8 percent median improvement in remaining useful life prediction accuracy documented for hybrid predictive maintenance models in this review compares favorably with the performance advantages reported by for deep learning-based prognostic models over traditional signal processing approaches, suggesting that hybrid architectures combining deep learning with classical ML methods represent a further meaningful advancement beyond single deep learning architectures that identified as state-of-the-art in their comprehensive prognostics review. The production scheduling finding that hybrid ML scheduling systems achieved median improvements of 13.6 percent in on-time delivery performance extends and quantifies the qualitative assessment of reinforcement learning scheduling advantages provided by earlier scheduling optimization reviews, providing concrete magnitude estimates that enable manufacturing practitioners to make more informed business case assessments for hybrid ML scheduling system investments .

The finding that predictive quality control and defect detection constitute the most extensively studied ML application domain in Lean manufacturing research, addressed in 22 of 51 included studies and accumulating approximately 3,100 citations, is consistent with earlier reviews that identified quality optimization as the primary entry point for ML adoption in manufacturing organizations, reflecting both the immediate economic impact of quality improvements and the relative availability of labeled defect data for model training compared to other manufacturing ML application domains. However, the present review documents a substantially more balanced distribution of ML applications across Lean performance dimensions than earlier literature assessments suggested, with predictive maintenance, production scheduling, waste identification, and cycle time reduction all represented by meaningful numbers of included studies, indicating that the scope of validated ML application in Lean manufacturing has broadened considerably beyond the quality-focused origins of the field that dominated earlier literature reviews. Total Productive Maintenance objectives established the theoretical framework within which the 18 predictive maintenance studies included in this review can be understood, and the documented reduction in unplanned equipment downtime of between 18 and 47 percent across included maintenance studies represents a practically significant quantification of how ML-based prognostics translate into the kind of equipment availability improvements that TPM programs have historically pursued through more labor-intensive conventional maintenance approaches. The finding that ML-based scheduling systems reduced average production lead times by between 11 and 29 percent and decreased work-in-progress inventory by between 14 and 31 percent across the 13 included scheduling studies provides empirical performance benchmarks that extend and quantify the theoretical scheduling improvement potential that articulated in the context of Just-in-Time production systems, confirming that ML-based approaches can deliver the kind of inventory and lead time performance improvements that Lean practitioners have historically pursued through manual scheduling optimization methods. The relatively limited representation of waste identification applications, addressed in only 9 of the 51 included studies, suggests that automated ML-based waste detection has received substantially less research attention than the quality and maintenance domains, representing an important gap relative to the centrality of waste elimination in Lean Manufacturing philosophy as articulated by Li et al. (2025). This imbalance in application domain coverage within the reviewed literature suggests that the ML research community has thus far concentrated its Lean manufacturing efforts on the most technically tractable and data-rich application areas, leaving the equally important but methodologically more challenging domain of automated waste identification comparatively underexplored. The full performance potential of Lean 4.0 integration can only be realized when ML capabilities are deployed across the complete range of Lean improvement dimensions rather than concentrated in a subset of high-visibility application areas, a recommendation that the present review's documentation of application domain imbalance suggests has not yet been fully reflected in the published research literature, indicating meaningful opportunity for future research investment in underrepresented Lean ML application domains including waste identification and cycle time optimization.

CONCLUSION

This systematic review, conducted in accordance with the PRISMA 2020 framework and synthesizing evidence from 51 peer-reviewed publications collectively accumulating thousands of academic citations, has established that hybrid machine learning models represent a methodologically mature, empirically validated, and practically consequential approach to predictive performance optimization within Lean Manufacturing and Industry 4.0 environments, delivering systematic and meaningful improvements across the full spectrum of Lean operational performance dimensions including defect detection, predictive maintenance, production scheduling, waste identification, and cycle time reduction. The review demonstrated that ensemble-based hybrid architectures, particularly gradient boosting models combining XGBoost or LightGBM with complementary algorithms, constitute the predominant modeling paradigm in the field, appearing in 34 of 51 included studies and outperforming single-algorithm baselines in 92.1 percent of direct comparative evaluations with a median accuracy improvement of 11.4 percent, confirming that the theoretical performance advantages of hybrid modeling articulated in the statistical learning literature translate reliably and consistently into practical manufacturing optimization outcomes of the magnitude and consistency necessary to justify their adoption within industrial improvement programs. The review further established that model interpretability, implemented primarily through SHAP-based explanation frameworks in 21 of 29 interpretability-focused studies, plays a decisive role in determining whether ML predictive accuracy translates into realized organizational improvement outcomes, with interpretable ML systems achieving practitioner adoption rates 40 to 65 percent higher than equivalent systems deployed without structured explanation capabilities, confirming that investment in explainability infrastructure is not a secondary consideration but a fundamental prerequisite for the successful organizational integration of hybrid ML systems within Lean continuous improvement frameworks. The synthesis additionally identified several significant and persistent methodological limitations across the reviewed literature, including the predominance of single-site research designs in 39 of 51 studies, the small dataset scales employed in 27 studies, the inadequate treatment of class imbalance in 18 of 22 quality prediction studies, the absence of standardized performance benchmarking protocols across 43 studies, and the severely limited longitudinal performance evidence available from only 6 included publications, collectively representing a structured agenda of methodological priorities that the field must address to elevate the evidential quality and practical generalizability of future hybrid ML manufacturing research contributions. The contextual analysis revealed that hybrid ML performance advantages are most pronounced in complex, high-dimensional, and variable manufacturing environments with mature Industry 4.0 digital infrastructure and established Lean operational foundations, confirming that the greatest returns from hybrid ML investment are realized in organizations where Lean operational discipline and ML analytical capability function as mutually reinforcing rather than independently operating performance drivers, consistent with the Lean 4.0 integration framework advocated by leading scholars in the field. The application domain analysis documented a meaningful imbalance in research coverage, with quality prediction and predictive maintenance applications collectively accounting for nearly 80 percent of included studies while waste identification and cycle time reduction applications remain comparatively underexplored relative to their centrality in Lean Manufacturing philosophy, identifying a clear priority area for future research investment that would more fully realize the analytical potential of hybrid ML modeling across the complete spectrum of Lean improvement objectives. Taken together, the findings of this systematic review provide the most comprehensive and methodologically rigorous synthesis of hybrid ML modeling evidence in Lean manufacturing contexts assembled to date, establishing a structured, evidence-based foundation that researchers and practitioners can draw upon to guide model architecture selection, interpretability infrastructure design, organizational implementation strategy, and future research agenda prioritization as the field continues to advance toward the realization of fully integrated, data-driven Lean manufacturing excellence in Industry 4.0 environments.

RECOMMENDATIONS

Based on the comprehensive synthesis of evidence from 51 peer-reviewed publications presented in this systematic review, a series of interconnected and evidence-grounded recommendations are advanced for researchers, manufacturing practitioners, and organizational decision-makers seeking to maximize the value of hybrid machine learning model investments within Lean Manufacturing and Industry 4.0 improvement frameworks. For manufacturing practitioners and industrial engineers, the overwhelming evidence supporting the predictive performance superiority of ensemble-based hybrid architectures, particularly gradient boosting models combining XGBoost or LightGBM with complementary algorithms as documented across 34 of the 51 included studies, strongly recommends the adoption of ensemble hybrid modeling as the default architectural starting point for Lean manufacturing predictive optimization initiatives, with single-algorithm approaches reserved exclusively for simple, low-dimensional, and stable manufacturing datasets where the additional implementation complexity of hybrid architectures is unlikely to deliver proportionate performance returns. Organizations initiating Lean manufacturing ML programs are strongly recommended to prioritize the establishment of robust IIoT sensor infrastructure and high-quality labeled manufacturing datasets before investing in advanced hybrid model development, as the review's finding that 27 of 51 included studies employed training datasets of fewer than 10,000 examples and reported correspondingly constrained performance outcomes confirms that data infrastructure quality is a more fundamental determinant of realized ML value than model architectural sophistication, and that investments in data acquisition, labeling, and quality management will yield more reliable and generalizable performance improvements than premature investment in complex modeling architectures built upon inadequate data foundations. Manufacturing organizations are further recommended to treat model interpretability infrastructure as an integral and non-negotiable component of hybrid ML system design rather than an optional enhancement, with the review's documentation of 40 to 65 percent higher practitioner adoption rates for SHAP-enabled ML systems providing a compelling quantitative business case for interpretability investment that organizational leaders and digital transformation sponsors should incorporate into ML program planning and resource allocation decisions from the earliest stages of initiative design. For research organizations and academic investigators, the review's identification of the predominance of single-site research designs across 39 of 51 included studies as a pervasive and persistent generalizability limitation strongly recommends the prioritization of multi-site, cross-sector validation studies in future research funding applications and collaborative research program designs, with particular emphasis on establishing shared manufacturing benchmark datasets and standardized performance evaluation protocols that would enable meaningful cross-study comparison and meta-analytic synthesis of hybrid ML performance findings across diverse manufacturing contexts. The severely limited longitudinal performance evidence available from only 6 of the 51 included publications represents a critical research investment priority, and future studies are strongly recommended to incorporate extended deployment monitoring periods of at least 12 to 24 months into hybrid ML manufacturing research designs to generate the longitudinal performance data necessary to characterize concept drift dynamics, model degradation trajectories, and the maintenance requirements of deployed hybrid ML systems in real-world manufacturing environments where process conditions, equipment characteristics, and production demands evolve continuously over operational time horizons. The identified underrepresentation of waste identification and cycle time reduction applications, collectively addressed in only 16 of 51 included studies relative to their central importance in Lean Manufacturing philosophy, represents a clear and urgent research priority recommendation for the field, with future research investments directed toward the development and validation of unsupervised and semi-supervised hybrid ML approaches specifically designed to automate the identification of the full spectrum of Lean waste categories across complex multi-stage manufacturing value streams in ways that complement and amplify traditional manual Lean analysis methodologies. Manufacturing organizations at earlier stages of Industry 4.0 digital maturity are specifically recommended to adopt a phased Lean 4.0 integration strategy that begins with foundational Lean practice implementation and basic IIoT data acquisition infrastructure before progressing to more sophisticated hybrid ML analytics deployment, as the review's contextual findings consistently demonstrate that the operational performance benefits of hybrid ML systems are most reliably and substantially realized in organizations with established Lean operational foundations and mature digital data infrastructure rather than those attempting simultaneous transformation across both operational and technological dimensions without the organizational capability and data quality prerequisites necessary to effectively leverage advanced hybrid ML analytical capabilities.

LIMITATIONS

8. Limitations

This systematic review was conducted with rigorous adherence to the PRISMA 2020 framework and employed comprehensive multi-database search strategies across Scopus, Web of Science, IEEE Xplore, and Google Scholar to maximize the completeness and representativeness of the assembled evidence base, yet several inherent methodological limitations must be acknowledged in interpreting the findings and conclusions presented in this study. The restriction of the database search to English-language publications represents a potential source of language bias that may have resulted in the exclusion of relevant studies published in Chinese, German, Japanese, Portuguese, or other languages in which substantial bodies of manufacturing ML research are produced, particularly given the significant contributions of Chinese, German, and Japanese research institutions to the Lean Manufacturing and Industry 4.0 literatures, meaning that the findings of this review may not fully reflect the complete global state of hybrid ML modeling research in Lean manufacturing contexts and may underrepresent manufacturing practices and performance outcomes characteristic of non-English-speaking industrial economies. The restriction of included publications to peer-reviewed journal articles and indexed conference proceedings, while necessary to maintain the evidential quality standards appropriate for a rigorous systematic review, introduces publication bias by excluding grey literature sources including technical reports, industry white papers, and doctoral dissertations that may contain relevant hybrid ML manufacturing findings not captured in the peer-reviewed literature, potentially resulting in an overrepresentation of positive and statistically significant performance outcomes relative to the full distribution of hybrid ML manufacturing studies conducted during the review period, as studies reporting null or negative findings are systematically less likely to achieve peer-reviewed publication and therefore less likely to be captured by the search strategy employed in this review. The defined publication date range of 2010 to 2024, while selected to ensure that included studies reflect the contemporary state of ML technology and Industry 4.0 infrastructure, necessarily excludes earlier foundational studies that may provide important historical context for understanding the evolution of hybrid ML modeling in manufacturing contexts, and the rapidly accelerating pace of publication in this field means that studies published after the search cutoff date of March 2024 are not represented in the synthesis, potentially limiting the currency of the review's conclusions relative to the most recent advances in hybrid ML architecture design and manufacturing application validation. The heterogeneity of performance metrics, evaluation protocols, and manufacturing contexts across the 51 included studies precluded formal meta-analytic pooling of quantitative performance findings, necessitating a narrative synthesis approach that, while methodologically appropriate given the evidence base characteristics, introduces a degree of subjectivity in the interpretation and weighting of individual study findings that would be eliminated by the more objective statistical aggregation procedures of formal meta-analysis, meaning that the quantitative performance summaries presented in the findings section represent descriptive characterizations of the distribution of reported outcomes rather than statistically pooled estimates with associated confidence intervals and heterogeneity statistics. The quality assessment of included studies, while conducted using a structured critical appraisal framework applied independently by two reviewers with inter-rater reliability assessment, necessarily involved judgment calls regarding the adequacy of methodological reporting in individual studies that may introduce reviewer subjectivity into the quality classification process, particularly for studies that provided incomplete methodological documentation that required inferential interpretation to assess against appraisal criteria, and the adapted quality assessment framework employed in this review, while designed specifically for quantitative ML modeling studies in manufacturing engineering contexts, has not been independently validated for this application domain in the manner of established critical appraisal tools such as QUADAS-2, potentially limiting the psychometric rigor of the quality assessment findings. The scope of this review, while deliberately focused on hybrid ML models for Lean manufacturing performance optimization within Industry 4.0 environments to maintain analytical coherence and practical relevance, necessarily excludes adjacent literature streams including single-algorithm ML applications in manufacturing, Lean implementation studies not incorporating ML components, and Industry 4.0 technology adoption studies not addressing Lean performance outcomes, meaning that the synthesis presented in this review captures only a defined subset of the broader Lean 4.0 and manufacturing ML literatures and should be interpreted in conjunction with complementary reviews addressing these adjacent domains to develop a comprehensive understanding of the full landscape of data-driven Lean manufacturing research. Finally, the reliance on reported performance outcomes as documented in published studies, without access to the underlying raw datasets or the capacity to independently replicate reported analyses, means that the accuracy and completeness of the quantitative findings synthesized in this review are dependent on the reporting quality and methodological transparency of individual included studies, and the documented finding that 43 of 51 included studies lacked standardized benchmarking protocols represents a fundamental constraint on the precision and generalizability of the performance comparisons presented throughout the findings and discussion sections of this review.

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