ACADEMIC SCIENCE PRESS

INTERNATIONAL JOURNAL OF DIGITAL ENGINEERING, ARCHITECTURE AND TECHNICAL SCIENCES
ISSN: 3143-6064

Digital Twins, AI, Blockchain, and Lean Six Sigma in Manufacturing: Strategies for Operational Excellence and Bottleneck Reduction

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ARTICLE INFO

Keywords:
Digital Twins, Artificial Intelligence, Blockchain Technology, Lean Six Sigma, Bottleneck Reduction.

Vol.01, **No**.05, 2026

https://doi.org/10.5281/zenodo.23805753

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ABSTRACT

Digital twins (DTs), artificial intelligence (AI), blockchain, and Lean Six Sigma (LSS) provide a holistic solution for enhancing operational excellence and minimizing bottlenecks in the context of Industry 4.0 manufacturing systems. In this study, the technologies are analyzed and discussed with regard to their integration to improve production monitoring, predictive maintenance, production process optimization, quality management and supply chain traceability. Digital twins create real-time virtual models of physical assets and manufacturing systems, and AI-based algorithms make it possible to detect anomalies, predict outcomes and make intelligent decisions. The secure transaction records and automated compliance mechanisms introduced by blockchain enhance data integrity, transparency, and accountability. Lean Six Sigma complements these technologies by systematically eliminating waste, reducing process variation and continuously improving processes. Applications of engineer to order, make to order, assemble to order and make to stock manufacturing strategies are covered with an emphasis on capacity planning, decoupling points, buffer management and constraint identification. In addition to these, manufacturing execution systems and discrete event simulation aid in the identification and measurement of bottlenecks, including throughput, cycle time and Equipment Effectiveness. The practical aspects of implementation that need to be addressed include interoperability, data quality, cyber security, model validation, scalability, and human supervision, especially in legacy-based facilities. A phased adoption strategy beginning with high value pilot applications, followed by ongoing validation and expansion is recognized as a viable adoption approach. In general, the integrated framework has the promise of increasing manufacturing productivity, product quality, operational resiliency and transparency of the supply chain.

1. Introduction

Industry 4.0 is a revolution in manufacturing, in which intelligent digital technologies, data-driven decision making and automated production processes have entered the domain. Smart manufacturing integrates digital twins (DTs), artificial intelligence (AI), blockchain, IIoT, and Lean Six Sigma (LSS) to boost productivity, product quality, operational efficiency and sustainability [1]. These technologies help to make systems more connected, adaptive and responsive to varying market demands. Digital twins are virtual copies of physical machines, manufacturing processes and manufacturing systems. Digital twins enable ongoing monitoring, predictive performance, fault diagnosis and scenarios testing by incorporating real-time sensor data along with simulation and analytical models. AI improves these uses with its pattern recognition, anomaly detection, predictive maintenance, intelligent scheduling and autonomous optimization [2]. With the help of smart contracts and data that is impossible to tamper with, blockchain ensures data integrity, traceability and transparent information exchange. Lean six Sigma, however, offers a structured approach to reduce process variation, improve quality, eliminate waste, and find production constraints. These technologies are integrated together and allow for operational excellence to be achieved for all manufacturing strategies, such as engineer to order, make to order, assemble to order and make to stock. There are different inventory management, production planning, lead time and customer responsiveness requirements in each of these strategies [3]. The decoupling point is the point at which the activities of a production method change from forecast driven to demand driven. The reliable replenishment, adequate safety stock and coordination of capacity

planning are essential for managing these points. Implementing digital monitoring and predictive analytics helps to recognize emerging constraints, ensure production flow, and minimize delays in the interconnected process. One of the primary goals of smart manufacturing is to reduce the bottlenecks. Constraints can include insufficient machine capacity, machine failure, delays in inspection, inefficient workflows or lack of skilled workers [4]. The digital twin and AI tools can detect peaks and valleys, predict possible disruptions, and simulate future production scenarios to prevent issues before they become problematic. Lean Six Sigma adds to these abilities by using systematic problem solving and ongoing improvements to resolve the root cause and maintain the improvements. While these benefits are compelling, the implementation is complex due to issues with data quality, interoperability, latency, cybersecurity, and the challenge of understanding AI-based decisions [5]. Scalability of the blockchain and the reliability of predictive models are also issues that needed to be addressed. Inter-operability and information exchange can be enhanced with standards such as OPC UA and MTConnect, semantic data models and modular architectures. Ultimately, implementing the right technology, conducting clear governance, training staff and constantly assessing performance is essential to a successful integration. Digital twins, artificial intelligence, blockchain and lean six sigma create a seamless solution to enhance manufacturing resilience, traceability, throughput and future operational performance [6].

Digital Twin Enabled Manufacturing Strategies and AI Driven Operational Optimization

Digital twin is a manufacturing technology that combines real-time monitoring, simulation, artificial intelligence (AI) and data-driven decision making to enhance the efficiency, quality of products and reliability of the production process. Digital twins are virtual copies of physical items, processes, and manufacturing systems which can be used to evaluate system performance, identify faults, make predictions and simulate scenarios, without impacting any real systems [7]. Implementation is frequently rolled out first with the more valuable or important parts of the production process, and then on a wider scale of the production line and/or facilities to show tangible gains and to ensure that shop floor operations are linked to enterprise goals. Developing a digital twin is a process that must involve data from sensors, programmable logic controllers, supervisory control and data acquisition systems, manufacturing execution systems, enterprise resource planning systems, maintenance, and quality management databases. The ability to simulate manufacturing conditions and to make informed decisions is further improved by engineering drawings, physical models [8], AI algorithms, and three dimensional visualizations. All these capabilities enable predictive maintenance, quality control, product design optimization, energy management, and production planning. Shop floor digital twins are concerned with the performance of the shop floor, while enterprise digital twins are involved in coordinating between various facilities, departments and supply networks. Virtual validation also enables proposed changes to be assessed before putting them into effect, minimising operational risks, avoid unnecessary investment, and redesign. These strategies are supported by AI's ability to detect bottlenecks in real time, perform root cause analysis, use predictive modelling, and automate workflow coordination [9]. Operational records, such as technical specifications, inspection reports, bills of material, maintenance logs, etc. are relevant and can be used to identify the causes of delays and appropriate action. AI systems can come up with insights about equipment failures, inspection queues, material shortages, labour constraints, and information delays. Automated agents can help coordinate the corrective action that has been approved, but for safety, financial, contractual and delivery risks, human supervision is still necessary. Overall Equipment Effectiveness (OEE) is one way of measuring operational performance by combining the three components of availability, performance and quality [10]. But, each part needs to be analyzed as well since what may appear as a positive change in one area can be a negative change in another. Throughput, cycle time, queue length, completed production, and first pass quality are complementary indicators of the effectiveness of bottle neck interventions in yielding sustained improvement. Standardized downtime classification also aids in root cause analysis by differentiating equipment failures, material shortages, labour constraints and work delays, and environmental issues. Predictive maintenance models rely on equipment condition information, past experience, and sensor measurements to predict potential failures before they happen and disrupt

production [11]. Computer vision can be used along with traditional telemetry to recognize workstation states, as well as cycle time and work-in-progress.

Blockchain Applications in Manufacturing Performance Systems

Blockchain technology facilitates the manufacturing performance system by providing greater traceability, transparency, data integrity, and compliance with regulations in complex supply chains. Secure, distributed records enable tracking of product movements and transactions from sourcing raw materials to distribution of finished goods [12]. This visibility allows for quicker detection of quality issues, more precise product recalls and less impact on production processes. As a result, traceability with blockchain enhances operational resilience, supplier accountability and reliable performance management. Smart contracts also enhance manufacturing governance by automating specific actions that take place when certain conditions are met. These actions can include quality verification, certification checks, compliance notifications, and recall procedures [13]. Automated workflows can help to decrease administrative load, eliminate human mistakes, and enhance audit readiness. When blockchain is combined with the current evaluation systems, it is capable of ensuring traceability and allowing for ongoing optimization, quality control and evidence-based decision making. From manufacturing in the automotive industry to the food and beverage industry, blockchain traceability has shown potential in a variety of sectors. Immutable transaction records can aid in the verification of components' origins, movements, and the detection of counterfeit parts in automotive manufacturing. Similar systems can be utilized for establishing product authenticity and verifying details from suppliers by electronics manufacturers. Traceability logs are used in the food and beverage industry to track the origins of ingredients, the processing history of the product, and its adherence to the safety standards [14]. These help to make things clearer, and allow stakeholders to research discrepancies and narrow down the list of affected products. ERP, manufacturing execution system, warehouse management, transportation management and quality management systems can be integrated into blockchain platforms (Table 1). The integration helps authorized persons to get data on forward and backward traceability on interconnected supply networks. Consumer interfaces, such as QR codes, can also be used to verify the origin and distribution history of products via product histories [15]. These can boost consumer confidence, minimize the amount of labour needed to conduct traceability investigations and enhance the accuracy of product recalls. However, for effective implementation, interoperability, data entry reliability, cyber security, governance structures, and access control are critical. Blockchain does not automatically ensure accuracy of data added to the system, and the incorporation of legacy systems can be costly and technically challenging. Therefore, a careful system design is needed to consider the transparency, confidentiality, scalability, and operational efficiency [16]. With digital twins, AI and Lean Six Sigma, blockchain can offer a trustworthy information base for identifying bottlenecks, moving faster to correct them, enhance supplier performance, and keep continuous improvement going throughout manufacturing networks.

Table 1: Mapping Industry 4.0 Technologies and Lean Six Sigma to Manufacturing Core Capabilities

Technology	Primary Operational Role	Bottleneck & Waste Elimination Impact	Reference
Digital Twins (DT)	Real-time virtual representation, physics-based simulation, & multi-facility scenario testing	Detects throughput peaks/valleys, models process constraints, and validates layout changes virtually	[1], [7], [8], [22], [33]
Artificial Intelligence (AI)	Pattern recognition, anomaly detection, autonomous scheduling, & computer vision analysis	Predicts equipment failure, optimizes inspection queues, and mitigates material/labor shortages	[2], [9], [11], [34], [35]
Blockchain Technology	Immutable ledger transactions, smart contract	Eliminates administrative delays, prevents counterfeit	[12]–[16]

	execution, & supplier verification	parts, and streamlines compliance workflows	
Lean Six Sigma (LSS)	Structured process variation reduction, waste elimination, & root-cause problem solving	Removes non-value-added activities, stabilizes process yields, and resolves systemic flow constraints	[17], [18], [21]
Integrated Framework (DT + AI + Blockchain + LSS)	End-to-end digital optimization, automated auditability, & resilient manufacturing control	Maximizes Overall Equipment Effectiveness (OEE), accelerates cycle times, and prevents bottleneck recurrence	[23], [26], [32], [41]

Lean Six Sigma Implementation in High Tech Manufacturing Environments

Lean Six Sigma (LSS) is a systematic methodology for enhancing the efficiency of operations, minimize process variations and eliminate waste in high tech manufacturing. Lean thinking methods, which focus on ensuring that manufacturing has optimal flow of materials and waste are being minimized, in addition to utilizing Six Sigma methods for data driven problem solving, can benefit manufacturing organizations to increase throughput, product quality, equipment effectiveness and production reliability (Table 2) [17]. Such enhancements are especially significant in complex manufacturing systems with highly linked processes, demanding quality standards, and time-sensitive production schedules that could impact the value chain as a whole. The Theory of Constraints (TOC) can help implement LSS by pinpointing the process or piece of equipment that has the greatest impact on a system's overall production rate. Prioritization of improvement activities is done around this constraint to ensure that the available resources are maximised. After the constraint is enhanced, the production system is reassessed to find new constraints. This is an iterative process so that the efforts required for improvement are not spread amongst low priority activities, and the benefits in terms of performance gain are maintained [18]. Organized production areas and standard operating procedures are provided by the visual management, 5S and standardized work (Figure 1). Clear working procedures, easily achievable performance indicators and task sequences allow operators to recognize deviations in a timely manner and avoid unnecessary error. These practices are complimentary to six sigma methods and help achieve more consistency in the process and reduce the root causes of defects in high precision manufacturing. The flow of production can be managed using Kanban systems and line control techniques which coordinate the flow of materials with actual requirements and constraint capacities [19]. These practices help minimise excess work in progress, prevent material build up and facilitate faster lead times. The Total Productive Maintenance (TPM) serves to increase equipment reliability through systematic maintenance activities, and Single Minute Exchange of Die (SMED) is a technique used to lower the setup and change over time. These approaches will help maximize equipment availability, enhance production flexibility and minimize downtime for maintenance or even for transitioning between products [20]. The use of digital technologies also contributes to the implementation of LSS in advanced manufacturing. Digital twins are used for virtual testing of process changes, and artificial intelligence for real-time monitoring, anomaly detection, predictive maintenance, and performance analysis. However, for effective implementation, the availability of reliable data, participation of employees, standard procedures, and performance monitoring are required. Combining Lean Six Sigma with digital twins and AI provides a continuous improvement process that boosts manufacturing strength, minimizes waste, accelerates the lead time, and ensures operational excellence [21].

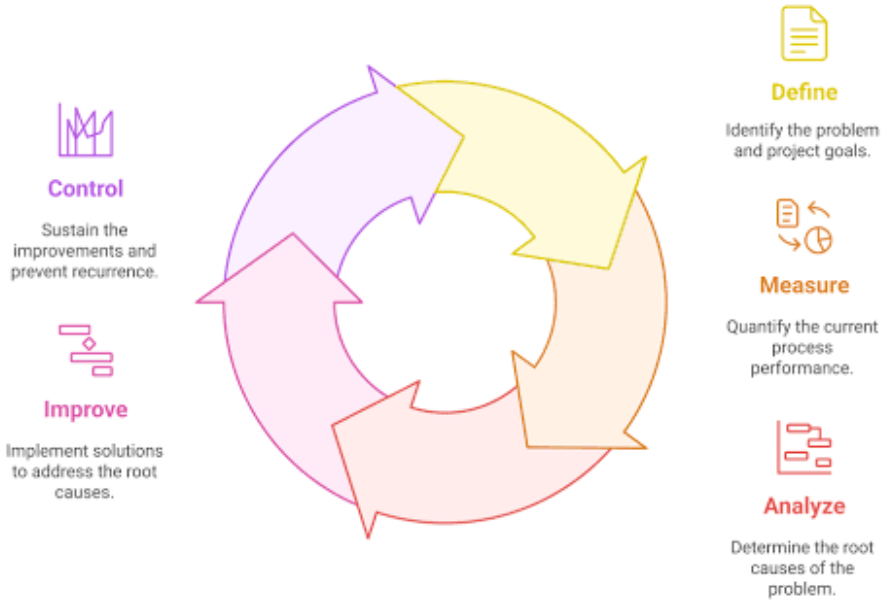

Figure 1. The DMAIC Cycle in Manufacturing [42]

Table 2: Manufacturing Execution Strategies, Constraint Characteristics, and Mitigation Techniques

Manufacturing Strategy	Demand Decoupling Point & Planning Drivers	Digital Twin, AI, & LSS Mitigation Interventions	Reference
Engineer to Order (ETO)	Design phase (forecast-driven engineering to custom order execution)	Critical path tracking, AI capacity forecasting, and virtual modeling of engineering workflows	[3], [23], [39]
Make to Order (MTO)	Raw material inventory (production initiated upon confirmed customer order)	Single Minute Exchange of Die (SMED), rapid order scheduling, & real-time queue tracking via MES	[3], [20], [40]
Assemble to Order (ATO)	Sub-assembly / Component buffer (assembly initiated upon order receipt)	Buffer management, Kanban pull control, real-time replenishment tracking, & line balancing	[3], [19], [24], [40]
Make to Stock (MTS)	Finished goods inventory (forecast-driven high-volume production)	AI demand forecasting, predictive maintenance, Total Productive Maintenance (TPM), & LSS yield optimization	[3], [20], [25], [40]
Cross-Domain / Legacy Systems	Edge sensor integration & hybrid physics-ML data modeling	Industrial IoT retrofit, edge computing, MQTT/OPC UA middleware, & discrete event simulation (DES)	[27]–[31]

Integrated Framework for Lean Six Sigma, and Manufacturing Bottleneck Reduction

Combining the four technologies – digital twins, artificial intelligence (AI), blockchain and Lean Six Sigma (LSS) – offers a comprehensive approach for using digital technologies to boost manufacturing performance, operational excellence and bottleneck management. Digital twins provide real-time simulation of physical assets, production processes, and supply networks, which allows them to be monitored, analyzed, and simulated throughout the production process [22]. AI improves these capabilities by analyzing patterns, detecting anomalies, optimizing processes, and making intelligent decisions. Lean Six Sigma facilitates a systematic approach to waste removal, variability reduction and

continuous improvement; blockchain enhances data integrity, traceability and accountability by ensuring secure data and automated compliance processes. The reduction strategies for bottlenecks should also take the nature of the various manufacturing systems into consideration [23]. When building in engineer to order environments, products are designed to individual customer needs and early engineering coordination, capacity planning, and finding a critical path are essential. By tracking engineering activities, supplier lead times and work in progress, delays during the production process are avoided. Digital twins can model different processes, AI can help optimise resources and capacity planning can benefit from early warnings of capacity issues (Figure 2). Assemble to order manufacturing involves using standardised parts and putting them together into finished products when you get an order [24]. Having an adequate inventory of components and not running out of parts on the assembly line are key factors to being efficient. Digital monitoring is used for replenishing components, prioritizing assembly work and managing buffers which helps production systems to meet changing customer demands while keeping down delays. Make to stock manufacturing is focused on production based on forecast and ensuring stock is available. To reduce bottlenecks, reliable forecasting is needed, coordinated capacity planning and controlled work-in-progress around bottlenecks [25]. Digital twins can test production scenarios and AI can fine-tune schedules and spot new inefficiencies. Lean Six Sigma can help ensure consistent output, minimize defects, and promote continuous improvement, and blockchain can help to enhance material transparency and chain transparency. In all four manufacturing strategies, machine state monitoring, queue analysis, cycle time measurement and Equipment Effectiveness (OEE) evaluation can be used to assist with the identification of constraints in manufacturing execution systems and discrete event simulation [26]. When combined with digital twins, AI, blockchain, and Lean Six Sigma, these techniques can be used together to optimize the process of bottleneck elimination, production flow, product traceability, and the maintenance of efficient manufacturing processes, all while ensuring they are responsive and resilient.

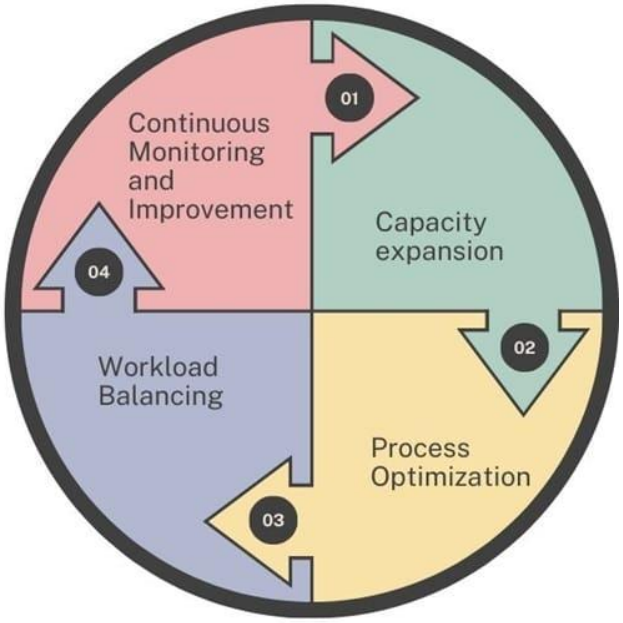

Figure 2. Key Strategies for Managing and Reducing Manufacturing Bottlenecks [43]

Cross Domain Strategies and Practical Applications of Digital Twins and AI

Bottleneck management should be achieved through coordinated strategies that take into account the production constraints, process variability and interdependencies. The use of decoupling points and strategically placed buffers to buffer constrained operations from external shocks upstream and downstream. Manufacturing execution systems (MES) help with this process by gathering machine states, production events, work in progress and performance indicators, allowing for bottlenecks to be identified in a timely fashion [27]. Planning can also be facilitated by discrete event simulation (DES) to model production dynamics, assess cycle time variability and test alternative interventions before implementation. Constraints often change after improvements are made, so ongoing measurement and

reassessment is required to maintain throughput improvements. Corrective actions need to be taken to address root causes and not just increase labour and equipment without addressing scheduling or quality or workflow issues [28]. Digital twin and artificial intelligence deployments prove the power of data driven solutions in safety critical operations, legacy manufacturing environments and integrated supply networks. Edge based digital twins can be used for quick fault detection or active monitoring of operations in safety-sensitive applications. Predictive models should provide accurate and timely predictions and interpretable outputs should enable operators to identify abnormalities and decide on the necessary interventions [29]. For maintaining predictive accuracy and operational safety, continuous performance monitoring, model drift detection, and periodic retraining are crucial. Challenges also exist in existing manufacturing facilities as many machines are typically powered by different controllers, lack documentation, and have incompatible data infrastructures. Using industrial IoT sensors and edge devices can help gather more data and using interoperability technologies like OPC UA, MQTT and middleware will enable communication between previously disconnected systems [30]. A hybrid digital twin model integrates Physics based representations and machine learning techniques to infer the behavior of equipment or predict performance under conditions where full engineering information is limited, with the ability to identify anomalies. Overall, cross domain applications emphasize the need for trustworthy data integration, ongoing model validation, well-structured implementation and proper governance. Digital twins, when leveraged with AI, simulation, and iterative improvement techniques, can enhance operational visibility, identify bottlenecks, optimize resource usage, and facilitate adaptive decision making within interconnected industrial systems and manufacturing environments [31].

Discussion

Digital twins (DT), artificial intelligence (AI), blockchain and Lean Six Sigma (LSS) bring a new dimension to smart manufacturing, enabling an integrated perspective on operational excellence, bottleneck reduction, and continuous process improvement. The overall architecture of the solution tackles a number of long-standing manufacturing issues, such as equipment failures, delays in production, process variability, inefficient use of resources, lack of traceability and scattered operational data [32]. The framework brings together real time monitoring, predictive intelligence, secure information management and structured improvement methods not as separate entities, but as interconnected components of a shared solution to these challenges. However, only when it is implemented well, technological systems are compatible, and organizations are capable of converting digital touchpoints into tangible, operational gains. The digital twin serves as the basis for this integration by creating virtual versions of physical assets, production lines and connected manufacturing systems [33]. These models can be updated with ongoing data exchange and used for monitoring performance and prediction, as well as testing scenarios. Virtual environments can then be used to make manufacturing decisions prior to making changes in a physical manufacturing environment. It is especially useful for production changes that require significant capital expenditures, complex equipment interactions or any potential safety concerns. Digital twins can minimize uncertainty and optimize resource use by allowing for the comparison of different production schedules, staffing plans, maintenance strategies, and equipment configurations. AI enhances the capabilities of digital twins by pattern recognition, fault detection, failure prediction, and decision optimization [34]. Past history data and actual sensor data can be used to compare performance with the expected, and determine the probability of equipment failures. Predictive maintenance consequently becomes a proactive alternative to purely reactive maintenance practices. Rather than only responding when a machine fails, maintenance interventions can be scheduled based on the condition of the machine and the predicted deterioration. However, the completeness, consistency and representativeness of training data influence the accuracy of prediction. Reduced reliability can result from inaccurate maintenance records, changing operating conditions, or model drift [35]. Continuous validation, uncertainty estimation, and human supervision are thus required, especially if the AI recommendations impact safety-critical processes. Bottleneck reduction becomes a key use case of digital twin and AI. The manufacturing constraints can be due to lack of machines, long inspection time, unreliable machines, shortage of materials, shortage of manpower, or inefficient flow of information. These constraints often work together in a way that

makes it impractical to improve the throughput of a process by merely fixing one constraint. Digital twins can depict relationships between production stages, and AI can detect any abnormal queue accumulation, equipment deterioration and prolonged cycle times [36]. Manufacturing execution systems can be used to supply the operational details to help separate real constraints from short-term shifts. Discrete event simulation also allows alternative interventions to be tried with varying demand and resource scenarios. This integration helps to make evidence-based decisions and decreases the need for trial and error. Digital technologies and Lean Six Sigma are closely interwoven because the use of technology does not automatically mean process improvement [37]. While Lean principles concentrate on the elimination of waste, improvement of flow and reduction of unnecessary activities, Six Sigma concentrates on process consistency and reducing defects. These methods, when combined, offer a framework that can be used to understand digital insights and take appropriate action to fix these. For instance, if a digital twin detects ongoing traffic jams at an inspection station, the root cause could be that an inspection package is not capable of covering enough people to stations, that the inspection procedures are not consistent, or that the material is defective, or that documentation is delayed [38]. Raising capacity of equipment without exploring these causes can yield only marginal gains. Therefore, the following elements are crucial to achieving lasting improvements: root cause analysis, standardization, buffering, and continuous measurement. The effectiveness of the combined framework is also dependent on the manufacturing strategy used. With engineer to order environments, product specification and production requirements can vary significantly from project to project, and therefore require engineering coordination, critical path monitoring and capacity planning up front [39]. Make to order facilities enjoy speedy order processing, component preparation and scheduling that are based on confirmed orders. Assemble to order systems need appropriate component buffers, and the synchronization between inventory availability and final assembly. Increase reliance on demand forecasting, low production variation, and inventory management in make to stock operations. Digital twins and AI can complement all four strategies, but the type of digital twin and the metrics used for measuring performance should be different for each environment [40]. A single strategy would miss these differences and might result in ineffective interventions. Legacy machines might not have the latest and greatest sensors, standardized interfaces, or full engineering drawings. When integrating these assets, more sensors, edge computing devices, middleware and communication protocols (OPC UA, MQTT) are typically needed. Accurate synchronization between physical operations and digital models can be hindered by data quality issues, incompatible formats, and inconsistencies in definitions. A phased implementation is therefore better than taking an enterprise wide deployment [41]. Starting with a high value bottle line provides organisations with an effective baseline of data, an opportunity to validate the digital twin, to assess operational benefits and to adjust the implementation process before it goes to scale on other production lines.

Conclusion

The integration of digital twins, artificial intelligence, blockchain, and Lean Six Sigma provides a comprehensive framework for enhancing manufacturing operational excellence and reducing bottlenecks. Digital twins enable real time monitoring and simulation, AI supports predictive analytics and intelligent optimization, blockchain strengthens traceability and accountability, and Lean Six Sigma facilitates systematic waste elimination and quality improvement. Successful implementation requires reliable data, interoperable systems, cybersecurity, workforce training, and appropriate human oversight. By aligning these technologies with manufacturing requirements and continuous improvement practices, organizations can improve productivity, reduce operational costs, strengthen supply chain resilience, and achieve sustainable performance improvements.

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