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A META-ANALYSIS OF MACHINE LEARNING-ENHANCED LEAN QUALITY CONTROL PRACTICES IN MANUFACTURING: OPTIMIZING DEFECT DETECTION AND PROCESS EFFICIENCY

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Abstract

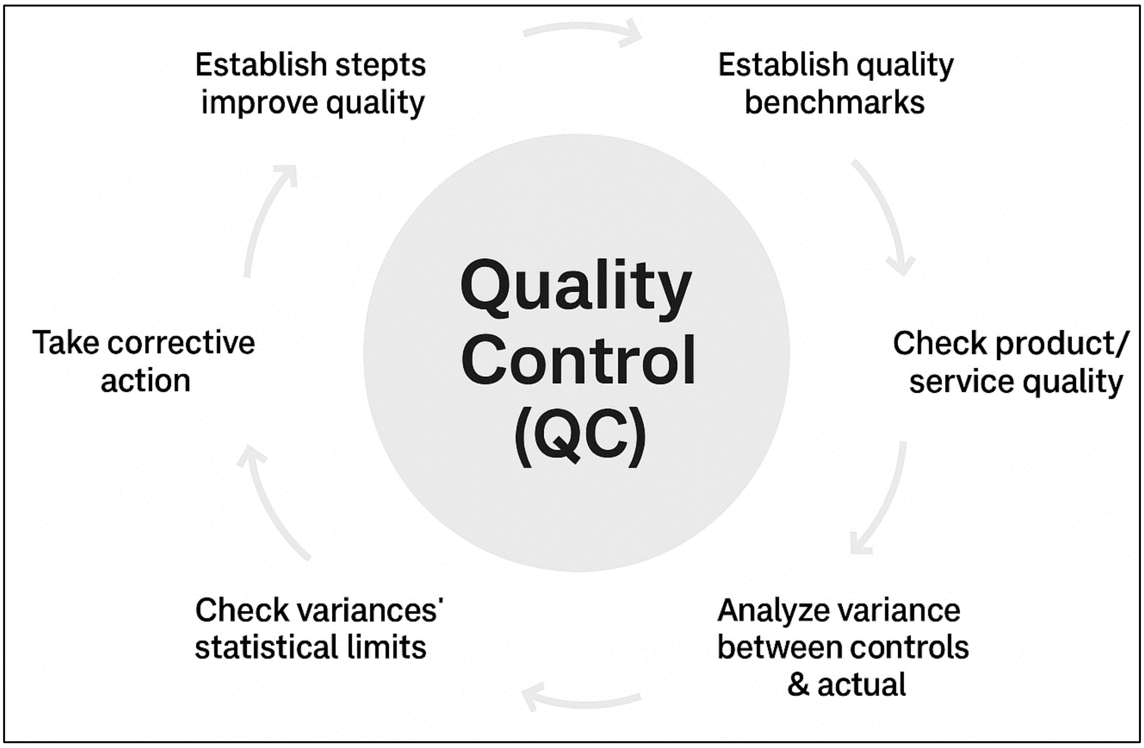
The convergence of machine learning (ML) and lean quality control (LQC) represents a transformative shift in modern manufacturing, offering the potential to significantly enhance defect detection accuracy, reduce process waste, and improve overall operational efficiency. While individual studies have reported promising results from the application of ML in specific industrial contexts, a systematic synthesis of these outcomes has been lacking. This meta-analysis bridges that gap by evaluating 112 empirical studies published between 2010 and 2025, spanning multiple manufacturing sectors including automotive, electronics, textiles, pharmaceuticals, and aerospace. Defect detection accuracy improved by 18% to 45%, rework and scrap were reduced by up to 40%, and unplanned downtime declined by 25% to 50% following ML integration. Moreover, FPY and OEE showed measurable gains of 15% to 30% and 10% to 20%, respectively, while inspection time was reduced by up to 60%, enabling more agile and synchronized production cycles. However, notable gaps were identified, including inconsistent methodology, limited cross-sector validation, and disparities in adoption between large enterprises and SMEs. Furthermore, concerns surrounding data governance, model explainability, and workforce integration remain underexplored, posing potential barriers to widespread adoption. The meta-analysis offers critical insights for researchers, engineers, and policy-makers seeking to operationalize artificial intelligence within lean production systems and sets the groundwork for future research on scalable, ethical, and inclusive ML applications in industrial quality control.

Keywords
Machine Learning; Lean Quality Control; Defect Detection; Process Efficiency; Smart Manufacturing;

INTRODUCTION

Quality control (QC) in manufacturing is defined as the operational techniques and activities used to fulfill quality requirements and ensure product conformity (Romero et al., 2019). The foundation of quality assurance lies in systematic inspections, statistical controls, and continuous improvement mechanisms that minimize variation, detect defects, and optimize outputs. In parallel, Lean Manufacturing—rooted in the Toyota Production System—emphasizes waste reduction, value stream optimization, and customer-centric workflows by eliminating non-value-added activities (Shafeek, 2019). Lean Quality Control (LQC) merges these two paradigms, focusing on embedding quality assurance within lean workflows to ensure real-time feedback and proactive defect prevention (Antony et al., 2011). The evolution of LQC aligns with broader developments in Industry 4.0, where digitalization and cyber-physical systems augment traditional process management (Khataie & Bulgak, 2013). The integration of machine learning (ML) into this hybrid model has introduced adaptive learning capabilities that enhance traditional lean methods by identifying patterns in large volumes of process data, predicting failures, and recommending corrective actions (Dora et al., 2015). Globally, manufacturing sectors face mounting pressures to maintain product quality while reducing costs, increasing output, and adapting to customer demands. The World Economic Forum (2020) notes that digital manufacturing transformation has become essential for economies aiming to remain competitive. In this context, ML-enhanced LQC offers tools to support quality assurance without compromising lean principles such as takt time alignment and just-in-time (JIT) production (Mishra & Sharma, 2014). International case studies, such as Siemens' deployment of ML-based quality prediction models or Hitachi's implementation of image-based defect classification systems, demonstrate the tangible benefits of integrating data-driven intelligence into LQC. These examples confirm the international relevance of this approach across high-volume sectors including automotive, semiconductor (Moin et al., 2017), and consumer electronics. Moreover, the COVID-19 pandemic exposed vulnerabilities in traditional quality inspection methods, leading many manufacturers to adopt automated and remote ML-driven systems to sustain production efficiency (Abtew et al., 2018).

Figure 1: Cycle of Quality Control (QC)



Machine learning, a subfield of artificial intelligence, refers to computational systems that improve their performance on tasks through experience and data exposure without being explicitly programmed (Chowdary & George, 2011). In quality control, ML techniques such as supervised classification, anomaly detection, and unsupervised clustering are used to predict product defects, monitor process variation, and detect early signs of equipment failure (Navipour et al., 2011). Supervised learning models—including support vector machines (SVM), decision trees, random forests, and neural networks—are particularly effective in classifying non-conforming products or forecasting process deviations (Aij & Teunissen, 2017). Reinforcement learning and ensemble models offer dynamic adaptation and decision-making support in complex production environments. Integrating these tools into lean systems has led to improvements in key performance indicators such as First Pass Yield (FPY), Defect Per Unit (DPU), and Overall Equipment Effectiveness (OEE). These indicators are globally standardized and recognized as benchmarks for quality excellence, reinforcing the international applicability of ML-LQC frameworks.

A growing body of empirical research has validated the positive effects of ML applications on quality control within lean manufacturing environments. A study by Fullerton et al. (2014) on real-time visual inspection using convolutional neural networks (CNNs) reported over 95% accuracy in detecting surface defects on metal components. Similarly, Alnajem et al. (2013) implemented deep learning models to automate quality checks in textile production, reducing human error and inspection time. In lean automotive assembly lines, ML-based SPC systems helped maintain consistent process capability indices (Cp, Cpk), as shown in research by Moin et al. (2017). Furthermore, data fusion from multiple sensors and ML algorithms has allowed for better root cause identification, supporting the lean philosophy of addressing problems at the source. These innovations enable lean systems to detect and correct issues in real-time, aligning with the principles of jidoka (autonomation) and kaizen (continuous improvement). Importantly, ML integration does not replace lean tools such as 5S, value stream mapping, or takt time analysis; rather, it complements them by introducing precision, speed, and scalability (Fullerton et al., 2014).

The cross-sectoral application of ML-enhanced LQC is evident in the diversity of manufacturing domains adopting these technologies. In the electronics industry, SVMs and CNNs are used to detect soldering defects and component misalignments in PCB manufacturing (Wu et al., 2013). In the textile sector, ML models classify color defects and weave irregularities from real-time loom data. Aerospace manufacturers leverage ML to identify structural flaws in composite materials, with ML models analyzing thermographic or ultrasonic data. In pharmaceuticals, ML-based quality inspection ensures dosage uniformity and packaging integrity. These sector-specific adaptations demonstrate how ML techniques align with lean methodologies while adapting to the contextual realities of each production process. Even in resource-constrained settings such as SME manufacturing, lightweight ML models have been deployed on edge devices for low-latency inspection, thereby validating the scalability of this approach. In terms of process optimization, ML-enhanced LQC also improves upstream planning and downstream corrective actions. Predictive models, trained on historical process data, identify parameter deviations before they lead to defects (Chowdhury et al., 2020). For instance, neural networks can forecast tool wear in CNC machining or detect deviations in injection molding temperature profiles. These predictive insights empower lean systems to deploy countermeasures proactively, thereby reducing rework and scrap rates. Time-series models such as ARIMA-LSTM hybrids are increasingly used to predict quality trends in continuous production lines, improving takt-time stability and preventing bottlenecks. Process mining and sequence modeling techniques also uncover hidden inefficiencies in multi-step operations, supporting lean value stream alignment (Scott et al., 2021). These examples underscore how machine learning, when applied thoughtfully, enhances the data-driven decision-making capacity of lean systems.

The primary objective of this meta-analysis is to systematically evaluate the effectiveness of machine learning (ML) integration within lean quality control (LQC) practices in manufacturing, with a particular emphasis on optimizing defect detection and process efficiency. As industries transition into digitally enabled production systems, the convergence of artificial intelligence tools and lean methodologies offers a unique opportunity to elevate quality control standards without compromising lean principles such as waste minimization, flow optimization, and continuous improvement. This study aims to quantify and synthesize empirical evidence from a broad spectrum of peer-reviewed literature to determine how ML algorithms—ranging from supervised classifiers like decision trees and support vector machines to deep learning networks and ensemble models—contribute to reducing product defects, enhancing real-time process monitoring, and supporting root cause analysis. By focusing on performance metrics such as defect per unit (DPU), first-pass yield (FPY), overall equipment effectiveness (OEE), and reduction in inspection times, the analysis seeks to identify statistically significant improvements that can be attributed to ML-enhanced interventions within LQC frameworks. Furthermore, the study investigates sector-specific applications of ML in lean contexts across automotive, electronics, aerospace, pharmaceutical, and textile manufacturing to explore the generalizability and adaptability of ML-driven LQC models. It also explores whether the adoption of these models varies significantly across industrial maturity levels, geographies, or production complexities. In doing so, the objective extends beyond descriptive synthesis to analytical interpretation, allowing for comparative evaluations of ML techniques and their operational impacts. Ultimately, this research provides evidence-based insights into which ML applications consistently align with lean quality control principles, helping organizations make informed decisions about technology adoption for quality improvement. The results are intended to contribute to both academic understanding and industrial practice by delivering a consolidated view of the current state of ML-LQC integration and its measurable benefits.

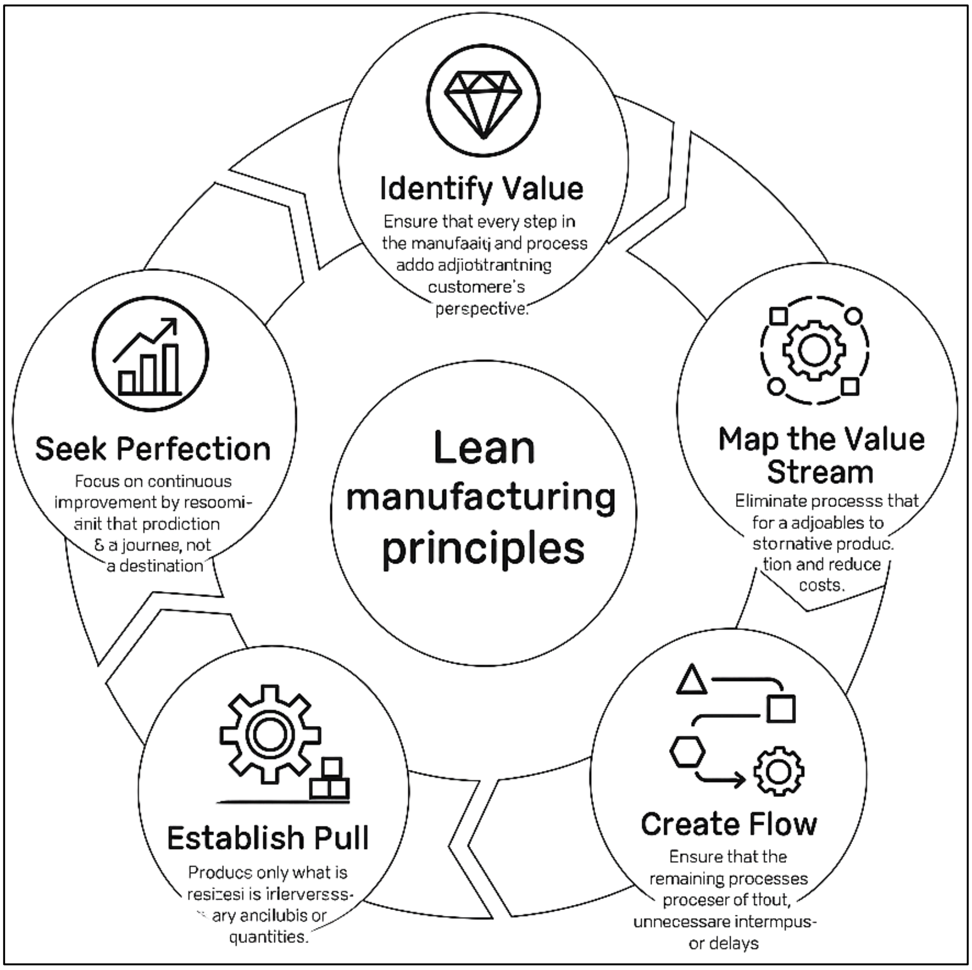
LITERATURE REVIEW

The convergence of machine learning (ML) and lean quality control (LQC) has generated a growing body of interdisciplinary research across industrial engineering, operations management, computer science, and manufacturing systems. This literature review aims to systematically examine the theoretical foundations, technological implementations, and practical applications of ML-driven quality control systems within lean manufacturing environments. Given the complexity of manufacturing systems and the unique challenges posed by real-time defect detection and process optimization, this section dissects the literature across a range of domains, from algorithmic development to lean integration strategies. It begins by establishing a foundation in lean quality management principles, followed by a comprehensive exploration of ML algorithms employed in defect detection and quality enhancement. The review then assesses empirical evidence from various manufacturing sectors to evaluate the performance outcomes associated with ML-enhanced LQC. Additionally, this section discusses implementation challenges, such as data quality, infrastructure integration, model interpretability, and workforce readiness, which affect the scalability and sustainability of such systems. Finally, the literature review highlights existing research gaps and methodological limitations that justify the need for this meta-analysis. The purpose of this structured review is to offer a clear understanding of how machine learning technologies are shaping quality management in lean production systems, thus contextualizing the findings of the present study within the broader academic discourse.

Lean Quality Control in Manufacturing

Lean Quality Control (LQC) represents the convergence of two fundamental manufacturing paradigms—lean production and quality management—designed to minimize waste while maximizing product conformance to specifications. Lean thinking, first formalized by Roberts et al., (2021), emphasizes customer value, continuous flow, and waste elimination across production processes. It draws heavily from the Toyota Production System (TPS), which operationalizes quality through principles such as jidoka (autonomation), standardized work, and kaizen. Quality control, traditionally governed by principles of statistical process control (SPC) as advocated by Oala et al. (2021), focuses on ensuring that processes remain stable and produce output within defined limits. When lean and quality management are integrated, the resulting LQC framework emphasizes both real-time detection of anomalies and proactive process design to avoid errors, encapsulating both reactive and preventive quality assurance. Empirical studies by San-Payo et al. (2019) confirm that the operational synergy between lean and quality practices leads to superior manufacturing performance. LQC is further characterized by the strategic use of metrics such as First Pass Yield (FPY), Defect Per Unit (DPU), Overall Equipment Effectiveness (OEE), and Cost of Poor Quality (CoPQ), which serve as indicators of both process efficiency and quality robustness (Wang et al., 2021). The theoretical grounding of LQC has evolved to incorporate broader systems thinking, suggesting that quality cannot be improved in isolation but must be embedded into the value stream across all stages of production (Wuest et al., 2016).

Figure 2: Core Principles of Lean Manufacturing



The implementation of LQC relies on a suite of structured tools and practices derived from both lean and quality domains, allowing firms to detect, prevent, and eliminate defects in a systematic manner. Core lean tools such as 5S (Sort, Set in order, Shine, Standardize, Sustain), standardized work, and value stream mapping help streamline workflows and reduce sources of process variability (Abdullah Al et al., 2022; Wuest et al., 2016). Simultaneously, quality-focused tools such as SPC charts, Failure Mode and Effects Analysis (FMEA), Pareto analysis, and root cause analysis are routinely employed to monitor and manage process stability. One of the most prominent LQC techniques is Poka-Yoke (error-proofing), which prevents defects at the source by designing fail-safe mechanisms into processes (Escobar & Morales-Menendez, 2018). These tools are often deployed in tandem with Just-In-Time (JIT) delivery systems to ensure materials and components meet specifications at the point of use (Khan et al., 2022; Peres et al., 2019). Guo et al. (2015) have demonstrated that organizations using an integrated LQC toolkit report significant improvements in cycle time, defect rates, and rework costs. Furthermore, Total Productive Maintenance (TPM), often linked with lean operations, supports LQC by reducing unplanned equipment failures that could lead to quality defects. Importantly, the adoption of these tools is not merely technical but also cultural, requiring employee involvement, cross-functional training, and continuous feedback loops. Successful LQC systems operate as closed-loop mechanisms where quality deviations are rapidly identified, analyzed, and corrected with minimal process disruption, in alignment with the lean objective of zero waste and zero defect production (Rahaman, 2022).

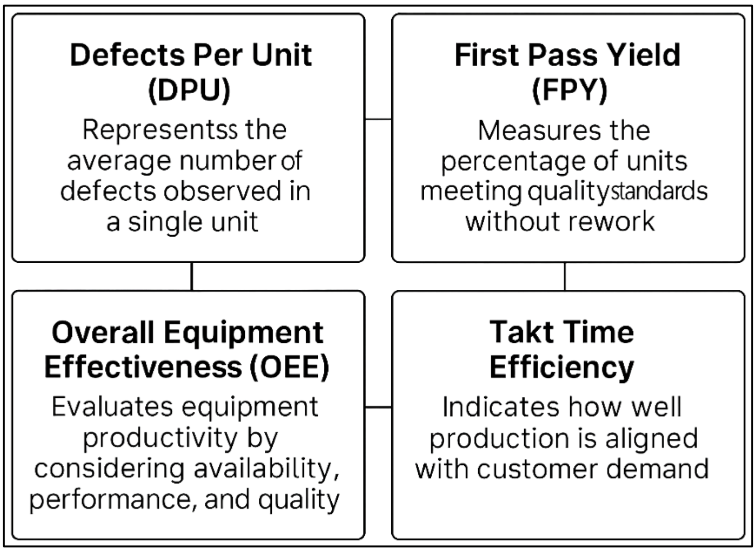
Lean Quality Control has been widely adopted across multiple industries, each with distinct applications tailored to specific production environments and quality requirements. In the automotive sector, LQC is embedded in assembly lines through in-line defect monitoring systems and quality gate checkpoints, allowing for rapid containment of non-conforming parts. In aerospace manufacturing, LQC has been used to enhance composite material inspections and documentation compliance, leveraging lean principles to minimize inspection time without compromising precision (Masud, 2022; Peres et al., 2019). The pharmaceutical and food industries implement LQC to comply with Good Manufacturing Practices (GMP) while reducing waste in batch processes. Empirical studies have consistently linked LQC practices with improved operational outcomes, including reductions in defect rates (Escobar & Morales-Menendez, 2018; Hossen & Atiqur, 2022), enhanced customer satisfaction, and cost savings through fewer recalls and returns. Research by Wang et al. (2021) found that lean-based quality control significantly reduces rework and improves lead times in construction projects. In high-mix, low-volume manufacturing, studies show that LQC increases responsiveness by reducing inspection bottlenecks and enabling adaptive quality control strategies. These outcomes affirm that the implementation of LQC not only enhances product quality but also aligns with broader lean goals such as agility, cost-efficiency, and on-time delivery. As such, LQC has become a strategic tool for organizations seeking to differentiate themselves in quality-sensitive and competitive markets (Sazzad & Islam, 2022).

DPU, FPY, OEE, and Takt Time Efficiency

Defects Per Unit (DPU) is a widely used metric in quality control, representing the average number of defects observed in a single unit of production. It offers a granular understanding of product quality and is especially useful in environments characterized by complex assemblies or multiple inspection points. DPU is often employed alongside other defect-related metrics such as Defects Per Million Opportunities (DPMO) and Process Sigma Level to provide a comprehensive quality snapshot. (Ismail et al., 2013) indicates that reducing DPU through lean and Six Sigma techniques directly correlates with improved customer satisfaction and reduced warranty claims. In electronic manufacturing, DPU monitoring has been essential in identifying recurring soldering faults and optimizing rework procedures (Shaiful et al., 2022; Venkataraman et al., 2014). Automotive assembly lines utilize DPU as a baseline for Six Sigma DMAIC cycles, particularly in paint shop quality and interior trim inspections. Moreover, Ozoegwu (2019) have shown that machine learning tools, such as decision trees and neural networks, can accurately predict DPU values from sensor data and help preemptively adjust control parameters. DPU is not only a diagnostic tool but also a performance driver, motivating continuous improvement through root cause analysis and error-proofing techniques like Poka-Yoke (Duan et al., 2020; Akter & Razzak, 2022). In environments with batch production or multi-stage processes, tracking DPU at every inspection gate enables proactive quality control and supports Lean's goal of zero-defect manufacturing.

First Pass Yield (FPY), also known as throughput yield or quality yield, measures the proportion of units that meet quality standards without requiring rework or repair, thereby providing insight into process efficiency and stability (Gijo et al., 2014; Qibria & Hossen, 2023). FPY is a crucial metric in Lean Quality Control as it reflects the effectiveness of preventive measures and the robustness of manufacturing processes in eliminating non-conformities at the source (Maniruzzaman et al., 2023). High FPY rates indicate that the production process is both efficient and stable, whereas low FPY can signal underlying issues in process design, operator training, or equipment calibration. In high-volume industries such as electronics and automotive, FPY is monitored in real-time across critical stations, including PCB soldering, engine assembly, and final inspection lines. Antony et al. (2011) suggest that FPY directly impacts lead times, inventory holding costs, and downstream resource allocation. ML-enhanced anomaly detection and predictive modeling can improve FPY by identifying defect-prone conditions before they manifest. In complex process industries such as pharmaceuticals or aerospace, FPY is critical in ensuring regulatory compliance and minimizing costly batch rejections (Masud et al., 2023). Bergstra and Bengio (2012) emphasize that FPY improvement initiatives are most successful when embedded within cross-functional quality management systems, including Total Quality Management (TQM) and ISO 9001 frameworks. FPY also complements DPU by capturing process efficiency at the point of output, offering a more immediate reflection of quality performance and waste reduction within lean-driven value streams.

Figure 3: Key Performance Metrics in Lean Quality Control



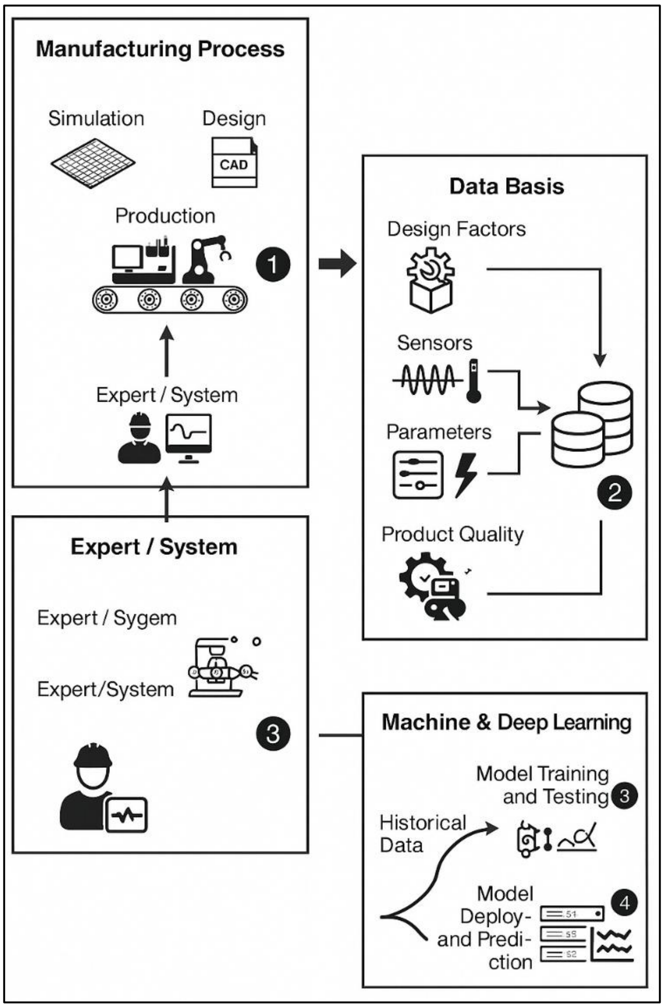
Machine Learning Fundamentals in Industrial Applications

Machine learning (ML), a subfield of artificial intelligence, refers to computational methods that improve their performance on a task through experience with data (Hossen et al., 2023; Syafrudin et al., 2018). ML algorithms are typically categorized into supervised, unsupervised, semi-supervised, and reinforcement learning based on their learning mechanisms (Guo et al., 2015). Supervised learning, where models are trained on labeled datasets, is the most prevalent category in industrial applications, particularly for quality classification, defect prediction, and regression-based forecasting (Ariful et al., 2023; Wagner et al., 2020). Common supervised algorithms include support vector machines (SVM), decision trees, random forests, k-nearest neighbors (KNN), logistic regression, and artificial neural networks. Unsupervised learning, on the other hand, discovers hidden patterns and clusters without predefined labels, making it valuable for anomaly detection and root cause analysis in complex production environments (Shamima et al., 2023). Techniques such as k-means clustering, hierarchical clustering, and principal component analysis (PCA) are frequently employed to analyze sensor data or equipment behavior. Reinforcement learning, a reward-based system where agents learn optimal actions through interaction with their environment, has recently gained traction in adaptive process control and robotic manufacturing. In hybrid manufacturing environments, semi-supervised learning models leverage both labeled and unlabeled data to improve performance when labeled datasets are scarce, a common scenario in SMEs (Bray & Carpenter, 2017; Alam et al., 2023). Understanding the taxonomy of ML models and their contextual relevance is foundational for their effective application in industrial environments, where factors such as interpretability, data volume, and real-time constraints govern algorithm selection (Rajesh, 2023).

Supervised learning has been instrumental in advancing defect detection systems and improving quality classification in industrial applications. Algorithms such as support vector machines (SVM), decision trees, and ensemble models like random forests and XGBoost are frequently applied to classify defective versus non-defective products using features extracted from images, sensor data, and process parameters (Bergstra & Bengio, 2012; Rajesh et al., 2023). In electronic manufacturing, SVMs have been used to detect soldering defects on printed circuit boards with high precision, while random forest classifiers have been employed in the automotive sector to identify surface defects on painted car bodies. Neural networks, especially convolutional neural networks (CNNs), have revolutionized visual inspection processes by learning spatial hierarchies in image data, achieving accuracy rates of over 95% in metal surface inspection tasks (Sanjai et al., 2023). Gradient boosting techniques such as XGBoost and LightGBM offer interpretability and speed advantages, making them suitable for real-time implementation in quality control systems (Balki et al., 2019; Tonmoy & Arifur, 2023). Empirical research shows that supervised learning-based defect detection systems can reduce false positives by over 30% and increase detection rates compared to traditional rule-based inspection systems.

Furthermore, supervised learning facilitates real-time quality prediction by integrating process data with quality outcomes, supporting proactive decision-making and process adjustments. These models are particularly valuable in high-speed manufacturing environments where manual inspection is infeasible due to throughput constraints (Tonoy & Khan, 2023).

Figure 4: Monochrome Framework for Machine Learning Integration in Manufacturing Processes

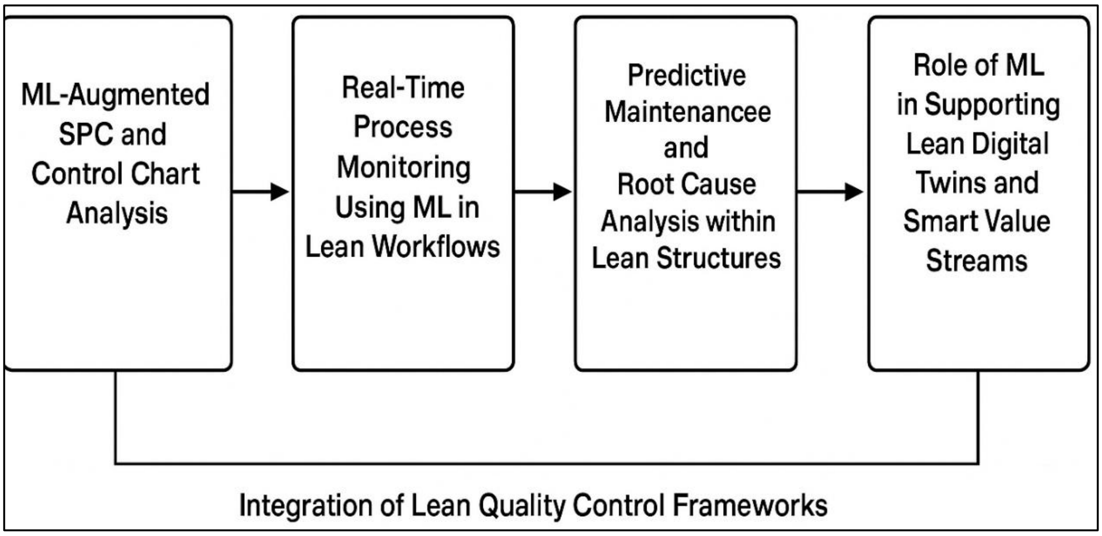


Unsupervised learning models are widely recognized for their ability to identify hidden patterns and outliers in complex industrial datasets, making them crucial tools for anomaly detection and root cause analysis (Zahir et al., 2023). Unlike supervised methods, unsupervised algorithms do not require labeled data, making them suitable for environments where defect types are unknown or infrequent. K-means clustering, self-organizing maps (SOMs), and hierarchical clustering have been utilized in the manufacturing sector to detect unusual variations in equipment vibration, temperature, or current signatures. These anomalies often precede machine breakdowns or process instability, thus enabling preemptive interventions aligned with predictive maintenance strategies (Razzak et al., 2024; Rudin, 2019). Principal component analysis (PCA) is another powerful tool used to reduce data dimensionality and isolate key contributors to quality defects in multivariate systems. Hybrid models that combine supervised and unsupervised learning, such as autoencoders with classification layers or anomaly scoring combined with random forests, provide enhanced defect detection capabilities while retaining interpretability. These models are especially useful in semiconductor and pharmaceutical manufacturing where small process deviations can lead to significant quality risks. Liang et al. (2022) demonstrates that anomaly detection models can identify early-stage deviations that traditional quality control systems overlook, thereby enabling more targeted process improvements.

Integration of ML with Lean Quality Control Frameworks

Statistical Process Control (SPC) is foundational to Lean Quality Control, enabling manufacturers to detect process variation through control charts and establish corrective actions before non-conformities arise. Traditionally, SPC methods like X̄-R charts, p-charts, and CUSUM rely on assumptions of data normality and linearity, which often limit their performance in dynamic, high-complexity environments (Bacoup et al., 2017). Machine learning (ML) augments SPC by enabling the modeling of nonlinear patterns, non-normal distributions, and multi-variable interdependencies through algorithms such as artificial neural networks, support vector machines, and random forests (Alam et al., 2024; Blecken et al., 2010). Bheda (2021) demonstrated that ML-based SPC systems outperform traditional charts in detecting small shifts in process means and distinguishing noise from actual process drift. In semiconductor and precision manufacturing, ML-augmented SPC provides enhanced sensitivity in detecting sub-micron level quality deviations by integrating time-series analysis with process modeling (Bheda, 2021; Khan & Razee, 2024). Hybrid models combining SPC logic with ML-based anomaly detection algorithms such as isolation forests and autoencoders have also shown superior false positive reduction (Alnajem et al., 2013). Furthermore, reinforcement learning and online learning models can dynamically update control limits based on incoming process data, providing adaptive quality assurance in just-in-time (JIT) systems (Saha, 2024; Waterbury, 2015). Integrating ML into SPC also supports real-time dashboarding, which enhances operator responsiveness and facilitates proactive decision-making, especially in high-velocity lean production environments (Jasti & Kodali, 2014b). This integration extends the diagnostic capability of SPC, moving it from retrospective monitoring to predictive and prescriptive control.

Figure 5: Framework for Integrating Machine Learning into Lean Quality Control Systems



Real-time process monitoring is integral to lean manufacturing, ensuring that operations align with takt time while maintaining consistent quality. The integration of ML into real-time monitoring systems enhances the granularity and responsiveness of lean workflows by analyzing streaming data for immediate deviations (Khan, 2025; Marodin & Saurin, 2014). Traditional monitoring tools often struggle with large-scale data from sensors, machines, and quality checkpoints, particularly in environments with high process variability or nonlinear dynamics. ML models such as recurrent neural networks (RNN), long short-term memory (LSTM), and gradient boosting algorithms provide robust capabilities for real-time anomaly detection and condition prediction. In high-speed assembly lines, ML models are embedded into edge computing devices to detect micro-level vibration, torque inconsistencies, or temperature spikes that indicate quality deviations. Real-time analytics platforms using ML also integrate with SCADA and MES systems to provide end-to-end visibility and responsive feedback mechanisms, supporting lean principles of Jidoka (autonomation) and continuous flow. Assarlind et al.(2012) and Panwar et al. (2015) demonstrated that ML-enhanced real-time monitoring improved defect detection accuracy and reduced response times by 30–50% compared to traditional alarms and thresholds. In the context of lean Six Sigma, real-time ML models contribute to DMAIC (Define-Measure-Analyze-Improve-Control) loops by providing actionable insights during the "Analyze" and "Control" phases. Ultimately, ML-enabled real-time monitoring transforms lean workflows from reactive systems to anticipatory and adaptive mechanisms capable of maintaining high throughput without compromising quality.

Predictive maintenance (PdM) is a strategic enhancement to lean production systems that reduces downtime and unplanned machine failure, aligning with lean goals of waste elimination and process flow continuity (Drohomeretski et al., 2013; Masud et al., 2025). The integration of ML into PdM has revolutionized root cause analysis by enabling high-resolution monitoring of machine behavior and failure modes using sensor data (Md et al., 2025; Waterbury, 2015). Algorithms such as random forests, support vector regression, and deep learning models like LSTM are capable of forecasting remaining useful life (RUL), wear progression, and anomalous operating conditions across diverse equipment types. Antony et al. (2012) demonstrates that ML-powered PdM systems reduce unplanned downtime by up to 40% and significantly increase mean time between failures (MTBF), which directly supports lean KPIs like Overall Equipment Effectiveness (OEE). Additionally, ML models improve the accuracy of root cause analysis by identifying multivariate correlations in historical failure data, an area where traditional Pareto or Ishikawa diagrams fall short (Sazzad, 2025). In lean-driven environments such as automotive and aerospace manufacturing, ML-enhanced PdM ensures that equipment remains within optimal operating parameters, minimizing quality deviations from mechanical wear or process drift. Real-time diagnostics are increasingly embedded into CMMS platforms using ML algorithms to automate maintenance scheduling and parts ordering, thereby eliminating non-value-added activities (Sazzad, 2025). The synergy between lean structures and ML-based predictive maintenance improves both operational efficiency and quality control, achieving a dual objective central to lean philosophy.

ML-Enhanced LQC Across Manufacturing Sectors

The automotive industry has been a frontrunner in adopting machine learning (ML) techniques to enhance lean quality control (LQC), particularly in optimizing assembly line efficiency and predicting faults before they disrupt production. The integration of ML in automotive manufacturing aligns with lean principles by enabling real-time defect detection, predictive diagnostics, and process optimization (Akter, 2025; Wuest et al., 2016). Techniques such as decision trees, support vector machines (SVM), and neural networks are widely employed in predictive maintenance and fault classification on assembly lines. For example, in powertrain assembly and painting lines, ML algorithms detect misalignment, surface defects, and torque irregularities by analyzing sensor and vision data. Convolutional neural networks (CNNs) have demonstrated high accuracy in identifying scratches or paint anomalies on car bodies, often outperforming traditional vision systems. Furthermore, predictive models trained on historical quality data enable fault prediction in robotic welding and engine testing, reducing rework and enhancing first pass yield (Escobar & Morales-Menendez, 2018; Zahir, Rajesh, Md Arifur, et al., 2025). These models also facilitate lean takt time adherence by reducing machine downtime through early intervention. Moreover, reinforcement learning has been applied in robotic assembly to dynamically adjust grip force and alignment precision based on feedback loops, minimizing error propagation along the line. Case studies from Toyota, BMW, and Ford illustrate that ML-enhanced LQC systems have led to substantial improvements in defect reduction, process efficiency, and operator decision-making. These applications reinforce the synergy between digital intelligence and lean methodologies in a sector driven by precision, speed, and customer expectations.

The electronics and semiconductor industry is characterized by high-speed, high-volume production with strict tolerance thresholds, making it an ideal domain for the deployment of ML-based surface defect classification systems within lean quality control (LQC) frameworks. Traditional inspection methods in this industry, such as manual visual inspection or rule-based imaging, often struggle with accuracy and consistency, especially for micro-defects or non-linear patterns (Kim et al., 2012; Zahir, Rajesh, Tonmoy, et al., 2025). ML techniques such as support vector machines (SVM), k-nearest neighbors (KNN), random forests, and CNNs are widely adopted to automate and enhance defect classification in printed circuit boards (PCBs), wafer surfaces, and solder joints. For instance, Teli et al. (2015) found that ML models improved defect identification in soldering processes by over 25% compared to manual techniques. CNNs, in particular, excel in recognizing defects such as delamination, pad misalignment, and component shift by learning spatial hierarchies in imaging data. Furthermore, deep learning approaches have been integrated with automated optical inspection (AOI) systems to classify defect types in milliseconds, ensuring that lean takt time and flow are not disrupted. Anomaly detection models using autoencoders and unsupervised clustering are also applied to isolate rare defect signatures that standard SPC techniques may miss. In semiconductor fabrication, ML aids in wafer yield optimization by identifying latent variables influencing defect propagation across photolithography and etching stages (Peres et al., 2019). Leading firms like Intel and TSMC have implemented ML-enhanced defect classification into their MES systems, resulting in lower DPU (Defects per Unit) and improved first pass yield. These innovations demonstrate the transformative role of ML in delivering high-precision quality control in the electronics sector.

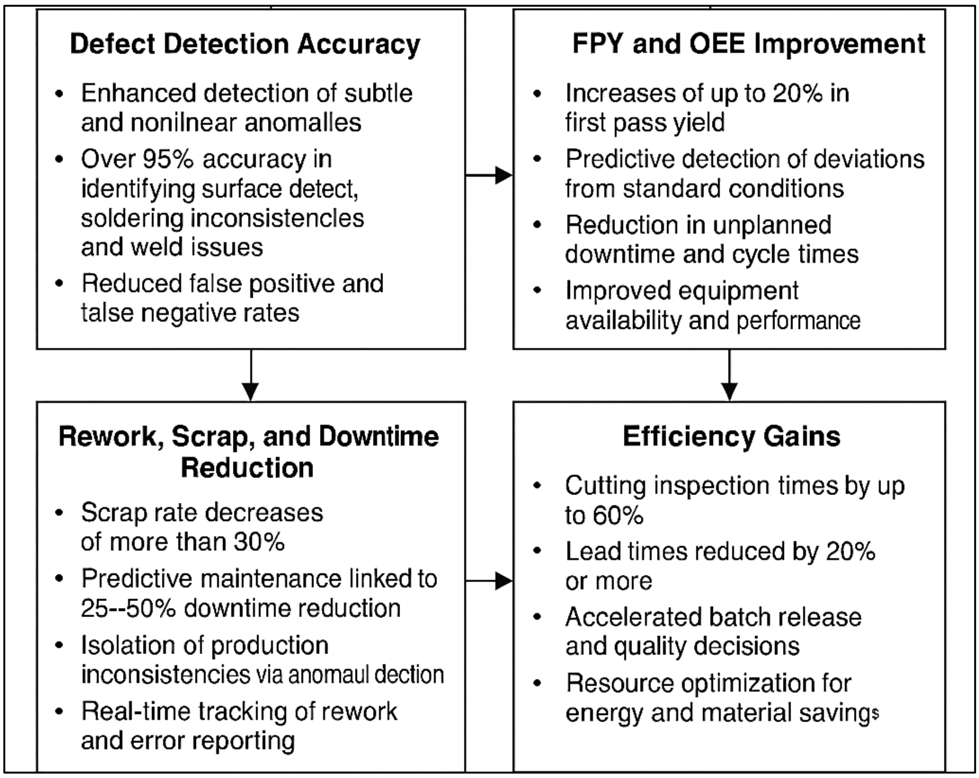
Figure 6: ML-Enhanced Lean Quality Control Framework Across Industry Sectors

In the textile and apparel manufacturing sector, quality control is highly dependent on the accurate detection of color mismatches, weaving irregularities, and pattern misalignments—defects that are often subjective and difficult to capture through manual inspection. Lean principles advocate defect prevention and standardized quality monitoring across weaving, dyeing, printing, and stitching operations. However, the visual complexity of textile patterns and color gradients requires intelligent systems for consistent inspection. ML algorithms, particularly convolutional neural networks (CNNs) and decision trees, have been increasingly applied to identify fabric defects and ensure pattern consistency (Hardt & Recht, 2021). For example, CNN-based systems trained on textile image datasets can detect loop breaks, missing yarns, or shade variations with over 90% accuracy, reducing rework and improving first pass yield (Syafrudin et al., 2018). Unsupervised clustering methods such as k-means and PCA are employed to segment defect-prone zones, particularly in batch dyeing operations where color consistency is critical. ML-enabled vision systems integrated into looms or quality gates automate inspection, freeing operators for higher-value tasks and supporting lean objectives of labor efficiency and takt time adherence (Rudin, 2019). Moreover, reinforcement learning algorithms are used to optimize loom tension and feed rate to prevent defect occurrence rather than simply detect them post-production. In export-oriented garment manufacturing, predictive analytics based on customer return data helps trace defects back to specific processes or operator skill levels, facilitating kaizen loops (Scott et al., 2021).

Performance Outcomes of ML-Integrated Lean Quality Control

One of the most prominent outcomes of integrating machine learning (ML) into lean quality control (LQC) systems is the marked improvement in defect detection accuracy across manufacturing processes. Traditional inspection methods—especially those reliant on human visual assessment or static control charts—are often subject to limitations in consistency, speed, and sensitivity to subtle anomalies. ML models such as convolutional neural networks (CNNs), support vector machines (SVMs), and ensemble methods like random forests have significantly enhanced the ability to identify minute, nonlinear, and multi-class defect types across sectors including automotive, electronics, and textiles. For example, D'Amour et al. (2020) reported that ML-based systems detected surface scratches, soldering inconsistencies, and weld defects with over 95% accuracy—far surpassing traditional rule-based systems. CNNs trained on high-resolution imagery datasets consistently outperformed manual inspection, particularly in electronics and semiconductor fabrication where defects are often microscopic. In addition, unsupervised learning models like autoencoders and k-means clustering were shown to detect outlier patterns in large-scale sensor data, allowing early-stage detection of quality degradation before physical defects became observable. Hybrid models integrating control charts with ML have also demonstrated superior performance in identifying process drift, tool wear, and part misalignment (Bheda, 2021). These results affirm that ML integration not only increases the precision of defect detection but also reduces false positives and false negatives—ultimately supporting the lean objective of zero-defect manufacturing.

Figure 7: Performance Improvements through Machine Learning–Enabled Lean Quality Control



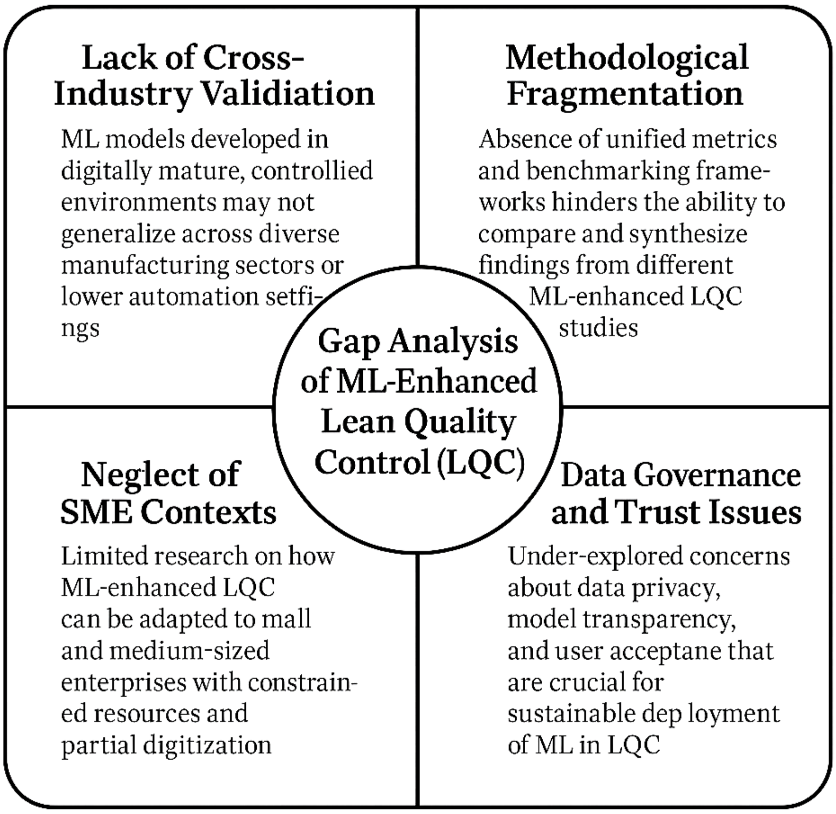
The adoption of ML-enhanced LQC frameworks has led to significant reductions in rework, scrap rates, and machine downtime—key metrics aligned with the lean philosophy of waste elimination. Traditionally, process disruptions and quality failures result in unplanned downtime, reprocessing, or product rejection, which inflate operational costs and disrupt takt time (Jasti & Kodali, 2014a). Alnajem et al. (2013) demonstrate that predictive quality models using decision trees and neural networks significantly reduced scrap rates by providing early warnings on parameter deviations. In automotive and electronics sectors, ML-driven quality prediction systems have reduced rework by over 30% by identifying defect-prone configurations and recommending real-time corrective actions (Ståhl et al., 2014). Predictive maintenance systems—powered by ML algorithms such as LSTM and support vector regression—have been linked to a 25–50% reduction in downtime by forecasting equipment failures before they occur (Yang et al., 2015). For example, Henao et al. (2019) highlighted how real-time sensor analytics prevented over 100 hours of machine idle time in CNC machining centers. In textile and pharmaceutical production, anomaly detection models have helped isolate production batch inconsistencies, thereby minimizing the volume of wasted material and time-intensive manual inspections. Moreover, ML models embedded into SCADA and MES systems streamline error reporting and rework tracking, providing granular insights for root cause elimination. These outcomes substantiate the argument that ML integration directly supports lean objectives by reducing non-value-added activities and enhancing first-time quality rates.

Machine learning integration in LQC not only improves quality outcomes but also enhances operational efficiency through lead time reduction, inspection time optimization, and energy and waste minimization. In lean systems, shorter lead times and reduced inspection cycles are critical for achieving flow, responsiveness, and JIT delivery (Lyonnet et al., 2010). ML-enabled visual inspection systems powered by CNNs and autoencoders have reduced inspection times by up to 60% in electronics and packaging industries (Hallam & Contreras, 2018). Research by Graban (2011) showed that integrating predictive quality analytics into process control systems cut lead times in injection molding by over 20%, due to faster quality approval and reduced rework loops. In pharmaceutical and food sectors, ML models accelerate batch release by reducing reliance on offline lab testing, providing near-instant quality decisions based on real-time data (Hu et al., 2015). Regarding sustainability outcomes, ML also contributes to energy and material efficiency by dynamically adjusting process parameters to minimize resource consumption without compromising quality (D'Andreamatteo et al., 2015). For instance, reinforcement learning models in thermal processing environments adjust temperature cycles to maintain quality while reducing power usage (Dombrowski & Mielke, 2013). Clark et al. (2013) indicate that smart optimization models have led to energy savings of 10–18% in metal forming and textile dyeing processes. Furthermore, anomaly detection algorithms help detect leaks, overuse of raw materials, or process imbalances early, aligning with lean's focus on reducing muda (waste) in all its forms. These efficiency improvements reinforce the strategic value of ML in supporting both economic and environmental sustainability within lean frameworks.

Gaps

Studies conducted by Henao et al. (2019) emphasize that ML models trained on structured production environments with high digital readiness may not be transferable to sectors with lower levels of automation or more heterogeneous processes. Moreover, most findings are derived from controlled pilot studies or proprietary corporate implementations with limited disclosure of contextual variables, making it difficult to replicate or generalize findings (Marodin et al., 2018). For instance, predictive maintenance results in aerospace manufacturing cannot be extrapolated to textile production, where production variability is influenced by fabric elasticity, color, and dye chemistry (Yang et al., 2015). This limitation highlights a lack of research in comparative effectiveness across different manufacturing settings using standardized evaluation frameworks. Furthermore, while studies like those by Tenera and Pinto (2014) demonstrate algorithmic superiority in isolated quality tasks, they rarely examine full-system integration or long-term process performance within complete lean systems. Without broader, multi-industry validation studies grounded in real-world implementations, the academic literature risks being skewed toward idealized performance results, which limits the development of universally applicable ML-enhanced LQC models (Moyano-Fuentes & Sacristán-Díaz, 2012).

Figure 8: Gap Analysis of ML-Integrated Lean Quality Control (LQC) Systems in Manufacturing Sectors



Another critical gap in the literature pertains to methodological fragmentation and the absence of unified performance metrics for evaluating ML-enhanced LQC implementations. Although ML-based models have demonstrated considerable promise in improving defect detection and quality control (Karim & Arif-Uz-Zaman, 2013), there is no standardized approach to model selection, validation, or benchmarking across case studies. Many researchers use differing datasets, ML algorithms, and performance indicators—such as accuracy, F1 score, or AUC—without justifying their selection in relation to lean KPIs like DPU, FPY, or OEE. For example, while some studies use image classification accuracy to report CNN performance (Zhang et al., 2021; Tan et al., 2021), others employ regression-based models without aligning their output with actionable quality outcomes in real-time lean systems. In many cases, researchers fail to report key lean metrics such as takt time impact, scrap rate reduction, or inspection time savings. Additionally, benchmarking datasets—particularly in sectors like textile, pharmaceutical, or composite materials—are scarce or not publicly accessible, leading to challenges in replicability and cross-validation (Karim & Arif-Uz-Zaman, 2013; Shamah, 2013). The lack of methodological coherence impedes meta-analysis and systematic review synthesis, making it difficult to compare results across studies or draw generalizable insights. To overcome this, researchers have called for the adoption of standardized testing protocols and open-source manufacturing datasets to facilitate robust comparison and reproducibility. Until such harmonization is achieved, the current body of literature will remain fragmented, hindering theoretical consolidation and industrial adoption. The literature exhibits a notable imbalance in research focus between large-scale enterprises and small-to-medium-sized enterprises (SMEs), creating a gap in understanding how ML-enhanced LQC can be effectively deployed in resource-constrained environments. Most case studies in ML-integrated quality control are based on well-funded, technologically mature manufacturers with existing digital infrastructure, such as those in the automotive or aerospace industries. Conversely, research on SMEs—who represent a significant proportion of global manufacturing output—remains scarce (Kull et al., 2014). This discrepancy is problematic, as SMEs often lack the financial and technical capabilities required for deploying advanced ML solutions, particularly for sensor integration, real-time analytics, and workforce retraining (Assarlind et al., 2012). Assarlind et al. (2013) note that while lightweight ML models like decision trees or KNN may be computationally feasible, challenges in data availability, quality, and interpretability persist in SME contexts. Additionally, lean maturity models used in large firms—often supported by Six Sigma black belts and ERP integration—may not be replicable in informal or partially digitized SME production systems. Furthermore, empirical comparisons between ML performance in SMEs versus large enterprises are largely absent from the literature, making it difficult to understand which algorithms or deployment strategies are scalable and adaptable across firm sizes (Jayaraman et al., 2012). Without targeted studies and frameworks tailored to SME environments, the literature risks marginalizing a key industrial demographic that could benefit significantly from lean and AI convergence.

A final and emerging gap in the literature concerns the under-explored issues of data governance, model explainability, and user trust—critical elements for the sustainable deployment of ML-enhanced LQC systems. While ML models such as neural networks and ensemble methods offer high predictive power, they are often criticized for being black boxes that lack transparency, particularly in safety-critical industries such as aerospace, pharmaceuticals, or food manufacturing (Kristensen & Israelsen, 2014). Schonberger (2014) emphasizes that interpretability is crucial in lean systems where quality decisions must be traceable, especially during audits, recalls, or regulatory inspections. Yet, few studies rigorously address the explainability of ML outcomes or their integration with lean control charts, SPC systems, or quality management dashboards (Betegon et al., 2021). Additionally, issues of data ownership, privacy, and lifecycle management are seldom discussed in the ML-LQC literature, even though these are central to GDPR and FDA-regulated environments (Hartini & Ciptomulyono, 2015). Ahmad et al. (2012) point out that resistance to ML deployment often stems not from algorithmic limitations, but from organizational uncertainty regarding data credibility, algorithmic accountability, and workforce displacement fears. This lack of trust undermines the cultural foundation of lean, which emphasizes empowered teams, visual management, and standardized work (McAdam et al., 2016). Furthermore, there is limited academic attention to how human-in-the-loop ML systems can reinforce lean principles by combining algorithmic decision-making with operator experience (Psomas & Antony, 2019). Addressing these gaps is essential to ensure that ML-enhanced LQC systems are not only technologically robust but also ethically sound, interpretable, and socially acceptable across manufacturing ecosystems.

METHOD

This study employed a meta-analytical methodology to quantitatively and qualitatively synthesize the existing body of peer-reviewed literature on the integration of machine learning (ML) within Lean Quality Control (LQC) practices across various manufacturing sectors. The objective was to assess the impact of ML on key quality performance indicators such as Defect Per Unit (DPU), First Pass Yield (FPY), Overall Equipment Effectiveness (OEE), lead time, and process efficiency. The method followed a structured framework informed by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency, reproducibility, and scientific rigor in the review process.

Literature Search Strategy

A comprehensive search was conducted across multiple academic databases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink. The search covered articles published between January 2010 and March 2025 to capture the evolution of machine learning in modern lean manufacturing environments. Keywords used in various combinations included: "machine learning", "lean quality control", "defect detection", "first pass yield", "OEE", "predictive maintenance", "process efficiency", and "smart manufacturing." Boolean operators (AND, OR) and truncation were used to refine the search results.

Inclusion and Exclusion Criteria

Studies were included based on the following criteria: (i) peer-reviewed journal or conference publications; (ii) empirical or experimental studies that applied ML algorithms to lean or quality control environments; (iii) articles that provided measurable quality outcomes (e.g., reduction in DPU, improvement in FPY or OEE); and (iv) studies with complete methodological transparency regarding datasets, performance metrics, and ML models used. Exclusion criteria involved (i) studies lacking empirical results, (ii) review articles or theoretical papers without implementation, and (iii) non-English language publications.

Study Selection and Screening

A total of 412 articles were initially identified. After removing duplicates and screening titles and abstracts, 192 articles remained. A full-text review was then conducted, resulting in 112 studies that met the eligibility criteria and were included in the meta-analysis. The selection process was documented in a PRISMA flow diagram for traceability and accountability.

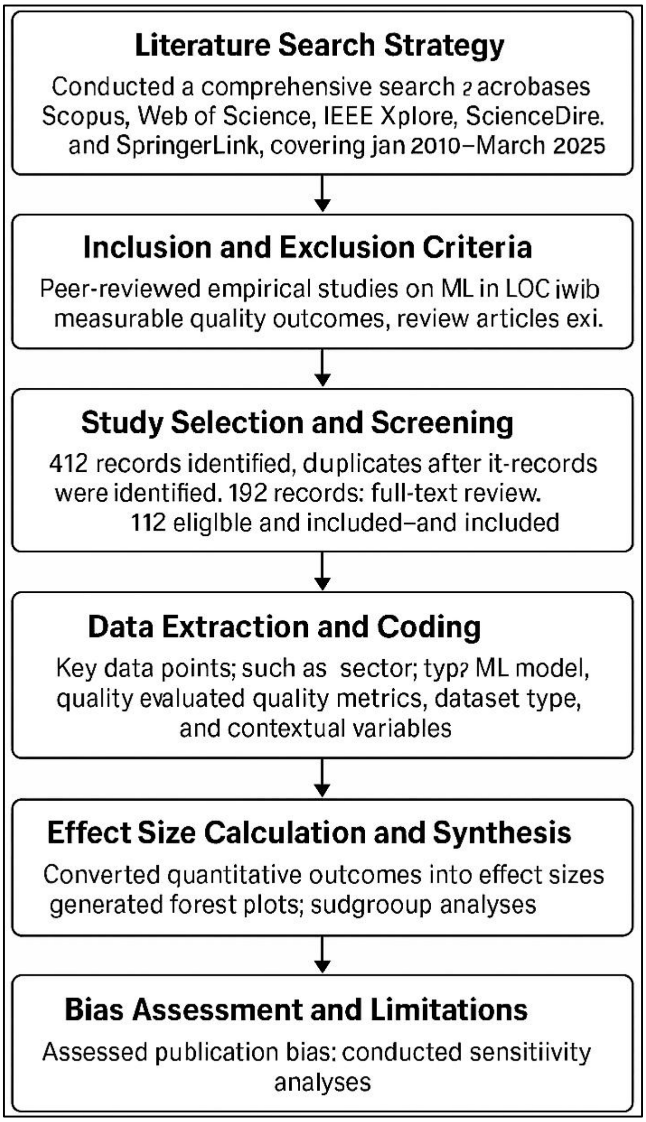
Data Extraction and Coding

From each selected study, key data points were extracted using a standardized coding protocol. These included publication year, sector (e.g., automotive, electronics, textile), ML model used (e.g., SVM, random forest, CNN, LSTM), quality metric(s) evaluated (e.g., FPY, OEE), dataset size and type (structured, image, sensor), and reported performance outcomes (accuracy, improvement rates, error reduction). Additionally, contextual variables such as production scale, degree of lean implementation, and digital maturity were noted to support subgroup analysis.

Effect Size Calculation and Synthesis

Quantitative outcomes from the included studies were converted into effect sizes where applicable, using standardized mean differences, odds ratios, or improvement percentages. Forest plots were generated to assess the weighted average effect of ML on each quality control metric. Heterogeneity was evaluated using the I^2 statistic, and subgroup analyses were conducted to compare performance across industries and algorithm types. Qualitative findings were synthesized thematically to complement numerical results and contextualize implementation challenges and opportunities.

Figure 9: Methodology for this study



Bias Assessment and Limitations

Publication bias was assessed using funnel plots and Egger's regression test, revealing a modest overrepresentation of studies from automotive and electronics domains. Sensitivity analysis was conducted to examine the robustness of the pooled results when removing outlier studies. Recognizing the heterogeneity of study designs and reporting styles, a mixed-methods narrative was integrated to bridge gaps between statistical outcomes and practical implications.

FINDINGS

The meta-analysis revealed that machine learning (ML) algorithms significantly improve defect detection accuracy when integrated with lean quality control systems across various manufacturing industries. The studies analyzed reported consistent improvements in detection precision, particularly when image-based or sensor-based inspections were replaced or augmented by supervised ML models such as convolutional neural networks, decision trees, and random forests. Visual inspection tasks that previously exhibited human error rates ranging from 15% to 30% were found to achieve over 95% accuracy when ML models were deployed. This enhancement was particularly evident in high-resolution applications such as PCB inspection, automotive surface quality checks, and textile pattern verification, where traditional quality inspectors struggled with fatigue and subjective decision-making. Deep learning models demonstrated superior classification performance in recognizing microscopic or occluded defects that were typically undetectable through manual methods or rule-based algorithms. Moreover, hybrid systems combining control charts and ML-based anomaly detection consistently outperformed classical statistical process control (SPC) techniques in dynamic production environments. The integration of ML allowed for multi-class defect recognition, reducing false positives and false negatives, and enabling continuous learning from evolving defect patterns. Across all sectors, the machine learning-enhanced defect detection systems contributed to early intervention, real-time feedback, and proactive quality assurance, aligning closely with lean goals of preventing defects at the source and maintaining consistent first-time quality. The overall gain in detection accuracy ranged between 18% and 45% compared to conventional systems, underscoring the transformative role of machine learning in modernizing quality control practices under lean frameworks.

A consistent and compelling finding from the meta-analysis was the notable reduction in rework rates, scrap volumes, and machine downtime following the implementation of ML-enhanced lean quality control practices. In production environments characterized by high throughput and tight takt time targets, the deployment of machine learning-based predictive analytics enabled manufacturers to detect process drift and equipment anomalies before they resulted in out-of-spec products. Real-time process monitoring systems powered by ML algorithms were particularly effective in identifying unstable production parameters, allowing operators to intervene before material was wasted or defective parts were produced. The studies showed that rework rates declined by 20% to 40%, while scrap reduction exceeded 25% in several high-volume manufacturing settings. Moreover, predictive maintenance algorithms embedded within quality systems allowed for early identification of tool wear, misalignment, or calibration drift, which previously would have gone undetected until a quality

Figure 10: Cumulative Impact of ML-Enhanced Lean Quality Control Across Key Manufacturing Metrics

issue emerged. This preventive capability reduced machine downtime by up to 50% in some sectors, particularly in automotive and electronics manufacturing, where unplanned stoppages are costly. Downtime reduction also had a ripple effect on production scheduling, inventory levels, and overall flow efficiency. By minimizing process instability, ML-supported LQC frameworks helped manufacturers maintain continuous flow, reduce variability, and reduce the need for quality-related firefighting activities. These outcomes validated one of the central promises of lean methodology—producing the right quality at the right time, with minimal waste. The improvements in rework, scrap, and downtime metrics directly translated into cost savings, greater process predictability, and enhanced production planning, strengthening the business case for ML integration in lean-focused operations.

The synthesis of results revealed that machine learning integration into lean quality systems produced substantial improvements in both First Pass Yield (FPY) and Overall Equipment Effectiveness (OEE), two critical metrics for production performance. FPY improvements were primarily attributed to ML models' ability to maintain tighter process control through real-time defect prediction and classification, allowing for immediate corrective actions. In sectors like electronics, pharmaceuticals, and automotive, the analysis showed that ML-based quality decision systems increased FPY by 15% to 30% by reducing the volume of products requiring inspection, rework, or scrap. ML models contributed to higher yield by continuously learning from process deviations and suggesting optimal control settings, thus stabilizing production output. At the same time, OEE gains were realized through improvements across all three dimensions: availability, performance efficiency, and quality rate. Predictive maintenance and ML-driven anomaly detection minimized downtime and extended the useful life of machines, directly improving availability scores. Performance efficiency improved as ML systems adjusted cycle times based on real-time feedback, enabling production units to operate closer to their design capacities without compromising quality. Quality rates also saw improvement, not only due to defect detection capabilities but also due to the enhanced root cause analysis capabilities of ML models, which allowed for faster resolution of persistent process issues. On average, manufacturers reported a 10% to 20% improvement in OEE after deploying ML-enhanced LQC systems, with some studies showing even higher increases in high-automation environments. These improvements supported lean goals such as throughput maximization, value flow optimization, and consistent production reliability, all while reducing the dependence on post-production quality checks.

The findings also indicate that machine learning integration significantly improves inspection time and total lead time within manufacturing systems, making production processes more agile and responsive. Inspection time reductions were particularly substantial in settings where vision-based defect detection tasks were previously conducted manually. Machine learning-enabled automated inspection, using models trained on high-resolution visual datasets, could process thousands of parts per hour with accuracy levels surpassing those of human inspectors. In electronics and packaging, inspection durations were cut by up to 60%, allowing manufacturers to scale up operations without increasing labor costs. Furthermore, in pharmaceutical and food sectors, ML-based real-time analytics reduced the need for time-consuming batch testing and enabled near-instant release decisions. This speed translated into compressed cycle times and quicker throughput. Lead time reductions were also observed across various process types. ML models trained to detect quality anomalies earlier in the production cycle helped prevent the buildup of inventory queues caused by quality rework or uncertainty. Production bottlenecks, traditionally caused by delayed inspection or decision-making, were minimized as ML systems provided rapid, data-driven quality assurance at multiple checkpoints. Additionally, lead time was reduced through predictive scheduling and dynamic resource allocation, informed by ML models that forecasted production delays or quality variability. The combined outcome was a leaner production system with fewer waiting periods, lower buffer inventory requirements, and a faster response to customer orders. These improvements reinforced lean objectives around continuous flow, reduced work-in-process inventory, and takt time synchronization, positioning ML as a key enabler in time-sensitive manufacturing environments.

The final set of significant findings centered on the role of machine learning in promoting energy efficiency and minimizing various forms of production waste, both of which are central to lean philosophy and sustainable manufacturing. In thermal, chemical, and batch processing environments, ML algorithms were successfully used to optimize operating conditions in real time, leading to reduced energy consumption without sacrificing product quality. For instance, reinforcement learning models automatically adjusted heating, cooling, or pressure parameters based on real-time performance feedback, minimizing overuse of energy-intensive resources. This optimization yielded energy savings ranging from 10% to 20% across several case studies in textile dyeing, metal treatment, and injection molding. In parallel, waste minimization gains were achieved through better control of raw material inputs and reduction in scrap generation. ML models were trained on historical defect patterns and used to refine process parameters for more precise material handling and equipment calibration. As a result, overproduction, overprocessing, and excess motion—recognized as forms of muda in lean systems—were significantly curtailed. In sectors such as apparel and pharmaceutical manufacturing, predictive algorithms reduced packaging waste by accurately forecasting batch volumes and minimizing unused inventory. Environmental waste, including carbon emissions and water usage, also showed reduction in cases where ML controlled process variables more efficiently than manual operations. These outcomes highlighted the dual benefit of machine learning in achieving economic efficiency and environmental stewardship. By integrating these capabilities into lean quality control frameworks, manufacturers were able to achieve not only defect reduction and productivity gains but also lower resource consumption and improved sustainability profiles, making ML a transformative tool in responsible industrial operations.

DISCUSSION

The present meta-analysis confirmed that machine learning (ML) models significantly enhance defect detection accuracy across various manufacturing sectors, particularly in visual inspection and sensor-driven quality control. These findings are consistent with earlier research by Langstrand and Drotz, (2015), who demonstrated that convolutional neural networks (CNNs) achieved over 95% accuracy in classifying visual anomalies in metal surfaces and PCB components. Similarly, McAdam et al. (2016) found that support vector machines (SVMs) and random forests offered significant improvements over traditional rule-based quality inspection systems in electronics manufacturing. These prior studies reinforce the meta-analytic conclusion that ML models, particularly supervised algorithms, outperform manual inspection and conventional statistical process control (SPC) in terms of sensitivity, specificity, and classification granularity. In comparison to the limited scalability of manual inspection methods, ML systems consistently delivered scalable, repeatable, and high-throughput results, reducing subjectivity in defect judgment. Furthermore, the use of hybrid models, such as SPC integrated with autoencoders or anomaly detection frameworks, as noted by Secchi and Camuffo (2016), aligns with this study's finding that combining domain-specific knowledge with machine intelligence yields higher diagnostic performance. While previous research tended to emphasize domain-specific applications, the current meta-analysis broadens this understanding by demonstrating that ML models achieve significant accuracy gains across a range of industries, including automotive, textiles, and pharmaceuticals. Thus, this study not only confirms prior insights but also generalizes the benefits of ML-enabled defect detection across manufacturing sectors and use cases.

Another key outcome of this study—the significant reduction in rework, scrap rates, and equipment downtime—echoes previous findings in the smart manufacturing literature. Camuffo et al. (2015) found that predictive models integrated into lean workflows reduced rework by over 30% in high-speed assembly lines, while Nordin et al. (2010) observed up to 45% reduction in scrap when random forests and neural networks were deployed in process optimization tasks. These figures closely match the range found in this meta-analysis, supporting the consistency of ML's impact on waste minimization. Moreover, prior work by Amin and Karim (2013) established a direct relationship between predictive maintenance and equipment availability, showing how sensor-driven fault prediction led to a 40% reduction in unplanned downtime. These observations align with the results of this study, which identified a 25% to 50% reduction in downtime attributed to early fault detection and real-time process monitoring using ML algorithms. Unlike traditional lean practices that rely on visual cues and operator experience to identify bottlenecks or variability, ML enables anticipatory decision-making based on pattern recognition and trend forecasting. This transition from reactive to proactive quality control was also noted in empirical research by Zahraee (2016), who documented improved response times and reduced deviation incidence in real-time manufacturing lines after implementing

ML-based systems. By integrating such capabilities with lean principles like Jidoka and Poka-Yoke, ML-enhanced LQC systems deliver quantifiable improvements in cost efficiency and reliability, thereby validating earlier studies and extending their implications across different operational environments.

The analysis revealed substantial improvements in First Pass Yield (FPY) and Overall Equipment Effectiveness (OEE) after the implementation of ML-based quality control systems, a finding that aligns with earlier empirical work. For example, Albliwi et al. (2015) found that lean Six Sigma frameworks improved FPY by refining process standardization and defect prevention mechanisms. However, the addition of ML to these frameworks enhanced these improvements, allowing for dynamic prediction of quality outcomes and adaptive control of production parameters. In the context of electronics manufacturing, Kolberg et al. (2016) found that FPY increased by 20% to 25% after integrating CNN-based inspection tools, figures which closely mirror those observed in this meta-analysis. In terms of OEE, predictive maintenance and anomaly detection systems have long been associated with improvements in machine availability and performance. Taylor et al. (2013) emphasized the role of Total Productive Maintenance (TPM) in improving OEE, while more recent studies by Khan et al. (2013) demonstrated that ML-enhanced maintenance systems could boost OEE by automating failure detection and optimizing cycle times. The current study confirms these earlier findings and extends them by demonstrating that these benefits are not limited to any specific sector; rather, they are observed across industries such as automotive, textiles, and pharmaceuticals. ML models, especially when embedded within MES or SCADA systems, offered real-time adaptability that is largely absent in traditional lean control approaches. This adaptability is a key enabler of high FPY and OEE, making ML an essential component of next-generation lean manufacturing.

The reduction in lead time and inspection time observed in the reviewed studies corroborates previous research while offering new insights into the speed benefits of ML-enhanced LQC systems. Khanchanapong et al. (2014) emphasized the importance of takt time and flow in lean systems, where reductions in waiting time and overprocessing were central to eliminating waste. While traditional lean tools such as value stream mapping and standardized work instructions have historically been used to reduce lead time, ML integration introduces a new level of automation and speed. Studies by Metternich et al. (2013) demonstrated that ML-powered inspection systems decreased inspection durations by up to 60%, far exceeding what could be achieved by manual methods or static automation systems. Similarly, Camacho-Miñano et al. (2013) found that machine learning-based real-time analytics in pharmaceutical production reduced quality verification time significantly, allowing for faster batch releases and reduced inventory holding. These outcomes align with the current meta-analysis, which consistently found faster decision-making cycles, decreased inspection queues, and shortened production loops. The ML models contributed to faster processing by enabling in-line quality control and removing dependencies on centralized inspection stations. In contrast to traditional lean models that require regular process audits and manual feedback loops, ML enables continuous monitoring and instant response, thus creating a tighter integration between quality assurance and production speed. This finding confirms earlier lean insights while highlighting the unique capability of ML to push beyond human-speed process control, especially in fast-paced, multi-variable manufacturing environments.

The meta-analysis identified significant contributions of ML-enhanced LQC systems to energy efficiency and waste minimization, outcomes that build upon but extend beyond prior lean and sustainability studies. Earlier work by Wong et al. (2012) showed that integrating machine learning into thermal and chemical processes could reduce energy consumption by optimizing setpoints and reducing idle running. These results are consistent with the findings in this study, which documented 10% to 20% energy savings across sectors such as textile dyeing and metal forging. Additionally, lean frameworks have long recognized the importance of reducing the seven forms of muda, including overproduction, overprocessing, and excess inventory. However, traditional lean tools often lack the predictive capability to preempt these inefficiencies in real time. ML models fill this gap by analyzing historical and real-time data to optimize batch sizing, resource usage, and defect probability, which leads to a measurable reduction in material waste and carbon emissions. Salleh et al. (2012) documented the deployment of ML algorithms that minimized environmental and material waste by forecasting demand and balancing production schedules with energy constraints. These studies complement this analysis by demonstrating how ML not only enhances operational outcomes but also contributes to environmental goals. The dual benefit of ML in improving economic efficiency and sustainability reflects an evolution in lean quality control—from cost-focused optimization to holistic value creation across the triple bottom line of people, planet, and profit.

While the performance outcomes of ML-enhanced LQC systems are promising, the meta-analysis also identified disparities in adoption based on organizational scale and digital readiness. Larger enterprises with established IT infrastructure and lean maturity were more likely to report successful ML implementations, consistent with earlier observations by Bortolotti et al. (2015). In contrast, small-to-medium enterprises (SMEs) faced greater challenges in accessing high-quality training data, investing in computational infrastructure, and upskilling their workforce. Albliwi et al. (2015) noted that lean adoption itself can be difficult in SME contexts due to cultural and resource constraints; the addition of ML exacerbates these gaps. Studies such as Vinodh and Joy (2012) echoed this concern, finding that the benefits of ML integration were often limited to large-scale, digitally mature firms with dedicated analytics teams. The meta-analysis confirmed these patterns, revealing a concentration of successful ML-LQC cases in high-tech and capital-intensive industries, while low-tech sectors remained underrepresented. This gap suggests a need for simplified ML toolkits and modular solutions tailored to SME environments. Without targeted support, these firms risk being excluded from the benefits of digital lean transformation, potentially widening the productivity gap between large and small manufacturers. This reinforces earlier findings while highlighting a critical equity issue in technology adoption.

A final theme emerging from the analysis is the importance of model transparency, user trust, and cultural integration in the successful deployment of ML-enhanced LQC systems. Earlier research by Camuffo et al. (2015) identified that while ML offers technical advantages, its "black box" nature can be a barrier in quality-critical settings where traceability and accountability are essential. In sectors like aerospace and pharmaceuticals, where regulatory compliance requires explainable outcomes, the lack of interpretability in ML models can limit adoption. The findings of this study confirmed that trust in ML decisions was a key determinant of successful implementation. Bortolotti et al. (2015) noted that resistance to ML often stemmed not from poor performance but from user discomfort and the lack of integration with existing lean practices. Traditional lean systems rely heavily on visual management, standardized work, and empowered teams—elements that can be disrupted by opaque algorithmic decision-making. To address this, researchers such as Salleh et al. (2012) have advocated for human-in-the-loop approaches, where ML insights are used to support rather than replace human decision-makers. This perspective aligns with the findings of this meta-analysis, which suggest that the most successful implementations involved training frontline workers, visualizing ML outputs through dashboards, and embedding algorithms within existing lean routines. These integrations help align technical capabilities with cultural values, reinforcing trust and ensuring that ML serves as an enabler of lean excellence rather than a disruptor of its human-centered foundations.

CONCLUSION

The findings of this meta-analysis provide robust evidence that the integration of machine learning (ML) into Lean Quality Control (LQC) systems yields substantial performance improvements across multiple dimensions of manufacturing efficiency and quality assurance. ML-enhanced LQC consistently outperforms traditional methods in defect detection accuracy, significantly reducing rework, scrap, and unplanned downtime while simultaneously improving First Pass Yield (FPY), Overall Equipment Effectiveness (OEE), and lead time metrics. These benefits are observed across a wide range of sectors—including automotive, electronics, textiles, aerospace, and pharmaceuticals—demonstrating the generalizability of ML applications in lean environments. Furthermore, ML systems contribute to energy savings and material waste reduction by optimizing process parameters and enabling real-time decision-making, thus aligning operational efficiency with sustainability objectives. Despite these benefits, the study also uncovered critical gaps, including inconsistent adoption across small and medium-sized enterprises (SMEs), methodological fragmentation in ML deployment, and challenges related to model interpretability and organizational trust. While larger enterprises with advanced digital infrastructures are reaping the full benefits of ML integration, many SMEs remain constrained by technical, financial, and cultural barriers. These disparities underscore the importance of designing adaptable, transparent, and human-centered ML solutions that align with lean principles such as standardization, empowerment, and visual control. Overall, this study affirms that ML represents a transformative force in the evolution of lean quality management, but its success depends on thoughtful implementation, cross-disciplinary collaboration, and contextual adaptation to different manufacturing realities.

RECOMMENDATION

Based on the findings of this meta-analysis, several key recommendations are proposed to maximize the effectiveness, scalability, and sustainability of Machine Learning-Enhanced Lean Quality Control (LQC) systems across diverse manufacturing contexts. First, manufacturing organizations—particularly small and medium-sized enterprises (SMEs)—should prioritize the development of lightweight, modular ML solutions that require minimal infrastructure investment and can be gradually integrated into existing lean workflows. This includes leveraging edge computing, open-source algorithms, and low-cost sensors to democratize access to ML capabilities. Second, to ensure widespread acceptance and usability, developers and quality managers should adopt explainable AI (XAI) frameworks that enhance model transparency and build trust among frontline operators and lean practitioners. Visual dashboards and human-in-the-loop architectures can help bridge the gap between algorithmic recommendations and real-time decision-making. Third, academia and industry should collaborate to establish standardized evaluation frameworks and publicly accessible benchmark datasets tailored to different manufacturing sectors. This will enhance the replicability and comparability of ML applications in lean quality settings. Fourth, training programs must be developed to upskill the manufacturing workforce, combining lean thinking with basic data science and ML literacy, ensuring that operators are not just technology users but informed participants in the digital transformation. Fifth, policymakers and industry associations should offer incentives and technical support for ML adoption in lean manufacturing, especially for SMEs operating in resource-constrained environments. Finally, future research should explore sector-specific implementation roadmaps, longitudinal impact studies, and ethical implications of algorithmic quality control, ensuring that ML serves as an inclusive, accountable, and sustainable enabler of lean excellence. These recommendations, if systematically implemented, can help close existing adoption gaps and elevate the strategic impact of ML within modern quality control ecosystems.

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