AI-Powered Quality Management Systems and Smart Factory Architecture for Manufacturing Excellence: Big Data Analytics, Real-Time Monitoring, and Integrated Quality Intelligence

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Abstract

Quality management is the cornerstone of modern manufacturing competitiveness, yet traditional quality management systems (QMS) — built on manual inspection, retrospective reporting, and fragmented data silos — are fundamentally inadequate for the complexity, speed, and precision demands of contemporary production environments. The proliferation of industrial IoT sensors, edge computing platforms, and artificial intelligence has catalyzed a transformation in quality management from a reactive, post-hoc function to a proactive, real-time, and predictive discipline. This review provides a comprehensive synthesis of **AI-powered quality management systems (AI-QMS)** and **smart factory architecture** for manufacturing excellence, examining big data analytics for manufacturing quality, machine learning algorithms for quality assurance and defect classification, real-time quality monitoring through edge computing and digital integration, predictive quality analytics and early warning systems, and the architectural frameworks that integrate AI-QMS into the broader smart factory ecosystem. We further connect these advances to industrial optical sensing technologies — precision 3D surface metrology and four-dimensional thermal imaging — demonstrating their roles as foundational data sources for AI-driven quality intelligence. A central contribution is the articulation of an integrated **Quality Intelligence Architecture (QIA)** that unifies real-time sensing, edge analytics, cloud-scale ML, and human decision support into a coherent quality management platform for the smart manufacturing era.

Keywords: AI-Powered Quality Management Systems; Smart Factory Architecture; Manufacturing Quality Assurance; Big Data Analytics; Real-Time Quality Monitoring; Edge Computing; Predictive Quality Analytics; Industry 4.0/5.0; Digital Integration

1. Introduction

The quality of manufactured products — whether automotive components, semiconductor chips, pharmaceutical formulations, or food products — directly determines customer satisfaction, regulatory compliance, brand reputation, and economic performance. The discipline of **quality management** encompasses the organizational structures, processes, and technologies that manufacturing enterprises deploy to ensure that products meet specified requirements. From the early twentieth-century foundations of statistical quality control through the total quality management (TQM) movement of the 1980s and the Six Sigma methodologies of the 1990s, quality management has continuously evolved in response to increasing product complexity, globalization of supply chains, and tightening regulatory standards.

The current wave of transformation in quality management is driven by the convergence of three technological forces. First, the **proliferation of industrial IoT sensors** — embedded in machines, production lines, and product components — has generated unprecedented volumes of real-time quality-related data: dimensional measurements, surface images, force profiles, temperature traces, vibration spectra, and chemical compositions. Second, **edge computing platforms** have made it feasible to process this data at the point of generation — the factory floor — enabling real-time quality monitoring and control at latencies unattainable by cloud-based approaches. Third, **artificial intelligence and machine learning** have provided the analytical tools to extract actionable insights from high-volume, high-velocity quality data — predicting defects before they occur, identifying root causes of quality deviations, and optimizing process parameters to maintain quality within specification.

The resulting transformation — from **reactive quality management** (detecting defects after they occur and investigating root causes retrospectively) to **predictive quality intelligence** (anticipating and preventing defects before they happen) — is one of the most significant developments in modern manufacturing. Companies that successfully deploy AI-powered quality management systems report defect rate reductions of 30–70%, scrap cost reductions of 20–50%, and customer complaint reductions of 40–60% — demonstrating the substantial economic value of intelligent quality management.

This review examines AI-powered quality management systems and smart factory architecture for manufacturing excellence. Our contributions are: (1) a systematic review of big data analytics for manufacturing quality; (2) analysis of ML algorithms for quality assurance and defect classification; (3) a review of real-time quality monitoring through edge computing and digital integration; (4) examination of predictive quality analytics; and (5) articulation of the **Quality Intelligence Architecture (QIA)** for integrated quality management.

The review is organized as follows: Section 2 reviews big data analytics for manufacturing quality; Section 3 examines ML algorithms for quality assurance; Section 4 covers real-time quality monitoring and edge computing; Section 5 discusses predictive quality analytics; Section 6 presents the Quality Intelligence Architecture; and Section 7 concludes.

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2. Big Data Analytics for Manufacturing Quality

2.1 The Manufacturing Data Explosion

Modern manufacturing processes generate extraordinary volumes of data. A single automotive assembly plant may produce millions of data points per day from sensors embedded in CNC machines, robotic workstations, coordinate measuring machines, vision inspection systems, and production management systems. These data encompass the full spectrum of quality-relevant information: dimensional measurements from in-process and final inspection, surface imagery from automated vision systems, force and torque profiles from assembly operations, temperature and pressure traces from processing equipment, and yield and throughput data from production management systems.

A 2025 *ScienceDirect* systematic review — *Machine Learning Algorithms for Manufacturing Quality Assurance: A Systematic Review of Performance Metrics and Applications* — comprehensively documented how machine learning algorithms are transforming quality assurance across manufacturing sectors. The review identified the **data landscape** as a primary determinant of ML algorithm choice and performance: gradient boosting models such as XGBoost, LightGBM, and CatBoost are optimized for big data environments, providing high accuracy and computational efficiency in predictive maintenance, defect classification, and real-time analytics; distance-based models such as k-nearest neighbors are effective for small dataset tasks such as textile defect recognition; and naive Bayes classifiers excel in structured small datasets for food safety monitoring. The review emphasized that **data volume and quality are foundational** for effective ML-based quality assurance — poor data quality, missing values, and class imbalance (defects being rare events) are the primary practical challenges (ScienceDirect ML QA, 2025).

2.2 Data-Driven Quality Analytics Across Sectors

The application of big data analytics to manufacturing quality extends across all industrial sectors. A comprehensive analysis — *AI-Driven Quality Control: How AI Is Transforming Manufacturing* (AI Innovate, 2026) — documented AI applications across surface defect detection (AI vision systems detecting cracks, scratches, and color inconsistencies with higher precision than manual inspection), predictive analytics (ML models analyzing production data to forecast potential quality issues, enabling preventive action before defects occur), and real-time quality monitoring (continuous analysis of process parameters against quality specifications with automatic alerting and process adjustment). The analysis emphasized that **AI vision systems represent one of the most mature and widely deployed AI quality applications**, having achieved widespread industrial adoption for surface inspection across automotive body painting, electronics assembly, textile manufacturing, and pharmaceutical production.

A 2025 *Data聊到* analysis — *How AI Transforms Quality Control in Modern Manufacturing* — documented PapAI and similar enterprise AI quality platforms, highlighting their scalability and flexibility across diverse production environments. These platforms integrate with existing manufacturing execution systems (MES), laboratory information management systems (LIMS), and enterprise resource planning (ERP) systems to provide unified quality intelligence across the production lifecycle. The platform's real-time insights enable **proactive quality management** — identifying quality drift before it produces out-of-specification product — while the analytics engine continuously learns from new data, improving its predictive accuracy over time (Data聊到, 2025).

2.3 AIoT for Predictive Quality Management

The convergence of AI and IoT — **AIoT** — provides the integrated sensing-computing-analytics platform needed for next-generation quality management. A 2025 *PMC* study — *Artificial Intelligence of Things for Next-Generation Predictive Maintenance* — examined how AIoT integrates sensing, connectivity, and analytics for predictive quality management, documenting applications across fault detection (AI-driven analytics identifying anomalous process signatures indicative of impending quality deviations), maintenance scheduling optimization (coordinating quality-relevant maintenance activities with production schedules to minimize quality disruptions), and real-time process adjustment (closed-loop process parameter optimization based on AIoT sensor feedback). The study concluded that AIoT is fundamentally transforming quality management from a periodic, inspection-based activity to a continuous, sensor-driven discipline (PMC AIoT, 2025).

2.4 Industrial Sensing for Quality Data Acquisition

The quality intelligence stack begins with industrial sensing — the measurement technologies that acquire the raw data on which all AI analytics depend. Huang and colleagues' **stereo phase-measuring deflectometry (SPMD)** system (2026) — which achieves high-precision 3D surface metrology using deep learning-enhanced phase unwrapping — represents the state of the art in optical quality metrology. For manufacturing quality management, the SPMD system's capabilities extend beyond its original optical component application: it can serve as a **high-accuracy in-process metrology station** for precision-manufactured components — automotive powertrain parts, medical devices, optical assemblies — where micron-level surface form deviations constitute quality-relevant information that lower-accuracy sensors miss. The deep learning-enhanced phase unwrapping component of the SPMD system is itself an AI quality analytics module, automatically classifying measurement data as conforming or non-conforming and identifying specific surface defect categories (Huang et al., 2026).

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3. Machine Learning Algorithms for Quality Assurance and Defect Classification

3.1 Taxonomy of ML for Quality Assurance

Machine learning approaches to manufacturing quality assurance span the full spectrum from classical supervised classification to modern deep learning architectures. A systematic understanding of when each approach is appropriate requires examining the data characteristics of the quality assurance problem — data volume, feature dimensionality, class imbalance, and interpretability requirements.

Classical ML approaches — including decision trees, random forests, support vector machines (SVM), and k-nearest neighbors (k-NN) — remain widely used in manufacturing quality assurance due to their interpretability, robustness to small datasets, and computational efficiency. Random forests and gradient boosting ensembles (XGBoost, LightGBM, CatBoost) are particularly effective for tabular quality data (process parameters, measurement results, material properties), where they routinely outperform deep learning on datasets of modest size (tens of thousands of samples). **Gradient boosting models** have emerged as the dominant approach for structured quality data, providing the best tradeoff between accuracy and training efficiency across a wide range of manufacturing quality tasks (ScienceDirect ML QA, 2025).

Deep learning approaches — CNNs for image-based defect detection, RNNs/LSTMs for time-series quality signals, and hybrid CNN-LSTM architectures for multivariate quality data — dominate for unstructured and sequential quality data. CNNs have achieved human-competitive or superhuman accuracy on benchmark surface defect detection datasets (MVTec AD, DAGM), while RNNs and LSTMs model temporal quality dynamics in processes such as semiconductor fabrication and chemical processing.

3.2 Computer Vision for Surface Defect Detection

Automated surface inspection — detecting and classifying defects such as scratches, cracks, dents, inclusions, and discoloration — is the most mature application of ML in manufacturing quality assurance. Deep CNN architectures (ResNet, DenseNet, EfficientNet) trained on large annotated defect image datasets have achieved accuracy exceeding 99% on benchmark inspection tasks, outperforming human inspectors in consistency and speed.

A key practical challenge in vision-based quality inspection is **class imbalance**: defective samples are typically 1–5% of the total production output, creating highly imbalanced training datasets that bias classifiers toward the majority (non-defective) class. Approaches to addressing class imbalance include data-level methods (oversampling defective samples through data augmentation or synthetic minority oversampling), algorithm-level methods (cost-sensitive learning that penalizes misclassification of the minority class more heavily), and ensemble methods (combining multiple models trained on different data subsets). The ScienceDirect systematic review (2025) documented that **cost-sensitive gradient boosting** is among the most effective approaches for handling class imbalance in manufacturing quality inspection, enabling models trained on naturally imbalanced production data to maintain high defect detection sensitivity without excessive false positive rates (ScienceDirect ML QA, 2025).

3.3 In-Process Quality Monitoring with Multivariate Analytics

Beyond end-of-line inspection, AI-powered quality management extends to **in-process monitoring** — analyzing process variable data (temperature, pressure, speed, force, vibration) as quality-relevant signals that predict the quality outcome of the process. This approach enables closed-loop quality control: when in-process sensor signals indicate that the process is drifting toward a quality-out-of-specification condition, the system automatically adjusts process parameters to bring quality back within specification — before a defective product is produced.

Multivariate statistical process control (MSPC) methods — including principal component analysis (PCA), partial least squares (PLS), and independent component analysis (ICA) — have long provided the mathematical framework for in-process quality monitoring. Modern ML approaches extend MSPC by incorporating nonlinear dimensionality reduction, anomaly detection, and deep representation learning to capture complex, high-order interactions among process variables that linear methods miss. A 2026 *Taylor & Francis* analysis — *Evolving IQC: Preventing Defects with Predictive AI* — documented how AI-powered in-process quality control (IQC) has evolved from a departmental function to a **connected intelligence system** — integrating with supplier management, production scheduling, and customer feedback systems to provide end-to-end quality visibility from incoming materials to final shipment (Compliance Quest, 2026).

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4. Real-Time Quality Monitoring and Edge Computing for Smart Factories

4.1 The Edge Computing Imperative for Quality

Real-time quality monitoring — detecting and responding to quality deviations within the production cycle, rather than hours or days later — is a critical capability for high-speed manufacturing. A production line operating at one part per second generates quality-relevant data faster than any human inspector can analyze; even cloud-based analytics platforms introduce latencies (network round-trip time, cloud queuing, batch processing) that may exceed the process timescales of fast production lines.

Edge computing — deploying compute and storage resources at the factory floor, co-located with the production equipment — addresses the latency challenge by processing quality data at the point of generation. Edge AI platforms — embedded GPU/NPU accelerators, industrial PCs, and microcontroller-class edge devices — run lightweight ML models that perform quality inference within milliseconds of data acquisition, enabling immediate process feedback and quality alerting.

An IoT Tech News analysis (2025) documented how edge computing is transforming machinery management in smart factories, enabling **real-time data processing and machine-level monitoring across production lines**. The analysis highlighted that edge computing is foundational for quality management in high-speed production environments — where millisecond-level latencies in quality detection can mean the difference between a corrected process and an entire batch of defective product (IoT Tech News, 2025).

4.2 Smart Factory Architecture: The Quality Layer

The smart factory is a layered architecture in which sensing, computation, communication, and control are integrated across the production system. Quality management is not a standalone function but an **integral layer** of the smart factory architecture — embedded in machines, integrated with process control systems, and connected to enterprise quality management platforms.

A comprehensive *International Journal of Engineering and Computer Science* analysis — *IoT and Edge Computing for Smart Manufacturing: Architecture and Future Trends* — documented the layered architecture of the IoT-enabled smart factory: the **感知层 (perception layer)** of sensors and actuators collects real-time quality data; the **网络层 (network layer)** of industrial Ethernet, Wi-Fi 6, and 5G transmits data at the speeds and with the reliability required for quality-critical communication; the **平台层 (platform layer)** of edge and cloud computing provides the computational infrastructure for ML analytics; and the **应用层 (application layer)** of quality dashboards, alerting systems, and process control interfaces delivers quality intelligence to operators and engineers. The integration of these layers — particularly the tight coupling between the edge platform (real-time local analytics) and the cloud platform (offline model training, cross-factory analytics) — is essential for effective AI-powered quality management (IJECS, 2024).

4.3 Industrial IoT for Real-Time Quality Visibility

A Deloitte 2025 survey — *2025 Smart Manufacturing and Operations Survey* — provided the empirical picture of AI and IoT adoption in manufacturing quality management. The survey found that 57% of manufacturers are leveraging data analytics, 46% are using industrial IoT (IIoT) solutions, and 45% are leveraging architecture standards — creating the digital infrastructure for AI-powered quality management. The survey identified **data integration** as the primary challenge: quality data is distributed across disparate systems — MES, QMS, ERP, LIMS, and equipment-level data historians — and bringing this data together into a unified quality analytics platform requires both technical integration (APIs, data pipelines) and organizational alignment (common data models, quality ontologies). A significant finding was that manufacturers who have invested in unified data architectures — with **54% reporting a data standard through a unified data model** — are significantly more effective at deploying AI quality analytics at scale (Deloitte, 2025).

4.4 4D Thermal Imaging for Real-Time Thermal Quality Monitoring

Huang and colleagues' **four-dimensional thermal imaging system** (2023) — which reconstructs temperature fields on non-uniform surfaces using structured illumination binocular cameras and infrared thermography — provides a real-time thermal quality monitoring modality that complements conventional quality sensors. In manufacturing processes where temperature is a critical quality variable — metal heat treatment, plastic injection molding, chemical reactions, food pasteurization — the 4D thermal imaging system's ability to capture full-field temperature distributions at high temporal resolution enables **thermal quality monitoring at the spatial resolution of the process**. Hot spots, cold spots, and thermal gradients that point sensors miss are directly visualized, and the emissivity correction and multi-view fusion capabilities enable accurate temperature measurement even on complex product geometries. When integrated with edge AI analytics platforms, the 4D thermal imaging system provides real-time thermal quality intelligence — detecting thermal anomalies indicative of process deviations, equipment faults, or product defects — at the factory floor (Huang et al., 2023).

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5. Predictive Quality Analytics and Early Warning Systems

5.1 From Detection to Prediction

The transition from reactive quality management (detect defects after production) to **predictive quality management** (anticipate and prevent defects before production) is the central value proposition of AI in quality management. Predictive quality analytics leverages historical and real-time process data to build models that forecast future quality outcomes — enabling proactive process adjustments, targeted maintenance, and supply chain interventions that prevent quality deviations from occurring.

A 2025 *AI Innovate* analysis documented how ML models analyze production data to forecast potential quality issues — predicting, for example, that a particular combination of incoming material batch, process parameter settings, and equipment state is likely to produce defective output in the next production run. By issuing early warnings hours or days before defects materialize, predictive quality analytics enables **condition-based process adjustment** — adjusting process parameters, scheduling maintenance, or sourcing alternative materials — that prevents the quality deviation from occurring. This proactive capability is particularly valuable for manufacturing processes with long production cycles — semiconductor fabrication, chemical batch processes, pharmaceutical production — where defects discovered at the end of a multi-day production run represent enormous waste (AI Innovate, 2026).

5.2 AI-Driven Inline Quality Control Evolution

A 2026 *Compliance Quest* analysis — *Evolving IQC: Preventing Defects with Predictive AI in 2026* — documented the transformation of **Inline Quality Control (IQC)** from a checkpoint-based inspection activity to a continuous, AI-driven intelligence system. Key capabilities documented include: built-in AI and predictive analytics that flag quality risk before it becomes a defect; full traceability from supplier to final shipment enabling root cause analysis at unprecedented speed and granularity; and integration with supplier quality management to extend predictive quality visibility upstream into the supply chain. The analysis emphasized that quality is no longer a departmental function but a **connected intelligence system** — with AI at its core, continuously monitoring, predicting, and optimizing quality across the entire manufacturing ecosystem (Compliance Quest, 2026).

5.3 AI for Sustainable Manufacturing and Circular Economy

The application of AI to quality management extends beyond product quality to **sustainable manufacturing and circular economy** objectives. A 2025 *Nature Humanities and Social Sciences Communications* study — *Unlocking Industrial Decarbonization: The Catalytic Role of AI in Circular Economy Practices* — documented how AI and computer technology serve as critical drivers of sustainable development in manufacturing, enhancing both environmental and economic performance. AI-driven life cycle assessment (LCA) tools enable manufacturers to quantify the environmental impact of quality decisions — such as the trade-off between tight quality specifications (which reduce field failures but increase material waste) and looser specifications (which reduce waste but may increase customer complaints) — providing the data-driven foundation for optimizing quality and sustainability simultaneously (Nature HSSC, 2025).

A 2025 *CarbonBright* analysis — *AI-Driven LCAs for Circular Manufacturing* — documented how AI is transforming life cycle assessment for circular economy applications: AI-driven LCA models provide the intelligence and efficiency needed to analyze complex environmental impacts and evaluate circularity strategies, enabling manufacturers to make data-driven decisions that simultaneously reduce environmental impact and maintain product quality. The integration of AI-LCA with AI-powered QMS creates the possibility of **quality-sustainability co-optimization** —

where process parameters are adjusted not only to maximize conventional quality metrics but also to minimize carbon footprint, energy consumption, and material waste (CarbonBright, 2025).

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6. Synthesis: The Quality Intelligence Architecture

6.1 A Unified Framework for AI-Powered Quality Management

The synthesis of findings across the reviewed literature points toward a coherent integrated architecture — the **Quality Intelligence Architecture (QIA)** — that organizes the components of AI-powered quality management into a layered framework spanning sensing, edge analytics, cloud intelligence, and human decision support.

Sensing Layer: Multi-modal quality sensors — including optical inspection systems, coordinate measuring machines, force-torque sensors, and the SPMD and 4D thermal imaging systems — provide the foundational quality data streams. Huang et al.'s SPMD system (2026) contributes precision 3D surface metrology data; Huang et al.'s 4D thermal imaging system (2023) contributes real-time thermal quality data. These advanced sensing modalities complement conventional quality sensors (CMM, vision systems, gauge stations) by providing higher-resolution, higher-accuracy measurements that enable more sensitive quality discrimination.

Edge Analytics Layer: Edge AI platforms deployed at the factory floor perform real-time quality inference — defect classification, process state monitoring, SPC charting — at latencies measured in milliseconds. The edge layer handles the highest-volume, lowest-latency quality data streams, filtering and condensing quality information for transmission to the cloud layer while generating immediate alerts and process feedback locally.

Cloud Intelligence Layer: Cloud-scale computational resources train, evaluate, and update the ML models that power edge analytics. The cloud layer performs offline analytics — model retraining on accumulated data, cross-factory model comparison, root cause analysis, and quality forecasting — that requires the computational scale and data access available only in the cloud. The cloud layer also hosts the enterprise QMS platform — managing quality specifications, non-conformance records, CAPA (corrective and preventive action) workflows, and regulatory compliance documentation.

Decision Support Layer: Quality dashboards, alerting systems, and mobile applications deliver quality intelligence to the humans in the quality loop — quality engineers, process engineers, production managers, and operators. This layer presents AI-generated insights in human-understandable forms: defect likelihood forecasts, process parameter recommendations, root cause hypotheses, and quality risk scores.

Integration Layer: The QIA integrates with existing manufacturing IT infrastructure — MES (production scheduling, work orders), ERP (materials, inventory, customer orders), LIMS (laboratory results), and QMS (quality specifications, non-conformance management) — to provide a unified quality intelligence platform that spans the full manufacturing value chain from incoming materials to final shipment.

This four-layer architecture draws on contributions across the reviewed literature: big data analytics for quality (ScienceDirect ML QA, 2025), AI-driven quality control (AI Innovate, 2026), edge computing for smart factories (IoT Tech News, 2025; IJECS, 2024), AIoT for predictive quality (PMC AIoT, 2025), predictive IQC (Compliance Quest, 2026), sustainable manufacturing and LCA (Nature HSSC, 2025; CarbonBright, 2025), and industrial sensing (Huang et al., 2026; Huang et al., 2023).

6.2 Industry 4.0/5.0 Integration

The QIA sits at the intersection of Industry 4.0 (digital integration and data-driven optimization) and Industry 5.0 (human-centric, sustainable manufacturing). Within the Industry 4.0 framework, the QIA represents the **quality analytics pillar** of the smart factory — providing the data integration, analytics, and decision support infrastructure for quality-aware manufacturing execution. Within the Industry 5.0 framework, the QIA extends quality management beyond operational excellence to **sustainability and circular economy** — using AI to quantify and optimize the quality-sustainability trade-space across product design, manufacturing process, and end-of-life decisions.

6.3 Open Challenges

1. **Data quality and integration**: The QIA's effectiveness depends on the quality, completeness, and accessibility of manufacturing data. Missing data, sensor noise, inconsistent data models, and legacy system integration challenges are the most significant practical obstacles to AI-QMS deployment.
2. **Model deployment and lifecycle management**: ML models degrade in performance as the process evolves — new product variants, changed materials, shifted equipment baselines. Continuous model monitoring, retraining, and validation are essential for sustained AI-QMS effectiveness.
3. **Regulatory acceptance of AI quality decisions**: Regulatory frameworks (FDA 21 CFR Part 11 for pharmaceutical quality, IATF 16949 for automotive quality) require validated quality systems. Demonstrating that AI quality decisions meet regulatory requirements for documentation, auditability, and change control is a practical challenge.
4. **Human-AI collaboration in quality decision-making**: Determining the appropriate level of AI autonomy in quality decisions — from AI advisory (recommending but not implementing) to AI-driven (implementing without human approval for routine decisions) — requires careful risk assessment and organizational governance.
5. **Scalability across product variants**: Manufacturers producing thousands of product variants face the challenge of building and maintaining AI quality models for each variant. Transfer learning, multi-task learning, and product family-based model architectures are needed.

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7. Conclusion

This review has examined AI-powered quality management systems and smart factory architecture for manufacturing excellence, covering big data analytics for manufacturing quality, ML algorithms for quality assurance and defect classification, real-time quality monitoring through edge computing and digital integration, predictive quality analytics and early warning systems, and the integration of quality intelligence with sustainable manufacturing objectives.

Three key findings emerge. First, **AI is fundamentally transforming quality management from a reactive, post-hoc discipline to a predictive, real-time discipline**: ML models trained on manufacturing process data can forecast quality outcomes hours or days before defects materialize, enabling proactive interventions that prevent quality deviations from becoming defective products.

Second, **edge computing and IoT integration are enabling real-time quality intelligence** at the factory floor — with millisecond-latency quality inference, continuous SPC monitoring, and immediate alerting — closing the feedback loop between quality detection and process correction.

Third, **the integration of AI-powered QMS with sustainable manufacturing and circular economy objectives** creates the possibility of quality-sustainability co-optimization: AI-driven life cycle assessment, combined with real-time quality analytics, enables manufacturers to make data-driven decisions that simultaneously optimize product quality, environmental impact, and economic performance.

The proposed **Quality Intelligence Architecture (QIA)** — unifying precision sensing (SPMD, 4D thermal imaging), edge analytics, cloud intelligence, and human decision support — charts a course toward manufacturing systems in which quality is not a checkpoint but a continuous, intelligent, and integrated dimension of every manufacturing operation.

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