

## THE IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE IN QUALITY MANAGEMENT

Radosław WOLNIAK

Silesian University of Technology, Organization and Management Department, Economics and Informatics  
Institute; [rwolniak@polsl.pl](mailto:rwolniak@polsl.pl), ORCID: 0000-0003-0317-9811

**Purpose:** The purpose of this publication is to analyse the potential of Ai implementation in quality management.

**Design/methodology/approach:** Critical literature analysis. Analysis of international literature from main databases connecting with researched topic.

**Findings:** The analysis demonstrates that the integration of Artificial Intelligence (AI) into Quality Management (QM) represents a paradigmatic shift from reactive, compliance-oriented systems toward adaptive, predictive, and data-driven frameworks. The study identifies that AI technologies—particularly machine learning, deep learning, natural language processing, and digital twins—enable real-time quality prediction, anomaly detection, and process optimization, thereby enhancing efficiency, accuracy, and customer satisfaction. It also finds that the successful implementation of AI in QM necessitates robust data governance, ethical frameworks compliant with ISO/IEC 42001 and the EU AI Act, and new managerial competencies such as data literacy and algorithmic interpretability. Moreover, the research emphasizes that the adoption of AI transforms organizational culture by fostering interdisciplinary collaboration and continuous learning. While AI offers considerable strategic and economic benefits, it introduces challenges related to data integrity, cybersecurity, algorithmic opacity, and the sustainability of computational resources. The findings conclude that the future of AI in quality management—termed *Quality 5.0*—will rely on hybrid human-machine intelligence systems that integrate ethical governance with technological innovation to achieve sustainable and context-aware quality ecosystems.

**Originality/Value:** Detailed analysis of all subjects related to the problems connected with the usage analysed scientific problem.

**Keywords:** Artificial Intelligence; Quality Management; Quality 4.0; Quality 5.0; Machine learning; Deep learning; Digital Twins; Predictive analytics; Total Quality Management (TQM); Industry 4.0; Industry 5.0.

**Category of the paper:** literature review.

## 1. Introduction

The emergence of Artificial Intelligence (AI) as a paradigm-altering technological paradigm has reshaped the operational and strategic landscapes of modern organizations. Its application in Quality Management (QM) is arguably one of the most robust developments in the general Industry 4.0 and the new emerging Industry 5.0 frameworks. Quality management, which previously handled process control, improvement, and satisfaction, has shifted from reaction-based and manual controls to data-driven, predictive, and adaptive models. Use of AI technologies—from machine learning (ML), deep learning (DL), and natural language processing (NLP) to expert systems and cognitive automation—is one of the biggest accomplishments in the march towards Quality 4.0, a buzzword that suggests digitalization, analytics, and intelligent decision-making in quality improvement and assurance (Jacobs, Merwe, 2026; Qin et al., 2025).

Quality in the classical TQM model was something that operated through standard procedures, culture, and human potential. The AI-based model, by contrast, puts quality into an adaptive, self-improving system in real-time whose parameters it ongoingly optimizes using information in real-time. AI in QM is not a matter of technological replacement but an epistemic and operational redesign: from human decision-making to hybrid human–machine intelligence systems. The paper elaborates on the various dimensions of AI application in quality management, including conceptual foundations, technological infrastructure, managerial implication, and ethical and organizational problems associated with such change.

The purpose of this publication is to analyse the potential of Ai implementation in quality management.

## 2. Conceptual Foundations: From TQM to Quality 4.0

The development from traditional quality management to AI-enabled quality systems is mapped through three paradigms converging: TQM, Quality 3.0, and Quality 4.0. TQM philosophy depended on process standardization, statistical control, and people involvement. Automation, computerized data acquisition, and use of statistical software ushered in Quality 3.0. Quality 4.0, which was formulated by the American Society for Quality (ASQ) and subsequent researchers, utilizes digital technologies such as the Internet of Things (IoT), cyber-physical systems, cloud computing, and artificial intelligence (AI) for developing self-optimizing systems that are capable of predictive quality assurance (Garcia-Garcia, 2025; Xiong, 2025).

AI makes the largest contribution to Quality 4.0 through the ability to model complexity and uncertainty. Machine learning software, for instance, is able to identify slight deviations in the conditions of manufacturing before they cause defects. Neural networks are capable of foreseeing product failure, and reinforcement learning is able to optimize control systems in real time. These abilities enhance the conventional Six Sigma or Statistical Process Control (SPC) methodology in the sense that they allow systems to learn from new data in real time instead of being founded on static statistical models (Chauhan et al., 2025; Sadyraliev et al., 2025).

Further, AI supplants the epistemology of quality itself. Conventional quality metrics had depended on determinate control parameters and discrete thresholds. AI enables learning from continuous streams of non-linear interdependencies among process variables, customer input, and environmental factors, and redefine quality metrics as adaptive, dynamic attributes. This epistemological change demands a change in managerial cognition—from considering quality as conformance to specifications to considering it an emergent, dynamic attribute of smart systems.

AI implementation for quality control requires a four-layered technology stack consisting of four interconnected fields viz. data acquisition, data warehouse, analytics, and decision execution.

Data ingestion is where vision machines, sensors, and IoT systems converge to take in real-time feeds of operational information. Factory vibration, temperature, and sound sensors, for instance, supply data to predictive maintenance and quality control algorithms as inputs. Most valuable is not so much the quantity of data but its quality, traceability, and synchronization across the different steps in production.

Data integration and storage are premised on edge computing or cloud infrastructure. Cloud infrastructure delivers data aggregation at scale and model training that is centralized, whereas edge computing delivers local inference and response that is rapid. Robust data governance systems are required to ensure data integrity, cybersecurity, and compliance with standards such as ISO 9001:2015 and ISO/IEC 42001 (AI management systems).

Analytics constitutes the brains of AI-driven quality management. Machine learning algorithms find application in anomaly detection, defect classification, predictive modeling, and root cause analysis. For instance, convolutional neural networks (CNNs) will automatically scan product surfaces, whereas support vector machines (SVMs) will classify production conditions underlying deviations. Natural language processing facilitates the analysis of unstructured text data such as customer complaints or operator reports with a view to identifying latent quality defects.

Decision execution is filling control systems and management processes with AI outputs. It could be in the form of closed-loop feedback—direct manipulation of process parameters by the AI system—or decision-support displays providing actionable suggestions to human operators. In more advanced applications, digital twins—virtual replicas of manufacturing

systems—are the simulation space where AI algorithms dictate virtual interventions before being applied live on actual operations. The combination of AI and digital twins is one of the strongest enablers of predictive and prescriptive quality management (Barathkumar, Devi, 2025; Kumar, 2025; Gueorguiev, 2025; Preascilla Ioana et al., 2025; Sharma et al., 2025).

Table 1 describes aspects of AI implementation within quality management frameworks, merging technological and humanistic perspectives. It demonstrates how AI transforms the epistemological, operational, and ethical foundations of quality systems.

**Table 1.**

*Implementation of artificial intelligence in quality management*

Area of implementation	Analytical description
Conceptual Transformation	The integration of Artificial Intelligence redefines quality management from a reactive, compliance-oriented activity into a predictive, adaptive, and data-driven system. Quality becomes an evolving property of intelligent processes capable of self-learning and continuous optimization.
Technological infrastructure	AI-based quality systems are grounded in interconnected technologies such as machine learning, the Internet of Things, cloud computing, and digital twins. These elements enable real-time data collection, analytics, and feedback loops supporting autonomous quality control.
Process control and optimization	Machine learning algorithms detect anomalies, forecast process deviations, and suggest optimal parameter adjustments. Reinforcement learning enables dynamic process adaptation, minimizing variability and stabilizing product or service outcomes.
Product and service quality assurance	Computer vision and deep learning automate inspection, classification, and compliance verification. Expert systems evaluate conformity to standards and refine quality thresholds based on accumulated data.
Decision support and root cause analysis	Artificial intelligence enhances diagnostic and analytical reasoning through causal modeling, knowledge graphs, and Bayesian inference. It allows for the identification of complex interdependencies responsible for variations in process performance.
Organizational and managerial change	The introduction of AI necessitates new managerial competencies, including data interpretation, algorithmic awareness, and interdisciplinary collaboration. The role of quality managers shifts toward the supervision and governance of intelligent systems.
Ethical and governance frameworks	Effective implementation requires adherence to international AI management and ethical standards, including ISO/IEC 42001 and the EU AI Act. Transparency, accountability, and fairness become integral to quality governance.
Strategic and economic impact	The deployment of AI improves efficiency, reduces costs, and enhances customer satisfaction through predictive and prescriptive analytics. Quality becomes a strategic instrument of competitiveness and innovation.
Barriers and risks	Implementation challenges arise from data inconsistency, algorithmic opacity, cybersecurity threats, and organizational resistance. The maturity of data governance and employee readiness determines long-term success.
Future prospects (Quality 5.0)	The future of AI in quality management emphasizes human–machine collaboration, contextual awareness, and sustainability. Intelligent systems will complement human judgment, creating ethically aligned, adaptive quality ecosystems.

### **3. Managerial Implications and Organizational Transformation**

Application of AI to quality management cannot be reduced to a technological advancement; it entails profound organizational redesign and managerial adaptation. AI systems transform the conventional decision-making structures by decentralizing decisions and substituting them with algorithmic entities invested with autonomous reasoning capacities. Managers are therefore forced to cede control of operations for meta-management—managing the design, training, and verification of intelligent systems (Borsetto et al., 2025; Yu et al., 2025).

AI adoption requires quality departments to have newer skill sets. Algorithmic thinking, data literacy, and ability to read machine learning outcomes become managerial necessities. Cross-functional collaboration between quality engineers, data scientists, and IT professionals is the order of the day. Organizational cultures must also change from compliance-oriented to experimentation-oriented. AI applications thrive on iterative learning, which requires embracing uncertainty and error as part of innovations.

Strategically, AI enables real-time alignment between organizational and quality goals. Predictive analytics enable organizations to foresee deviations before they affect performance measures such as Overall Equipment Effectiveness (OEE) or customer satisfaction levels. The predictive capability provides pre-allocation of resources and enabling greater resilience to disruption. In service industries, AI-powered quality management enables personalization, adaptive process configuration, and continuous improvement through user feedback loops.

The shift also involves reimagining the role of human expertise. AI technologies do not replace human decision-makers but supplement them with more compact analytical insights. Managers' task is to develop hybrid intelligence systems that blend algorithmic power and human contextual sense-making. Ethical governance, interpretability, and accountability checks must be instituted to avoid algorithmic recommendations that are incomprehensible and indefensible to the organizational quality policy (Al Jabri, Elgeddawy, 2025; Olteanu, Gheorge, 2025; Abduvaxidov et al., 2025).

### **4. Toward a Framework for AI-Based Quality Management**

Despite the promise, AI uptake in quality management is beset by technical, organizational, and ethical problems. Technically, AI algorithms require huge volumes of high-quality data, yet heterogeneity, noise, and missing values typically undermine performance. In industry, legacy systems are not AI-friendly, so integration with AI architectures is costly retrofitting or data migration.

Organizationally, there is resistance to change. Quality professionals who are used to determinist approaches are wary of probabilistic or black-box models. Moreover, the lack of prescriptive regulation and standardization regimes renders certification of AI-based quality systems complicated. Although ISO 42001 (Artificial Intelligence Management System) offers a good starting point, large-scale adoption does not occur.

Ethical and legal challenges also confront AI adoption. Algorithmic bias, data privacy, and accountability for algorithmic decisions question the foundations themselves. For example, if a prediction model incorrectly classifies a product as compliant and a defect reaches market, somebody must be accountable for having made such an error—human or algorithmic. AI governance is therefore integrated into modern quality management systems. Auditable model documentation, explainable artificial intelligence (XAI) methods, and continuous auditability must be provided to ensure the ethical and legal behavior of intelligent quality systems (Salogub et al., 2025; Kaur et al., 2025; Naga Suneetha et al., 2025).

Besides this, the green aspect cannot be ignored. AI training and inference processing capacity generates energy consumption that can work in opposition to sustainability objectives. Quality management systems are therefore needed to adopt notions of green AI—model efficiency optimization, avoiding data redundancy, and congruent alignment with ESG (Environmental, Social, Governance) performance indicators.

In order to institutionalize the benefits of AI and minimize its constraints, organizations must take a converged strategy to AI-enabled quality management. This can stand on five pillars:

- **Strategic Alignment** – All AI undertakings must be directly extracted from organizational quality goals and customer requirements so that smart systems augment—not replace—the established quality mission.
- **Data Governance** – Standardized data cleansing, labeling, and acquisition processes are a must. Conformity to ISO 8000 (data quality) and ISO/IEC 27001 (information security) standards is a good starting point.
- **Model Lifecycle Management** – Ongoing monitoring, retraining, and testing of AI models discourage performance drift. Interoperability with ModelOps or QualityOps platforms allows for lifecycle visibility.
- **Human–AI Collaboration** – Applying interpretability procedures and feedback loops keeps human experience at the center. Training sessions must develop cognitive harmonization between humans and machines.
- **Ethics and Compliance with Regulations** – Following AI governance law, like the EU AI Act, keeps systems within legal and ethical bounds to ensure ongoing trust and accountability.

This model does not envision AI as an additive layer over existing quality systems but rather as an inward pressure that reshapes the entire quality landscape. The company is now a culture of learning, with data, feedback, and knowledge constantly circulating back and forth between smart algorithms and human actors.

Next-generation AI in quality management will transition into what may be labeled as Quality 5.0—a human-centered school of thought alongside Industry 5.0 philosophies. Automation and predictive analytics are the mainstays of Quality 4.0, but symbiosis between human and machine intelligence is what Quality 5.0 focuses on. Cognitive flexible, context-aware, and ethically autonomous next-generation quality systems will be the outcome.

New technologies such as generative AI, neurosymbolic machines, and quantum machine learning will further strengthen the analytical potential of quality management. Generative AI will be able to automatically generate optimal production parameters for optimum design, whereas quantum algorithms will be able to calculate multidimensional quality information at unprecedented velocities. Incorporation of AI within sustainability models (e.g., Agile-LCA, Q&I-LCA) will also enable multiple criteria optimization of quality, cost, and environmental impact simultaneously.

Nevertheless, human judgment will remain invincible. Although the European Commission emphasizes in the AI Act, final responsibility for safety and quality must lie with responsible human control. Therefore, ultimately, the path forward for AI to proceed in quality management will not just depend on technical capability but on ethical expertise—the ability to apply AI responsibly to advance human prosperity and organisational integrity.

## 5. Conclusion

Application of Artificial Intelligence in quality management is a transition from mechanistic to cognitive control and improvement systems. AI renders quality a predictive, adaptive, and learning process rather than a reactive discipline. Through the application of machine learning, digital twins, and autonomous analytics, organizations are able to introduce additional reliability, accuracy, and customer satisfaction. Effective deployment, however, is not merely the adoption of the technology but involves complete organizational transformation, ethical regulation, and continuous human intervention.

The next ten years will be the transition years when AI will either be a means to operational efficiency or an inherent part of organisational capability. The task ahead of researchers and practitioners is to develop frameworks that can maintain the humanist essence of quality while also taking advantage of the computational powers of artificial intelligence. That is the true promise of Quality 4.0—and the challenge for Quality 5.0.

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