

Enabling Smart Manufacturing through Automated Quality Management Systems in the Era of the Fourth Industrial Revolution

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تمكين التصنيع الذكي من خلال أنظمة إدارة الجودة الآلية في عصر الثورة الصناعية الرابعة

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Abstract:

This study aimed to enable smart manufacturing through automated quality management systems (AQMS) in the era of the Fourth Industrial Revolution. It explores this through a systematic review of contemporary literature. By analyzing key studies, this paper identifies a crucial shift from end-of-line defect detection to proactive, real-time monitoring, supported by the Internet of Things (IoT) and cyber-physical systems (CPS).

The findings highlight several key pillars of this digital transformation: the application of artificial intelligence (AI) and machine learning (ML) for quality prediction; the use of digital twins for comprehensive personalization; and the application of blockchain technology for digital tracking and regulatory compliance, particularly in sensitive sectors such as medical device manufacturing. Furthermore, the study addresses the "human factor," emphasizing that the successful implementation of AQMS depends on upskilling the workforce and fostering seamless human-machine collaboration. This research proposes a comprehensive conceptual model that bridges the gap between traditional total quality management and the demands of the Fourth Industrial Revolution, providing a strategic roadmap for achieving self-regulating quality systems within a modern industrial context..

Keywords: Smart Manufacturing, Quality Management, The Fourth Industrial Revolution, Automated Quality Management Systems (AQMS), Predictive Quality.

المخلص

سعت الدراسة الى البحث في كيفية تمكين التصنيع الذكي من خلال أنظمة إدارة الجودة الآلية (AQMS) في سياق الثورة الصناعية الرابعة (الصناعة 4.0)، وأظهرت الدراسة الفجوة المتزايدة بين مناهج إدارة الجودة التقليدية - القائمة أساسًا على الكشف التفاعلي عن العيوب - ومتطلبات بيانات التصنيع المتكاملة رقميًا التي تولد كميات هائلة من البيانات الآنية من الآلات وأجهزة الاستشعار وأنظمة الإنتاج.

كما اعتمدت منهجية البحث على مراجعة منهجية للأدبيات، حيث يحلل الدراسات الأكاديمية ذات الصلة المسترجعة من قواعد بيانات مثل سكوبس وساينس دايركت من مجموعة أولية تضم حوالي خمسين منشورًا، تم اختيار عشر دراسات رئيسية بناءً على صلتها بإدارة الجودة والتصنيع الذكي وتقنيات الصناعة 4.0. يركز التحليل على تحديد العناصر التكنولوجية والتنظيمية والتشغيلية اللازمة للتطبيق الفعال لأنظمة إدارة الجودة الآلية في بيئات الإنتاج الحديثة.

وتشير النتائج إلى أن التطور نحو الجودة 4.0 يمثل تحولاً جوهرياً في إدارة الجودة الصناعية إذ تُستبدل أساليب الفحص التقليدية في نهاية خط الإنتاج بشكل متزايد بأنظمة مراقبة الجودة التنبؤية واللحظية، المدعومة بتقنيات متقدمة مثل إنترنت الأشياء الصناعي (IoT)، والذكاء الاصطناعي (AI)، والتعلم الآلي، وتحليلات البيانات الضخمة، والأنظمة السيبرانية الفيزيائية (CPS)، والتوائم الرقمية لتُمكن هذه التقنيات من المراقبة المستمرة لعمليات الإنتاج، والكشف المبكر عن العيوب المحتملة، واتخاذ إجراءات تصحيحية آلية تُقلل من الهدر، وفترات التوقف، وتكاليف الإنتاج.

فقد حددت الدراسة خمسة محاور رئيسية تُمكن التصنيع الذكي من خلال أنظمة إدارة الجودة الآلية (AQMS) أولاً، يُتيح التحكم في الجودة ومراقبة العمليات في الوقت الفعلي الإشراف المستمر على أنشطة الإنتاج من خلال أجهزة الاستشعار وأنظمة الفحص الآلية. ثانياً، تستخدم تحليلات الجودة التنبؤية نماذج التعلم الآلي لتوقع حالات الفشل أو عدم المطابقة قبل حدوثها. ثالثاً، تضمن أطر التتبع الرقمي وضمان الجودة الامتثال لمعايير مثل ISO 9001 و ISO 13485 من خلال الحوسبة السحابية وسلامة البيانات القائمة على تقنية سلسلة الكتل (البلوك تشين). رابعاً، تستخدم أنظمة التصنيع الذكية تقنيات الذكاء الاصطناعي المتقدمة لدعم اتخاذ القرارات المستقلة وتمكين التخصيص الشامل في بيئات الإنتاج. أخيراً، تنفيذ أنظمة تخطيط وإدارة الإنتاج الذكية من التوائم الرقمية وتكامل البيانات في الوقت الفعلي لتحسين الجدولة والاستجابة الديناميكية لاضطرابات سلسلة التوريد.

على الرغم من الفوائد الكبيرة لتطبيق أنظمة إدارة الجودة الآلية، تُسلط الدراسة الضوء على عدة تحديات قد تعيق تبنيها، وتشمل هذه التحديات محدودية التوافق بين الأنظمة المختلفة، وعدم كفاية المهارات الرقمية لدى القوى العاملة، وارتفاع متطلبات البنية التحتية، وغياب أطر عمل موحدة تُواءم معايير إدارة الجودة مع تقنيات الثورة الصناعية الرابعة. ويُحدد العنصر البشري كعنصر أساسي للنجاح، مما يُؤكد على الحاجة إلى تدريب القوى العاملة والتعاون الفعال بين الإنسان والآلة المدعوم بتقنيات مثل الواقع المعزز والواقع الافتراضي.

ونستنتج بأن البحث يُلخص إلى أن أنظمة إدارة الجودة الآلية تُمثل عنصرًا أساسيًا في التصنيع الذكي، مما يُتيح التحول من مراقبة الجودة التفاعلية إلى أنظمة ببنية استباقية، قائمة على البيانات، وذاتية التنظيم. ومن خلال دمج التحليلات التنبؤية، والمراقبة في الوقت الفعلي، والتتبع الرقمي، تُوفر أنظمة إدارة الجودة الآلية للمصنعين القدرة على تحقيق إنتاج خالي من العيوب، وكفاءة تشغيلية عالية، وتحسين الامتثال للوائح التنظيمية. توصي الدراسة بإعطاء الأولوية لتقييمات جاهزية الرقمية، وتطوير أطر عمل موحدة للتوافق التشغيلي، والاستثمار في رفع مستوى مهارات القوى العاملة لدعم الانتقال الناجح نحو الجودة 4.0 وأنظمة التصنيع الذكية.

الكلمات المفتاحية: التصنيع الذكي. إدارة الجودة، الثورة الصناعية الرابعة، أنظمة إدارة الجودة الآلية، الجودة التنبؤية.

1. Introduction

The history of quality management dates back to the early twentieth century, and over time it has become an essential element in business management, as it includes the most prominent forms of quality management known as Total Quality Management (TQM), as well as the European Foundation for Quality Management standards and quality systems, and developments based on the requirements of the ISO 9001 standard. (Hamrol & Grabowska, 2026).

The Fourth Industrial Revolution, launched as a major strategic initiative for industry in 2011 by the German government, quickly evolved into a digital transformation through the integration of the Internet of Things (IoT) and information technology. (Zaidin et al., 2018)

The Fourth Industrial Revolution, or the concept of the smart factory, involves factories adopting cyber-physical space systems (CPS) that integrate numerous physical and electronic technologies, thus facilitating the intensive integration of previously separate and independent systems. (Chen, B., Wan, J., Shu, L., Li, P., Mukherjee, M. and Yin, B., 2018).

Perhaps the concept of smart manufacturing, which is the basis of Industry 4.0, is a system that is adaptable to different conditions and changing products, where flexible production lines automatically adapt production processes to meet the needs of different types of products and changing conditions, providing improved quality, efficiency and flexibility, in addition to large-scale and sustainable production of customized products thanks to reduced resource consumption. (Tripti Saxena, 2025)

In this regard, Witkowski adopted the impact of using Fourth Industrial Revolution technologies, including big data and the Internet of Things, as an innovative approach to supply chain management. He concluded that the Fourth Industrial Revolution has provided opportunities to develop logistics and supply chain management services, thereby meeting customer needs and improving service delivery times. (Sader et al., 2019).

Mrojalska and Werwicka, on the other hand, focused on the impact of the Fourth Industrial Revolution on lean manufacturing technologies. These technologies have been successfully tested in the integrated mass production environment of the Fourth Industrial Revolution. (Sader et al., 2019).

The future of production under smart manufacturing and the Industry 4.0 revolution is expected to be characterized by significant gains, mainly through sequential digital integration and intelligence in manufacturing processes. This integration occurs on the horizontal axis through all participants in the entire value chain and on the vertical axis through all organizational levels. Under smart manufacturing and the industry 4.0 revolution, fully integrated and networked factories, machines, and products will operate in an intelligent and semi-autonomous manner that requires minimal manual and human intervention. (Agolla, 2018).

The integration of Industry 4.0 technologies into manufacturing operations generates massive volumes of heterogeneous data from sensors, machines, and production systems. While these data streams offer unprecedented opportunities for real-time quality monitoring and predictive analytics, they also create new challenges for quality management professionals who must process, interpret, and act upon this information effectively. The gap between the capabilities of traditional quality management systems and the demands of digitally integrated production environments has become increasingly apparent.

1.1 Research problem

Despite the widespread adoption of Fourth Industrial Revolution (FIR) technologies in the manufacturing sector, a significant gap remains in integrated and automated quality management systems capable of operating effectively within smart manufacturing environments. This problem manifests itself in several aspects, most notably that current quality management approaches are largely reactive rather than proactive. Traditional quality control methods focus on detecting defects after they occur, leading to increased waste, rework, and production delays. The shift to proactive quality management using big data analytics and artificial intelligence to predict and prevent defects before they happen remains underdeveloped in practice, despite the considerable technological potential.

The absence of standardized frameworks for automated corrective actions also hinders manufacturers' ability to leverage FIR technologies for real-time quality improvement. This reflects a significant alignment gap between established quality management standards and emerging smart manufacturing models. Digital twins, cyber-physical production systems, and other FIR innovations are not adequately reflected in updated quality specifications, leaving practitioners without clear benchmarks for implementing quality management in digitally transformed environments.

1.2 Research Questions

Based on the identified problem, this research seeks to address the following questions:

1. What are the key components and architectural requirements for an automated quality management system (AQMS) suitable for smart manufacturing environments in the Industry 4.0 era?
2. How can real-time quality monitoring and predictive analytics be effectively integrated into automated quality management systems to enable proactive defect prevention?
3. What technological, organizational, and human factors influence the successful implementation and operationalization of AQMS in smart manufacturing settings?
4. How can interoperability be achieved among heterogeneous quality-related data sources and systems across the horizontal value chain and vertical organizational levels?
5. What frameworks and guidelines are required to align quality management standards with the demands of smart manufacturing and Industry 4.0 technologies?

1.3 Aim & objective

This research holds significant theoretical and practical importance for the advancement of quality management in the era of Industry 4.0. Theoretically, the study contributes to the body of knowledge by bridging the gap between traditional quality management paradigms and emerging smart manufacturing concepts. It provides a structured framework for understanding how automated quality management systems can be designed, integrated, and operationalized within digitally transformed production environments.

To address the aforementioned research questions, this study pursues the following aim:

1. To develop a comprehensive conceptual model for an automated quality management system tailored to smart manufacturing environments that integrates real-time monitoring, predictive analytics, and autonomous corrective capabilities.

2. To identify and analyze the critical technological, organizational, and human factors that affect the successful deployment of AQMS in Industry 4.0 contexts.
 3. To examine the mechanisms for achieving seamless system interoperability and end-to-end quality traceability across the manufacturing value network.
 4. To propose updated quality management frameworks and guidelines that reflect the technological capabilities and requirements of smart manufacturing.
 5. To empirically validate the proposed conceptual model through case studies and pilot implementations in real smart manufacturing settings.
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2. Conceptual framework

Quality management in the context of smart manufacturing and Industry 4.0 involves the integration of advanced digital technologies such as the Industrial Internet of Things (IIoT), artificial intelligence (AI), big data analytics, cyber-physical systems (CPS), and digital twins into manufacturing processes to enhance efficiency, flexibility, and product quality. This transformation is often referred to as "Quality 4.0," which emphasizes data-driven, real-time, and interconnected approaches to quality assurance and continuous improvement Mourtzis, 2024, Open reference preview(Mourtzis, 2024), Khalifa, Yacout & Bassetto, 2021, Open reference preview(Khalifa, Yacout & Bassetto, 2021), Kumar & Channi, 2025, Open reference preview(Kumar & Channi, 2025), Wu et al., 2025, Open reference preview(Wu et al., 2025), Abdulhussain et al., 2026, Open reference preview (Abdulhussain et al., 2026).

Advanced analytics and big data are central to Quality 4.0, enabling predictive quality control, continuous improvement, and actionable insights for decision-making Khalifa, Yacout & Bassetto, 2021, Open reference preview(Khalifa, Yacout & Bassetto, 2021), Abdulhussain et al., 2026, Open reference preview (Abdulhussain et al., 2026), Ammar et al., 2022, Open reference preview(Ammar et al., 2022).

Data-driven approaches support the development of advanced quality management systems, including software suites, electronic logs, and statistical process control (SPC) Ammar et al., 2022, Open reference preview(Ammar et al., 2022).

Quality 4.0 focuses on achieving zero manufacturing defects through advanced analytics, real-time monitoring, and interconnected systems Wu et al., 2025, Open reference preview(Wu et al., 2025), Abdulhussain et al., 2026, Open reference preview(Abdulhussain et al., 2026).

It is characterized by a data-centric approach, where digital technologies generate large, actionable data streams for predictive and continuous quality improvement Abdulhussain et al., 2026, Open reference preview(Abdulhussain et al., 2026).

Quality 4.0 practices contribute to environmental sustainability by enabling resilient manufacturing systems that adapt to market and regulatory changes Abdulhussain et al., 2026, Open reference preview(Abdulhussain et al., 2026).

Smart manufacturing systems are defined as fully integrated and collaborative, responding in real time to changing demands in the factory, supply network, and customer needs Lu & Weng, 2018, Open reference preview(Lu & Weng, 2018).

Integration in Industry 4.0 involves aligning quality management programs with company strategy and human resource systems, facilitated by technologies like AR and digital twins Kumar & Channi, 2025, Open reference preview(Kumar & Channi, 2025), Ostadi, Barrani & Aghdasi, 2024, Open reference preview(Ostadi, Barrani & Aghdasi, 2024).

The transition to smart manufacturing requires significant investment in infrastructure, skilled personnel, and technology upgrades, as well as the development of clear strategies for technology adoption Mourtzis, 2024, Open reference preview(Mourtzis, 2024), Mourtzis, 2024, Open reference preview(Mourtzis, 2024), Parhi et al., 2022, Open reference preview (Parhi et al., 2022).

The adoption of Quality 4.0 and smart manufacturing practices is still limited by gaps in digital skills and knowledge among employees Jamwal, Agrawal & Sharma, 2022, Open reference preview(Jamwal, Agrawal & Sharma, 2022), Parhi et al., 2022, Open reference preview (Parhi et al., 2022).

Table 1: Technologies and Their Quality Management Roles

Technology	Role in Quality Management	Key Benefits
IIoT & Sensors	Real-time data collection, process monitoring	Predictive maintenance, cost reduction Mourtzis, 2024, Open reference preview(Mourtzis, 2024), Cozzolino, Papa & Lopresto, 2026, Open reference preview(Cozzolino, Papa & Lopresto, 2026)
AI & Machine Learning	Process optimization, defect detection, predictive quality	Waste reduction, improved accuracy Mourtzis, 2024, Open reference preview(Mourtzis, 2024), Qian et al., 2024, Open reference preview(Qian et al., 2024), Jamwal, Agrawal & Sharma, 2022, Open reference preview(Jamwal, Agrawal & Sharma, 2022)
Digital Twins	Virtual asset monitoring, predictive analytics	Reduced downtime, enhanced compliance Kumar & Channi, 2025, Open reference preview(Kumar & Channi, 2025), Maharjan et al., 2025, Open reference preview(Maharjan et al., 2025)
Big Data Analytics	Advanced SPC, continuous improvement	Actionable insights, error reduction Khalifa, Yacout & Bassetto, 2021, Open reference preview(Khalifa, Yacout & Bassetto, 2021), Abdulhussain et al., 2026, Open reference preview(Abdulhussain et al., 2026), Ammar et al., 2022, Open reference preview(Ammar et al., 2022)
AR/VR/MR	Training, inspection, human-machine integration	Enhanced operator performance Ammar et al., 2022, Open reference preview(Ammar et al., 2022), Ostadi, Barrani & Aghdasi, 2024, Open reference preview(Ostadi, Barrani & Aghdasi, 2024), Fortuna et al., 2024, Open reference preview(Fortuna et al., 2024)

3.Methods

Several aspects of the systematic literature review were identified within the framework of the problem presented, from which keywords such as (quality), (smart manufacturing), (Fourth Industrial Revolution), (automated quality), and (quality management) were extracted. The criteria included awareness starting from the year (), open access, and the type of article (review articles and research articles) for the research conducted. Databases such as Scopus and ScienceDirect were used to conduct the search. Since the start of the work, (50) results related to the topic of the study were found, and (10) documents were selected from them that deal with quality management and smart manufacturing related to Fourth Industrial Revolution technologies, based on the definition of the current research question: **How can smart manufacturing be enabled through automated quality management systems in the era of the Fourth Industrial Revolution?**

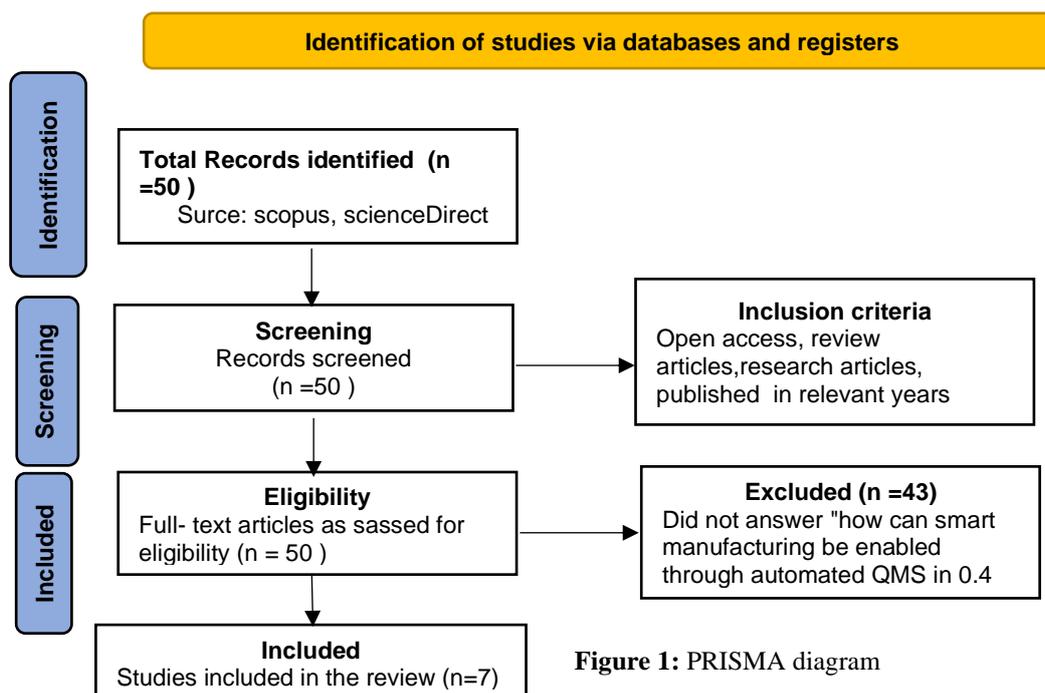


Figure 1: PRISMA diagram

This figure is called the PRISMA diagram, and it is used in scientific research (especially reviews) to organize the process of selecting studies.

4. Result

4.1 Systematic literature review

Table 2 presents a summary of the most relevant methods and applications identified through the literature review

	Topic	Subtopic	Application	Method	Reference
1	Smart Manufacturing Applications for Inspection and Quality Assurance	Machine Learning Artificial Vision Inspection Support Statistical Process Control (SPC) Quality Assurance Smart Manufacturing	<ul style="list-style-type: none"> • Improve processes while reducing costs • Avoid incorrect operations or failures, Real-time defect detection • Measure/evaluate control loops and quality control • Improve small batch production and process capacity • Monitor digitization and industrial automation implementation • Performance measurement and capability assessment 	<ul style="list-style-type: none"> • Edge cloud computing technology • SMCMM and machine vision-based identification • Smart Manufacturing Capability Maturity Model (SMCMM) 	(Galindo-Salcedo et al., 2022)
2	Smart Manufacturing Applications for Inspection and Quality Assurance	Artificial Vision Inspection Support Statistical Process Control (SPC) Quality Assurance	<p>Improving processes while reducing costs and creating predictive models to decrease necessary inspections.</p> <p>Improving small-batch production capacity and automating production optimization.</p> <p>Monitoring digitization implementation and providing supervision for data-driven decision making.</p>	Shewhart control charts, Six Sigma methodology, and the fusion of SPC with TPM and APC.	(Maganga & Taifa, 2022)
3	Smart Manufacturing Conceptual Framework for QMS Digitalization	Networking & Storage Decision Support Process Actuation Framework Validation	<p>Associating unique identities (UIDs) and locations with all process entities (Material, Machine, Human, etc.).</p> <p>Monitoring the real-time state or parameters of manufacturing activities for corrective or preventive actions.</p> <p>Storing sensed information as digital evidence for audits and as empirical data for future decision-making.</p>	<p>Integration of sensors, equipment PLCs, and IoT monitoring systems to capture data directly from machines or products.</p> <p>Utilization of Statistical analysis</p> <p>Implementation of various levels of automation (manual, majorly digital, or fully digital) to stimulate the manufacturing process.</p>	(Kannaraya et al., 2025)

4	Quality 4.0 (The Digitalization of Quality Management)	Quality Control (QC) & Process Monitoring Predictive Quality Assurance (QA) & Planning	Real-time defect detection and non-conformity management . Integrating ISO 9001 requirements with I4.0 features. Integrating I4.0 with strategies like Six Sigma and Kaizen.	Advanced automatic monitoring and alerting systems. Internet of Things (IoT) and Cyber-Physical Systems (CPS) for real-time data capture End-to-End Integration (digital integration across the entire product value chain).	(Saihi et al., 2021)
5	AI-Driven Production Management and Control for Mass Personalization	Intelligent Manufacturing (IMFG) Production Planning & Management Quality Control & Maintenance	<ul style="list-style-type: none"> • Creating highly-personalized digital experiences for specific audiences. • Predictive maintenance to reduce unplanned downtime. 	<ul style="list-style-type: none"> • Data Analytics and audience insights • Industrial IoT (IIoT) for hyperconnected digital-physical cooperation . • Sensors & PLC integration for continuous monitoring. 	(Mourtzis, 2022)
6	Implementation of Smart Statistical Process Control (SSPC) in Industry 4.0	Digital Transformation Strategy Smart Statistical Process Control (SSPC) Cyber-Physical Systems (CPS)	<ul style="list-style-type: none"> • Protecting sensitive production data from unauthorized access . • Ensuring the system aligns with industry standards. • Real-time, automated monitoring of production processes . 	<ul style="list-style-type: none"> • Digitalization Assessment to evaluate current facilities . • Strategic Manufacturing Indicators (Lead time, productivity, efficiency). • Integration of Sensors & PLCs for automated data capture . 	(Goecks et al., 2024)
7	Intelligent Framework Design for Quality Control in Industry 4.0	Pre-production Quality Control Post-production Quality Control Data Preprocessing	Monitoring the health of manufacturing machines (specifically the gear system of induction motors) to ensure they are in good working order. Continuous analysis of data streams to send timely alerts and prevent unexpected shutdowns or the distribution of faulty products.	Use of vibration sensors (accelerometers) to collect real-time data. Data is analyzed using Artificial Neural Networks (ANN) to predict and classify six different fault conditions.	(Ali et al., 2024)

4.2 Systematic Literature Review Findings

The synthesis of the included research highlights a clear evolution from traditional, manual quality methods toward Quality 4.0—a data-centric, interconnected ecosystem. The results are categorized into five primary pillars that answer the research question: How can smart manufacturing be enabled through automated quality management systems?

Table 3: Summary of Methods and Applications.

Topic	Subtopic(s)	Application	Method/Technology	Reference
Smart Mfg. Apps for Inspection & QA	Machine Learning, Artificial Vision, SPC	Real-time defect detection; cost reduction.	Edge cloud; SMCMM; Machine Vision.	(Galindo-Salcedo et al., 2022)
Smart Mfg. Apps for Inspection & QA	Artificial Vision, SPC, Quality Assurance	Predictive models; production optimization.	Shewhart charts; Six Sigma; SPC+TPM+APC.	(Maganga & Taifa, 2022)
QMS Digitalization Framework	Networking, Decision Support, Actuation	UIDs for process entities; real-time sensing.	IoT monitoring; Sensors/PLC; Statistical analysis.	(Kannaraya et al., 2025)
Quality 4.0 (Digitalization)	QC, Process Monitoring, Predictive Quality	Real-time defect detection; ISO 9001 + I4.0.	IoT & CPS; End-to-End Integration.	(Saihi et al., 2021)
AI-Driven Production	Intelligent Mfg (IMFG), Planning, Maintenance	Predictive maintenance; personalized digital exp.	IIoT; Data Analytics; Sensors & PLC.	(Mourtzis, 2022)
Smart SPC (SSPC) Implementation	Digital Strategy, SSPC, Cyber-Physical Systems	Automated monitoring; data security.	Digitalization Assessment; Strategic Indicators.	(Goecks et al., 2024)
Intelligent Framework for QC	Pre/Post-production QC, Data Preprocessing	Machine health monitoring; fault alerts.	Vibration sensors; ANN; Machine Vision.	(Ali et al., 2024)

4.3 Quality Control (QC) & Process Monitoring

Quality Control (QC) and process monitoring have undergone a fundamental shift from reactive, "end-of-line" inspections to real-time, proactive surveillance. The analyzed studies emphasize that the integration of automation and advanced sensors enables continuous monitoring of the production line, which is particularly critical for high-variety, small-batch production environments. Applications of this shift are evident in the detection of defects in diverse materials, such as steel, rubber, and complex medical device components. The primary methodology driving this evolution is the convergence of the Internet of Things (IoT) and Cyber-Physical Systems (CPS). For instance, Ali et al. (2024) demonstrate a dual-layered approach where vibration sensors are utilized to monitor machine health—representing pre-production quality control while machine vision systems are simultaneously employed for automated product inspection to ensure post-production quality.

4.4 Predictive Quality

Predictive quality represents a strategic shift toward "zero-defect" manufacturing by identifying potential issues before they physically manifest in a final product. From the perspective of the reviewed literature, systems have evolved beyond the simple identification of "bad" parts to predicting the likelihood of defects based on a complex interplay of environmental and machine parameters. This approach is applied to anticipate maintenance needs and reduce waste or rework by enabling the real-time adjustment of process parameters. Methodologically, this is achieved through the utilization of Big Data Analytics and Machine Learning (ML) models. As highlighted by Galindo-Salcedo et al. (2022), the implementation of these predictive models significantly reduces the total number of physical elements requiring manual or automated inspection, thereby optimizing both operational time and production costs.

a. Quality Assurance (QA) & Planning

Quality Assurance (QA) and planning within the context of Industry 4.0 focus on the digital infrastructure and regulatory frameworks necessary to guarantee that products meet rigorous standards, such as ISO 9001 or ISO 13485. From a research perspective, contemporary QA is increasingly characterized by "digital traceability," where every phase of a product's lifecycle is recorded as digital evidence, effectively replacing traditional, error-prone paper-based documentation. This application is particularly critical in high-stakes sectors like the medical device industry; as noted by Kannaraya et al. (2025), digital systems such as the "Drip O Meter" and IoT integrations provide the precise, real-time data logs required for stringent certification audits. The methodology supporting this shift relies on Cloud Computing for centralized, scalable data storage and Blockchain technology to ensure immutable and transparent records across the entire global supply chain.

b. Intelligent Manufacturing (IMFG)

Intelligent Manufacturing (IMFG) represents an advanced level of automation where manufacturing systems possess "cognitive" abilities comparable to those of a skilled human worker. According to Mourtzis (2022), IMFG is characterized by the system's ability to perceive, reason, and act autonomously, marking an evolution from Smart Manufacturing by minimizing human intervention in complex decision-making processes. This capability is applied in high-stakes environments such as autonomous 24/7 production and "Mass Personalization," where systems automatically reconfigure themselves to manufacture unique, individualized products for specific customers. The methodology driving IMFG involves advanced Artificial Intelligence (AI) techniques including Deep Learning, Neural Networks, and Fuzzy Logic which are increasingly processed at the Industrial Internet of Things (IIoT) Edge to ensure the low-latency response times required for truly autonomous operations.

c. Production Planning & Management

Production Planning and Management within an Industry 4.0 environment involves the high-level coordination of resources, demand forecasting, and shop-floor scheduling. According to the analyzed literature, there is a distinct shift from traditional static planning to a "Smart Production Planning" paradigm that is inherently dynamic. This modern approach allows systems to respond instantly to supply chain disruptions or sudden shifts in customer demand. A primary application of this agility is "Mass Personalization," a strategy where high revenue volatility and short production lead times are common. Methodologically, this is supported by the use of Digital Twins, which allow for the simulation of production scenarios in a virtual environment before physical execution. Furthermore, the integration of Knowledge Graphs and Recommendation Systems assists planners in optimizing the flow of materials and labor by leveraging real-time data directly from the shop floor.

5. Discussion

The collective findings from the seven analyzed studies illustrate a paradigm shift where traditional quality management is being replaced by an interconnected, data-driven, and autonomous ecosystem known as Quality 4.0. This discussion explores how these technologies enable a more resilient and efficient manufacturing landscape. The integration of automated quality management systems (AQMS) within the smart manufacturing landscape represents a fundamental shift in how industrial excellence is achieved. The synthesis of the core studies reveals a multifaceted transformation that moves beyond simple automation toward a cognitive, data-driven, and proactive quality ecosystem.

The most significant finding across the reviewed literature is the obsolescence of reactive quality control. Traditional methods, focused on "end-of-line" inspections, inevitably result in material waste and increased costs when defects are discovered post-production. As highlighted in the works of Ali et al. (2024) and Galindo-Salcedo et al. (2022), the convergence of IIoT and Machine Learning allows for "Predictive Quality." By analyzing real-time data streams from vibration sensors and machine vision, systems can now identify the "pre-symptoms" of failure. This shift not only ensures zero-defect manufacturing but also optimizes operational costs by reducing the frequency of physical inspections.

The transition to Intelligent Manufacturing (IMFG), as discussed by Mourtzis (2022), signifies a level of autonomy where machines possess human-like cognitive abilities. The methodology of processing AI at the "IIoT Edge" is critical here; it allows for low-latency decision-making, enabling production lines to reconfigure themselves autonomously. This is the cornerstone of "Mass Personalization," allowing manufacturers to meet individualized customer demands without sacrificing the efficiency of mass production. By utilizing Digital Twins to simulate production scenarios, manufacturers can now produce individualized products at a scale and cost previously only possible through mass production. The discussion suggests that AI is no longer just a tool for analysis but the central nervous system of the modern factory.

A critical organizational factor identified is the need for immutable data records. In highly regulated sectors, such as the medical device industry, Kannaraya et al. (2025) demonstrate that digital traceability is mandatory for regulatory compliance (ISO 13485). The move from paper-based documentation to digital Quality Management Systems (QMS) is essential for maintaining certification. Technologies like Blockchain and Cloud Computing provide the infrastructure for this "digital traceability," ensuring that every step of a product's lifecycle is recorded in a secure, immutable, and transparent manner. This "digital thread" connects the horizontal value chain—from raw material suppliers to the end consumer ensuring end-to-end quality assurance.

While the technological requirements are clear, the literature particularly Saihi et al. (2021) and Jamwal et al. (2022)—points to a significant "human factor" challenge. The implementation of Quality 4.0 requires a workforce skilled in data science and systems engineering. Technologies like Augmented Reality (AR) and Virtual Reality (VR) are proposed not just for inspection, but as vital tools for training operators to interact with complex Cyber-Physical Systems (CPS). The discussion emphasizes that the "Smart" in smart manufacturing is as much about human-machine collaboration as it is about autonomous algorithms.

Despite these benefits, the transition to Smart Statistical Process Control (SSPC) remains complex. Goecks et al. (2024) provide a strategic roadmap emphasizing that companies must first assess their "digital readiness" before investing in advanced technologies. The research highlights a persistent barrier: the lack of interoperability among heterogeneous data sources. A standardized roadmap is necessary to align diverse machines and software suites. Without a unified framework for data exchange, the potential of Big Data remains untapped. Future quality management standards must evolve to reflect these digital capabilities, providing practitioners with clear benchmarks for "Smart Compliance."

In conclusion, the proposed conceptual model bridges the gap between traditional Total Quality Management (TQM) and Industry 4.0. It moves the conversation from "How do we automate inspection?" to "How do we create an autonomous, self-healing quality ecosystem?" By integrating real-time monitoring, predictive analytics, and digital traceability, the AQMS framework provides a viable answer to the demands of the Fourth Industrial Revolution, ensuring that quality remains a competitive advantage in an increasingly digitized global market.

6. Thematic Results

1. Quality Control has shifted from reactive "end-of-line" inspection to real-time, proactive surveillance. The integration of Internet of Things (IoT) and Cyber-Physical Systems (CPS) allows for continuous monitoring of the production line. For instance, Ali et al. (2024) utilizes vibration sensors (accelerometers) to monitor machine health (pre-production) alongside machine vision for product inspection (post-production).
 2. Predictive quality leverages Big Data Analytics and Machine Learning (ML) to identify potential defects before they manifest. By analyzing a complex interplay of environmental and machine parameters, systems can predict the likelihood of non-conformity. Galindo-Salcedo et al. (2022) highlight that these models significantly reduce the total number of physical elements requiring inspection, thereby optimizing time and costs.
 3. In Industry 4.0, QA is defined by "digital traceability." Every step of a product's lifecycle is recorded as digital evidence, replacing paper-based documentation. This is critical in the medical device industry (Kannaraya et al., 2025) to meet ISO 13485 standards. Technologies like Blockchain and Cloud Computing provide the infrastructure for secure, immutable data logs.
 4. IMFG represents systems that possess "cognitive" abilities, allowing them to perceive, reason, and act autonomously. According to Mourtzis (2022), processing AI at the IIoT Edge ensures the low-latency response times required for production lines to reconfigure themselves automatically. This enables Mass Personalization, where unique products are created at mass-production efficiency.
 5. Modern planning has moved from static scheduling to a dynamic, "Smart Production Planning" paradigm. By using Digital Twins, manufacturers can simulate various production scenarios in a virtual environment before physical execution. This allows the system to respond instantly to supply chain disruptions or sudden shifts in customer demand.
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7. Conclusion

The shift towards the Fourth Industrial Revolution has redefined the standards of industrial excellence, moving the focus from mere production volume to data-driven, intelligent quality. Research has shown that enabling intelligent manufacturing through Automated Quality Management Systems (AQMS) is not simply a technological upgrade, but a fundamental paradigm shift towards Quality 4.0. The integration of the Industrial Internet of Things (IIoT) and artificial intelligence (AI) has transformed quality control from a reactive, detection-and-repair model to a proactive, predictive, and preventative one. Furthermore, the rise of Intelligent Manufacturing (IMFG) has enabled simulation, inference, and action systems with a high degree of human intervention. In highly controlled environments, the digital thread, supported by blockchain and cloud computing, ensures unchanging traceability and transparency.

Globally, the success of Quality 4.0 remains inextricably linked to the human element. This transformation necessitates a strategic focus on workforce skills development and the use of technologies such as augmented reality to facilitate effective human-machine collaboration.

8. Recommendations

1. Digital readiness should be prioritized before investing in advanced technologies.
2. Companies should conduct a digital readiness assessment to ensure their infrastructure can support complex systems such as Statistical Process Control (SSPC).

3. The workforce should be equipped to enhance its skills in data science and systems engineering, with a focus on human-machine collaboration rather than relying solely on autonomous algorithms.
4. Professionals should focus on creating standardized frameworks for data exchange to overcome the lack of interoperability between different devices and software suites.
5. Recommendations include combining traditional methodologies such as Six Sigma and Statistical Process Control (SPC) with modern technologies such as machine learning and the Industrial Internet of Things (IIoT) to improve forecasting quality.

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