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IMPACT OF DIGITAL MATURITY ON QUALITY PROCESS PERFORMANCE: AN INTEGRATED QUALITY ENGINEERING APPROACH

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ABSTRACT: This paper examines the impact of digital maturity on quality process performance through an integrated quality engineering approach. Drawing on digital maturity models and quality management literature, it analyses how levels of digitalization influence key quality outcomes such as process traceability, real-time monitoring capabilities, and continuous improvement effectiveness. The study proposes a conceptual framework linking digital maturity stages to quality performance indicators, while addressing risks across processes, people, and technology domains. Maturity assessments emerge as diagnostic tools for planning digital quality transformations. Future research directions emphasize artificial intelligence and predictive analytics for proactive quality management, offering organizations a methodological foundation to evaluate and enhance quality processes in digital contexts.

KEYWORDS: Digital maturity; quality engineering; Industry 4.0; process performance; digital transformation; quality management systems; real-time monitoring; predictive analytics; maturity models; continuous improvement

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1. INTRODUCTION

In The rapid diffusion of digital technologies such as cyber-physical systems, industrial internet of things (IoT), advanced analytics and cloud platforms is transforming how organisations design, monitor and improve their quality processes. In many industries, quality management is shifting from paper-based, reactive control towards integrated, data-driven systems that rely on real-time information flows and automated feedback loops [1].

Within this broader digital transformation, the digital maturity of an organisation has emerged as a critical determinant of its capability to exploit digital technologies for operational and quality performance. Digital maturity models describe how organisations progress from ad-hoc, fragmented digital initiatives to fully integrated, optimised and continuously improving socio-technical systems [2]. However, there is still limited understanding of how specific levels of digital maturity translate into measurable improvements in quality process performance, traceability and continuous improvement capability in an engineering context [3].

Previous studies have explored the role of digitalisation in quality management and identified both opportunities and challenges, including new roles for quality professionals, the need for enhanced data competencies and tensions between standardisation and innovation [1]. At the same time, Industry 4.0–oriented digital maturity models for manufacturing focus mainly on technology deployment and organisational capabilities, without explicitly linking maturity stages to key quality performance indicators or to the design of quality processes [2]. This gap limits the ability of organisations to use maturity models as practical tools for diagnosing the state of their digital quality systems and for planning targeted improvement roadmaps.

The present paper addresses this gap by examining the impact of digital maturity on the performance of quality processes from an integrated quality engineering perspective. Specifically, the paper analyses how digital maturity models and their underlying dimensions relate to the degree of integration of digital technologies in quality processes, including automation, real-time monitoring and system interoperability. Building on insights from digital transformation, quality management and maturity model literature, the paper proposes an integrated approach in which quality performance indicators are explicitly linked to process digitalisation, real-time data use and the ability of quality systems to support knowledge-based decision-making [3].

In addition, the paper discusses risks and constraints associated with the digitalisation of quality processes across three main domains: processes, people and technology [1]. These include issues such as data quality and integrity, resistance to change, skill gaps, legacy systems, interoperability limitations and cybersecurity concerns, which can hinder both digital transformation and quality improvement [2]. The role of digital maturity models as diagnostic and planning instruments is examined, highlighting how maturity assessments can guide organisations in prioritising investments, aligning stakeholders and sequencing digital quality initiatives [2].

Finally, the paper outlines research directions related to the use of artificial intelligence (AI) and predictive analytics in quality management systems (QMS) [4]. Emerging work suggests that AI-enabled and analytics-driven QMS can move organisations from reactive defect detection to predictive and even prescriptive quality, enhancing process robustness and the ability to anticipate deviations before they materialise. The paper thereby provides a theoretical foundation for the development of a methodological framework that allows organisations to evaluate the impact of digital maturity on quality performance and to design concrete strategies for improving quality processes in line with their digital transformation journey [4]. Figure 1 is representing overall research scope showing how digital maturity influences quality process performance through integration of technologies, data use, and risks, leading to AI-enabled predictive quality.

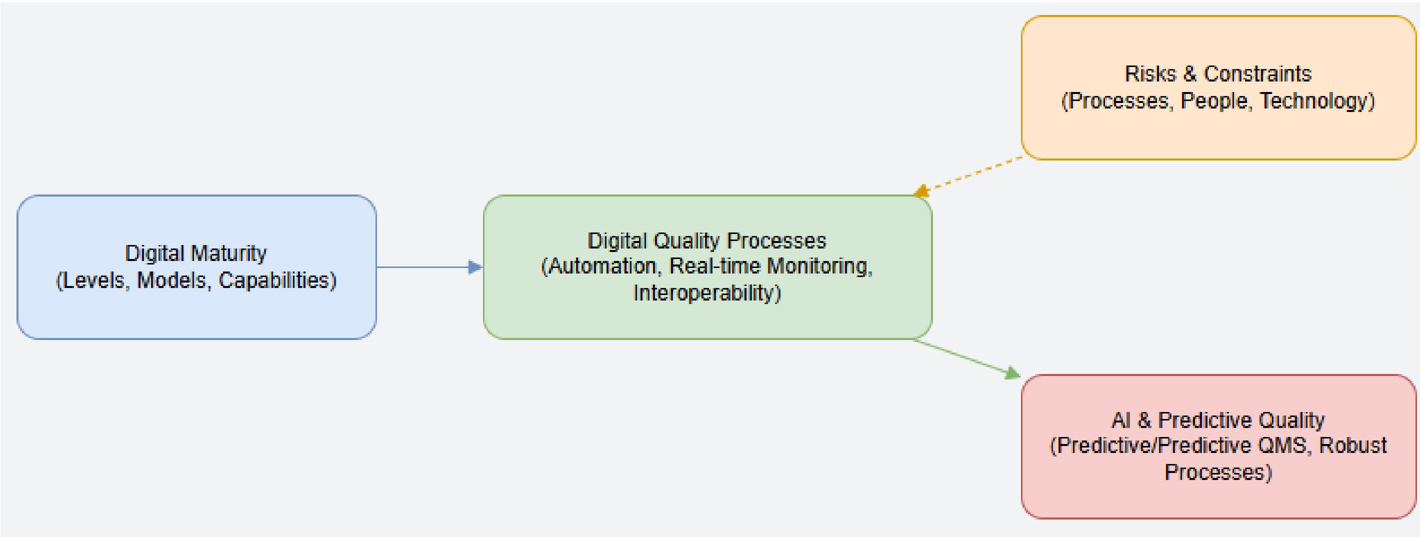

Figure 1. Research Scope and Logic

2. DIGITAL TRANSFORMATION AND DIGITAL MATURITY

Digital transformation refers to the pervasive integration of digital technologies into organisational processes, products and business models, fundamentally changing how value is created, delivered and captured [3]. In manufacturing and engineering, this evolution is often framed under the industry 4.0 paradigm, which emphasises connectivity, cyber-physical systems, industrial internet of things (IoT), cloud computing and advanced analytics across the value chain. Within this context, quality management is increasingly embedded into connected, data-rich environments, where information flows in near real time and supports faster detection, analysis and correction of process deviations.

Digital maturity captures the extent to which an organisation has systematically adopted and institutionalised such digital technologies, supported by appropriate structures, skills and governance mechanisms. Rather than representing a binary “digital or not” state, digital maturity is typically conceptualised as a multi-stage progression, where organisations evolve from isolated, ad-hoc digital initiatives towards fully integrated and optimised socio-technical systems. At higher maturity levels, digital solutions are aligned with business and quality strategies, processes are instrumented for continuous data collection, and decision-making increasingly relies on analytics and evidence rather than intuition [1]

Most digital maturity models for Industry 4.0 distinguish several core dimensions, commonly including technology (infrastructure, automation, data architecture), organisation (strategy, leadership, culture, skills) and processes (integration, standardisation, performance management). From a quality perspective, these dimensions are particularly relevant because they determine the organisation's ability to ensure traceability, maintain stable processes and implement effective continuous improvement routines. Technology-related maturity shapes the extent of process automation and real-time monitoring, while organisational maturity influences the capacity to define clear quality objectives, allocate resources and support data-driven problem solving [1–3].

As organisations progress in digital maturity, the role of data changes from simple record-keeping to an active asset that enables advanced quality assurance and improvement. At lower maturity levels, quality data are often fragmented across systems, reported with delays and used primarily for compliance and after-the-fact analysis. At intermediate stages, integrated information systems begin to consolidate quality-related data, supporting dashboards, trend analysis and more systematic root-cause investigations. At higher maturity levels, advanced analytics and, increasingly, artificial intelligence techniques can be applied to large and heterogeneous data sets, allowing the prediction of quality deviations, the optimisation of process parameters and the design of more robust processes.

In this sense, digital maturity is not only a descriptor of the technological landscape but also a driver of how quality engineering is practised. Organisations with higher digital maturity are better positioned to implement closed-loop quality control, where real-time data feed directly into control strategies and improvement cycles. Conversely, low digital maturity can limit the effectiveness of traditional quality tools, as they are applied to incomplete or delayed data and are not embedded in integrated workflows. Understanding digital maturity as a layered construct, encompassing technologies, processes and people, provides the basis for linking maturity stages to measurable quality performance outcomes and for using maturity models as practical instruments in quality-oriented digital transformation programmes [1–3]. In figure 2 is described the core dimensions of digital maturity in Industry 4.0 and their link to quality management.

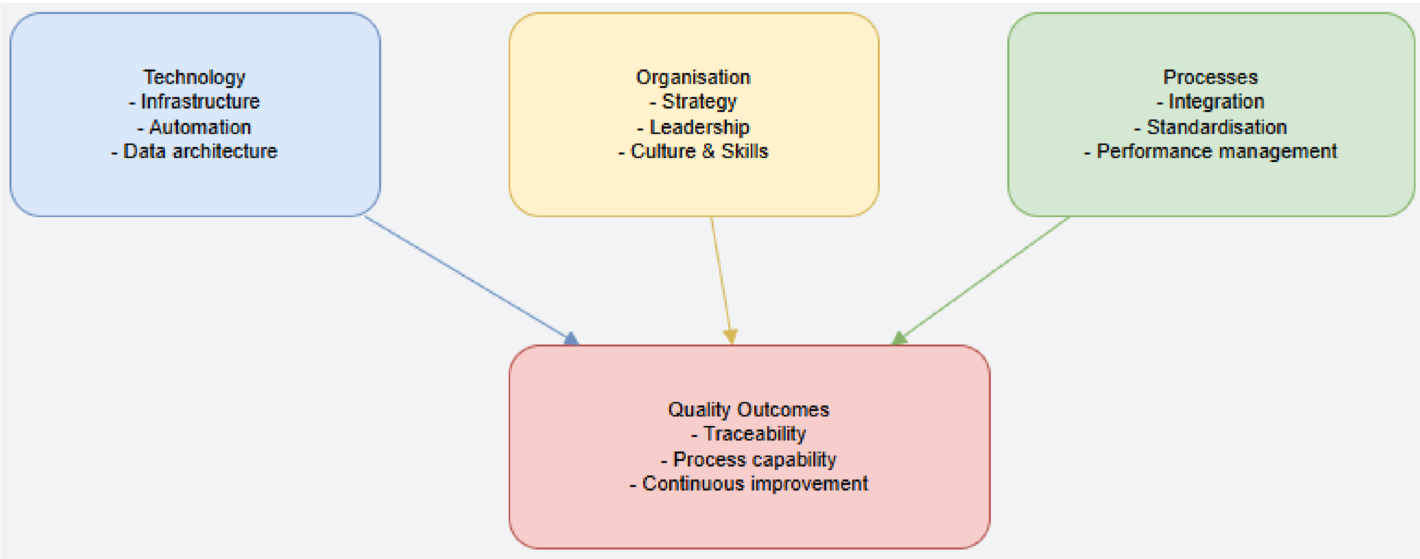

Figure 2. Digital Transformation and Digital Maturity

3. DIGITAL MATURITY IN QUALITY ENGINEERING

Quality engineering focuses on the systematic design, control and improvement of processes to ensure that products and services meet specified requirements and customer expectations. In a digitally transforming environment, quality engineering activities, such as process capability analysis, control charting, root-cause investigation and design for quality, depend increasingly on integrated data, interconnected systems and automated feedback loops. As a result, the digital maturity of an organisation directly shapes how effectively these quality engineering practices can be executed in real time and at scale.

From a process perspective, higher digital maturity typically implies that quality-relevant data are captured automatically at the source, stored in consistent formats and made available across functions through interoperable systems (e.g., MES, ERP, LIMS, QMS). This connectivity enables end-to-end traceability and supports rapid detection of deviations, since process parameters, inspection results and non-conformities can be monitored in a unified environment. At lower maturity levels, by contrast, data are often siloed, manually recorded or delayed, which constrains the use of advanced quality

tools and limits the organisation to reactive problem-solving based on partial information.
Recent discussions around Quality 4.0 emphasise that digital technologies such as IoT, cloud computing, advanced analytics and AI should be tightly integrated with traditional quality methods to create proactive, data-driven quality management systems. In this view, digital maturity reflects not only the presence of technologies, but also the organisation's capability to combine them with established quality tools (SPC, FMEA, PDCA, Six Sigma) in order to monitor and improve processes continuously. Maturity models and roadmaps for Quality 4.0 therefore describe how organisations can progress from basic digital support for quality documentation toward advanced, predictive and prescriptive control of quality processes
Digital maturity also influences the human and organisational side of quality engineering. Organisations that achieve higher maturity levels usually invest in analytical competencies, cross-functional collaboration and a culture that values data-driven decision-making. Quality engineers and process owners are then able to exploit digital tools, such as real-time dashboards, automated alerts or predictive models, to prioritise improvement actions, validate root causes and assess the impact of changes more systematically. In less mature settings, quality tools may still be used, but they are not fully integrated with digital systems, leading to fragmented analyses and slower learning cycles.
Taken together, these aspects suggest that digital maturity can be interpreted as an enabling context for modern quality engineering. As maturity increases, organisations move from document-centric and audit-focused quality practices towards data-centric and improvement-oriented approaches that leverage real-time information and predictive analytics. This view provides a foundation for defining digital-quality maturity levels and for linking each level to specific capabilities in areas such as automation of inspections, real-time monitoring, advanced analytics and closed-loop control of quality processes [6]. In figure 3 we have digital maturity enabling modern quality engineering through integrated data flows, system interoperability, and enhanced competencies.

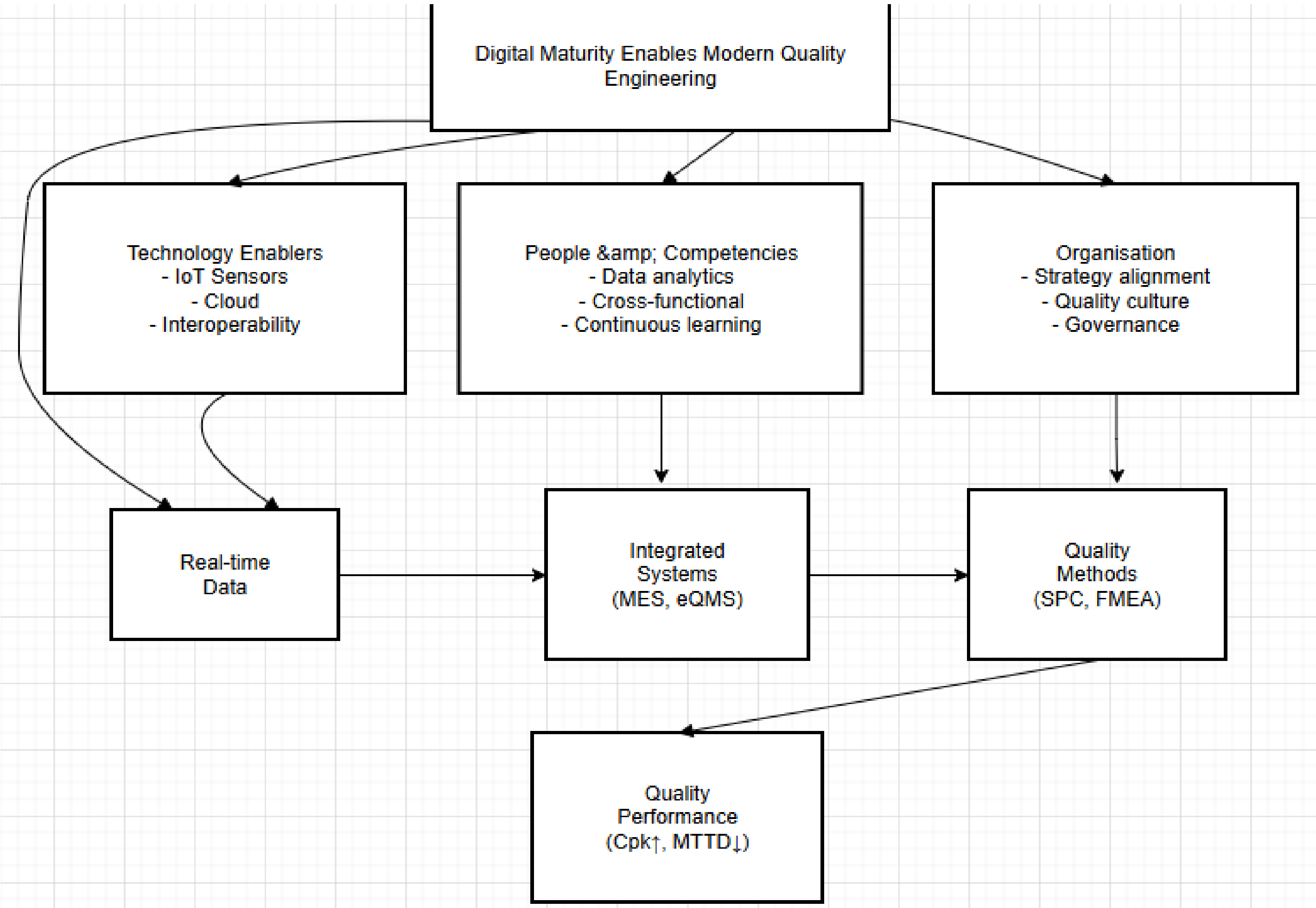

Figure 3. Digital Maturity in Quality Engineering

4. QUALITY PROCESS PERFORMANCE AND DIGITALIZATION

Quality process performance is traditionally measured through key indicators such as process capability (Cp, Cpk), defect rates (DPMO), first-pass yield, cycle time variation and effectiveness of corrective/preventive actions (CAPA closure rates). Digital maturity influences these indicators through three primary mechanisms: enhanced data availability, accelerated decision cycles and predictive process control. At higher maturity levels, organizations achieve greater process stability and capability because quality data flows continuously from production lines to analytical platforms, enabling real-time adjustments rather than periodic audits.

Real-time monitoring capabilities represent a critical inflection point in the maturity progression. Organizations at the "Connected" stage implement IoT sensors and digital twins that provide continuous visibility into critical process parameters, enabling statistical process control (SPC) to function as a live feedback system rather than retrospective analysis. Interoperability between manufacturing execution systems (MES), enterprise resource planning (ERP) and electronic quality management systems (QMS) becomes essential, as siloed data undermines the value of digital investments. [7]

At the highest maturity levels, organizations leverage machine learning models trained on historical quality data to predict process excursions and optimize setpoints preemptively. Predictive maintenance algorithms, anomaly detection and digital twins enable "virtual shakedown" of process changes, dramatically improving first-time-right rates and reducing scrap. These advanced capabilities require not only technological infrastructure but also mature data governance practices, cross-functional analytics teams and executive commitment to quality-as-strategy rather than quality-as-compliance.

The correlation between digital maturity and quality performance manifests most clearly in process robustness, the ability to maintain capability under varying conditions. Digitally mature organizations demonstrate lower coefficient of variation in critical parameters, higher sigma levels and more stable control charts, as continuous data streams replace periodic sampling [8]. This stability translates into measurable business outcomes: reduced warranty costs, higher customer satisfaction and competitive advantage through reliable delivery of high-quality products. The table below (Figure 4) illustrates how typical quality KPIs evolve across digital maturity stages:

Maturity Level	Data Capture	Process Capability (Cpk)	Defect Detection Time	CAPA Closure Rate
Low (Manual)	Periodic, paper	<1.0 (unstable)	Days/weeks	<70%
Medium (Digitized)	Partial automation	1.0-1.33 (capable)	Hours	70-90%
High (Connected)	Real-time sensors	1.33-1.67 (excellent)	Minutes	90-95%
Advanced (Predictive)	AI/ML analytics	>1.67 (world-class)	Seconds (proactive)	>95%

Figure 4. Quality KPIs by digital maturity level

5. INTEGRATED CONCEPTUAL FRAMEWORK

The proposed framework integrates digital maturity dimensions with quality performance indicators, creating a diagnostic tool for organisations to assess their current state and plan targeted improvements. This model conceptualises digital quality maturity as a four-stage progression, Initial, Digitised, Connected, and Predictive, where each stage represents distinct capabilities across technology, processes, people, and performance outcomes [9]. The framework explicitly links maturity levels to measurable quality KPIs [10], enabling organisations to benchmark progress and prioritise digital investments based on quality objectives. At the Initial stage, quality management relies on manual data collection and periodic audits, resulting in unstable processes (Cpk <1.0) and long mean time to detection (MTTD: days/weeks). Digital tools exist but operate in silos, limiting their impact on process performance. Transitioning to the Digitised stage involves electronic documentation and basic automation (e.g., digital forms, automated reporting), achieving capable processes (Cpk 1.0-1.33) with MTTD reduced to hours [11].

The Connected stage represents a fundamental shift toward real-time quality management, enabled by IoT sensors, system interoperability (MES-QMS-ERP), and live dashboards. Process capability reaches excellent levels (Cpk 1.33-1.67), with MTTD dropping to minutes through automated alerts and closed-loop control. Statistical process control evolves from retrospective analysis to live feedback, enabling proactive interventions before defects occur. Finally, the Predictive stage leverages machine learning, digital twins, and advanced analytics to anticipate process excursions and optimise parameters pre-emptively. Organisations achieve world-class capability (Cpk >1.67) with near-zero MTTD through anomaly detection algorithms and virtual shakedown testing. Quality becomes a strategic differentiator rather than a compliance function, as self-optimising processes deliver consistent first-pass yield above 99%. On Figure 5 we have a four-stage Digital Quality Maturity Model showing progression from Initial (Cpk <1.0, manual processes) to Predictive (Cpk >1.67, AI-enabled self-optimisation). Each stage links specific capabilities to quality KPIs, guiding organisations from reactive to proactive quality management.

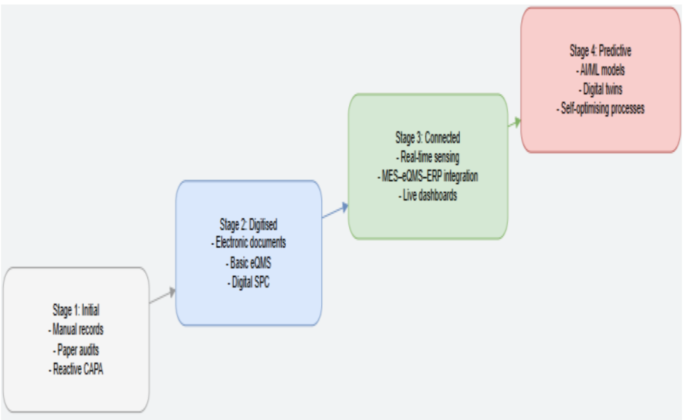

Figure 5. Four-stage Digital Quality Maturity Model from Initial to Predictive stage.

The framework's diagnostic value lies in its multi-dimensional assessment approach. Organisations score current capabilities across 12 dimensions (3 technology, 4 process, 3 people, 2 performance) to determine their composite maturity level and identify specific gaps. Transition roadmaps then prioritise high-impact initiatives, such as MES-QMS integration for Connected stage or AI model deployment for Predictive stage, based on quality ROI projections. This structured approach addresses the common failure mode of digital transformation: deploying technologies without corresponding process and people readiness.

6. RISKS, CONSTRAINTS AND MATURITY MODELS AS DIAGNOSTIC TOOLS

Digital transformation in quality management introduces significant risks across three domains: processes, people, and technology. Process-related challenges include data integrity issues, where automated systems generate inconsistent or incomplete quality records that undermine statistical analysis reliability. Legacy processes designed for manual control often resist digital workflows, creating hybrid environments where paper and digital documentation coexist, leading to compliance gaps and audit failures.

People-related constraints manifest as skill gaps between traditional quality practitioners and digital requirements. Quality engineers trained in manual SPC, and root-cause analysis may lack competencies in IoT data interpretation, machine learning model validation, or real-time dashboard utilisation. Organisational resistance emerges when digital initiatives threaten established roles or require cross-functional collaboration beyond comfort zones. Cultural inertia, prioritising compliance over innovation, further slows adoption of predictive quality paradigms.

Technology constraints encompass interoperability failures between siloed systems (MES, ERP, QMS), cybersecurity vulnerabilities in connected production environments, and scalability limitations of initial digital pilots. organisations frequently underestimate the data architecture requirements for Quality 4.0, deploying sensors without corresponding storage, cleansing, and governance capabilities. The result is often "digital debt", accumulated technical complexity that hinders rather than accelerates quality improvement.

Maturity models serve as diagnostic instruments to systematically identify these risks and constraints while providing actionable roadmaps. By assessing current capabilities across validated dimensions (technology readiness, process integration, competency profiles), organisations generate maturity heatmaps that reveal critical gaps. For example, a Connected-stage organisation scoring low on data governance faces immediate cybersecurity exposure, while Predictive aspirants lacking analytics talent risk failed AI deployments.

The diagnostic process follows a structured sequence:

1. **Baseline Assessment**: Score 12-15 capability dimensions using validated rubrics
2. **Gap Analysis**: Compare current vs. target maturity levels against quality KPIs
3. **Risk Prioritization**: Map constraints to business impact (scrap rates, audit findings, customer complaints)
4. **Roadmap Development**: Sequence initiatives by ROI and dependency (e.g., MES integration precedes AI deployment)
5. **Progress Monitoring**: Quarterly reassessments track movement across maturity stages

This methodology transforms abstract maturity concepts into concrete action plans, addressing the common pitfall of technology-first transformations that neglect process and people readiness. Maturity models also facilitate executive buy-in by quantifying quality ROI, typically 3-5x returns on digital investments through reduced scrap (15-30%), faster MTTD (70-90%), and improved capability indices (Cpk +0.5-1.0). By making risks visible and progress measurable, these diagnostic tools bridge the gap between digital ambition and quality execution.

7. FUTURE DIRECTIONS: AI AND PREDICTIVE ANALYTICS IN QMS

Artificial intelligence and predictive analytics represent the next frontier in quality management systems, transitioning organizations from reactive detection to proactive prevention of quality deviations. Machine learning models trained in historical process data can identify subtle patterns preceding defects, enabling pre-emptive parameter adjustments that maintain capability without human intervention. Unlike traditional SPC, which signals deviations after they occur, AI-driven systems forecast excursions hours or days in advance, dramatically reducing scrap and rework.

Anomaly detection algorithms scan multivariate process streams in real time, flagging unusual behaviour patterns that exceed statistical control limits. For example, neural networks analysing vibration, temperature, and pressure data from CNC machines can predict tool wear 24–48 hours before failure, preventing downstream quality issues. Digital twins—virtual replicas of physical processes enable "what-if" simulations of parameter changes, allowing virtual shakedown testing without production risk.

Prescriptive analytics extends prediction by recommending optimal corrective actions. Reinforcement learning algorithms continuously optimize process setpoints based on real-time feedback, achieving self-tuning processes that adapt to raw material variation, environmental conditions, and equipment degradation. In pharmaceutical manufacturing, for instance, prescriptive models balance yield maximization with regulatory compliance, automatically adjusting mixing parameters to maintain critical quality attributes within specification.

Generative AI introduces novel applications in root-cause analysis and CAPA generation. Natural language processing models extract insights from unstructured quality records (audit reports, technician notes, customer complaints), while large language models generate hypotheses and action plans ranked by historical effectiveness. This accelerates problem resolution from weeks to hours while institutionalizing best practices across global sites.

Research gaps remain in several critical areas:

- Explainability: Black-box AI models hinder regulatory acceptance in life sciences and automotive sectors
- Data quality: Garbage-in-garbage-out remains the primary barrier to reliable predictions
- Change management: Quality professionals require reskilling for AI governance and model validation
- Standardization: ISO 9001 lacks guidance for AI-enabled QMS certification

Future studies should validate hybrid human-AI quality teams, were domain expertise guides model development and deployment. Longitudinal research tracking ROI across maturity stages will quantify the premium of Predictive quality over Connected implementations. Standardization bodies must develop AI-Quality maturity models incorporating model drift detection, ethical AI guidelines, and continuous validation protocols.

The convergence of AI with Quality 4.0 promises unprecedented process robustness, where deviations become as rare as mechanical failures in modern aviation. Organizations pioneering these capabilities will redefine quality leadership, transforming compliance functions into strategic innovation engines.

8. CONCLUSIONS

This paper examined the interdependence between digital maturity and quality process performance through an integrated quality engineering perspective, proposing a conceptual framework that bridges the gap between abstract maturity concepts and measurable quality outcomes. The analysis demonstrates that digital maturity is not merely a technological descriptor but a systemic capability that fundamentally shapes the effectiveness of quality management practices. Key findings include: (1) organizations progressing through the four maturity stages, Initial, Digitized, Connected, and Predictive, achieve compounding improvements in process capability (from Cpk <1.0 to >1.67), defect detection time (from days to seconds), and CAPA closure rates (from <70% to >95%) ; (2) digital maturity models function as practical diagnostic tools that identify risks across process, people, and technology domains, enabling structured roadmaps prioritized by quality ROI ; (3) Quality 4.0 paradigms integrating IoT, cloud computing, and advanced analytics with traditional quality methods create unprecedented opportunities for closed-loop, predictive quality control. The framework highlights the critical role of organizational readiness. Technology deployment alone is insufficient, organizations must simultaneously build analytical competencies, foster data-driven cultures, and integrate digital tools with established quality routines. The diagnostic methodology presented (baseline assessment, gap analysis, risk prioritization, roadmap development, progress monitoring) provides a replicable approach for quality leaders to accelerate transformation while managing implementation risks. Looking forward, artificial intelligence and predictive analytics represent transformative capabilities that shift quality from compliance-focused to strategy-driven functions. Anomaly detection, digital twins, and prescriptive analytics enable organizations to anticipate and prevent deviations rather than react to failures. However, research gaps persist in AI explainability, data quality standards, and ISO 9001 guidance for AI-enabled QMS [9]. Future work should quantify hybrid human-AI team effectiveness and develop standardized maturity models for AI-Quality integration [6]. For practitioners, the paper offers immediate value: a maturity assessment framework to baseline current state, a roadmap sequencing approach to prioritize investments, and evidence that digital maturity drives measurable quality and business improvement. For researchers, it provides a foundation for longitudinal studies tracking ROI across maturity stages, case analyses of industry-specific Quality 4.0 implementations, and empirical validation of hybrid human-AI quality teams. The path toward predictive, self-optimizing quality systems is achievable for any organization willing to view digital transformation as a systemic change rather than a technology purchase. The organizations that combine digital capabilities with quality discipline and organizational commitment will emerge as quality leaders, delivering unprecedented process robustness and customer value in an increasingly demanding market.

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