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DEVELOPMENT OF QUALITY MANAGEMENT SYSTEMS IN THE CONTEXT OF DIGITAL TRANSFORMATION

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Abstract: The accelerating pace of digital transformation is fundamentally reshaping quality management systems (QMS) across industries, necessitating a comprehensive theoretical and empirical re-examination of established frameworks. This paper investigates the developmental trajectory of QMS in the context of digital transformation, with particular emphasis on the integration of artificial intelligence (AI), Internet of Things (IoT), blockchain, digital twin technologies, and cloud-based platforms into quality governance architectures. Grounded in the Total Quality Management (TQM) framework, the ISO 9001:2015 risk-based process approach, and the dynamic capabilities perspective, the study proposes a five-level Digital Quality Management System (DQMS) Maturity Model as a novel methodological instrument for assessing and guiding organisational digital quality transitions. A mixed-methods research design — combining systematic literature synthesis, expert Delphi weighting (n = 34), and a structured survey of 312 quality and operations professionals across manufacturing, services, and technology sectors in 11 countries — was employed to validate the model empirically.

Key words: digital quality management, QMS digitalisation, ISO 9001, Industry 4.0, AI in quality, digital twin, DQMS maturity model, cost of quality.

INTRODUCTION

The fourth industrial revolution — characterised by the convergence of cyber-physical systems, advanced analytics, and autonomous decision-making — has generated transformational pressures across all domains of organisational management. Among the most profoundly affected domains is quality management, where decades of institutionalised practice built around ISO 9001 certification cycles, statistical process control, and human-led inspection are being systematically disrupted by digital technologies capable of monitoring, predicting, and correcting quality deviations in real time, at scale, and with minimal human intervention. This disruption is not merely technological; it represents an epistemological shift in what quality assurance means — from reactive conformance checking to proactive, data-driven value creation.

The urgency of this transition is underscored by the scale of economic loss attributable to poor quality. The American Society for Quality (ASQ) estimates that the global cost of quality — encompassing prevention, appraisal, and failure costs — ranges between 5% and 40% of annual revenue depending on sector maturity (ASQ, 2023). More recently, McKinsey & Company (2022) reported that organisations at the frontier of digital quality management achieve cost of quality reductions of 20–35%, cycle time improvements of 30–50%, and customer satisfaction score increases of 15–20% relative to peers using conventional QMS architectures. These performance differentials provide compelling empirical justification for the urgency of QMS digital transformation.

However, despite growing practitioner and scholarly interest, the literature on digital QMS remains fragmented. Contributions addressing AI in quality (Kusiak, 2020; Wang et al., 2022), IoT-enabled process monitoring (Lu et al., 2021), digital twins for quality (Grieves & Vickers, 2017; Tao et al., 2022), and blockchain in supply chain quality assurance (Kouhizadeh et al., 2021) largely develop in isolation, without an integrative framework connecting these technologies to established QMS theory and practice. Furthermore, extant QMS maturity models — most notably the Capability Maturity Model Integration (CMMI) and the European Foundation for Quality Management (EFQM) Excellence Model — were developed prior to the Industry 4.0 era and lack the conceptual apparatus to evaluate digital quality capabilities systematically. This gap motivates the present research.

This paper makes three principal contributions. First, it develops and validates a five-level Digital Quality Management System (DQMS) Maturity Model that provides a comprehensive, theoretically grounded instrument for assessing and guiding organisations' digital quality transformation journeys. Second, it synthesises the impact of four transformative digital technologies — AI/ML, IoT/cyber-physical systems, blockchain, and digital twin — across six QMS dimensions, generating an integrated impact taxonomy that advances the fragmented literature. Third, it proposes a five-phase DQMS Implementation Framework with phase-specific key performance indicators (KPIs), offering practitioners a scalable, policy-aligned roadmap applicable across organisational sizes and sectors.

REVIEW OF LITERATURE ON THE SUBJECT

The evolution of quality management from craft-based inspection to digitally integrated governance represents one of the most significant transformations in management science over the past century. As detailed in Table 1 below, six distinct developmental eras can be identified, each characterised by a paradigm shift in the conceptual understanding of quality, the institutional standards codifying it, and the technological tools operationalising it.

The scholarly conceptualisation of this shift has been anchored in two principal theoretical frameworks. Deming's (1986) Plan-Do-Check-Act (PDCA) cycle, while conceived in an analogue context, has been shown to be algorithmically instantiable in digital environments, with AI systems capable of executing accelerated PDCA iterations across thousands of process variables simultaneously (Li et al., 2022). Crosby's (1979) 'zero defects' philosophy, long considered aspirational rather than achievable, has been partially rehabilitated by AI vision systems achieving defect detection accuracies exceeding 99.5% in controlled manufacturing environments (Wan et al., 2023).

Artificial intelligence applications in quality management span predictive quality analytics, automated visual inspection, natural language processing for quality documentation, and reinforcement learning for process optimisation. Kusiak (2020) demonstrated that machine learning models trained on multivariate sensor data can predict product quality deviations with up to 92% accuracy 24 hours before they manifest in physical products, enabling truly proactive quality intervention. Computer vision systems — combining convolutional neural networks (CNNs) with high-resolution imaging — have achieved defect detection performance surpassing human inspectors in precision, consistency, and throughput across semiconductor, pharmaceutical, and automotive sectors (Wang et al., 2022). More recently, large language models (LLMs) have demonstrated capability in automating quality procedure documentation, interpreting complex customer complaint patterns, and generating FMEA (Failure Mode and Effects Analysis) inputs from operational data streams (Zhang et al., 2023). The emergence of explainable AI (XAI) applications in quality contexts addresses a long-standing concern regarding the opacity of 'black box' quality decisions in regulatory and safety-critical environments (Gunning et al., 2019).

IoT-enabled quality monitoring represents perhaps the most operationally immediate digital technology disruption in QMS practice. By embedding sensor networks throughout production environments, organisations can achieve continuous, multivariate process monitoring at costs that have declined by approximately 85% since 2010 (IDC, 2023). Lu et al. (2021) documented a 67% reduction in process-related quality failures in automotive supply chains following IoT-based monitoring deployment. Cyber-physical systems (CPS) extend this capability by creating bidirectional digital-physical feedback loops in which quality monitoring triggers automatic process correction without human intervention, achieving what Kagermann et al. (2013) termed "quality at the speed of production".

Blockchain's contribution to quality management is concentrated in supply chain quality transparency, product traceability, and audit trail integrity. Kouhizadeh et al. (2021) conducted a systematic review of 112 articles on blockchain in supply chain management, concluding that immutable distributed ledger records can reduce counterfeit product incidence by up to 78% and decrease supply chain audit duration by 45–60%. The pharmaceutical industry's implementation of blockchain-based serialisation (EU Falsified Medicines Directive, 2019) provides the most mature regulatory application, with demonstrated efficacy in product provenance verification across multi-tier supply chains. Smart contracts enable automated triggering of quality non-conformance responses — including quarantine instructions, supplier corrective action requests, and customer notifications — without manual intermediation.

Digital twin technology — creating virtual replicas of physical products, processes, and systems that are continuously synchronised with real-world counterparts through sensor data — represents the most transformative long-term enabler of digital QMS (Grieves & Vickers, 2017). Tao et al. (2022) demonstrated that digital twin-enabled quality management in aerospace manufacturing reduced first-pass yield failures by 31% through virtual process optimisation conducted before physical production commenced. The convergence of digital twins with AI creates particularly powerful quality management synergies: AI models trained on digital twin simulation data can develop quality optimisation strategies that would require years of physical experimentation to generate through conventional empirical methods.

RESEARCH METHODOLOGY

This study employs a sequential exploratory mixed-methods design (Creswell & Plano Clark, 2018) comprising three integrated methodological phases: (i) a systematic literature synthesis to establish the theoretical foundations and generate DQMS capability descriptors; (ii) an expert Delphi study to validate and weight DQMS maturity criteria; and (iii) a quantitative cross-industry survey to empirically test model propositions and gather implementation evidence. This triangulation strategy was selected to combine the conceptual rigour of systematic review methodology with the normative validation of expert consensus and the generalising power of quantitative survey research. A systematic literature search was conducted across the Scopus, Web of Science, and ScienceDirect databases using the search strings: ("digital quality management" OR "QMS AND digital transformation" OR "ISO 9001 AND Industry 4.0") AND ("artificial intelligence" OR "IoT" OR "blockchain" OR "digital twin"). The search was restricted to peer-reviewed articles published between 2015 and 2024. Initial screening of titles and abstracts yielded 1,847 documents; application of inclusion criteria (empirical or conceptual papers addressing QMS and digital technology integration; English language; indexed in Scopus or WoS) reduced this to 218 eligible papers, which constituted the systematic review corpus. Synthesis followed the PRISMA protocol (Page et al., 2021).

ANALYSIS AND RESULTS

The systematic literature synthesis identified six QMS dimensions most profoundly affected by digital transformation: defect detection and prevention, document and knowledge management, risk management, supplier quality assurance, customer satisfaction management, and continuous improvement. Table 2 presents the synthesised impact of the four principal digital technologies across these dimensions, constituting the integrated impact taxonomy developed in this study (Table 1).

Table 1. Digital technology impact taxonomy across Six QMS Dimensions[1]

QMS Dimension	AI / ML	IoT / Cyber-Physical	Blockchain	Digital Twin
Defect detection & prevention	Predictive defect models; CV-based visual inspection (99.2% accuracy)	Real-time sensor fusion; vibration & thermal anomaly detection	Immutable defect traceability across supply chain	Virtual stress-testing before physical production
Document & knowledge management	NLP-powered search; automated procedure updates	Sensor-linked calibration records auto-updated	Tamper-proof audit trails; smart contract compliance	Process documentation auto-generated from twin data
Risk management (ISO 9001 §6.1)	Risk scoring models; scenario simulation; FMEA automation	Live risk dashboards; threshold-based alerts	Supplier risk transparency; fraud-resistant records	Monte Carlo risk simulations on digital replicas
Supplier quality assurance	Supplier ESG & quality scoring models	Remote real-time monitoring of supplier processes	Verified certificates of conformity on-chain	Virtual supplier process audits
Customer satisfaction & feedback	Sentiment analysis; churn prediction	Smart product telemetry; NPS data collection at point of use	Verified product provenance increasing consumer trust	Customer-facing twin for product customisation
Continuous improvement (CI)	ML-optimised PDCA cycles; A/B testing at scale	Process drift detection enabling instant CI triggers	Immutable CI action logs and KPI history	Rapid iteration via virtual process experiments

1 Source: Authors' synthesis from systematic literature review (n = 218 papers). CV = computer vision; NCR = non-conformance report; ESG = Environmental, Social & Governance.

The taxonomy reveals that AI/ML offers the broadest transformative potential across all six QMS dimensions, with particularly acute impact in defect detection (where computer vision systems achieve 99.2% accuracy versus 94.5% human-inspector baseline) and continuous improvement (where ML-optimised PDCA cycles enable improvement iteration timescales of hours rather than weeks). IoT/CPS delivers the most operationally immediate impact in defect prevention and risk management through real-time sensor fusion. Blockchain's impact is concentrated in supplier quality assurance and document integrity, where its immutability and distributed verification properties address long-standing audit trail vulnerabilities. Digital twin technology's most distinctive contribution lies in enabling quality scenario testing before physical production commitment — a capability with profound implications for new product quality costs.

Drawing on the Delphi expert consensus (n = 34; CV < 0.20 achieved in Round 3) and the systematic literature synthesis, a five-level Digital Quality Management System (DQMS) Maturity Model was constructed. The model positions organisations along a continuum from Level 1 (Initial/Reactive) to Level 5 (Optimising/Autonomous), with each level defined by empirically grounded digital capability descriptors and a quantitative DQMS Score on a 0–100 scale. Table 3 presents the full model (Table 2).

Table 2. DQMS maturity model: five-level framework for digital quality assessment[2]

Level	Maturity Stage	Characteristics	Typical Capabilities	DQMS Score*
1	**Initial / Reactive**	Ad hoc quality practices; paper-based records; inspection-only approach	Manual data collection; siloed departmental quality; no predictive capability	**0–20 / 100**
2	**Developing / Aware**	Partial digitisation; ERP integration begins; some process monitoring	SPC software; quality dashboards; ISO 9001 certification sought	**21–40 / 100**
3	**Defined / Systematic**	Standardised digital workflows; real-time KPI monitoring; risk-based thinking applied	Automated NCR tracking; supplier portal; cloud-based QMS platform	**41–60 / 100**
4	**Managed / Predictive**	AI-assisted quality prediction; IoT-enabled process control; cross-functional data lakes	Predictive maintenance; digital audit trails; ML-based root cause analysis	**61–80 / 100**
5	**Optimising / Autonomous**	Self-correcting systems; digital twins; real-time quality loop closure; zero-defect ambition	Autonomous quality assurance; full traceability chain; ecosystem-level transparency	**81–100 / 100**

The model makes several methodological advances over existing quality maturity frameworks. First, each level is anchored in specific, observable digital capability descriptors rather than abstract improvement narratives, enabling more reliable and reproducible organisational assessment. Second, the DQMS Score provides a continuous measurement instrument rather than categorical level assignment, allowing organisations to track sub-level progress. Third, the Level 5 descriptor — 'autonomous quality loop closure' — introduces a genuinely new quality management concept with no precedent in conventional QMS theory, reflecting the fundamental nature of AI-enabled quality governance. Survey validation of the maturity model revealed that 71% of respondents from organisations self-assessed at Level 3 or below agreed that the model accurately characterised their quality digitalisation constraints, while 84% of Level 4–5 organisations confirmed that the Level 5 capability descriptors reflected achievable near-term ambitions. The mean DQMS Score across survey respondents was 52.3 (SD = 18.7), corresponding to a mid-Level 3 average — consistent with industry analyst estimates of average Industry 4.0 QMS adoption (Deloitte, 2023). Table 4 presents the results of the cross-industry survey (n = 312) across ten key propositions corresponding to the principal dimensions of the DQMS framework (Table 3).

2 Source: Authors' elaboration based on Delphi expert study (n = 34) and systematic literature synthesis. *DQMS Score calculated as weighted composite of 28 digital capability items (Delphi-validated weights).

Table 3. Cross-industry survey results: professional perceptions of DQMS Transformation (n = 312, Five-Point Likert Scale)[3]

Survey Proposition	SA (%)	A (%)	N (%)	D (%)	SD (%)	Mean (5-pt)
AI integration significantly improves defect detection accuracy	48	36	9	5	2	**4.23**
IoT-based monitoring reduces quality-related downtime effectively	42	39	11	6	2	**4.13**
Digital QMS reduces the cost of quality (CoQ) measurably	35	41	14	7	3	**3.98**
Blockchain enhances supply chain quality transparency	28	38	20	10	4	**3.76**
Digital twin enables effective quality scenario testing	31	40	17	9	3	**3.87**
ISO 9001 effectively accommodates digital QMS requirements	22	34	24	14	6	**3.52**
DQMS implementation faces significant cultural resistance	40	32	14	10	4	**3.94**
Data security risks are a major barrier to DQMS adoption	46	35	10	6	3	**4.15**
DQMS delivers measurable competitive advantage within 3 years	33	42	15	7	3	**3.95**
SMEs face disproportionately higher DQMS adoption barriers	52	31	9	5	3	**4.24**

Survey results reveal consistent professional consensus across the proposition set, with mean scores ranging from 3.52 to 4.24. The highest agreement is recorded for AI integration's impact on defect detection accuracy (mean = 4.23; 84% agreement) and SME disproportionate adoption barriers (mean = 4.24; 83% agreement), followed by IoT-based monitoring's effectiveness in reducing quality-related downtime (mean = 4.13; 81% agreement). These findings align with the literature's identification of AI and IoT as the primary near-term quality management transformation vectors. The proposition receiving the lowest mean score — ISO 9001's effective accommodation of digital QMS requirements (mean = 3.52; 56% agreement) — is theoretically significant. This finding suggests that a substantial minority (44% neutral or disagreeing) of quality professionals perceive the current ISO 9001:2015 framework as inadequately responsive to digital QMS realities, representing an important policy signal for ISO/TC 176. The proposition that cybersecurity risks constitute a major adoption barrier recorded a mean of 4.15 (81% agreement), confirming that digital quality governance introduces security vulnerability dimensions that conventional QMS frameworks are not equipped to address. The proposition on cultural resistance (mean = 3.94; 72% agreement) underscores that the primary barriers to DQMS adoption are as much organisational as they are technological.

Cross-referencing survey-reported performance data with self-assessed DQMS maturity levels revealed statistically significant performance differentials across maturity levels. Organisations at DQMS Level 4–5 reported a mean cost of quality (CoQ) reduction of 28.4% (95% CI: 24.1–32.7%) relative to pre-DQMS baseline, compared to 9.2% for Level 2–3 organisations ($t = 8.34$, $p < 0.001$). Defect detection accuracy improvements were 34.7% for Level 4–5 organisations versus 11.3% for Level 2–3 ($t = 9.12$, $p < 0.001$). Overall equipment effectiveness (OEE) improvements showed a similar gradient: 22.1% at Level 4–5 versus 7.8% at Level 2–3 ($t = 7.61$, $p < 0.001$). These performance differentials provide strong empirical validation of the maturity model's discriminant validity — organisations at higher DQMS maturity levels systematically achieve superior quality performance outcomes. Based on synthesis of the literature review, Delphi expert inputs, and survey findings, a five-phase DQMS Implementation Framework was constructed to provide practitioners with an operationally grounded, sequenced roadmap for digital quality transformation. The framework explicitly links implementation activities, expected outcomes, and measurable KPIs for each phase, addressing a critical gap in existing implementation guidance. Table 5 presents the complete framework (Table 4).

3 Source: Authors' primary survey data (2023–2024). $\alpha = 0.91$; CFI = 0.96; RMSEA = 0.043. SA = Strongly Agree; A = Agree; N = Neutral; D = Disagree; SD = Strongly Disagree.

Table 4. Five-Phase DQMS implementation framework with phase KPIs[4]

Phase	Duration	Key Activities	Expected Outcomes	Success Indicators (KPIs)
I	Months 1–4	Digital readiness audit; DQMS maturity baseline; stakeholder mapping; data architecture design	Current-state DQMS score; gap analysis report; technology roadmap approved	Maturity score established; >80% stakeholder buy-in; data gaps identified
II	Months 5–10	ERP/MES quality module deployment; IoT sensor installation; cloud QMS platform configuration; staff training	Real-time quality dashboards live; automated NCR workflow; 60% paperless processes	Dashboard adoption >75%; NCR closure time ↓40%; paper reduction >60%
III	Months 11–18	AI/ML defect prediction models trained; SPC automation; supplier portal launch; digital audit trails	Predictive quality alerts operational; supplier ESG scorecards live; audit time ↓50%	Defect prediction accuracy >85%; supplier compliance rate >90%
IV	Months 19–28	Digital twin deployment for critical processes; blockchain pilot for supply chain traceability; CI algorithm integration	Virtual process optimisation capability; immutable traceability records; autonomous CI loops	Process yield improvement >15%; traceability coverage >95%
V	Months 29–36	Full ecosystem integration; autonomous quality loop closure; DQMS Level 4–5 certification; continuous optimisation	Self-correcting quality system; zero-undetected-defect ambition; DQMS score ≥80	CoQ reduction >25%; OEE improvement >12%; DQMS maturity ≥Level 4

The framework's five phases are designed on three foundational principles. The principle of progressive complexity ensures that each phase builds on the digital infrastructure and capability base established in preceding phases, preventing technology deployment outpacing organisational capability absorption — a pattern identified as the primary cause of DQMS implementation failure by 62% of survey respondents who reported partial implementation setbacks. The principle of measurable accountability anchors each phase to specific, quantitative KPIs rather than qualitative implementation milestones, enabling objective progress assessment and adaptive management. The principle of ecosystem readiness acknowledges that full DQMS potential is realised only when supplier and customer digital interfaces are integrated — a consideration addressed explicitly in Phase III and IV activities.

A systematic mapping of DQMS adoption barriers and recommended mitigation strategies, developed from the literature synthesis and validated through the expert Delphi study, is presented in Table 6. Barriers are organised across four categories — technological, organisational, financial, and data quality/ecosystem — and assigned severity ratings based on Delphi expert consensus scores (Table 5).

4 Source: Authors' elaboration. Duration estimates based on survey respondent implementation timelines and validated by Delphi expert panel. OEE = Overall Equipment Effectiveness; NCR = Non-Conformance Report; CoQ = Cost of Quality.

Table 5. DQMS adoption barriers, severity ratings, and mitigation strategies[5]

Category	Barrier / Challenge	Severity*	Recommended Mitigation Strategy
Technological	Legacy system incompatibility and high integration cost	**High**	API-first architecture; phased legacy migration; cloud-native QMS platforms
Technological	Cybersecurity vulnerabilities in IoT-connected quality systems	**Very High**	Zero-trust security architecture; IEC 62443 compliance; encrypted data pipelines
Organisational	Cultural resistance to data-driven decision-making	**High**	Change management programmes; quality champion networks; transparent communication
Organisational	Skills gap: shortage of data-literate quality professionals	**High**	Structured reskilling; QMS-data science cross-training; university partnerships
Financial	High upfront DQMS investment costs, especially for SMEs	**Very High**	Phased ROI-linked deployment; green/digital bonds; government co-investment schemes
Regulatory	ISO 9001 framework lagging behind digital QMS capabilities	**Medium**	Active participation in ISO/TC 176 revision; adopt supplementary Industry 4.0 standards
Data Quality	Inconsistent, incomplete, or biased training data for AI models	**High**	Data governance frameworks; master data management; synthetic data augmentation
Ecosystem	Supply chain partners at widely divergent digital maturity levels	**Medium**	Supplier development programmes; tiered compliance requirements; shared platforms

The barrier analysis highlights that cybersecurity vulnerabilities (Very High severity) and financial barriers for SMEs (Very High severity) represent the most acute systemic risks to DQMS adoption. These findings carry important policy implications: the designation of cybersecurity as the most severe technical barrier argues for embedding IEC 62443-compliant security architecture as a foundational requirement of any DQMS deployment, rather than treating security as an add-on layer. The SME financial barrier — confirmed by 83% of survey respondents as a significant adoption obstacle — suggests that public co-investment mechanisms analogous to those developed for green technology adoption (e.g., EU SME Digital Innovation Hubs, EBRD Digital Economy programmes) represent a high-leverage policy intervention for broadening DQMS adoption beyond large enterprise contexts.

The results of this study carry multiple theoretical implications for quality management scholarship. Most fundamentally, the DQMS Maturity Model's five-level taxonomy challenges the implicitly continuous improvement narrative embedded in conventional QMS theory since Deming (1986). The transition from Level 4 (Managed/Predictive) to Level 5 (Optimising/Autonomous) represents not merely an incremental improvement in quality practice but a categorical change in the nature of quality governance — from human-centred to algorithm-centred decision-making. This transition introduces novel theoretical questions about accountability, auditability, and the role of quality professionals that QMS scholarship has not yet systematically addressed. The integrated technology impact taxonomy (Table 2) contributes to the literature by demonstrating that the four principal digital technologies create qualitatively distinct value contributions across QMS dimensions rather than being interchangeable enablers. AI/ML's breadth across all six dimensions positions it as the foundational technology layer of DQMS, while blockchain's concentrated impact in traceability and supplier governance suggests a complementary rather than competing role. Digital twin technology's unique contribution in enabling pre-production quality optimisation reframes the temporal logic of quality management — shifting the primary quality intervention point from production to design, consistent with Taguchi's (1987) parameter design philosophy but now operationally feasible at industrial scale.

CONCLUSIONS AND SUGGESTIONS

This paper has presented an integrated investigation of quality management system development in the context of digital transformation, making three distinct contributions to the theoretical and practical literature. The DQMS Maturity Model provides a theoretically grounded, empirically validated five-level framework for assessing and guiding digital quality transformation, advancing beyond existing maturity models by embedding specific digital capability descriptors and a continuous scoring instrument. The integrated technology impact

5 Source: Authors' synthesis from Delphi expert study (n = 34) and systematic literature review. *Severity ratings: Very High = CV-weighted expert score ≥ 4.5/5; High = 3.5–4.4; Medium = 2.5–3.4.

taxonomy systematises the contributions of AI/ML, IoT, blockchain, and digital twin technologies across six QMS dimensions, resolving a significant fragmentation in the existing literature. The five-phase DQMS Implementation Framework, with its phase-specific KPI architecture, provides practitioners with an operationally actionable roadmap that directly addresses the implementation guidance gap identified in both practitioner and scholarly communities.

Empirically, the study demonstrates that DQMS maturity progression delivers substantial, measurable performance returns: organisations at DQMS Level 4–5 achieve a 28.4% reduction in cost of quality, a 34.7% improvement in defect detection accuracy, and a 22.1% gain in overall equipment effectiveness relative to pre-DQMS baselines. These differentials provide compelling justification for executive investment in digital quality transformation and confirm that partial digitisation — capturing adoption costs without achieving higher maturity levels — generates substantially inferior performance outcomes.

The study's policy implications are threefold. For standards bodies (ISO/TC 176), the finding that 44% of respondents question ISO 9001's adequate accommodation of digital QMS requirements signals a need for the development of supplementary digital QMS guidance — whether through a new ISO 9001 revision, a dedicated ISO standard for Quality 4.0, or integration of Quality 4.0 concepts into the ISO 9004 performance improvement guidance. For public policy makers, the identification of SME financial barriers as a Very High severity obstacle argues for dedicated DQMS co-investment mechanisms analogous to existing digital innovation support programmes. For organisations themselves, the primacy of cultural resistance as an adoption barrier argues for reframing DQMS implementation as an organisational transformation programme rather than a technology deployment project.

As digital transformation continues to accelerate across all sectors of the global economy, the ability to manage quality in real time, predictively, and autonomously will increasingly define organisational competitiveness, regulatory compliance, and customer trust. The DQMS Maturity Model and Implementation Framework developed in this study provide the conceptual and operational foundations for organisations to navigate this transformation systematically, accountably, and with measurable results.

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