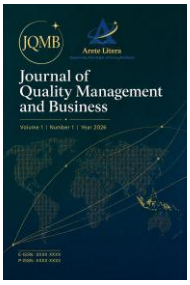

Journal of Quality Management and Business (JQMB)

Vol. 1, No. 1 (2026), pp. 37–44
ISSN: XXX (Print) XXX (Online) Journal homepage: https://jurnal.aretelitera.com/jqmb

Article type: Integrative Literature Review | Received: 11 July 2026 | DOI: To be assigned
Revised: 26 July 2026 | Accepted: 31 July 2026 | Published: 11 August 2026

ARTIFICIAL INTELLIGENCE ADOPTION IN QUALITY MANAGEMENT: OPPORTUNITIES, CHALLENGES, AND A STRATEGIC FRAMEWORK FOR EMERGING ECONOMIES

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ABSTRACT
Purpose-This article explains how organizations in emerging economies can adopt artificial intelligence (AI) in quality management without reproducing infrastructure, capability, and governance models designed for resource-rich settings. Design/methodology/approach-An integrative literature review synthesizes research on Quality 4.0, AI-enabled quality control, technology adoption, responsible AI, dynamic capabilities, and development constraints, supplemented by evidence from the World Bank and UN Trade and Development. Findings-AI creates value through augmented inspection, predictive prevention, process optimization, customer-feedback intelligence, traceability, and organizational learning. These benefits are constrained by fragmented data, limited connectivity and compute, skills shortages, vendor dependence, explainability and bias risks, cybersecurity, and weak accountability. The proposed Quality-AI Readiness and Responsible Adoption (QAR-RA) framework sequences adoption through six gates: strategic quality problem, foundational readiness, bounded pilot, human-governed validation, scaled integration, and continuous assurance. Four cross-cutting enablers-leadership, workforce capability, ecosystem collaboration, and proportionate governance-support every gate. Originality/value-The article shifts the debate from technology acquisition to quality-value realization under constraint. It integrates quality management discipline with responsible AI and development readiness, and provides a staged framework suitable for SMEs and other organizations in emerging economies.

Keywords: artificial intelligence; quality management; Quality 4.0; emerging economies; responsible AI; SMEs

1. INTRODUCTION

Artificial intelligence is moving quality management from retrospective control toward continuous sensing, prediction, and decision support. Computer vision can identify surface defects, machine-learning models can anticipate process deviation, natural-language processing can classify customer complaints, and generative systems can support documentation and root-cause exploration. These applications extend the Quality 4.0 agenda: the integration of established quality principles with connected, data-intensive, and intelligent technologies (Sony et al., 2020; Javaid et al., 2021; Liu et al., 2023). The strategic promise is not automation alone. It is the ability to detect weak signals earlier, learn across processes, and direct scarce improvement resources toward the quality risks that matter most.

Adoption conditions are uneven, however. The World Bank (2025) reports that purposeful firm-level AI use remains limited and identifies four foundations—connectivity, compute, context, and competency—as necessary for effective adoption in low- and middle-income countries. UNCTAD (2025) similarly warns that AI benefits are concentrated and that developing countries risk becoming passive technology consumers. For firms in emerging economies, especially SMEs, investment constraints interact with weak data architecture, shortages of quality and analytics skills, dependence on foreign platforms, unreliable infrastructure, and regulatory uncertainty. A technically accurate model may therefore fail to create quality value because it cannot be embedded in work routines, trusted by employees, localized to operating conditions, or governed throughout its lifecycle.

Existing scholarship offers valuable but fragmented insights. Quality 4.0 reviews classify technologies and organizational practices; manufacturing studies examine computer vision, predictive maintenance, and autonomous control; technology-adoption research identifies perceived usefulness, readiness, and environmental pressure; and responsible-AI literature emphasizes fairness, transparency, robustness, privacy, and accountability. What remains underdeveloped is a quality-centered adoption logic tailored to constrained environments. Many prescriptions begin with the technology, assume mature digital infrastructure, or treat implementation as a single decision rather than a sequence of evidence-based gates.

This article addresses that gap by asking: (1) through which mechanisms does AI improve quality management; (2) which constraints and risks are distinctive or amplified in emerging economies; and (3) how should organizations sequence adoption so that quality gains remain affordable, explainable, safe, and scalable? The contribution is the Quality-AI Readiness and Responsible Adoption (QAR-RA) framework. It links quality strategy, development readiness, human oversight, and lifecycle assurance in six gates. The framework rejects both technological determinism and blanket caution: adoption should advance only when each stage produces sufficient evidence of quality value and controllable risk.

2. CONCEPTUAL FOUNDATIONS

2.1. From conventional quality management to Quality 4.0

Conventional quality management combines customer focus, process control, continuous improvement, employee involvement, fact-based decision making, and supplier relationships. Quality 4.0 does not replace these principles. It changes the speed, granularity, and connectivity of evidence used to apply them. Sensors, cloud platforms, digital twins, advanced analytics, and AI can shorten the interval between deviation, diagnosis, and corrective action. Yet digitizing a poorly designed process can amplify error rather than eliminate it. Quality discipline must therefore precede and govern algorithmic intervention (Chiarini & Kumar, 2020; Asif, 2020).

AI contributes three distinct capabilities. Descriptive intelligence recognizes patterns in images, signals, text, and transactions. Predictive intelligence estimates future defects, failures, demand, or complaint escalation. Prescriptive or generative intelligence recommends actions, optimizes parameters, or produces draft knowledge artifacts. These capabilities should be evaluated against a defined quality objective such as lower false acceptance, reduced scrap, faster containment, improved first-contact resolution, or stronger compliance—not against model accuracy in isolation.

2.2. Adoption as a dynamic capability

Dynamic-capability theory explains why acquiring an AI tool is insufficient. Organizations must sense quality opportunities and threats, seize them through resource commitments and redesigned workflows, and transform routines as evidence accumulates (Teece et al., 1997). The unit of adoption is therefore a socio-technical capability that combines data, models, infrastructure, quality expertise, frontline judgment, governance, and learning. When these elements are complementary and difficult to imitate, AI-enabled quality management can support sustained improvement rather than a temporary efficiency gain.

2.3. Responsible AI as quality assurance for algorithms

Responsible AI and quality management share a central concern: fitness for intended use under controlled conditions. An AI system is not high quality merely because its average performance is high. It must remain reliable across relevant subgroups and operating conditions, protect

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confidential data, provide appropriate explanations, resist manipulation and drift, and assign clear accountability. ISO/IEC 42001 and the NIST AI Risk Management Framework formalize lifecycle governance, while AI trustworthiness research highlights validity, safety, security, transparency, explainability, privacy, and fairness (NIST, 2023; ISO/IEC, 2023). In emerging economies, proportionate governance is essential: controls must be rigorous enough to protect people and operations but feasible for smaller organizations.

3. REVIEW METHOD

3.1. Integrative review design

An integrative literature review was selected because the research problem spans quality management, information systems, operations, responsible AI, and development policy. Unlike a meta-analysis, the objective was not to estimate a pooled causal effect. The review sought to integrate complementary theoretical and empirical streams into a strategic framework. The process followed four stages: problem formulation, purposive evidence identification, concept extraction and comparison, and theory-building synthesis (Snyder, 2019; Torraco, 2016).

3.2. Evidence identification and eligibility

Searches were conducted through 8 August 2026 using combinations of “artificial intelligence,” “machine learning,” “Quality 4.0,” “quality management,” “quality control,” “SME,” “developing country,” “emerging economy,” “responsible AI,” and “technology adoption.” Priority was given to peer-reviewed journal articles, international standards, and authoritative development reports. Evidence was included when it explained an AI-enabled quality use case, adoption mechanism, organizational capability, risk, governance requirement, or emerging-economy constraint. Purely algorithmic studies without implementation relevance and promotional material without transparent evidence were excluded.

3.3. Analytical procedure and limitations

Evidence was coded into four domains: value mechanisms, readiness conditions, implementation risks, and governance/learning responses. Relationships among codes were compared to identify recurring sequences and failure points. The resulting framework was refined against three tests: quality relevance, feasibility under resource constraints, and lifecycle accountability. Because this is an integrative review, the evidence set is conceptually purposive rather than statistically exhaustive. Publication bias, rapid technological change, and limited longitudinal evidence in low-income settings constrain generalization. The framework should therefore be empirically tested across sectors and countries.

4. OPPORTUNITIES FOR AI-ENABLED QUALITY MANAGEMENT

4.1. Augmented inspection and defect detection

Computer vision can inspect products and processes at a speed and consistency difficult to achieve through manual sampling alone. It is particularly valuable for repetitive visual tasks, subtle surface anomalies, packaging verification, and safety monitoring. The principal benefit is not simply labor substitution; it is expanded coverage and earlier containment. Human inspectors remain important for ambiguous cases, changing defect taxonomies, and validation of economically consequential decisions. Hybrid inspection also supplies labeled examples for continuing model improvement.

4.2. Predictive prevention and process optimization

Machine learning can combine sensor histories, maintenance records, environmental conditions, supplier attributes, and process parameters to forecast deviation before nonconforming output occurs. This enables a shift from detection to prevention, consistent with the foundational quality principle that defects should be designed out rather than sorted out. Predictive maintenance reduces quality variation caused by equipment deterioration, while prescriptive analytics can

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suggest parameter adjustments. The risk is automation bias: recommendations must remain bounded by engineering limits and validated under realistic operating conditions.

4.3. Customer and service quality intelligence

Natural-language processing can synthesize complaints, reviews, call-center transcripts, warranty claims, and social-media feedback. Emerging patterns may reveal failure modes that structured surveys detect too slowly. In service settings, AI can route cases, support agents, identify compliance gaps, and personalize recovery. Local language, code-switching, dialect, and cultural context are critical. Imported models may misclassify sentiment or intent, so contextual validation and human appeal mechanisms are necessary.

4.4. Traceability, knowledge retention, and organizational learning

AI can connect dispersed quality records, retrieve prior corrective actions, compare root-cause patterns, and make tacit knowledge more accessible. This is valuable where staff turnover is high and expertise is concentrated in a small number of employees. Generative AI may assist with draft work instructions, audit preparation, and structured problem-solving, but outputs require source grounding and expert verification. Knowledge systems must preserve provenance so users can distinguish approved procedures from generated suggestions.

4.5. Resource efficiency and inclusive upgrading

Low-cost cloud services, open-source models, mobile interfaces, and shared digital infrastructure can reduce entry barriers. SMEs may access capabilities that previously required specialized laboratories or large IT departments. Adoption can also improve energy, material, and waste performance by identifying losses that conventional monitoring overlooks. Nonetheless, apparent affordability can conceal recurring costs for connectivity, inference, data preparation, integration, security, and vendor switching. Total cost of ownership and local capacity development must be included in investment appraisal.

5. CHALLENGES IN EMERGING ECONOMIES

5.1. Foundational and data constraints

AI systems depend on reliable electricity, connectivity, compute, sensors, storage, and interoperable records. Many organizations still operate with paper documents, isolated spreadsheets, inconsistent identifiers, and limited process measurement. Historical data may encode changing standards or undocumented workarounds. Small datasets, rare defects, and missing contextual variables increase uncertainty. The appropriate response is often not a larger model but better process definition, measurement discipline, and data stewardship.

5.2. Capability, work design, and trust

The skills gap is multidimensional. Data scientists may lack quality and process knowledge, while quality professionals may lack model-risk literacy. Frontline employees can perceive AI as surveillance or job displacement, reducing reporting quality and cooperation. Participatory design, role clarity, accessible explanations, and reskilling are therefore implementation controls, not optional change-management activities. Human oversight must be meaningful: reviewers need authority, time, information, and competence to challenge outputs.

5.3. Economic scale and vendor dependence

SMEs face uncertain return on investment, limited capital, and a narrow tolerance for failed pilots. Proprietary platforms can create dependency through data formats, model interfaces, and recurring fees. Foreign-hosted services may raise latency, data-sovereignty, and continuity concerns. Procurement should therefore assess portability, audit rights, service levels, exit arrangements, and the availability of local support. Shared testbeds, sector associations, universities, and public innovation programs can distribute fixed costs and reduce information asymmetry.

5.4. Bias, explainability, cybersecurity, and accountability

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Models trained on data from different products, populations, languages, or operating environments may underperform locally. False negatives can release defective products; false positives can create scrap, delay, or discriminatory denial of service. Connected quality systems also expand the attack surface and may expose trade secrets or personal data. Accountability becomes blurred when vendors, managers, engineers, and users each control only part of the system. Every use case needs an accountable owner, documented decision rights, incident procedures, and an escalation path.

5.5. Regulatory and institutional uncertainty

Organizations in emerging economies often operate across incomplete, evolving, or overlapping rules on data protection, consumer rights, sector safety, and AI. Waiting for perfect regulatory certainty is unrealistic, but unmanaged experimentation is equally problematic. International frameworks can provide a baseline, adapted to local law and sector risk. Regulators and development institutions can support adoption through regulatory sandboxes, shared standards, independent testing facilities, and procurement guidance that does not exclude SMEs.

6. THE QAR-RA STRATEGIC FRAMEWORK

The Quality-AI Readiness and Responsible Adoption (QAR-RA) framework treats implementation as six evidence gates. A project may pause, redesign, or stop at any gate. Progression is justified by demonstrated quality value and manageable residual risk, not by sunk cost or technological enthusiasm.

Gate	Decision focus	Minimum evidence	Advance when…
1. Quality problem	Define customer/process harm, baseline, owner, and target.	Validated problem statement; baseline cost/risk; non-AI alternatives considered.	AI has a plausible advantage over simpler controls.
2. Foundational readiness	Assess data, process stability, 4Cs, legal basis, and workforce.	Data-quality profile; infrastructure test; skills and governance gaps.	Critical gaps have owners, budgets, and feasible remedies.
3. Bounded pilot	Test one narrow use case in a controlled workflow.	Predefined metrics; representative validation set; human fallback; cost record.	Quality benefit exceeds threshold without unacceptable subgroup or safety failure.
4. Human-governed validation	Stress-test reliability, explanations, security, and work design.	Independent review; failure-mode analysis; user acceptance; incident simulation.	Accountability, override, appeal, and monitoring controls function in practice.
5. Scaled integration	Integrate with QMS, suppliers, training, and operational systems.	Process capability trend; interoperability; service levels; total-cost evidence.	Benefits persist across sites/conditions and controls scale with them.
6. Continuous assurance	Monitor drift, incidents, equity, value, and obsolescence.	Dashboards; audit trail; reassessment schedule; retirement/exit plan.	System remains fit for purpose—or is corrected, constrained, or retired.

Table 1. Quality-AI Readiness and Responsible Adoption (QAR-RA) evidence gates

6.1. Cross-cutting enablers

Four enablers operate across all gates. Leadership establishes a quality-first purpose and protects the authority to stop unsafe deployment. Workforce capability combines quality methods, domain expertise, data literacy, and model-risk awareness. Ecosystem collaboration provides access to universities, suppliers, associations, finance, shared infrastructure, and regulators. Proportionate governance matches controls to consequence: a drafting assistant requires different assurance from an autonomous release decision, but neither is exempt from ownership and verification.

6.2. Performance architecture

Evaluation should combine five metric families. Quality outcomes include defect escape, first-pass yield, complaint recurrence, service resolution, and process capability. Model outcomes include sensitivity, specificity, calibration, uncertainty, subgroup performance, and drift. Human outcomes include override quality, workload, trust calibration, and skills transfer. Economic outcomes include total cost, avoided loss, downtime, and payback. Responsibility outcomes include privacy incidents, explainability sufficiency, cybersecurity events, appeals, and corrective-action closure. A project that improves model accuracy while degrading customer fairness or frontline reliability has not achieved quality improvement.

6.3. Strategic propositions

Proposition 1. AI adoption improves quality performance when the use case is anchored in a measurable quality problem and complements stable process discipline.

Proposition 2. Foundational readiness—connectivity, compute, context, and competency—positively moderates the relationship between AI capability and realized quality value.

Proposition 3. Meaningful human oversight mediates the relationship between AI use and organizational trust, learning, and sustained adoption.

Proposition 4. Proportionate lifecycle governance reduces the negative effects of model opacity, drift, bias, and cybersecurity exposure on quality outcomes.

Proposition 5. Ecosystem collaboration strengthens SME adoption by lowering fixed costs, expanding specialized capability, and improving access to locally relevant data and assurance.

Proposition 6. Gate-based adoption produces more resilient quality value than technology-led scaling because it preserves reversibility and requires evidence before resource commitment.

7. DISCUSSION

The synthesis reframes AI adoption in quality management as a controlled organizational learning process. Opportunities arise when AI expands the sensing, prediction, and knowledge capabilities of the quality system. Challenges arise when organizations confuse model performance with process performance or import solutions without adequate local context. The QAR-RA framework integrates these findings by placing a quality problem before technology selection, readiness before piloting, human-governed validation before scale, and continuous assurance after deployment.

The framework extends Quality 4.0 research in three ways. First, it distinguishes the technical capability of AI from realized quality value. Second, it embeds responsible-AI controls within the quality lifecycle rather than treating ethics as an external compliance appendix. Third, it adapts adoption logic to emerging-economy constraints through staged investment, low-cost alternatives, ecosystem sharing, localization, and explicit attention to the World Bank's 4Cs. This makes the framework applicable beyond large manufacturing firms to SMEs, service organizations, healthcare providers, public agencies, and supply networks.

7.1. Managerial and policy implications

Managers should begin with a high-cost, high-frequency, or high-risk quality problem whose baseline is measurable. They should prefer narrow, reversible pilots and compare AI with simpler statistical, procedural, or automation alternatives. Procurement decisions should address data ownership, portability, auditability, local support, model updates, security, and exit costs. Quality leaders should chair cross-functional assurance, while frontline staff participate in defect definitions, validation, exception handling, and continuous improvement.

Policymakers can accelerate responsible diffusion by strengthening digital infrastructure and skills, enabling secure data-sharing arrangements, supporting local-language and sector-specific models, financing shared testing facilities, and establishing proportionate guidance. Public procurement can stimulate local innovation if requirements emphasize outcomes, interoperability, and assurance rather than brand or scale. Universities and professional bodies can bridge quality engineering, management, and data science through applied training and independent evaluation.

7.2. Research agenda

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Future research should test the framework longitudinally and compare organizations that advance through evidence gates with those that scale directly. Studies should examine sector-specific readiness thresholds, the economics of shared AI infrastructure, locally appropriate explainability, frontline trust calibration, and the long-term distribution of gains between firms, workers, and customers. Cross-country research should avoid treating emerging economies as homogeneous and should measure institutional quality, digital foundations, firm size, informality, and local-language data availability. Research should also report failed and discontinued pilots to reduce survivorship bias.

7.3. Limitations

The article is conceptual and does not claim causal validation of the proposed framework. The rapid evolution of AI means that technical costs and capabilities may change faster than organizational and regulatory evidence. English-language publishing may underrepresent local practice, especially in informal and micro-enterprise settings. Finally, the same safeguards cannot be applied uniformly; sector risk, decision consequence, organizational capacity, and legal context require calibrated implementation.

8. CONCLUSION

AI can strengthen quality management by expanding inspection, prevention, process optimization, customer intelligence, traceability, and learning. In emerging economies, however, adoption succeeds only when technology is matched to reliable data, stable processes, workforce capability, affordable infrastructure, local context, and accountable governance. The QAR-RA framework provides a practical sequence from quality problem definition to continuous assurance. Its central principle is simple: scale evidence, not enthusiasm. Organizations should advance AI only when each gate demonstrates that the system is useful, trustworthy, economically defensible, and fit for its intended quality purpose.

DECLARATIONS

Author contributions (CRediT): E.E.: Conceptualization, Methodology, Investigation, Formal analysis, Resources, Writing-original draft, Writing-review and editing, Visualization, and Project administration.

Funding: This research received no external funding.

Institutional review board statement: Not applicable. The study analyzed published literature, standards, and public reports and involved no human participants or identifiable personal data.

Informed consent statement: Not applicable.

Data availability statement: No new dataset was generated. The evidence sources and review procedure are described in the article.

Conflicts of interest: The author declares no conflict of interest.

Use of generative AI: Generative AI was used to assist language drafting, structural organization, and document formatting. The author reviewed, verified, and takes responsibility for the arguments, citations, and final content.

Acknowledgments: None.

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