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Collaborative Quality Management in Industrial Engineering from a Supply Chain Perspective: AI-Driven Enterprise Quality Optimization

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Abstract: Amidst the intensifying digital economy and global competition, supply chain quality management is evolving from traditional linear models toward networked systems characterized by data-driven and intelligent collaboration. This paper constructs an AI-driven "Supply Chain Quality Collaborative Management" framework through system optimization and artificial intelligence analytical capabilities from a supply chain perspective. The study first analyzes core challenges in supply chain quality collaboration across three dimensions: data fragmentation, standard discrepancies, and mechanism asymmetry. It highlights that traditional static and reactive quality controls struggle to adapt to complex, dynamic supply chain ecosystems. Subsequently, through systematic literature review and theoretical synthesis, the paper elucidates AI's role in multi-source quality data fusion, semantic alignment, standardized governance, and intelligent incentives. It proposes collaborative optimization pathways based on deep learning, blockchain, and reinforcement learning. Through case studies in the automotive and pharmaceutical industries, the research validates the feasibility of AI in predictive maintenance and cross-linkage collaborative decision-making, demonstrating AI's ability to significantly enhance the systemic resilience and decision-response capabilities of quality management. This paper innovatively integrates industrial engineering process optimization with cross-organizational governance mechanisms for supply chain quality management, providing a new theoretical framework and practical pathway for intelligent manufacturing and sustainable supply chain development.

Keywords: Supply chain quality management; Industrial engineering; Artificial intelligence; Quality collaborative optimization; Data-driven decision-making

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1. Introduction

Amidst of economic globalization and diversifying market demands, enterprises face dual pressures to reduce costs and enhance competitiveness. Consequently, supply chain quality management has become a core issue determining corporate competitiveness and risk resilience. Against the backdrop of accelerating global industrial transformation toward digitalization, networking, and intelligence, traditional linear supply chains are evolving into mesh ecosystems characterized by “data-driven-platform-collaborative” features. The focus of corporate competition has shifted from individual product performance to a comprehensive contest of overall supply chain real-time responsiveness and collaborative efficiency. However, within complex supply chain networks, quality issues at any link can propagate through upstream and downstream channels, amplifying their impact (e.g., the bullwhip effect or ripple effect), ultimately affecting overall output quality and customer satisfaction. Traditional quality management models, predominantly static, linear, and post-event inspection-based, struggle to adapt to dynamic external environments due to information silos and the absence of real-time sharing and cross-organizational collaboration mechanisms. Industrial Engineering (IE), emphasizing system optimization, process standardization, and statistical process control, exhibits inherent synergy with supply chain quality management. Both disciplines prioritize data-driven decision-making, closed-loop control systems, and cross-organizational collaboration. This convergence enables holistic quality robustness and overall optimization through localized improvements. Consequently, establishing an integrated, preventive, and platform-based supply chain quality collaboration, management system has become the critical pathway to mitigate quality transmission risks and overcome traditional management bottlenecks.

Supply chain quality management still faces numerous practical challenges. Quality data sources are highly dispersed and heterogeneous, with inconsistent standards, formats, and interfaces across different segments, leading to information asymmetry, traceability difficulties, and delayed decision-making. Cross-enterprise quality standards vary, and differing implementation and inspection methods impact collaboration efficiency and consistency in quality assessment. Furthermore, in dynamic and uncertain environments, supply chain collaboration mechanisms lack resilience, struggling to respond to demand fluctuations or even supply chain disruptions triggered by geopolitical tensions or public health events. Against this backdrop, this study focuses on the intersection of industrial engineering and supply chain management. It introduces artificial intelligence (AI) technology to construct a cross-enterprise quality collaboration analysis framework. Leveraging AI enables deep mining of quality data, predictive optimization, and intelligent decision-making. This approach deeply integrates the logic control with the concept of cross-organizational collaborative governance in SCM. It not only of IE, emphasizes process optimization and quality, fills a research gap in AI-enabled supply chain quality collaboration theory, but also provides a new research paradigm for quality management in complex supply chain scenarios.

2. Theoretical foundations and literature review

2.1. Supply chain quality management theory

Supply chain quality management (SCQM), serving as the core link connecting internal quality control and external collaboration, has seen its theoretical framework evolve alongside advancements in industrial structures and management paradigms. Early traditional quality management systems, such as total quality management (TQM), emphasized principles of full employee participation, process orientation, and continuous improvement, playing a vital role in enhancing internal quality standards. As supply chain integration deepens, TQM principles have gradually expanded to the supply chain level, forming a multi-stakeholder collaborative governance quality management system. Six Sigma, centered on the DMAIC model, achieves high-precision quality control at critical supply chain nodes (such as raw material screening, production assembly, and logistics) by reducing process variation and optimizing key processes. The introduction of collaborative management theory further advances the systematization and networking of supply chain quality governance. Its core lies in achieving coordinated optimization and dynamic responsiveness among upstream and downstream enterprises through unified standards, data sharing, and real-time monitoring mechanisms. With the integrated development of industrial internet, big data, and AI technologies, supply chain quality management is progressively evolving toward intelligent and data-driven approaches. This promotes supply chain transparency and resilience enhancement, establishing it as a critical support system for driving high-quality and sustainable enterprise development.

2.2. Quality optimization methods in industrial engineering

Quality optimization in industrial engineering can be summarized under two core pillars: "shop floor monitoring" and " upstream design." At the shop floor level, statistical process control (SPC) serves as the core methodology. By employing Shewhart and EWMA control charts to distinguish common from special cause variation, stable monitoring of the manufacturing process is achieved for special cause. Within the Industry 4.0 framework, SPC integrates with IoT sensors and MES systems to enable real-time data collection, automated charting, and closed-loop early warning [1]. At the design level, quality function deployment (QFD) and failure mode and effects analysis (FMEA) are widely employed for requirement translation and risk pre-control. However, methods have certain limitations: QFD is prone to mapping deviations under mass customization and rapidly fluctuating requirements, while demanding high levels of interdisciplinary collaboration and data resource support. Meanwhile, the risk priority number (used in traditional FMEA RPN) often distorts rankings due to the multiplication of ordinal metrics and heavily relies on expert judgment. To address these challenges, current research is evolving toward fuzzy/multi-criteria coupling methods, time-updated "dynamic FMEA", and digital twin-driven online risk assessment to enhance responsiveness and timeliness [2,3].

2.3. Current applications of AI in supply chain quality management

With the rapid advancement of AI technologies, the research paradigm in supply chain quality management is progressively shifting from experience-driven approaches toward data-driven and intelligent decision-making orientations. AI provides new technical support for quality control, risk prediction, and supply chain collaborative optimization through methods such as machine learning, deep learning, and intelligent reasoning. Machine learning models, leveraging their automated feature extraction and pattern recognition capabilities, can effectively predict product defect rates and optimize process control. For instance, random forest (RF) and support vector machines (SVM) can accurately predict defect occurrence probabilities and generate actionable insights for supply chain optimization [4]. Long short-term memory (LSTM) networks are suitable for time series modeling, enabling demand fluctuation forecasting and early supply chain risk warnings; while Bayesian networks provide intelligent reasoning frameworks for root cause analysis and optimal strategy generation in complex systems.

The convergence of AI and supply chain quality collaboration has emerged as a frontier topic of shared interest across academia and industry. AI-driven data fusion and sharing mechanisms provide tamper-proof transaction records, enhancing supply chain transparency and traceability. This boosts overall supply chain resilience and enables real-time decision-making and optimization [5]. Blockchain technology plays a pivotal role in ensuring data trustworthiness and traceability, delivering high-quality, transparent, and flexible training data for AI models [6]. Natural language processing technology can parse quality documents within and across organizations, enabling semantic-level standard mapping and specification unification; reinforcement learning supports dynamic decision-making in multi-agent environments, driving supply chains toward adaptability and continuous improvement in complex settings. However, current research and practice face limitations, often focusing on localized AI applications or single nodes while lacking a systematic supply chain quality collaboration framework. Data security and privacy protection mechanisms remain underdeveloped, with cross-enterprise data sharing encountering legal and trust barriers.

3. Challenges in supply chain quality collaborative management and AI-empowered pathways

3.1. Core challenges

Supply chain quality collaboration management in practice faces multidimensional challenges, primarily concentrated across three dimensions: data, standards, and mechanisms. At the data level, numerous participants with widespread distribution result in fragmented quality data characterized by inconsistent formats and incompatible standards. Concurrently, corporate concerns regarding data security and privacy protection limit the depth and breadth of information sharing. At the standards level, differences create barriers to information exchange, weakening collaborative effectiveness in quality management norms, testing methods, and defect criteria among enterprises. To achieve efficient coordination, it is imperative to establish unified quality management systems and data exchange standards. At the mechanism level, unequal distribution of benefits among supply chain members often leaves some suppliers lacking intrinsic motivation for quality improvement. Combined with imperfect collaborative decision-making and constraint mechanisms, this hinders the formation of sustained, effective momentum for quality collaboration.

3.2. AI-empowered solutions

AI technology offers a systematic solution to the complex challenges of collaborative quality management in supply chains. By integrating multi-source data, ensuring data security, unifying quality standards, and optimizing collaborative mechanisms, AI can significantly enhance supply chain efficiency, sustainability, and systemic resilience [7]. Deep learning and natural language processing (NLP) technologies enable the fusion and semantic alignment of multi-source, heterogeneous quality data, supporting unified modeling of quality information across different stages and formats. This improves data utilization efficiency and analytical accuracy [8,9]. Blockchain and smart contract technologies ensure data security at the mechanism level during circulation, traceability, and immutability, establishing a trusted foundation for cross-organizational collaboration [10]. At the standards level, AI aligns and automates the semantic interpretation of quality standards, inspection metrics, and defect classifications, driving the formation of standardized quality management systems [11]. Reinforcement learning enables intelligent incentives for quality improvement and resource allocation through real-time data-driven dynamic decision-making and adaptive optimization mechanisms in multi-agent collaborative environments, enhancing system responsiveness and stability [12,13]. Research indicates that AI-empowered supply chain collaborative optimization not only reduces defect rates and operational risks but also significantly boosts overall performance and long-term sustainability.

4. Industry case analysis

4.1. Automotive industry case

In automotive manufacturing, AI applications play critical roles in process quality control, planning and inventory optimization, and equipment maintenance. Time-series machine learning predicts geometric deviations in structural component hole positions during work-in-process stages, achieving approximately 15% higher prediction accuracy than baseline models while reducing tolerance violations [14]. Demand forecasting/inventory planning systems reduce manufacturing inventory costs by 10–20% and suppress supply fluctuations by about 12% [15]. Predictive maintenance combining AHP and PFMEA for failure mode identification with random forest modeling achieved nearly 80% accuracy in predicting failure cycles on actual production lines, enabling proactive interventions for unplanned downtime [16].

4.2. Pharmaceutical industry case study

Within pharmaceutical supply chains, AI is playing a role in temperature-controlled quality assurance and proactive recall risk assessment. Supervised learning based on route, time slot, and temperature sensor data can identify cold chain boundary risks before shipment. A Brazilian cross-regional transport study with 7,078 samples demonstrated that a multi-layer perceptron achieved 93.7% correct classification on imbalanced data with a Kappa statistic of 0.82. This directly supports scheduling and route adjustment decisions, establishing a “preemptive handling” mechanism for temperature control risks [17]. Recall risk scoring tailored to product and process complexity employs methods like the Minimum Absolute Shrinkage and Selection Operator to screen key descriptors (e.g., route of administration, dosage form, release pattern, half-life). With an accuracy rate of approximately 71%, this approach enables early identification of quality vulnerabilities throughout the product lifecycle and provides quantitative thresholds for change management [18].

5. Challenges and future research directions

5.1. Implementation challenges

Despite offering innovative opportunities such as predictive analytics, real-time monitoring, and automated decision-making for collaborative supply chain quality management, the implementation of AI still faces multiple obstacles, primarily centered around data sharing, technological transparency, and collaborative incentives. Research indicates that enterprises generally exhibit low willingness to share sensitive data, which may hinder AI applications in cross-organizational quality collaboration, although governance frameworks can mitigate such issues to some extent. The “black box” nature of AI models erodes managerial trust, leading to concerns about decision-making transparency and limiting practical adoption [20]. At the mechanism level, cross-enterprise incentive designs remain immature, with power asymmetries and misaligned motivations making it difficult for suppliers to actively engage in quality improvement.

5.2. Future directions

Future research may expand along the following directions to systematically advance AI-enabled collaborative supply chain quality management. Regarding data collaboration and privacy protection, distributed machine learning techniques like federated learning hold significant application potential. This approach enables multiple parties without sharing raw data to jointly build AI models, effectively balancing data utilization with commercial privacy protection and providing a feasible technical pathway for cross-enterprise quality data analysis and collaborative modeling. At the process mapping and dynamic simulation level, the deep integration of digital twins and AI will construct dynamic virtual representations of quality states across all supply chain segments. Such systems can map quality behaviors in physical supply chains in real time, simulate disturbance impacts, and predict potential risks, thereby providing high-fidelity, iterative simulation environments for quality early warning, strategy evaluation, and decision optimization. Regarding collaborative mechanisms and standardization, policy guidance and industry consensus should be strengthened to promote the development of cross-industry, cross-platform quality data sharing standards and collaborative decision-making processes. Unified data standards and collaborative frameworks will reduce system integration costs, enhance information exchange efficiency, and thereby boost the overall synergistic effectiveness of the supply chain ecosystem.

6. Conclusion

This study systematically investigates AI-enabled collaborative quality management within supply chains, proposing an integrated analytical framework that merges industrial engineering optimization principles with supply chain coordination mechanisms. It identifies and articulates feasible AI-driven pathways to overcome critical challenges, including cross-enterprise quality data silos, standardization gaps, and weak collaborative incentives. Through case studies in the automotive and pharmaceutical sectors, the research demonstrates AI's tangible benefits in enhancing operational efficiency and system reliability. Applications in quality monitoring, inventory optimization, equipment maintenance, and risk management highlight AI's capacity for precise prediction and proactive control. Notwithstanding these advances, the widespread implementation of AI in supply chain quality management continues to encounter obstacles such as data-sharing barriers, limited model interpretability, and underdeveloped incentive structures. Nevertheless, emerging technological frontiers, such as federated learning, dynamic FMEA, multi-modal data fusion, and policy-standard alignment, are steadily steering supply chain quality governance toward real-time responsiveness, adaptive decision-making, and trusted collaboration. Looking ahead, as AI technologies continue to evolve and cross-organizational governance models mature, AI-facilitated collaborative quality management is poised to achieve end-to-end optimization and strengthen systemic resilience across increasingly complex supply chain ecosystems. This progression will provide critical support for the transition toward high-quality and sustainable enterprise growth, establishing a new benchmark for intelligent supply chain operations in the digital era.

Disclosure statement

The authors declare no conflict of interest.

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