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Maturity Evaluation and Transformation Path Selection for Manufacturing Digital Transformation under Quality 4.0

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Abstract **Original Research Article**

As Industry 4.0 technologies spread, Quality 4.0 has emerged as a new paradigm that integrates digital technologies into quality management. This study constructs a maturity evaluation index system for manufacturing digital transformation under Quality 4.0 and proposes differentiated transformation paths. Based on the Technology-Organization-Environment (TOE) framework, a three-level index system is developed that covers technology capability, organizational readiness, and environmental support. The Analytic Hierarchy Process (AHP) and the entropy weight method determine index weights, and fuzzy comprehensive evaluation assesses maturity levels. Empirical analysis draws on survey data from Chinese manufacturing enterprises. The results identify four maturity stages (initial, growth, standardization, and optimization) and reveal the main barriers at each stage. Differentiated transformation paths and policy recommendations are then proposed for enterprises at different maturity levels. The study offers manufacturing enterprises a practical self-diagnosis tool and provides references for government industrial policy.

Keywords: Quality 4.0, digital transformation, maturity evaluation, TOE framework, manufacturing enterprises, fuzzy comprehensive evaluation.

1. Introduction

The fourth industrial revolution, built on cyber-physical systems, the Internet of Things (IoT), artificial intelligence (AI), and big data analytics, has reshaped manufacturing worldwide (Lasi et al., 2014). Quality 4.0 has emerged from this context as a concept that connects digital technologies with established quality management principles, moving quality control toward proactive, data-driven practice (Radziwill, N 2018). Traditional quality management relies heavily on post-production inspection and reactive corrective action; Quality 4.0 instead emphasizes real-time monitoring, predictive analytics, and autonomous decision-making across the product lifecycle (Psarommatis et al., 2020).

China is the world's largest manufacturing nation, and its enterprises face rising pressure to upgrade quality management as global competition intensifies and consumer expectations change. The government has promoted digital transformation through initiatives such as "Made in China 2025" and the "Digital China" strategy, which aim to move industry toward intelligent manufacturing (Xu et al., 2018). Yet despite this policy support and rapid technological progress, many manufacturers still lack systematic assessment tools and clear transformation roadmaps for Quality 4.0 (Mittal et al., 2018).

Existing Quality 4.0 research concentrates on technological enablers and conceptual frameworks; maturity evaluation models that combine technological, organizational, and environmental dimensions remain scarce (Sony & Naik, 2020). Most studies also treat transformation strategy as one-size-fits-all and ignore the different maturity levels and contexts of individual enterprises (Buer et al., 2018). This study responds to that gap by building a comprehensive maturity evaluation index system and proposing transformation paths tailored to enterprises at different maturity stages.

Three objectives guide the work: (1) to construct a multi-dimensional maturity evaluation index system for manufacturing digital transformation under Quality 4.0, based on the TOE framework; (2) to combine the Analytic Hierarchy Process (AHP) and the entropy weight method for indicator weighting, and to apply fuzzy comprehensive evaluation for maturity assessment; and (3) to identify the key barriers at each maturity stage and propose targeted transformation paths and policy recommendations.

The study contributes in two ways. Theoretically, it extends the TOE framework into the Quality 4.0 domain and combines several evaluation methods into a more robust assessment approach. Practically, the maturity evaluation tool lets enterprises benchmark their transformation progress, the differentiated paths give them actionable guidance, and the results support government agencies in designing targeted industrial policies.

The remainder of the paper is organized as follows. Section 2 reviews the literature on Quality 4.0, digital transformation, maturity models, and the TOE framework. Section 3 presents the theoretical framework and methodology. Section 4 details the index system. Section 5 reports the empirical analysis and results. Section 6 discusses the findings. Section 7 proposes transformation paths for each maturity stage. Section 8 concludes with limitations and future research directions.

2. Literature Review

2.1 Quality 4.0 Concept and Evolution

The American Society for Quality (ASQ) introduced the term Quality 4.0 to capture the impact of Industry 4.0 technologies on quality management (Radziwill, N 2018). The concept marks a shift from traditional quality control toward intelligent, interconnected quality management systems that draw on advanced digital technologies (Psarommatis et al., 2020). Its core features include real-time quality monitoring, predictive quality analytics, autonomous quality decision-making, and closed-loop feedback (Sony & Naik, 2020).

Quality management has evolved through four stages: inspection-based Quality 1.0, statistical process control as Quality 2.0, total quality management and Six Sigma as Quality 3.0, and digital and intelligent quality management as Quality 4.0 (Zonnenshain & Kenett, 2020). Each stage adds principles, methods, and technical capabilities to the ones before it. Quality 4.0 is distinctive because it embeds IoT sensors, machine learning, digital twins, and blockchain into quality processes, which gives enterprises far greater visibility, predictability, and control (Buer et al., 2018).

Recent studies examine specific Quality 4.0 applications, such as machine learning for predictive quality analytics (Zhuang et al., 2022), digital twins for virtual quality validation (Tao et al., 2018), and big data analytics for supply chain quality management (Tiwari et al., 2018). These studies mostly address individual technologies rather than the organizational readiness and overall maturity required for Quality 4.0 transformation. A recent systematic review of 146 Quality 4.0 studies confirms that the field remains largely conceptual, with empirical work on how organizations actually manage quality in the Industry 4.0 paradigm still scarce (Oliveira et al., 2024).

2.2 Digital Transformation in Manufacturing

Digital transformation in manufacturing reconfigures business processes, organizational structures, and value creation mechanisms through the adoption of digital technologies (Vial, G 2019).

In practice it takes the form of smart factories, intelligent production systems, connected supply chains, and data-driven decision platforms (Frank et al., 2019).

The drivers are multiple: technological push from advances in AI, IoT, and cloud computing; market pull from demand for customized products and faster delivery; and regulatory pressure from quality standards and environmental compliance (Moeuf et al., 2018). Implementation remains difficult for many enterprises, especially small and medium-sized firms, which face limited resources, skill shortages, and organizational inertia (Klotzer & Pflaum, 2017).

Existing research on manufacturing digital transformation centers on technological architectures, implementation frameworks, and case studies of leading enterprises (Kagermann et al., 2013). These studies offer useful insights into success factors, but they tend to overlook the heterogeneous capabilities and contexts of individual firms, which call for differentiated strategies (Buer et al., 2018).

2.3 Maturity Models in Quality Management

Maturity models are widely used in quality management and information systems research to assess organizational capability and guide improvement. The Capability Maturity Model Integration (CMMI) and the ISO 9000 series are among the most prominent (Chrissis et al., 2011). They typically define several maturity levels, from initial or ad-hoc practice to optimized continuous improvement, with structured criteria for each level.

Several models have been proposed for digital transformation readiness. The Industry 4.0 readiness model of Lichtblau et al. (2015) assesses six dimensions: strategy, organization, personnel, technology, culture, and communication. The Smart Industry Readiness Index (SIRI) of the Singapore Economic Development Board evaluates process, technology, and organization (EDB, 2019).

These models fall short for Quality 4.0 in three ways. First, they measure general digital capability rather than quality-specific dimensions. Second, their criteria are often too generic to capture Quality 4.0 requirements such as real-time quality analytics and predictive quality control. Third, they rely largely on subjective self-assessment without rigorous quantitative evaluation (Sony & Naik, 2020). A recent assessment framework for Quality 4.0 transition, developed in the context of Indian manufacturing, applies fuzzy-Delphi and DEMATEL to identify critical success factors, but remains country-specific and qualitative rather than a generic quantitative maturity tool (Joshi et al., 2024). A maturity evaluation model designed for the Quality 4.0 context is therefore needed.

2.4 TOE Framework Applications

The Technology-Organization-Environment (TOE) framework, proposed by Tornatzky and Fleischer (1990), analyzes how firms adopt and implement technology. It holds that adoption is shaped by three contexts: the technological context (availability and characteristics of relevant technologies), the organizational context (firm size, structure, resources, and culture), and the environmental context (industry structure, regulation, and competitive pressure).

The framework has been applied to enterprise resource planning (Pan & Jang, 2008), e-commerce (Zhu et al., 2006), and cloud computing (Low et al., 2011). In manufacturing, studies use it to examine Industry 4.0 adoption factors (Mittal et al., 2018) and smart manufacturing implementation (Kamble et al., 2018).

For Quality 4.0 maturity evaluation, the TOE framework fits well because its three dimensions cover the forces that shape transformation: technology capability captures the availability and use of enabling technologies, organizational readiness reflects internal preparation, and environmental support accounts for external pressure and assistance. This multi-dimensional view matches the systemic nature of Quality 4.0 transformation.

2.5 Research Gap Identification

The literature review reveals four gaps. First, systematic maturity evaluation models that integrate technological, organizational, and environmental dimensions are lacking for Quality 4.0. Second, existing assessment approaches depend heavily on subjective judgment without rigorous quantitative methods. Third, most studies propose generic strategies that ignore differences in enterprise maturity. Fourth, empirical research on Quality 4.0 maturity in the Chinese manufacturing context is scarce, even though China is central to global manufacturing.

The present study addresses these gaps by building a TOE-based maturity evaluation index system, combining AHP and entropy weighting with fuzzy comprehensive evaluation, and proposing differentiated transformation paths for enterprises at different maturity stages.

3. Theoretical Framework and Methodology

3.1 TOE Framework Adaptation for Quality 4.0

This study adapts the TOE framework to Quality 4.0 by defining three primary dimensions: Technology Capability, Organizational Readiness, and Environmental Support. Each dimension contains secondary and tertiary indicators that together reflect the maturity of manufacturing digital transformation.

Technology Capability covers the infrastructure, digital tools, and technical competencies relevant to Quality 4.0: IoT devices for quality sensing, big data analytics for quality pattern recognition, AI and machine learning for predictive quality control, digital twins for virtual validation, and cloud platforms for quality data management.

Organizational Readiness covers internal preparation, including leadership commitment, digital culture, employee skills, organizational structure, and investment strategy. Technology alone is not enough; organizational factors largely determine whether adoption succeeds or fails (Klotzer & Pflaum, 2017).

Environmental Support covers external conditions: government policy, the industry ecosystem, market demand for high-quality products, and supply chain collaboration. Transformation is embedded in a broader socio-economic context that can either enable or constrain it (Mittal et al., 2018).

3.2 Index System Construction Principles

The index system follows five principles. Comprehensiveness: it covers the critical dimensions of Quality 4.0 transformation without major omissions. Hierarchy: indicators are organized into primary, secondary, and tertiary levels. Measurability: each indicator can be assessed through objective data or expert scoring. Independence: redundancy and correlation among indicators at the same level are minimized. Relevance: every indicator relates directly to Quality 4.0 maturity.

3.3 Weight Determination Methods

3.3.1 Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP), developed by Saaty (1980), structures complex decisions through pairwise comparison. In this study it supplies subjective weights from expert judgment. The procedure builds pairwise comparison matrices at each level, derives local weights from the principal eigenvector, checks the consistency ratio (CR must be below 0.1), and aggregates local weights into global weights.

Comparisons use the standard 1-9 scale: 1 for equal importance, 3 for moderate, 5 for strong, 7 for very strong, and 9 for extreme importance, with intermediate values for finer distinctions.

3.3.2 Entropy Weight Method

The entropy weight method derives objective weights from the information content of the data. Indicators with greater variation across enterprises carry more information and receive higher weights. The procedure normalizes the raw data matrix, computes the information entropy of each indicator, and derives weights from the entropy values.

The method offsets the subjectivity of AHP by reflecting actual variation in the data, and combining the two approaches improves the robustness of the results.

3.3.3 Combined Weighting Approach

To balance expert judgment and data patterns, the study integrates the two sets of weights linearly:

$$W_j = \alpha \times W_j^{AHP} + (1 - \alpha) \times W_j^{entropy}$$

where W_j is the combined weight of indicator j, W_j^{AHP} and $W_j^{entropy}$ are the AHP and entropy weights, and α is a preference coefficient set at 0.5 to give equal weight to both sources.

3.4 Fuzzy Comprehensive Evaluation Method

Fuzzy comprehensive evaluation assesses maturity levels while acknowledging that maturity is a matter of degree rather than a crisp classification. The procedure has six steps.

First, define the factor set U = {u1, u2, ..., un} of assessment indicators. Second, define the grade set V = {V1, V2, V3, V4}, where V1 to V4 correspond to the Initial, Growth, Standardization, and Optimization stages. Third, determine the weight vector W with the combined weighting approach. Fourth, construct the fuzzy evaluation matrix R, in which each element rij is the membership degree of factor ui in grade Vj. Fifth, compute the comprehensive evaluation vector B = W · R using the weighted average operator M(·, +). Sixth, assign the maturity stage by the maximum membership principle or the weighted average score.

Membership functions for each grade use trapezoidal or triangular fuzzy numbers based on expert judgment and industry benchmarks. The grade boundaries are: Initial (0-25), minimal digital quality capability; Growth (25-50), partial adoption of digital quality tools; Standardization (50-75), systematic digital quality management; Optimization (75-100), intelligent and autonomous quality management.

4. Index System Construction

4.1 Primary Indicators

Based on the adapted TOE framework, three primary indicators are established: Technology Capability (T1), Organizational Readiness (T2), and Environmental Support (T3).

4.2 Secondary Indicators

Under Technology Capability (T1), five secondary indicators are defined: IoT and Sensing Technology (T11), Big Data Analytics (T12), Artificial Intelligence and Machine Learning (T13), Digital Twin Technology (T14), and Cloud Computing Platform (T15).

Under Organizational Readiness (T2): Leadership Commitment (T21), Digital Culture (T22), Employee Digital Skills (T23), Organizational Structure Adaptability (T24), and Investment Strategy (T25).

Under Environmental Support (T3): Government Policy Support (T31), Industry Ecosystem (T32), Market Demand Pressure (T33), and Supply Chain Collaboration (T34).

4.3 Tertiary Indicators

Each secondary indicator is broken into tertiary indicators that can be assessed quantitatively. Under IoT and Sensing Technology (T11), for example, the tertiary indicators cover the coverage of IoT sensors in production lines, real-time data collection capability, and sensor integration with quality management systems. Under Leadership Commitment (T21), they cover the existence of a digital transformation strategy, the allocation of a dedicated budget for digital quality initiatives, and top management involvement in quality digitalization projects.

The complete system contains 3 primary, 14 secondary, and 35 tertiary indicators. Table 1 lists all indicators. Each tertiary indicator has an explicit measurement method (questionnaire item, objective metric, or expert scoring criterion) so that assessment remains consistent across enterprises.

Table 1. Three-level evaluation index system for manufacturing digital transformation maturity under Quality 4.0

Primary dimension	**Secondary indicator**	**Tertiary indicator**
T1 Technology Capability	T11 IoT and Sensing Technology	T111 IoT sensor coverage of production lines; T112 Real-time data collection capability; T113 Sensor integration with quality management systems
	T12 Big Data Analytics	T121 Breadth and frequency of quality data collection; T122 Data quality and consistency; T123 Application depth of analytics tools
	T13 Artificial Intelligence and Machine Learning	T131 AI-based defect detection and classification; T132 Predictive quality analytics capability; T133 AI support for quality decision-making
	T14 Digital Twin Technology	T141 Digital twin coverage of core production processes; T142 Virtual validation capability for new products and processes; T143 Consistency between digital models and physical systems
	T15 Cloud Computing Platform	T151 Cloud-based quality data storage and sharing; T152 Platform interoperability with existing systems
T2 Organizational Readiness	T21 Leadership Commitment	T211 Existence of a digital transformation strategy; T212 Dedicated budget for digital quality initiatives; T213 Top management involvement in quality digitalization
	T22 Digital Culture	T221 Employee acceptance of digital tools; T222 Data-driven decision-making culture; T223 Tolerance for experimentation and change
	T23 Employee Digital Skills	T231 Digital literacy of quality management staff; T232 Coverage of digital skills training
	T24 Organizational Structure Adaptability	T241 Cross-functional collaboration mechanisms; T242 Dedicated digital transformation teams
	T25 Investment Strategy	T251 R&D investment intensity in digital quality; T252 Long-term investment planning; T253 Evaluation of returns on digital investment
T3 Environmental Support	T31 Government Policy Support	T311 Awareness and utilization of industrial policies; T312 Accessibility of subsidies and incentives
	T32 Industry Ecosystem	T321 Participation in industry platforms and alliances; T322 Availability of technology service providers
	T33 Market	T331 Customer requirements for quality and traceability; T332

	Demand Pressure	Competitive intensity in the target market
	T34 Supply Chain Collaboration	T341 Data sharing with supply chain partners; T342 Collaborative quality improvement programs with suppliers

5. Empirical Analysis

5.1 Data Collection and Sample Description

The empirical analysis uses survey data from manufacturing enterprises in China. A questionnaire based on the index system was distributed to quality managers, production managers, and IT directors across machinery, electronics, automotive components, and consumer goods industries. A total of 120 valid responses were collected, covering a range of firm sizes, ownership types, and industry sectors.

Ten experts also provided scoring data: academics in quality management and digital transformation, and industry practitioners with hands-on Quality 4.0 experience. They supplied the pairwise comparisons for AHP and the grade memberships for the fuzzy evaluation.

5.2 Weight Calculation Results

The AHP analysis produced the following primary indicator weights: Technology Capability (T1) = 0.382, Organizational Readiness (T2) = 0.319, and Environmental Support (T3) = 0.299. The consistency ratio stayed below 0.1 for all comparison matrices.

The entropy analysis, based on variation in the survey data, produced T1 = 0.356, T2 = 0.334, and T3 = 0.310. With $\alpha = 0.5$, the combined weights are T1 = 0.369, T2 = 0.327, and T3 = 0.304. Technology capability is therefore the most important dimension for Quality 4.0 maturity, followed by organizational readiness and environmental support.

5.3 Fuzzy Evaluation Results

The fuzzy evaluation of the sample shows that about 18% of the enterprises are at the Initial stage, 35% at Growth, 32% at Standardization, and 15% at Optimization.

By dimension, Technology Capability scores are generally higher than Organizational Readiness scores: firms have invested in digital technology but lag in organizational adaptation. Environmental Support scores vary widely across regions and industries, reflecting uneven policy implementation and ecosystem development.

5.4 Results Interpretation

Most surveyed manufacturers (65%) sit at the Growth or Standardization stages, which indicates moderate overall progress. The small share at the Optimization stage (15%) marks a clear gap between leading firms and the rest of the industry. The finding that organizational readiness trails technology capability is consistent with earlier work on transformation barriers (Klotzer & Pflaum, 2017) and points to the need to address organizational factors in transformation strategies.

6. Results and Discussion

6.1 Key Findings

The analysis produces three main findings. First, the TOE-based index system gives a comprehensive, structured way to assess Quality 4.0 maturity; its three dimensions capture the multi-faceted nature of digital transformation and allow systematic diagnosis. Second, combining AHP and entropy weights makes the evaluation more objective and reliable than either method alone. Third, fuzzy comprehensive evaluation handles the ambiguity inherent in maturity assessment and yields a nuanced classification.

Technology capability is the strongest dimension in the sample, with comparatively high adoption of IoT, big data analytics, and cloud platforms. Advanced technologies such as digital twins and AI-driven predictive quality control remain confined to leading enterprises. Organizational readiness is the weakest dimension, with notable gaps in digital culture, employee skills, and structural adaptability. Environmental support varies considerably: enterprises in regions with strong policy support and mature ecosystems show higher maturity.

6.2 Barrier Analysis by Maturity Stage

Barriers differ by stage. Enterprises at the Initial stage lack awareness of Quality 4.0 benefits, have limited financial resources for technology investment, and often have no dedicated digital transformation strategy; they typically rely on traditional inspection and have minimal digital infrastructure.

Growth-stage enterprises have moved past the initial awareness and resource barriers, but now face data silos, inconsistent data quality, and employee skill gaps. They have adopted basic digital tools, yet poor integration across systems limits the effectiveness of digital quality management.

Standardization-stage enterprises run systematic digital quality management but struggle to connect internal systems with external supply chain partners. Moving from internal optimization to ecosystem-level collaboration requires changes in governance and sustained trust-building.

Optimization-stage enterprises must sustain continuous innovation to hold their competitive advantage. They need to keep developing digital capabilities, explore emerging technologies, and share best practice with industry peers to drive ecosystem-wide improvement.

6.3 Comparison with Existing Studies

The results agree with earlier studies that identify organizational factors as important enablers or barriers to technology adoption (Mittal et al., 2018; Buer et al., 2018). The contribution here is a quantitative maturity assessment tool and differentiated transformation paths that offer more concrete guidance than previous work.

Compared with the Industry 4.0 readiness model (Lichtblau et al., 2015) and SIRI (EDB, 2019), the proposed index system pays more attention to quality-specific dimensions and brings technological and organizational factors into one framework. The combination of AHP, entropy weighting, and fuzzy evaluation also provides a more rigorous assessment than the subjective self-assessment typical of existing models.

7. Transformation Path Selection

7.1 Path for Initial-Stage Enterprises

Initial-stage enterprises should first build awareness and basic infrastructure. The recommended path has three phases: (1) assess current quality management practices and identify priority areas for digitalization; (2) invest in basic infrastructure such as IoT sensors at critical quality checkpoints and data collection systems; (3) train employees to build basic digital skills. Government support at this stage should include awareness campaigns, subsidized pilot programs, and technology demonstration centers.

7.2 Path for Growth-Stage Enterprises

Growth-stage enterprises should focus on data integration and process optimization: implement integrated quality management information systems to break down data silos; deploy analytics tools for quality pattern recognition and root-cause analysis; set up cross-functional teams for digital quality initiatives; and standardize digital quality processes. Government support can take the form of technical consulting, best-practice sharing platforms, and tax incentives for digital investment.

7.3 Path for Standardization-Stage Enterprises

Standardization-stage enterprises should pursue full integration and ecosystem collaboration: deploy digital twins for virtual validation and process simulation; link quality systems with supply chain partners through shared platforms; implement AI-driven predictive quality control; and join industry-wide quality data sharing initiatives. Government support should fund collaborative innovation projects, build industry quality data platforms, and recognize quality excellence.

7.4 Path for Optimization-Stage Enterprises

Optimization-stage enterprises should focus on continuous innovation and industry leadership: explore emerging technologies such as autonomous quality systems and generative AI for quality design; establish innovation labs for next-generation quality technology; mentor enterprises at lower maturity stages; and take part in international quality standards development. Government support should include R&D grants for breakthrough technologies, facilitation of international collaboration, and promotion of these firms as national quality champions.

8. Conclusion

This paper developed a maturity evaluation index system for manufacturing digital transformation under Quality 4.0, grounded in the TOE framework. By combining AHP, the entropy weight method, and fuzzy comprehensive evaluation, it offers a quantitative way to assess enterprise maturity. The empirical analysis of Chinese manufacturing enterprises shows that most firms are at the Growth or Standardization stages, and that technology capability runs ahead of organizational readiness.

The differentiated transformation paths recognize that one-size-fits-all strategies do not fit enterprises with different capabilities and contexts, and the findings give government agencies a basis for targeted industrial policy.

The study has limitations. The sample of 120 enterprises is modest, which restricts generalizability, and the reliance on self-reported survey data may introduce response bias. Future work could enlarge the sample, add objective performance metrics, and track maturity evolution over time in longitudinal studies. Cross-country comparisons would also show how different institutional and cultural settings shape Quality 4.0 trajectories. The framework could also be extended toward the human-centric and sustainability dimensions emphasized in the Industry 5.0 agenda (Maddikunta et al., 2022), linking quality maturity to workforce well-being and environmental outcomes in future research.

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