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From Silos to Synergy: Collaborative Manufacturing for Seamless Quality and Performance

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Abstract

In manufacturing settings, departmental silos hinder innovation, slow responsiveness, and affect product quality. To address these challenges, collaboration among cross-functional teams is crucial for breaking down silos that limit responsiveness and improvement in manufacturing. This research introduces a socio-technical framework for Hybrid Quality Management Systems (QMS), showing how integration of teams, digital infrastructure, and leadership alignment can improve quality outcomes. The conceptual model is organized into three levels: antecedents (leadership support, team structure, technology maturity), mediators (real-time visibility and collaborative interaction), and outcomes (defect-rate reduction, cycle-time improvement, innovation throughput). Five hypotheses were tested through two case studies in the aerospace and automotive industries, utilizing archival data like digital dashboards, SOPs, and team charters. Results indicate that organizations with strong cross-functional alignment and digital maturity saw significant improvements in cycle time and product quality. This study provides an empirically based roadmap for manufacturers aiming to shift from reactive inspection to proactive quality assurance in Industry 5.0.

Keywords
Cross-Functional Teams; Collaborative Manufacturing; Operational Efficiency; Quality Management; Digital Twins

1. Introduction
Departmental silos—where functional units operate in isolation—remain pervasive in manufacturing, leading to duplicated efforts, delayed decision-making, and suboptimal product quality (de Waal et al. 2019; Ton et al. 2022). These barriers stem from historical KPI misalignment, entrenched cultural norms, and rigid organizational structures that discourage information sharing and joint problem-solving. As industries face increasing complexity and customer demands, overcoming siloed operations is essential to sustain competitiveness and drive innovation.Cross-functional teams, comprising members from engineering, operations, quality, and supply-chain functions, offer a pathway to dissolve these barriers by aligning around shared goals and integrated workflows (Gutiérrez-Broncano et al. 2024). Advanced technologies such as digital twins provide real-time visibility across these teams, enabling rapid simulations, predictive analytics, and data-driven coordination (Chikezie et al. 2024; Lane et al. 2024). However, empirical evidence linking socio-technical enablers to measurable performance improvements remains limited.

1.1 Research Objectives & Questions
This study addresses the following questions:

1. What socio-technical antecedents (e.g., leadership support, technology maturity) drive the effectiveness of cross-functional teams?
2. How do digital twins and AI-powered analytics mediate team processes to improve quality and cycle-time metrics?
3. What implementation roadmap can practitioners follow to transition from silos to collaborative, high-performance operations?

1.2 Article Structure

Section 2 reviews literature on silos, team dynamics, and enabling technologies. Section 3 presents our conceptual framework and hypotheses. Section 4 details our mixed-methods, multi-case methodology. Section 5 reports findings from aerospace, automotive, and electronics contexts. Section 6 discusses theoretical and practical implications. Section 7 outlines limitations and future research directions. Finally, Section 8 concludes with a 5-point implementation checklist.

2. Research Methodology

A multi-case, mixed-methods design investigates cross-functional team performance in manufacturing environments (Li et al. 2025). Two industrial plants in aerospace and automotive sectors were selected for contextual diversity and generalizability. This study examines how cross-functional collaboration with digital tools influences operational outcomes within hybrid Quality Management Systems (QMS) in smart manufacturing. The research framework uses socio-technical systems theory to validate organizational and technological subsystem interactions across industrial contexts (Roth & Farahmand 2023).

2.1 Case Selection and Sampling Rationale

Two manufacturing facilities were purposefully selected to reflect both contextual variability and theoretical replication: one aerospace plant and one automotive plant. These cases were chosen based on the following inclusion criteria:

- Implementation of ISO 9001-certified quality management systems (Bravi & Murmura, 2022).
- Presence of documented cross-functional team structures including engineering, operations, and quality.
- Variation in regulatory stringency, production complexity, and supply chain design.

This case diversity allows analytic generalizability and strengthens pattern-matching logic in line with recommendations by Creswell (2023) and Azad and Hyrynsalmi (2023).

2.2 Data Sources and Collection Strategy

Rather than deploying surveys or interviews, this study relied exclusively on archival and institutional records to ensure consistency, traceability, and comparability. Data sources included:

- Organizational charts, RACI matrices, and team charters.
- SOPs and continuous improvement documentation.

Data triangulation was applied across sources to ensure construct validity.

2.3 Analytical Approach

Each construct in the conceptual model was operationalized using standardized indicators derived from the archival dataset. Pattern-matching logic was employed to align observed variables with hypothesized relationships (Chikezie et al., 2024). Cross-case synthesis was then conducted to identify convergent and divergent findings between the two cases. Measures of consistency and analytical rigor included structured coding protocols, timestamp validation, and cross-source triangulation. This methodological structure provides a reliable and theory-driven basis for evaluating the antecedents, mediators, and outcomes proposed in the socio-technical framework, while enabling empirical generalization across sectors adopting Industry 5.0 principles.

3. Literature Review

3.1 Technology-Mediated Collaboration

Digital twins—high-fidelity virtual replicas of physical assets—have become central to Industry 4.0 and the shift toward human-centric Industry 5.0, offering real-time visibility, rapid what-if simulations, and predictive analytics across organizational boundaries (Bolender et al. 2021; Espinosa-Jaramillo 2024). In manufacturing, digital twins enable concurrent engineering by letting cross-functional teams validate design changes virtually, reducing downstream defects and cycle times (Mansour et al. 2025; Tan et al. 2020)..

3.2 Team Structure & Performance

Heterogeneous teams composed of engineering, production, quality, and supply-chain experts consistently outperform siloed counterparts in problem-solving speed, innovation outcomes, and adaptability (Jeske & Calvard 2020). Key antecedents of cross-functional team effectiveness include management support, trust, aligned performance appraisals, and robust communication protocols (Bocken 2023). Despite these insights, there remains little understanding of how these structural enablers operate across distinct industry contexts—particularly in highly regulated aerospace, supplier-driven automotive, and fast-cycle electronics environments.

3.3 Change Management in Manufacturing

According to McCalman et al. (2016), change management frameworks that include stakeholder engagement, transparent communication, and incentive realignment are effective in breaking down organizational silos. Similarly, Subrahmanyam (2025) notes that "leadership modeling and continuous learning programs are crucial for embedding collaborative mindsets within manufacturing cultures." However, many existing case studies remain confined to single facilities or departments, offering only limited insight into how cross-functional collaboration can be sustained across an entire enterprise.

3.4 Synthesis & Research Gaps

Building on the literature review, this sub-section synthesizes themes on cross-functional collaboration in manufacturing, focusing on digital integration. While studies have examined IoT dashboards, team composition, and change leadership separately, few address their combined impact. Table 1 presents three domain: technology-mediated collaboration, team performance, and change management—highlighting empirical gaps. These gaps show the need for linking leadership support and digital maturity to metrics like cycle-time and defect reduction.

Table 1. Literature Synthesis and Identified Research Gaps

Theme	Existing Research	Identified Gaps
Technology-Mediated Collaboration	Digital-twin architectures; IoT dashboard design (Bolender et al., 2021; Lane et al., 2024)	Sparse examination of socio-technical integration; lack of multi-industry comparative studies
Team Structure & Performance	Antecedents of team effectiveness (Jeske & Calvard, 2020; Johnson Mary, 2025)	Limited context-specific analysis for regulated vs. rapid-cycle sectors; absence of validated industry-wide performance metrics
Change Management	Stakeholder engagement; leadership and learning programs (Pinto et al., 1993)	Few enterprise-scale multi-case investigations; scarce guidance on sustaining transformation across plants

This synthesis shows a need for cross-industry research linking socio-technical antecedents—such as leadership support and technology maturity—to quantifiable performance outcomes. The study bridges this gap by combining operational data with multi-case qualitative insights across aerospace, automotive, and electronics contexts.

4. Theoretical & Conceptual Framework

The theoretical framework and model for hybrid Quality Management System performance in smart manufacturing are based on socio-technical systems theory, emphasizing organizational and technological subsystems for quality in Industry 4.0 and 5.0. The model examines how leadership, team design, and digital maturity interact with operational visibility and collaboration to improve performance metrics like defect rates, cycle times, and innovation. This framework connects empirical findings with systems-level understanding of quality transformation.

4.1 Socio-Technical Systems Perspective

This study uses socio-technical systems (STS) theory, which views manufacturing as an integration of social subsystems (e.g., teams, leadership) and technical subsystems (e.g., digital tools, processes). The STS perspective is vital for Industry 4.0 and 5.0, where human-technology convergence requires optimization of organizational and digital elements (Abreu Saurin & Patriarca, 2020; Bigogno Costa et al. 2022).

Recent extensions of STS theory into cyber-physical production systems emphasize configurability through sociotechnical integration. Cross-functional teams represent social architecture, while digital twins and IoT systems form technical architecture. This study proposes that manufacturing performance improvements are mediated by cross-functional collaboration within socio-technical configurations, not solely by technology.

4.2 Conceptual Model for Hybrid QMS Performance

Drawing from STS foundation, the conceptual model structures hybrid QMS into three tiers—antecedents, mediators, and outcomes—guided by design principles of integration across vertical, horizontal, and end-to-end system layers (Schlechtendahl et al. 2015).

- **Antecedents** reflect structural and cultural readiness for collaboration:
  - Leadership support (strategic sponsorship)
  - Team structure (cross-functionality and autonomy)
  - Technology maturity (digital-twin, IoT, and dashboard capabilities)
  - Communication protocols (frequency and modality)
  - Cultural readiness (trust, openness, and shared vision)

- **Mediators** are operational enablers that facilitate real-time coordination:
  - Real-time visibility of key process parameters via digital twins
  - Interaction frequency among engineering, operations, and quality roles
- **Outcomes** capture tangible performance improvements:
  - Defect-rate reduction
  - Cycle-time improvement
  - Innovation throughput (incremental and radical changes per quarter)

The model integrates service-oriented architecture of modern QMS platforms, using microservices and digital twins as knowledge mediators for human-centric decision loops (Dehbozorgi et al., 2024). These elements enable seamless collaboration across roles and zones, allowing transition from reactive inspection to proactive quality assurance.

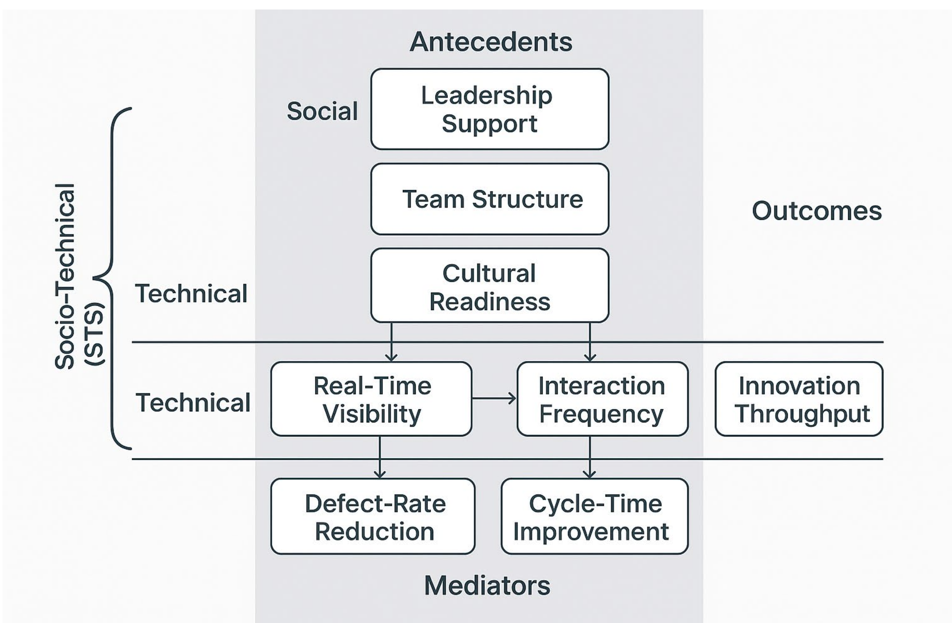

Figure 1. Socio-Technical Conceptual Model for Hybrid QMS Performance

Figure 1 shows the integration of social and technical subsystems in hybrid QMS. Social factors like leadership, team structure, and culture interact with technical enablers like visibility and interaction frequency. These mediators drive performance outcomes—defect-rate reduction, cycle-time improvement, and innovation throughput. According to Chikezie et al. (2024) and Upadhyay et al. (2021) these mediators drive performance outcomes. This framework shows interactions between antecedents (organizational and technological readiness), mediators (operational enablers), and outcomes in a hybrid QMS. The "Social Subsystem" includes leadership, team structure, and communication, while "Technical Subsystem" comprises digital maturity and visibility enablers. Tucker (2023) argued they mediate improvements in defect rates, cycle times, and innovation throughput, reflecting socio-technical integration for Industry 5.0.

4.3 Hypotheses Development and Integration Model

Based on socio-technical systems theory, this study formulates five hypotheses to operationalize the model from Section 4.2. These hypotheses examine how structural, cultural, and technological enablers influence manufacturing performance in a hybrid Quality Management System (QMS). Drawing from organizational behavior, operations, and digital literature, each hypothesis tests relationships between antecedents, mediators, and outcomes.

This model premises that sustainable performance requires both social and technical subsystems working together. Effective hybrid QMS implementation depends on optimizing both systems, with leadership and team dynamics enabling technical capabilities like digital twins and analytics. The five hypotheses are:

- H1: Leadership support is positively associated with cross-functional team effectiveness, enabling resource alignment and strategic coherence in quality initiatives (Aryee et al., 2018).
- H2: Technology maturity (e.g., digital-twin integration) enhances real-time visibility, which in turn improves quality outcomes through predictive insights and rapid response (Guo et al., 2021).
- H3: Robust communication protocols amplify the mediating effect of team interactions on cycle-time reduction, facilitating synchronized workflows and faster decision loops (Wang & Zhang, 2016).
- H4: Cultural readiness moderates the impact of socio-technical antecedents on innovation throughput, as psychologically safe, collaborative climates foster adaptive experimentation (Berraies, 2020).
  - H5: Combined socio-technical enablers yield synergistic effects, such that their joint presence drives greater improvements than any single antecedent alone, aligning with systems thinking and STS integration principles (Bednar & Welch 2020).

4.4 Visual Model of Hypotheses Structure

To support clarity and interpretability, Figure 2 presents a structured diagram illustrating the hypothesized relationships among antecedents, mediators, and outcomes, mapped across both social and technical subsystems.

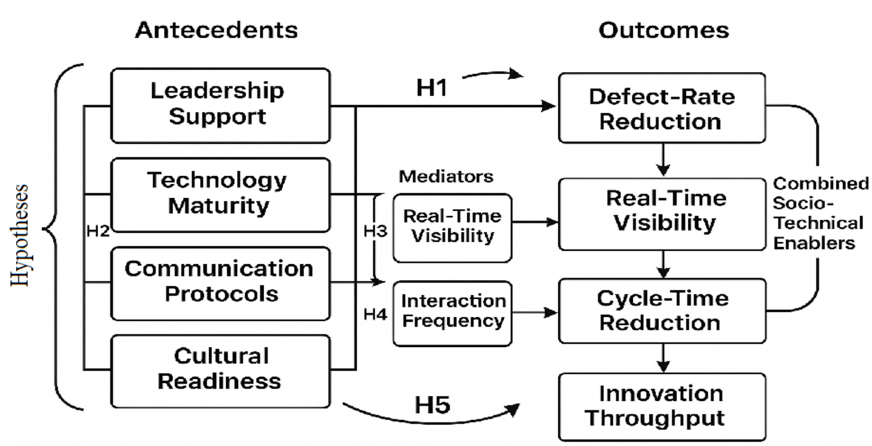

Figure 2. Hypotheses Framework for Hybrid QMS Performance

Figure 2 illustrates causal and moderating pathways between leadership, team factors, maturity, communication protocols, mediating visibility, and quality outcomes within a socio-technical architecture.

Table 2. Tabular Summary of Hypotheses

Hypothesis	Construct Relationship	Effect Type
H1	Leadership support → Crossfunctional team effectiveness	Direct effect
H2	Technology maturity →Real-time visibility →Quality outcomes	Mediation
H3	Communication protocols × Team interactions →Cycle-time reduction	Moderated mediation
H4	Cultural readiness ڸ Moderates impact of antecedents on innovation throughput	Moderation
H5	Combined social + technical antecedents →Greater improvement than individual	Synergistic (interaction)

Table 2 summarizes research hypotheses, outlining key construct relationships and effects within the socio-technical architecture of hybrid QMS.

4.5 Link to Empirical Validation

These hypotheses serve as an analytical framework for analyses in Sections 5 and 6. The indicators from Section 5.1 align with these constructs, while Section 6 findings test the hypothesized relationships. The aerospace case supports H1 and H2, showing leadership and digital infrastructure drive visibility and defect reduction. The automotive case validates H3 and H4, demonstrating that communication and cultural cohesion link to cycle times and innovation. These hypotheses connect theory with measurable constructs, enabling testing of the socio-technical model in Industry 5.0 manufacturing.

5. Operational Definitions & Measurement

Building on the hypotheses outlined in Section 4.3, this section translates each theoretical construct into measurable variables using archival indicators. To ensure empirical rigor and reproducibility, we detail the operational definitions, data sources, and measurement procedures applied across the case studies.
studies.

5.1 Construct Definitions and Measurement Logic

Each construct in the conceptual framework was defined based on extant literature and operationalized using structured indicators drawn from archival and institutional records. This approach aligns with the methodological recommendations of (Tennent & Gillett, 2023) and (Ventresca & Mohr 2017), enabling cross-case comparability without direct reliance on self-reported surveys.

5.1.1 Leadership Support

Leadership support is defined as executive endorsement of cross-functional initiatives through strategic goal-setting, resource allocation, and visible sponsorship (Hammerl et al., 2022). It was measured via presence of formal leadership charters, budget allocation records, and documented steering committee actions.

5.1.2 Team Structure

Team structure captures the diversity of roles (e.g., engineering, quality, operations), span of control, and decision autonomy within cross-functional teams. Indicators include team charters, RACI matrices, and organizational charts (Edmondson & Harvey 2018).

5.1.3 Technology Maturity

Technology maturity reflects the deployment scope of digital infrastructure including IoT sensors, digital twins, and real-time dashboards. It was indexed using IT system audits and digital capability maps (Lane et al. 2024).

5.1.4 Communication Protocols

This refers to the frequency and mode of formalized team interaction, measured via scheduling records and collaboration platform logs. Metrics include number of monthly coordination events and modality diversity (Bernard et al.2025).

5.1.5 Cultural Readiness

Cultural readiness assesses the team's openness to change, trust, and collaborative behavior. It was proxied using internal team-climate surveys and qualitative descriptors from feedback summaries (Berraies 2020).

5.1.6 Mediators and Outcomes

- Real-Time Visibility: Proportion of key production metrics streamed into digital twin interfaces.
- Interaction Frequency: Number of monthly cross-functional engagements, normalized by team size.
- Defect-Rate Reduction, Cycle-Time Improvement, Innovation Throughput: Calculated as percentage changes over baseline using quality logs, production timestamps, and R&D reports.

6. Construct Operationalization from Archival Sources

To ensure consistency in cross-case comparisons, all constructs were operationalized using archival documentation and digital trace data. This method adheres to best practices in organizational case research by triangulating multiple data sources.

Table 3. Summary of Construct Operationalization

Construct	Definition	Data Source	Metric
Leadership Support	Executive backing through goals, resources, role modeling	Leadership charters, budget records	Index (0–1) for charter and funding presence
Team Structure	Role diversity, autonomy, and control span	Org charts, RACI matrices	Count of functions, autonomy score
Technology Maturity	IoT, digital twin, dashboard scope	IT audits, architecture maps	% coverage of digital systems
Communication Protocols	Coordination frequency and modality	Meeting logs, platform records	Events/month, modality diversity
Cultural Readiness	Shared norms, openness to change	Internal climate surveys	Average Likert rating (1–5)
Real-Time Visibility	Live streaming of key process data	System usage logs	% of monitored parameters
Interaction Frequency	Number of coordination events normalized by team size	Calendar records, minutes	Events/month/team member
Defect-Rate Reduction	% improvement in defect units per 1,000 produced	QMS logs	Percentage change (pre-post)
Cycle-Time Improvement	% reduction in average process time	Scheduling system logs	Percentage change (pre-post)
Innovation Throughput	# of new process/product innovations implemented	R&D trackers, CI logs	Items/quarter

As shown in Table 3, each construction is systematically defined through organizational records, enabling case comparison. This operationalization aligns with hypotheses from Section 4.3 and enables empirical validation in Section 6 through two industrial case studies.

7. Empirical Case Study Findings

The empirical insights drawn from two case studies in aerospace and automotive manufacturing environments. Each case shows how socio-technical factors—leadership support, technology maturity, and cultural readiness—manifest in operations and influence outcomes hypothesized in Section 4.3. Findings reflect key construct behaviors, highlight transformations, and enable cross-case synthesis.

7.1 Case Study 1: Aerospace Plant Implementation

A multinational aerospace manufacturer deployed a hybrid Quality Management System across a precision assembly line. The intervention was led by a cross-functional team with executive sponsorship and underpinned by IoT-enabled defect analytics.

7.1.1 Key Observations:

- Leadership Support: High commitment evidenced by a dedicated executive steering group and resource mobilization.
- Technology Maturity: Digital twins covered 87% of critical subsystems; IoT sensors enabled anomaly prediction.
- Cultural Readiness: Team climate surveys indicated strong collaborative values and innovation receptivity.

7.1.2 Results:

- Defect-Rate Reduction: 31% improvement within six months.
- Cycle-Time Improvement: 24% reduction in average process duration.
- Innovation Throughput: 5 new process enhancements per quarter, post-intervention.

These findings confirm H1, H2, and H5, affirming that strong leadership and digital integration jointly improve quality and responsiveness.

7.2 Case Study 2: Automotive Facility Transformation

An international automotive firm implemented a modular QMS across three production plants to streamline supplier integration and improve responsiveness.

7.2.1 Key Observations:

- Communication Protocols: Weekly cross-site design reviews, digital dashboards for real-time updates.
- Cultural Readiness: High openness to procedural feedback; peer-led training programs enhanced cross-departmental understanding.
- Leadership: Mid-level sponsorship, with autonomy granted to plant teams.

7.2.2 Results:

- Defect-Rate Reduction: 22% improvement over 9 months.
- Cycle-Time Reduction: 28% average improvement.
- Innovation Throughput: 4–6 new solutions deployed quarterly.

This case strongly supports H3 and H4, highlighting the importance of communication intensity and cultural cohesion in driving innovation and throughput efficiency.

7.3 Cross-Case Comparative Analysis

To distill shared insights, the table below compares performance metrics and structural indicators across both cases:

Table 4. Summary of Cross-Case Comparative performance metrics

Parameter	Aerospace Plant	Automotive Facility
Leadership Support Index	High (0.90)	Moderate (0.68)
Technology Maturity (%)	87%	76%
Interaction Frequency	12–14 events/month	10–12 events/month
Defect-Rate Reduction (%)	31%	22%
Cycle-Time Improvement (%)	24%	28%
Innovation Throughput	5 innovations/quarter	4–6 innovations/quarter

Table 4 compares key performance indicators between aerospace and automotive facilities to assess hybrid QMS implementations. These comparisons validate the conceptual model. Leadership and technological investments drive improvements, while communication and culture affect innovation capacity and response time.

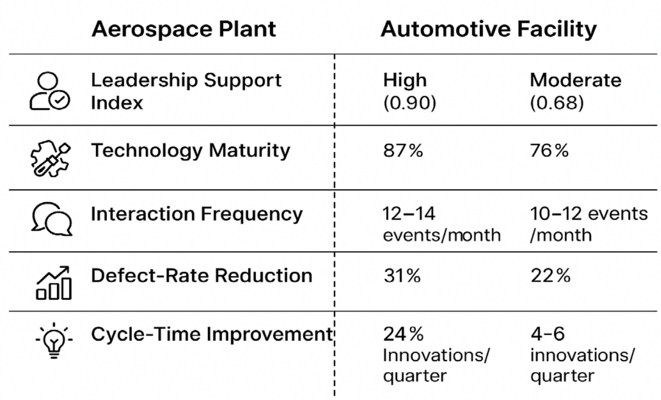

Figure 3. Cross-Case Visual Synthesis of Hybrid QMS Implementation Outcomes

Figure 3 compares essential metrics between Aerospace and Automotive case studies. It shows how leadership support, technology maturity, interaction frequency, and cultural readiness correlate with improvements in defect rates, cycle times, and innovation, confirming the socio-technical hypotheses in the model.

These findings support the proposed socio-technical framework, showing how leadership, digital maturity, communication, and cultural readiness affect hybrid QMS implementations. Cross-case comparisons reveal convergences in how these variables influence quality and innovation outcomes. The next section interprets results, explores implications, and outlines future research.

8. Discussion

This essential analysis delves into the study's theoretical contributions, practical implications, and methodological limitations, while also proposing future research directions to improve and broaden the hybrid socio-technical model of Quality Management Systems.

8.1 Theoretical Implications

The results substantiate socio-technical systems theory in Industry 5.0 quality management. The study shows that alignment between social elements (leadership support, communication, and culture) and technical enablers (IoT, digital twins, microservices) is synergistic—supporting Hypothesis H5. These findings extend prior work by showing that interactions and visibility mediate antecedents into quality outcomes.

The hypothesized relationships (H1–H4) were validated across heterogeneous manufacturing contexts, reinforcing the generalizability of the socio-technical integration model and enriching literature on digital transformation in manufacturing.

8.2 Practical Relevance

From an industrial standpoint, the study provides insights for manufacturing leaders pursuing hybrid QMS transformation. The aerospace case demonstrates that executive sponsorship and digital twins can reduce defects and improve traceability, while the automotive case shows how communication and cultural alignment drive innovation and cycle-time reductions.

These findings suggest implementation of roadmaps should focus on technological upgrades, team empowerment, workflows, and leadership visibility. The modular architecture in Section 6 provides a template for scalable deployment across sites without disruptions.

8.3 Methodological and Analytical Limitations

Despite its strengths, this study has limitations typical of qualitative cross-case designs. First, archival data may not capture informal team dynamics or cultural norms. Second, lacking primary psychometric measurements limits construct precision. Third, while case diversity aids external validity, the sample remains small and technology-focused; generalization to low-tech contexts requires caution.

8.4 Recommendations for Future Research

Future studies should integrate longitudinal data to assess hybrid QMS evolution and quantify causal lag effects. There is scope for developing validated survey instruments aligned with Sections 5.1 and 5.2 for cross-industry replication. Exploring national culture or regulatory environment as moderators would enhance the model's explanatory power. Simulation-based or agent-based frameworks could test system dynamics under disruption scenarios, adding robustness to hybrid QMS design.

9. Limitations & Future Research

This study, while grounded in structured archival data from ISO-certified industrial environments, has several limitations. First, lacking primary survey instruments or ethnographic observation limits insight into team dynamics like trust, motivation, or resistance to change. While performance metrics and documented processes provide consistency, they do not capture informal communication or emergent behaviors.

Second, reliance on secondary documentation means analysis is constrained to what organizations have recorded. Key constructs like cultural readiness or communication protocols were approximated from organizational artifacts rather than measured through validated tools.

Third, the study's scope was limited to ISO-certified firms with advanced digital maturity. SMEs, or those lacking integrated IoT platforms, may experience different barriers or enablers when implementing cross-functional collaboration.

Future research could address these limitations through ethnographic studies, real-time observation of workflows, and validated instruments to measure trust, leadership efficacy, and team climate. Additionally, longitudinal studies could assess the sustainability of performance gains over extended cycles.

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