Management Analytics for Smart Manufacturing Transformation: A Product Lifecycle Intelligence Framework

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Abstract

Smart manufacturing has advanced quickly, yet managerial adoption remains uneven because intelligence is often deployed as isolated applications rather than as a coordinated product-lifecycle system. This article develops a management-analytics perspective on smart manufacturing transformation and proposes a Product Lifecycle Intelligence framework that links strategy and organization, value-chain intelligence, management support processes, and infrastructure-capability layers through database-centered analytics. Instead of treating artificial intelligence, digital twins, industrial internet systems, and cloud-edge platforms as separate technologies, the framework interprets them as components of a common lifecycle data architecture. To operationalize the framework, the article introduces a structured scoring design across four lifecycle domains and five analytical dimensions: data integration, interoperability, decision analytics, resilience, and human-AI readiness. An illustrative management-analytics assessment is used to compare current readiness levels, identify integration gaps, and prioritize transformation actions under different enterprise scenarios. The results show that infrastructure capabilities usually mature faster than strategy-to-execution coordination, while the largest system-wide bottleneck lies in closed-loop integration between market intelligence, design knowledge, operations control, and managerial governance. The analysis further indicates that smart manufacturing programs create the greatest managerial value when database standardization, cross-functional metrics, and human-AI governance are developed together rather than sequentially. The article contributes by reframing smart manufacturing as a management-analytics problem, offering a lifecycle-wide intelligence architecture, and providing a practical roadmap that can guide enterprise transformation beyond fragmented pilot projects.

Keywords: Smart manufacturing; Management analytics; Product lifecycle management; Artificial intelligence; Industrial IoT; Digital twins; Database-centered architecture; Enterprise transformation

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1. Introduction

Smart manufacturing is increasingly framed as a strategic transformation rather than a narrow automation upgrade. Manufacturers now collect data from customer interfaces, product definition systems, planning modules, shop-floor sensors, quality stations, logistics networks, and service channels. Yet these signals are frequently stored and governed in fragmented databases, which makes enterprise-scale intelligence difficult to achieve. The result is a paradox: firms may possess abundant digital assets but still operate with weak cross-functional coordination.

From a management-analytics perspective, this problem cannot be solved by introducing more artificial intelligence applications in isolation. Managers need an architecture that explains how lifecycle data should be structured, how decisions should be synchronized across units, and how technical systems should support business outcomes such as responsiveness, resilience, quality, sustainability, and profitability. Without this architecture, digital twins, predictive models, IIoT platforms, or dashboard systems tend to remain locally useful but strategically disconnected.

A product lifecycle perspective provides the required integrative logic. Product lifecycle management spans customer insight, product design, process planning, production, logistics, service, and end-of-life activities. This lifecycle view is especially important in smart manufacturing because design choices influence production flexibility, production events influence quality and maintenance decisions, customer data shapes demand and service strategies, and support functions such as supply chain, risk, human resources, and sustainability increasingly depend on shared operational data.

This article develops a Product Lifecycle Intelligence framework for smart manufacturing transformation and interprets it as a database-centered management system. The term database-centered does not imply a single repository; rather, it emphasizes common lifecycle entities, semantic consistency, governed interfaces, and analytical traceability across systems. In such a system, lifecycle data becomes the basis for managerial analytics, cross-functional coordination, and adaptive decision support.

The article contributes in three ways. First, it reframes smart manufacturing as a management analytics challenge organized around lifecycle intelligence. Second, it proposes a structured architecture that links strategy and organization, value-chain intelligence, management support processes, and infrastructure-capability layers. Third, it demonstrates the framework through an illustrative scoring design that reveals readiness levels, integration gaps, and scenario-based transformation priorities.

Figure 1 presents the Product Lifecycle Intelligence architecture proposed in this study. It frames smart manufacturing as a database-centered management system rather than a collection of isolated technologies.

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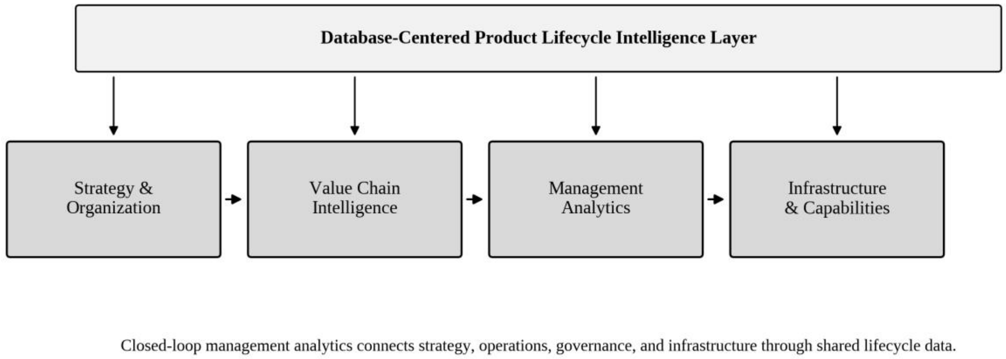

Figure 1. Product Lifecycle Intelligence architecture linking lifecycle domains through a database-centered management layer.

2. Literature Background and Problem Reframing

2.1 From fragmented tools to lifecycle intelligence

The literature on smart manufacturing has expanded around several strong themes. One theme emphasizes technological convergence, highlighting artificial intelligence, industrial internet of things, cyber-physical systems, cloud manufacturing, blockchain, and digital twins as the enabling backbone of adaptive manufacturing. This stream explains why manufacturing systems are becoming more data-rich, connected, and computationally capable. However, the analytical object is often the technology itself rather than the enterprise-wide management system that must absorb it.

A second theme focuses on product lifecycle management, where researchers underline the importance of linking market intelligence, design, planning, production, service, and end-of-life activities. This stream contributes a more complete process logic and shows why smart manufacturing should be treated as a lifecycle-spanning phenomenon. Yet many contributions remain descriptive at the architectural level and do not fully convert lifecycle thinking into a management-analytics design for decision making.

A third theme addresses management analytics more directly by examining supply chain intelligence, predictive maintenance, quality analytics, human-machine collaboration, and risk-sensitive optimization. This work demonstrates the operational value of data-driven decision tools. At the same time, it is frequently function-specific. Supply chain analytics is discussed apart from design intelligence, production analytics apart from customer intelligence, and human-resource analytics apart from operational strategy. Such fragmentation limits the realization of enterprise-wide intelligence.

2.2 Why management analytics matters in smart manufacturing transformation

The central gap, therefore, is not a shortage of digital tools but the absence of database-centered lifecycle architecture. In many firms, analytics pipelines are tied to department-specific data structures, local optimization objectives, and incompatible interfaces. This prevents the reuse of models, complicates explainability, and makes it difficult for managers to connect design, production, supply chain, sustainability, and service decisions within a single performance logic.

To address this issue, the article asks five recurring managerial questions: can lifecycle data be integrated across systems and actors; can heterogeneous platforms interoperate without extensive manual reconciliation; can analytics support forward-looking decisions rather than backward-

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looking reporting only; can the enterprise remain resilient under disruptions and variability; and can human decision makers trust, interpret, and govern AI-assisted outputs? These questions motivate the framework and its scoring design.

2.3 The database-centered research gap

This reframing also helps distinguish local digital maturity from enterprise transformation. A firm may have strong equipment connectivity yet weak strategy-to-execution coordination. It may have digital twins for assets but poor feedback from service operations to design. It may have advanced scheduling algorithms while human-AI governance remains underdeveloped. Management analytics becomes valuable when it makes these mismatches visible and actionable.

3. Framework Development and Analytical Design

3.1 Product lifecycle intelligence domains

The article adopts a conceptual-analytical design. To make the Product Lifecycle Intelligence framework operational, a structured assessment matrix is developed across four lifecycle domains and five managerial dimensions. The domains are strategy and organization, value-chain intelligence, management support processes, and infrastructure-capability systems. The dimensions are data integration, interoperability, decision analytics, resilience, and human-AI readiness.

The four domains represent the organizational locations where smart manufacturing intelligence must be stabilized. Strategy and organization concerns objective alignment, governance, and enterprise-wide KPI logic. Value-chain intelligence concerns how market, design, planning, production, logistics, and service information are linked. Management support processes capture supply chain, quality, risk, sustainability, and human-resource analytics. Infrastructure and capabilities include digital backbone systems, cybersecurity, AI capability, and human-machine collaboration.

Table 1. Product lifecycle intelligence domains and representative management-analytics questions.

Domain	Managerial focus	Illustrative analytical question
Strategy & organization	Strategic alignment, governance, KPI logic	Are digital investments tied to lifecycle objectives and shared performance metrics?
Value chain intelligence	Customer, design, planning, production, service integration	Can demand, design, operations, and service data be connected in closed-loop form?
Management support	Supply chain, quality, risk, sustainability, HR	Do support functions share data and models with core lifecycle decisions?
Infrastructure & capabilities	IT backbone, cybersecurity, AI capability, HMC	Can the enterprise scale lifecycle analytics securely and interpretably?

Table 1 transforms the conceptual domains into managerial diagnostic questions. The focus is not on labeling departments, but on identifying where lifecycle intelligence is generated, where it stalls, and where management action is required to reconnect fragmented data and decisions.

3.2 Scoring logic and analytical dimensions

The five dimensions were selected because they repeatedly determine whether local digital capability becomes enterprise intelligence. Data integration refers to the ability to connect lifecycle records across systems. Interoperability concerns semantic and technical compatibility. Decision analytics captures the use of diagnostic, predictive, and prescriptive models. Resilience

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reflects the capacity to adapt and recover under uncertainty. Human-AI readiness covers explainability, skills, intervention rights, and governance mechanisms.

The scores used in this paper are illustrative rather than survey-derived. They are intended to show how the framework can support managerial diagnosis and transformation sequencing. Because the goal is interpretation and prioritization, the analytical emphasis is on comparative patterns and threshold gaps rather than hypothesis testing.

Table 2. Analytical dimensions and transformation meaning in the proposed scoring design.

Dimension	Interpretation in this article	High score implies
Data integration	Ability to connect lifecycle records across systems	Managers can trace decisions to shared lifecycle data
Interoperability	Semantic and technical compatibility among platforms	Low reconciliation friction across units and sites
Decision analytics	Use of predictive, diagnostic, and prescriptive models	Forward-looking and scenario-based management control
Resilience	Capacity to absorb shocks and reconfigure operations	Analytics support adaptation under uncertainty
Human-AI readiness	Explainability, skills, governance, intervention rights	Trustworthy human-machine collaboration

The dimensions in Table 2 reflect the practical determinants of transformation success. They combine technical readiness and managerial usability so that the assessment can capture why firms with similar digital assets may still differ substantially in intelligence quality and transformation outcomes.

Figure 2 summarizes the illustrative maturity assessment across the four lifecycle domains and the five analytical dimensions. The purpose of the heatmap is diagnostic: it reveals uneven readiness patterns that are often hidden in technology-focused maturity narratives.

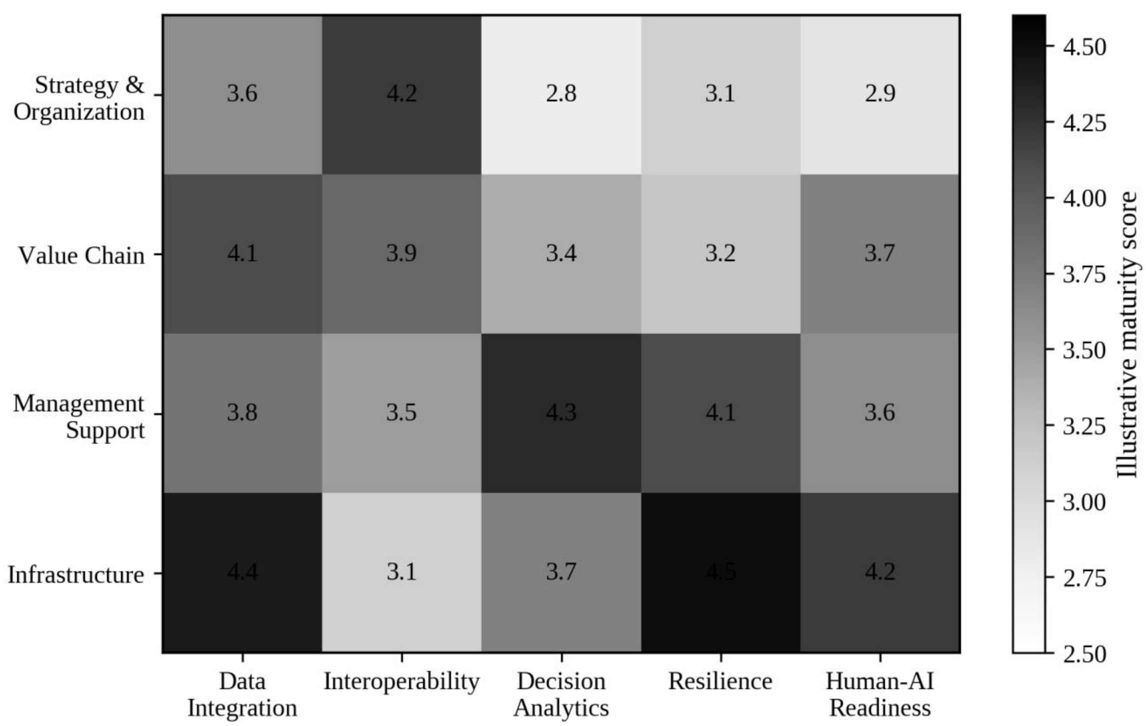

Figure 2. Illustrative lifecycle-domain maturity heatmap across five management-analytics

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dimensions.

4. Results: Structured Assessment of Product Lifecycle Intelligence

4.1 Domain-level maturity patterns

The first result is that lifecycle domains show uneven maturity. Infrastructure and capabilities typically exhibit the strongest readiness because investments in networking, sensors, cloud-edge processing, and cybersecurity are comparatively easy to fund and visualize. Strategy and organization, by contrast, often score lower because governance redesign, performance realignment, and cross-functional accountability are politically and managerially more difficult than technology acquisition.

Value-chain intelligence occupies a middle position. Many firms have made real progress in collecting lifecycle data, yet their flows remain only partially closed. Customer demand signals may feed production planning, but service knowledge may not return to design. Production data may support local optimization while failing to reshape upstream decisions. In lifecycle terms, the chain is digitized without becoming fully intelligent.

Management support processes also reveal a mixed profile. Supply chain analytics and quality monitoring are often stronger because benefits are quickly visible in service levels and defect reduction. Risk, sustainability, and human-resource analytics are commonly less integrated, even though they shape enterprise resilience and long-run competitiveness. This confirms that smart manufacturing transformation is as much a management problem as a technical one.

4.2 Integration gaps and threshold analysis

Figure 2 makes the unevenness concrete. Strategy and organization show comparatively low scores in human-AI readiness and interoperability, revealing that many enterprises still treat digital transformation as a portfolio of implementation projects instead of an evolving management system. Value-chain intelligence scores relatively well on data integration but less strongly on resilience because connected data does not automatically produce adaptive recovery capability.

Management support processes show the strongest relative score on decision analytics, which reflects the growing use of forecasting, optimization, and dashboarding. However, their interoperability remains constrained by department-specific systems and metrics. Infrastructure and capabilities show the highest overall profile, especially in data integration and resilience, but this technical strength does not by itself close the strategic and organizational gap.

Table 3 compares current readiness with the threshold required for enterprise-scale transformation. The largest shortfall appears in strategy and organization. This matters because it suggests that firms can overestimate digital maturity when they measure mostly automation intensity or equipment connectivity. The decisive transformation bottleneck often lies in how objectives, metrics, roles, and human-AI governance are coordinated.

Table 3. Illustrative readiness scores and required thresholds for enterprise-scale smart manufacturing transformation.

Domain	Current readiness	Required threshold	Gap	Interpretation
Strategy & organization	3.3	4.4	1.1	Governance and performance alignment lag behind infrastructure investments
Value chain intelligence	3.8	4.5	0.7	Cross-stage closure remains incomplete

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				despite strong local digitization
Management support	3.9	4.6	0.7	Support functions are analytical but insufficiently integrated
Infrastructure & capabilities	4.0	4.7	0.7	Technical base is strong, yet system-level orchestration remains unfinished

Table 3 clarifies that the integration problem is not marginal. In all four domains, current readiness remains below the threshold needed for enterprise-scale transformation. The most severe shortfall appears in strategy and organization, confirming that managerial alignment is the decisive bottleneck.

Figure 3 visualizes current readiness and remaining gap by lifecycle domain. This representation helps managers distinguish areas where additional technology investment will likely be productive from areas where governance redesign and process coordination should take priority.

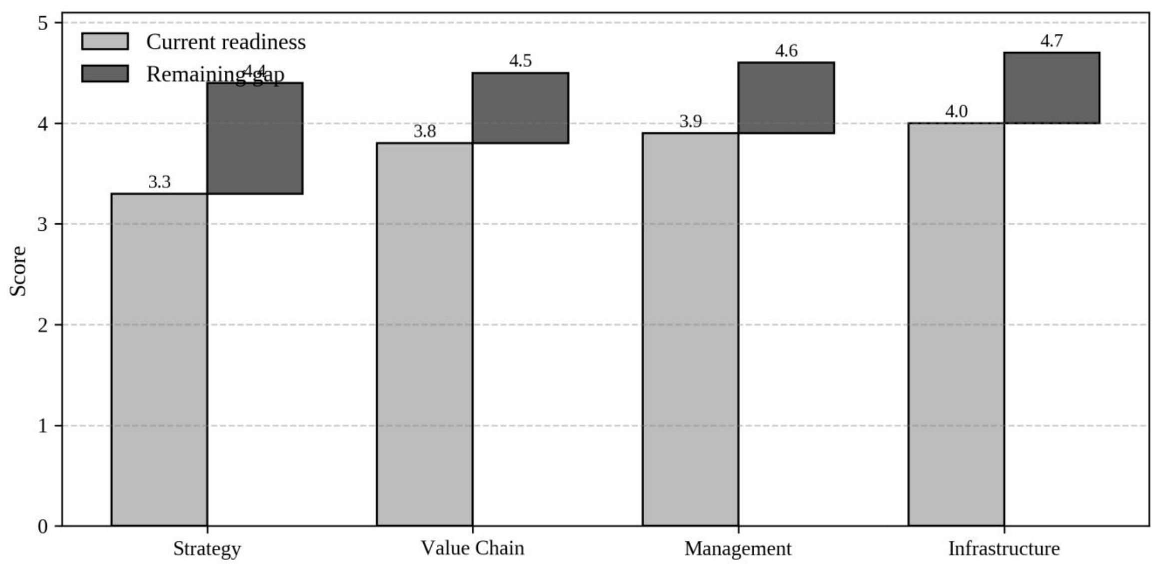

Figure 3. Current readiness and remaining gap by lifecycle domain in the illustrative Product Lifecycle Intelligence assessment.

5. Management Analytics and Transformation Priorities

5.1 Scenario-based prioritization

Not all enterprises should follow the same transformation sequence. Early-stage firms need stable data foundations before advanced AI orchestration becomes meaningful, whereas more mature organizations can emphasize closed-loop coordination and policy learning. To make this point explicit, the framework can be interpreted under three broad scenarios: foundational digitization, integrated analytics expansion, and lifecycle intelligence at scale.

Table 4. Priority actions under three smart-manufacturing transformation scenarios.

Scenario	Primary managerial priority	Secondary priority	Expected analytics outcome
Foundational digitization	Master data	Interoperable lifecycle	Reliable descriptive and

	standardization	identifiers	diagnostic reporting
Integrated analytics expansion	Cross-functional analytics cockpit	Design-to-operation feedback loops	Faster decision coordination and reduced delay
Lifecycle intelligence at scale	Closed-loop policy learning	Cross-site orchestration with governance controls	Adaptive, resilient, enterprise-level intelligence

Table 4 shows that transformation sequencing should follow the logic of cumulative lifecycle intelligence. Implementing advanced optimization before shared data and metrics are stabilized typically creates isolated models and limited managerial return. By contrast, interoperable lifecycle foundations make subsequent analytics easier to scale and govern.

5.2 Functional implications for supply chain, quality, risk, sustainability, and HR

Supply chain management benefits when demand intelligence, planning data, logistics events, and supplier signals are visible in a common analytical frame. Quality management benefits when product, process, and service evidence are connected rather than audited separately. Risk management becomes stronger when cyber incidents, planning deviations, and operational disruptions are evaluated together. Sustainability management gains credibility when energy, traceability, circularity, and waste indicators become integrated decision variables. Human resource management becomes more strategic when workforce skills, intervention patterns, and human-machine collaboration quality are tied to lifecycle performance rather than treated as administrative outputs.

These implications suggest that management analytics should act as the orchestration layer of smart manufacturing transformation. In that role, analytics defines shared metrics, interfaces, thresholds, and escalation rules through which lifecycle intelligence becomes operational. The stronger the orchestration layer, the more likely it is that local AI tools will accumulate into enterprise capability rather than remain isolated experiments.

5.3 A practical KPI system for lifecycle-oriented management analytics

Table 5. Suggested KPI architecture for lifecycle-oriented management analytics in smart manufacturing.

KPI family	Illustrative measures	Managerial use
Lifecycle responsiveness	Demand-to-design latency; design-to-production release time	Evaluate end-to-end reaction speed
Operational resilience	Recovery time after disruption; schedule reconfiguration rate	Assess adaptive capacity under uncertainty
Quality intelligence	Defect recurrence rate; root-cause closure time	Measure learning quality beyond defect counting
Data governance	Master-data completeness; interface exception rate	Monitor database-centered integration quality
Human-AI collaboration	Override rate; explanation usage; skill coverage	Evaluate trust, usability, and governance maturity

A lifecycle KPI system changes the role of performance measurement. Instead of optimizing isolated departmental targets, managers can see whether intelligence is moving effectively through the enterprise. KPI design thereby becomes a transformation lever rather than only a reporting requirement.

Figure 4 translates the article's logic into a phased roadmap. It emphasizes that smart manufacturing transformation is cumulative: data foundation enables integrated analytics, integrated analytics enables lifecycle intelligence, and lifecycle intelligence makes advanced

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orchestration credible and governable.

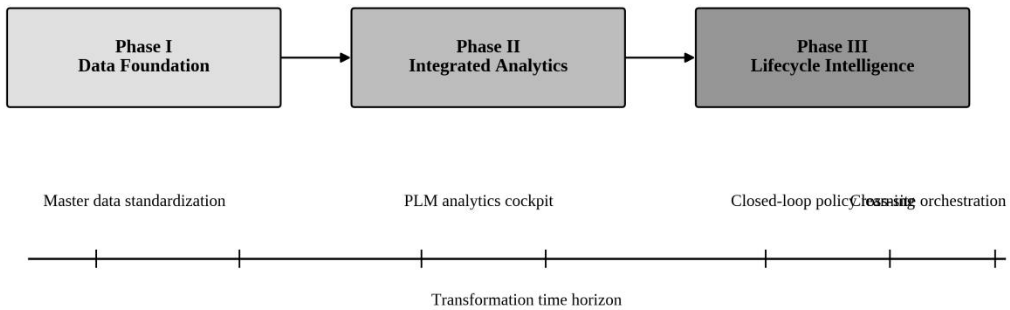

Figure 4. Phased roadmap for management-analytics-driven smart manufacturing transformation.

6. Discussion

Several managerial implications follow from these results. First, enterprises should move from project-based to architecture-based transformation. Instead of sponsoring disconnected pilots in maintenance, visual inspection, logistics optimization, or production scheduling, firms should define a lifecycle data architecture in which master data, events, and performance logic are reusable across use cases. This shifts digital investments from episodic wins to cumulative capability building.

Second, management dashboards should evolve into decision systems. Reporting environments are necessary, but they do not create intelligence on their own. Transformative management analytics links leading indicators, predictive models, scenario analysis, and recommended actions across lifecycle stages. That means connecting customer demand changes with design choices, production adjustments, supply chain responses, and managerial oversight within one decision logic.

Third, the human dimension is not peripheral. Low human-AI readiness is frequently a design failure rather than a resistance problem. When explanation, override, skill development, and accountability are poorly specified, intelligent systems may create more friction than value. Product Lifecycle Intelligence therefore requires credible arrangements for intervention and learning, not just higher model accuracy.

Fourth, resilience must be understood systemically. It is not only redundancy in buffers, suppliers, or machines. It is the capacity of the lifecycle intelligence system to detect deviations, reconfigure decisions, preserve operational quality, and learn over time. This makes resilience an analytics property as much as an operational one.

Finally, transformation sequencing matters. Table 4 indicates that early-stage firms should prioritize master-data standardization and shared lifecycle identifiers; middle-stage firms should strengthen cross-functional analytics and design-to-operation feedback; and advanced firms should focus on closed-loop policy learning, cross-site orchestration, and explainable automation. Management analytics is therefore not just an evaluation layer but a sequencing mechanism for transformation.

7. Conclusion

This article has argued that smart manufacturing transformation should be interpreted as a management analytics challenge organized around product lifecycle intelligence. The key issue is

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not simply whether advanced technologies are present, but whether enterprises can connect strategy, value creation, management support, and infrastructure through a shared lifecycle data architecture.

The Product Lifecycle Intelligence framework developed here provides a structured way to diagnose maturity, identify integration gaps, and prioritize transformation actions. The illustrative assessment shows that infrastructure capabilities often progress faster than strategic and organizational integration, and that the most persistent bottleneck lies in converting distributed digital maturity into closed-loop lifecycle intelligence.

For researchers, the framework offers a bridge between smart manufacturing scholarship and management analytics. For practitioners, it offers a practical roadmap for moving from fragmented pilots to system-level transformation. Future work can strengthen the framework through empirical field studies, longitudinal benchmarking, and database-aware performance research across industries. Even in its current form, however, the framework clarifies a central lesson: smart manufacturing becomes strategically meaningful only when intelligence is governed across the full product lifecycle.

8. Practical Implementation Risks and Governance Safeguards

Although the Product Lifecycle Intelligence framework is presented as a managerial architecture, its implementation raises practical risks that deserve explicit attention. The first risk is semantic drift across databases. Enterprises often begin with apparently simple integration efforts, only to discover that customer identifiers, product versions, resource records, process events, and service claims are defined differently across business units and legacy systems. These inconsistencies become especially problematic when analytical models are scaled from one use case to another. A predictive maintenance model trained on equipment events may not be directly reusable when spare-parts records follow different naming rules or when downtime classifications vary across plants. Database-centered architecture therefore requires semantic governance as a continuous managerial activity rather than as a one-time technical cleanup.

The second risk concerns the accumulation of hidden reconciliation costs. Firms often underestimate the managerial burden created by manual mapping, spreadsheet repair, ad hoc exception handling, and local workarounds. These activities are rarely visible in formal project evaluations, yet they consume analyst time, delay decisions, and reduce confidence in reported metrics. From a management-analytics viewpoint, one of the most important governance questions is not whether data integration exists at all, but whether it exists at a sustainable cost. Enterprises that fail to monitor reconciliation burdens often appear digitally mature on the surface while operating with fragile analytical pipelines underneath.

The third risk is decision opacity. Smart manufacturing systems increasingly rely on predictive and prescriptive models, but a model that improves forecast accuracy does not automatically improve managerial decision quality. In production and logistics contexts, opaque recommendations may create override behavior, local resistance, or blind compliance. Both outcomes are harmful. Excessive overrides reduce analytical value, while blind compliance transfers operational risk from human judgment to poorly understood model behavior. Human-AI readiness must therefore be designed through role clarity, explanation interfaces, escalation routes, and audit trails. In practical terms, trustworthy lifecycle intelligence is inseparable from governance transparency.

Cybersecurity and access-control design form a fourth governance priority. Database-centered architecture increases the strategic value of information assets because more lifecycle functions depend on shared data structures. This same dependence enlarges the potential cost of a breach, ransomware event, interface manipulation, or unauthorized model use. Governance safeguards

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should therefore include lifecycle-aware access segmentation, role-based permissions, model registries, version control, and incident escalation protocols tied directly to managerial processes. Without such safeguards, enterprises may hesitate to share information across units, thereby undermining the very integration logic on which smart manufacturing transformation depends.

A fifth implementation risk lies in metric overload. One common transformation failure is the proliferation of dashboards that track too many indicators without clarifying which ones matter for managerial decisions. Database-centered analytics makes it easy to produce more measures, but the managerial challenge is to identify the smallest set of indicators that can guide lifecycle coordination without creating noise. The KPI architecture proposed in this article should therefore be treated as a disciplined starting point rather than an invitation to uncontrolled reporting expansion. Good management analytics reduces ambiguity; it does not create more of it.

9. Future Research Agenda

Future research can develop the framework in several directions. The first direction is empirical validation through field studies. Longitudinal case evidence would allow researchers to trace how lifecycle intelligence evolves across different transformation stages, which domains mature first, and how governance redesign interacts with technology deployment over time. Such studies are particularly needed because many published smart manufacturing accounts remain architecture-rich but implementation-thin. A management-analytics perspective would benefit from evidence about how actual firms resolve conflicts among local optimization, enterprise integration, and organizational change.

The second direction is cross-industry benchmarking. Manufacturing sectors differ substantially in regulatory pressure, product complexity, service intensity, production variability, and supply-chain topology. These differences should shape the lifecycle configuration of management analytics. Process industries, for example, may prioritize traceability and resilience, while discrete manufacturers may emphasize design-to-production closure and engineering change responsiveness. Database-aware benchmarking across sectors could reveal whether the Product Lifecycle Intelligence framework requires different weighting logics under different industrial conditions.

The third direction concerns quantitative maturity assessment. The present article uses an illustrative scoring design to operationalize the framework. Future work could convert this design into a structured survey instrument or audit protocol, enabling broader comparative studies across firms and regions. Such work would not only enhance measurement precision but also make it possible to explore the relationship between lifecycle intelligence and outcomes such as lead-time reduction, quality stability, sustainability performance, or innovation speed.

A fourth direction involves the integration of newer AI paradigms. Large language models, multimodal systems, graph learning, causal analytics, and reinforcement learning may all play meaningful roles in lifecycle intelligence, but only if their outputs can be anchored in governed databases and human-AI collaboration structures. Research should therefore move beyond isolated AI-use cases and examine how advanced models interact with enterprise semantics, decision rights, and risk controls. In database-centered systems, model performance is important, but model fit with lifecycle governance may be even more decisive.

Finally, future research should engage more directly with managerial value capture. Smart manufacturing transformation is often justified through narratives of competitiveness, sustainability, or resilience, yet the mechanisms through which these outcomes are realized remain insufficiently specified. Management analytics can contribute by linking lifecycle intelligence to measurable improvements in response speed, coordination quality, recovery capability, resource efficiency, and strategic learning. A stronger evidence base on these

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mechanisms would help enterprises move from technology enthusiasm to more disciplined transformation investment.

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