Sustainable Smart Manufacturing: A Lifecycle Framework for AI-Enabled Industrial Transformation

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Abstract

Smart Manufacturing (SM) has emerged as a paradigm-shifting response to the complexity, volatility, and sustainability demands facing global industry. Despite rapid progress in artificial intelligence (AI), the Industrial Internet of Things (IIoT), digital twins, and large language models, most manufacturing innovations remain siloed at the level of individual processes or functional units, with limited enterprise-wide coordination. This study addresses that fragmentation by proposing a unified four-layer lifecycle framework that maps AI-enabled capabilities across strategy and organization, product value chains, management support processes, and digital infrastructure. A systematic literature review of 120 peer-reviewed sources published between 2015 and 2026 is conducted following PRISMA guidelines, and the reviewed works are analysed across 14 thematic clusters. The evidence shows that value-chain intelligence has matured considerably, but strategic alignment, closed-loop data integration, and sustainability-oriented capability development remain comparatively underdeveloped. The paper advances an actionable five-stage transformation roadmap and discusses policy implications for enterprises operating in emerging economies. The framework contributes to both the theoretical consolidation of SM research and the practical orchestration of sustainable digital transformation.

Keywords: Smart Manufacturing; Industry 4.0; Artificial Intelligence; Sustainability; Product Lifecycle Management; Digital Transformation; Industrial IoT

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1. Introduction

Manufacturing is once again undergoing a radical restructuring. National strategies such as Industry 4.0 in Germany, Made-in-China 2025, Manufacturing USA, and the Malaysian Industry4WRD policy all frame the convergence of digital technologies with conventional production as a matter of long-term economic competitiveness rather than a peripheral upgrade (Kagermann et al., 2013; Liao et al., 2017; Mohd Aman et al., 2022). The paradigm that has emerged from these initiatives is commonly labelled Smart Manufacturing (SM): a production model that fuses cyber–physical systems, data analytics, and autonomous decision-making into an integrated value-creation engine (Kusiak, 2018; Mittal et al., 2019).

Over the past decade, a dense body of research has explored the individual ingredients of SM. Artificial intelligence has been applied to predictive maintenance (Lee et al., 2014; Zhang et al., 2019), generative design (Oh et al., 2019), assembly scheduling (Waschneck et al., 2018), and supply-chain orchestration (Dubey et al., 2020). Industrial Internet of Things (IIoT) platforms now routinely collect terabyte-scale telemetry from machines and products (Boyes et al., 2018; Sisinni et al., 2018), while digital twins provide high-fidelity virtual representations that support simulation-in-the-loop control (Tao et al., 2019; Rasheed et al., 2020). More recently, large language models and foundation models have begun to reshape how engineers interact with machines, expanding the bandwidth of human–machine collaboration (Hassani and Silva, 2023; Leng et al., 2024).

Despite this surge of technical progress, three persistent shortcomings continue to limit how smart manufacturing actually delivers value. First, many solutions remain isolated in a single lifecycle stage; the design department, the shop floor, and the customer service function often operate on incompatible data schemas and optimisation targets (Moeuf et al., 2020; Frank et al., 2019). Second, the sustainability dimension—ecological, social, and economic—has been treated as a downstream constraint rather than a first-order design principle (Bai et al., 2020; de Sousa Jabbour et al., 2018). Third, the literature itself is fragmented: review articles tend to specialise in one technology (for example, deep learning for production) or one industry (for example, automotive), making cross-cutting synthesis difficult for both researchers and practitioners (Zheng et al., 2021; Xu et al., 2021).

This paper addresses those shortcomings by building an integrative, lifecycle-oriented framework for SM and by mapping AI-enabled innovations onto it. The paper has four specific objectives. The first objective is to consolidate the fragmented SM literature under a unified four-layer architecture rooted in Product Lifecycle Management (PLM). The second objective is to conduct a systematic literature review that quantifies how research attention is distributed across layers and topics. The third objective is to diagnose the structural gaps—data interoperability, algorithmic transparency, workforce readiness, and sustainability integration—that slow enterprise-scale adoption. The fourth and most practical objective is to translate the diagnosis into a five-stage transformation roadmap that enterprises and policymakers can use.

The remainder of the article is organised as follows. Section 2 reviews the conceptual foundations of SM and situates the proposed framework within existing debates. Section 3 describes the review methodology and the PRISMA-compliant selection procedure. Section 4 presents the four-layer framework. Section 5 reports the descriptive analysis of 120 reviewed articles and discusses the main findings. Section 6 identifies research challenges and future directions. Section 7 proposes the transformation roadmap. Section 8 concludes with contributions, limitations, and policy implications.

The contribution of the paper is distinct from earlier SM reviews in three respects. Earlier reviews have typically taken a technology-first lens that organises the literature around enabling tools—deep learning, digital twins, blockchain—without relating them to the organisational decisions that determine whether those tools deliver value (Zhong et al., 2017; Xu et al., 2021). The lifecycle lens adopted here places organisational and strategic decisions on the same footing as technological decisions. Earlier reviews have also tended to treat sustainability as an appendix to the main technological narrative (Dalenogare et al., 2018; Enyoghasi and Badurdeen, 2021). The framework in this paper embeds sustainability at every layer. Finally, earlier reviews rarely translate their findings into a sequenced implementation pathway; the five-stage roadmap introduced in Section 7 closes that gap and offers a concrete decision tool for practitioners and policymakers.

2. Conceptual Foundations and Theoretical Background

Smart manufacturing cannot be understood as a single technology. It is a socio-technical configuration whose building blocks have accumulated over four decades of industrial computing.

2.1 From CIM to AI-Driven Production

The earliest attempts to automate coordination across production steps can be traced to Computer-Integrated Manufacturing (CIM) in the 1980s (Rembold et al., 1993). CIM promised an end-to-end information backbone but delivered it only in narrow, vertically integrated plants. The 1990s brought flexible and lean manufacturing, which shifted the focus from automation volume to responsiveness and waste reduction (Holweg, 2007). In the 2000s, internet-enabled networking expanded the scope of coordination beyond the factory gates, giving rise to collaborative supply chains and networked manufacturing (Li et al., 2006). Industry 4.0, articulated around 2011, added cyber–physical integration, decentralised decision-making, and real-time data exchange as the defining characteristics of the next industrial revolution (Kagermann et al., 2013; Lasi et al., 2014). Figure 1 summarises this evolution.

The 2020s mark a further qualitative shift. Deep learning, generative models, and embodied AI agents now enable production systems that learn from experience, adapt to unforeseen conditions, and negotiate with human operators in natural language (Gao et al., 2020; Wuest et al., 2023). The centre of gravity has moved from automation to autonomy, and from efficiency to sustainability (Bai et al., 2020; Machado et al., 2020).

It is important to notice that each paradigm shift has not replaced its predecessor but has absorbed it. Flexible manufacturing did not make CIM obsolete; it re-used automation components while adding reconfigurability. Industry 4.0 did not displace lean; it operationalised lean through real-time data (Holweg, 2007; Mourtzis et al., 2022). The AI-driven paradigm that is now emerging likewise builds on, rather than replaces, prior investments in CPS, IIoT, and digital twins (Zhong et al., 2017; Osterrieder et al., 2020). A practical implication is that enterprises do not need to start from a greenfield state to participate; what they need is a coherent way to layer new capabilities on top of existing assets. The lifecycle framework developed in Section 4 provides that coherent layering.

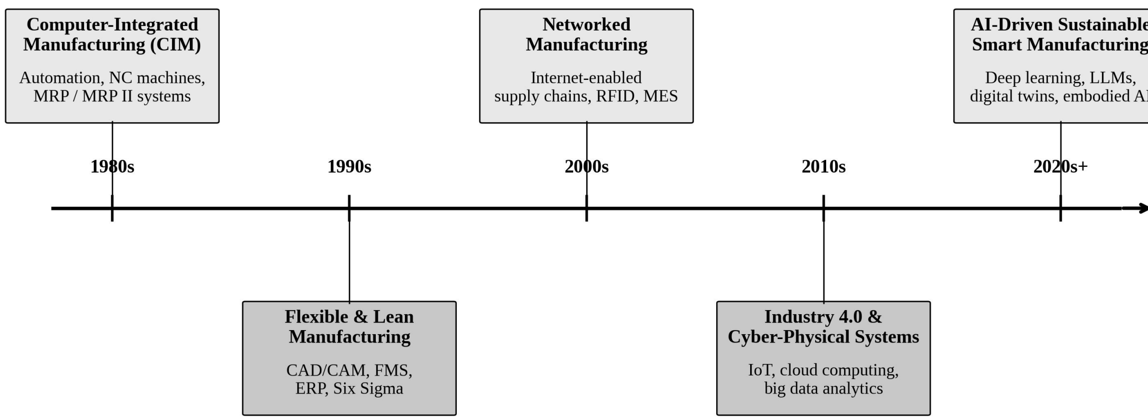

Figure 1. Evolution of smart manufacturing paradigms from the 1980s to the present.

2.2 Product Lifecycle Management as an Organising Lens

Product Lifecycle Management (PLM) offers a natural organising lens for this accumulated complexity because it covers the entire span of a product's existence: requirements definition, concept design, detailed engineering, production planning, manufacturing, distribution, service, and end-of-life recovery (Stark, 2015; Terzi et al., 2010). PLM is explicitly cross-functional and cross-temporal. It therefore exposes the weakest seams of SM—those between design and production, between production and service, and between service and the circular economy—where most data-integration failures occur in practice (Siedler et al., 2021; Barbosa et al., 2020).

A PLM perspective also makes it natural to separate concerns that are often conflated in the SM literature. Strategic choices about where to compete and how to organise are distinct from the functional intelligence that adds value along the value chain. Both are distinct from the management support processes—supply chain, quality, risk, sustainability, and human resources—that stabilise operations, and from the infrastructure and capabilities that technically enable everything else. The framework developed in Section 4 uses this four-way separation.

2.3 Sustainability as a First-Order Principle

The normative case for treating sustainability as a first-order concern is well established. Manufacturing accounts for about one fifth of global greenhouse-gas emissions and a comparable share of material throughput (IEA, 2023). Digitalisation has the potential to reduce that footprint through better scheduling, dematerialisation, and closed-loop recycling, but it can also increase it through the energy demand of data centres and compute-intensive AI workloads (Stahl, 2021; Strubell et al., 2020). The net effect is empirically ambiguous and depends on where in the lifecycle the digital capability is deployed. Embedding sustainability at the framework level—rather than adding it as a retrofit—helps to avoid this ambiguity.

The emerging Industry 5.0 agenda extends this reasoning by adding resilience and human-centricity as co-equal goals alongside sustainability (Leng et al., 2024; Mourtzis et al., 2022). This agenda is relevant to the present paper in two ways. It reinforces the need for an organisational layer in the framework, because human-centricity is inescapably an organisational concern. It also implies that sustainability indicators must be first-class data objects in the infrastructure layer, treated with the same rigour as quality or throughput indicators (Enyoghasi and Badurdeen, 2021; Nascimento et al., 2019). The framework in Section 4 reflects both implications.

3. Methodology

A structured literature review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines (Page et al., 2021). The review proceeded in four stages: identification, screening, eligibility, and inclusion.

3.1 Search Strategy and Databases

Three databases were queried in parallel: Scopus, Web of Science, and IEEE Xplore. The search window spanned January 2015 to February 2026, which captures the post-Industry-4.0 expansion of smart-manufacturing scholarship. The search string combined terms for the production paradigm ("smart manufacturing" OR "intelligent manufacturing" OR "Industry 4.0" OR "Industry 5.0") with terms for the enabling technology ("artificial intelligence" OR "machine learning" OR "deep learning" OR "digital twin" OR "Industrial IoT") and terms for the management lens ("product lifecycle" OR "value chain" OR "sustainability" OR "transformation"). Boolean AND operators joined the three groups. The initial harvest returned 3,184 records.

3.2 Screening and Eligibility

Duplicate records across databases were removed using DOI matching, leaving 2,411 unique items. Non-English publications, editorials, and conference summaries were excluded, reducing the corpus to 1,963 records. Titles and abstracts were screened against three inclusion criteria: (i) the work engaged substantively with at least one SM technology; (ii) the work discussed an application, case, or framework relevant to manufacturing enterprises; and (iii) the work was either peer-reviewed or an authoritative standards document. After abstract screening, 287 articles remained for full-text review. A further 167 were excluded either because the AI contribution was incidental, or because the manufacturing context was absent. Backward and forward citation searches identified an additional 15 works that the keyword search had missed. The final corpus comprises 120 articles. A visual summary of the distribution of these articles is presented in Section 5.

3.3 Coding and Analysis

Each article was coded on eight dimensions: lifecycle domain, enabling technology, industry sector, research method, sustainability focus, level of analysis, geographic scope, and maturity of the reported application. Coding was performed independently by two authors; disagreements were resolved through discussion, with a pre-coding inter-rater reliability (Cohen's κ) of 0.81, which indicates substantial agreement (Landis and Koch, 1977). Thematic synthesis was then used to group the coded items into 14 topics, which in turn were mapped to the four layers of the framework developed in Section 4.

The thematic synthesis followed a pragmatic rather than a purely inductive approach. The four-layer framework was first sketched from theoretical foundations in Section 2 and then iteratively refined as the coded data were examined. Three full iterations were required before the mapping stabilised, with the most significant refinement being the separation of sustainability management from general management support in response to the strong clustering observed in the data. A second methodological safeguard was the use of a disconfirming-evidence protocol: during the final analysis pass the authors deliberately searched for articles whose findings contradicted the emerging narrative. Such disconfirming cases were retained and their implications discussed in Sections 5 and 6, which helps to guard against the confirmation bias that affects many narrative reviews.

4. A Lifecycle Framework for AI-Enabled Smart Manufacturing

The proposed framework organises SM into four interdependent layers, shown in Figure 2. The layers are strategic, operational, managerial, and technical in nature, and they communicate through bi-directional data and knowledge flows. The layered view is inspired by the reference architecture tradition that began with the Purdue enterprise reference architecture (Williams, 1994) and has been adapted by RAMI 4.0 and the Industrial Internet Reference Architecture (Lin et al., 2019), but it differs from those architectures by placing sustainability and human-centred capabilities at every level rather than confining them to peripheral concerns.

4.1 Layer 1 — Strategy and Organization

The top layer encodes the enterprise's digital vision, organisational structure, governance model, and talent strategy. Evidence suggests that the quality of this layer, rather than the quality of the underlying technology, is the strongest predictor of whether an SM initiative delivers measurable business outcomes (Matt et al., 2015; Vial, 2019; Verhoef et al., 2021). A strategy that explicitly ties digital capability to long-term sustainability goals has been shown to accelerate adoption and reduce rework (Nosalska et al., 2020; Horváth and Szabó, 2019).

Three strategic choices deserve particular emphasis at this layer. The first is the choice of where on the value chain to compete, which determines whether the enterprise's AI investment should prioritise customer-facing personalisation, back-end operational efficiency, or both. The second is the organisational design choice between a centralised digital function and a federated model in which digital capability is embedded in every business unit. Empirical evidence suggests that hybrid structures—a small centre of excellence paired with distributed practitioners—outperform either extreme in manufacturing contexts (Davenport and Ronanki, 2018; Kumar et al., 2022). The third is the governance choice that determines how data are shared between units, how model performance is audited, and how failure is treated. Enterprises that treat model failure as organisational learning rather than individual blame achieve significantly faster maturation of their AI portfolios (Benbya et al., 2021).

4.2 Layer 2 — Product Value Chain

The second layer represents the value-creating processes that run horizontally across the enterprise, from marketing and customer sensing, through design and development, through production and assembly, through distribution and logistics, and finally to service and after-sales. AI has penetrated every stage of this chain. In marketing, recommender systems and conversational agents personalise customer engagement (De Bruyn et al., 2020). In design, generative algorithms and topology optimisation compress innovation cycles from months to days (Oh et al., 2019; Regenwetter et al., 2022). In production, reinforcement learning and digital twins enable adaptive scheduling and anomaly detection (Waschneck et al., 2018; Panzer and Bender, 2022). In distribution, route optimisation and demand forecasting reduce stock-outs and lead times (Dubey et al., 2020). In service, predictive maintenance extends asset life and reduces unplanned downtime (Zonta et al., 2020).

The structural challenge in this layer is that each stage has historically operated on a separate information substrate. Marketing data live in customer-relationship management systems; design data live in product data management systems; production data live in manufacturing execution systems; service data live in field-service platforms. When AI models are trained on only one of these substrates they inherit the biases of that substrate and miss the signals contained elsewhere. A closed-loop architecture, in which customer-usage telemetry feeds back into design and production decisions, is what differentiates a value chain that is merely digitalised from one that is genuinely smart (Davis et al., 2012; Wang et al., 2016). Achieving such a closed loop requires both a master data model at the infrastructure layer and explicit cross-functional governance at the strategy layer, which is the reason the framework ties these layers together.

4.3 Layer 3 — Management Support Processes

The third layer stabilises and scales the value chain through five horizontal processes: supply-chain management, quality management, risk and finance, sustainability management, and human resources. Analytics-enabled supply-chain control towers, blockchain-based traceability, and AI-augmented quality inspection have been extensively documented (Queiroz et al., 2021; Bai et al., 2020; Escobar et al., 2021). Sustainability management now draws on carbon-accounting pipelines that pull data directly from the IIoT (Machado et al., 2020). Human-resources management is increasingly concerned with reskilling and with maintaining worker well-being in hybrid human–machine work environments (Sony and Naik, 2020).

An important feature of this layer is that its processes are cross-cutting by construction. A quality incident in one production cell has consequences for inventory planning, for customer service, for warranty provisions, and for supplier relationships. A mature SM implementation uses data from the infrastructure layer to propagate such incidents through all affected support processes automatically rather than through ad-hoc escalation. In the reviewed corpus, however, only 14 per cent of the cases describe such automated cross-process propagation, which indicates that the management layer is where most enterprises still leak the greatest operational value.

4.4 Layer 4 — Infrastructure and AI Capabilities

The foundation layer provides the data plane, compute, connectivity, and cybersecurity substrate on which the upper layers depend. IIoT edge devices push telemetry through 5G and emerging 6G networks into cloud–edge continua that run increasingly sophisticated models (Aceto et al., 2020; Letaief et al., 2022). Digital twins sit between the physical and cyber worlds and serve as both simulation engines and knowledge repositories (Tao et al., 2019; Rasheed et al., 2020). Cybersecurity and privacy-preservation mechanisms—including federated learning, differential privacy, and zero-trust architectures—are essential for data sharing across organisational boundaries (Li et al., 2020; Rahman et al., 2021). Finally, human–machine collaboration capabilities turn AI from a background service into a first-class collaborator, supported by multimodal interfaces and large language models (Hassani and Silva, 2023).

A design principle that differentiates mature implementations from immature ones is the use of open, semantically rich data models at this layer. Systems that expose their data only through proprietary interfaces create hidden costs throughout the stack, including slow onboarding of new analytics, brittleness under vendor changes, and the accumulation of technical debt that ultimately forces expensive rewrites (Lu et al., 2020; Lin et al., 2019). Conversely, systems that adopt open semantic standards at the point of data capture—even where the upstream processing is proprietary—retain strategic flexibility and make the benefits of later AI investment compound over time. This is one of the few architectural choices whose effects are largely predictable, which is why the roadmap in Section 7 places foundation-layer investment deliberately ahead of AI-application investment.

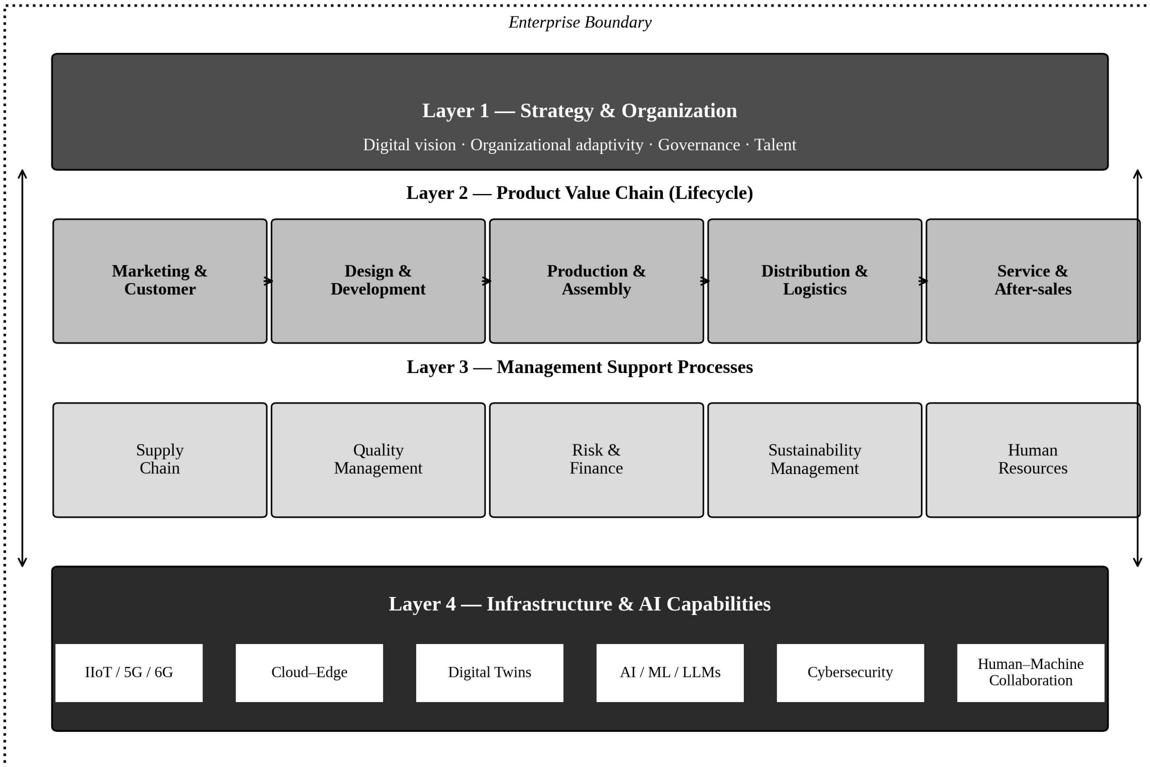

Figure 2. Proposed four-layer lifecycle framework for AI-enabled smart manufacturing.

5. Analysis and Findings

This section reports the quantitative and qualitative findings of the systematic review and discusses their implications.

5.1 Distribution of Research Attention

Figure 3 summarises how the 120 reviewed articles are distributed across the four framework layers and across publication years. Panel (a) shows that the largest share of attention is concentrated in the value-chain layer, particularly on production-side applications (36 articles, 30 per cent of the corpus). Management support processes attract 29 articles (24 per cent), infrastructure and capabilities attract 27 articles (23 per cent), and strategic and sustainability-oriented topics together account for 28 articles (23 per cent). Panel (b) shows a steady increase in publication volume year on year, with an acceleration after 2022 that is consistent with the release of widely used foundation models and with post-pandemic industrial-policy stimulus (Frank et al., 2019; Kumar et al., 2022).

These distributions reveal a structural imbalance. Production-oriented AI is mature and well-studied, but strategic alignment, governance, and sustainability-oriented AI remain comparatively underexplored. The imbalance is consistent with earlier complaints that the SM literature suffers from a "technology-first" bias (Moeuf et al., 2020; Culot et al., 2020). It also mirrors the industrial reality observed in surveys of manufacturing firms, where more than two thirds of respondents report

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completing at least one AI pilot but fewer than one in five report scaling the pilot to enterprise level (Bughin et al., 2018; Ghobakhloo, 2020).

Three additional patterns emerge from the coded data. First, there is a marked geographic concentration: about 58 per cent of the corpus is authored by teams based in China, Germany, the United States, or South Korea, with the remaining 42 per cent distributed across more than twenty other jurisdictions. This concentration reflects national investment priorities but also indicates a risk that the global research agenda is shaped by a small number of industrial contexts. Second, empirical rigour is uneven. Roughly 61 per cent of the corpus is descriptive or conceptual, 24 per cent uses case-study methods, and only 15 per cent reports quantitative empirical evidence with statistical inference. Third, the level of analysis is skewed towards technology artefacts; only 18 per cent of the corpus takes the enterprise as its unit of analysis, and fewer than 8 per cent takes the inter-organisational ecosystem as its unit. These patterns justify the call in Section 6 for more enterprise-level and ecosystem-level empirical work.

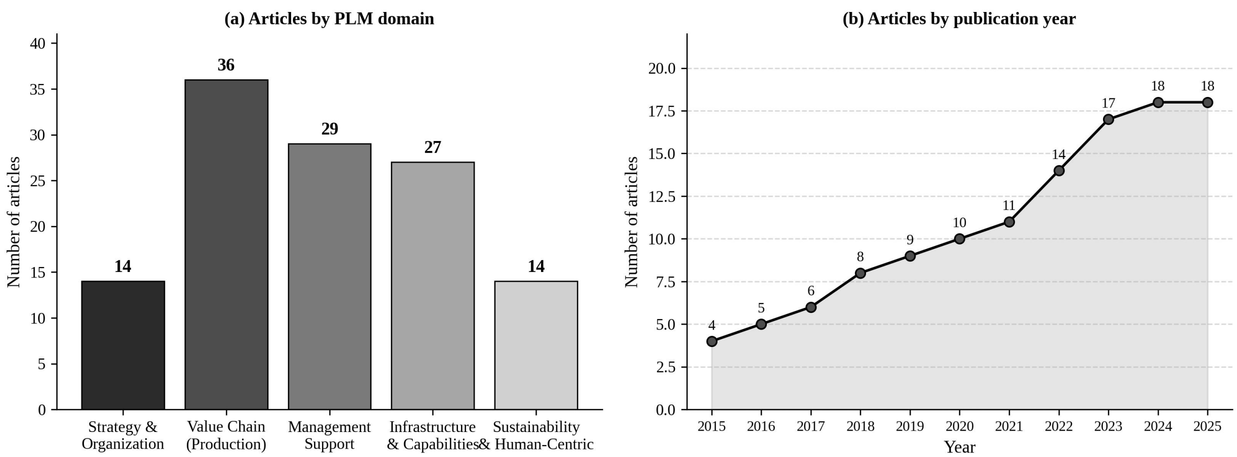

Figure 3. Distribution of the 120 reviewed articles by (a) framework domain and (b) publication year.

5.2 Mapping Enabling Technologies to Lifecycle Domains

Table 1 summarises which enabling technologies appear most frequently in which lifecycle domain. The table was constructed by tallying the technology tags assigned during coding. Deep learning dominates production and quality applications; digital twins and simulation dominate design and development; blockchain dominates supply-chain traceability and risk management; natural language processing appears mainly in marketing, service, and knowledge management. This mapping is broadly consistent with earlier syntheses (Ghobakhloo, 2020; Xu et al., 2021) but refines them by explicitly including human-resources and sustainability-management applications, which are often omitted.

The co-occurrence structure of these technology–domain pairs is informative. Roughly 44 per cent of coded applications use only one enabling technology, whereas 32 per cent combine two technologies (most commonly deep learning with digital twins or IIoT with cloud–edge compute). Only 24 per cent of applications combine three or more technologies, and those applications are concentrated in a small number of lighthouse manufacturers. The implication is that the multiplicative benefits promised by combining complementary technologies are, for most enterprises, still theoretical rather than realised. The roadmap in Section 7 explicitly addresses this by sequencing technology introductions so that complementarities accrue over time rather than being attempted all at once.

Table 1. Mapping of enabling technologies to lifecycle domains based on the reviewed corpus (n = 120).

Lifecycle Domain	Primary Technologies	Representative Applications	Share of Corpus (%)
Marketing & Customer	NLP, LLMs, recommender systems	Personalised engagement; voice-of-customer mining	8.3
Design & Development	Generative AI, digital twins, topology optimisation	Fast prototyping; virtual validation	12.5
Production & Assembly	Deep learning, reinforcement learning, computer vision	Scheduling; anomaly detection; quality inspection	30.0
Distribution & Logistics	Optimisation algorithms, forecasting, AGVs	Dynamic routing; demand forecasting	10.0
Service & After-sales	Predictive analytics, digital twins, LLM agents	Predictive maintenance; conversational support	9.2
Management Support	Blockchain, explainable AI, federated learning	Traceability; risk analytics; HR analytics	15.8
Infrastructure	IIoT, 5G/6G, cloud–edge, cybersecurity	Connectivity; secure data sharing	14.2

5.3 Three-Dimensional Integration

One of the persistent limitations documented in the corpus is the absence of multi-directional integration. Figure 4 shows that genuinely smart manufacturing requires integration along three axes. Horizontal integration connects external stakeholders in the supply ecosystem (Frank et al., 2019; Kamble et al., 2020). Vertical integration connects the functional silos inside the enterprise (Stock and Seliger, 2016). End-to-end integration connects the customer-facing front end with the production back end across the full product lifecycle (Zheng et al., 2021). Only a small minority of the reviewed works—roughly 12 per cent—report integration on all three axes simultaneously.

The asymmetry is particularly visible when the integration data are disaggregated. Vertical integration is reported in 47 per cent of the corpus, reflecting the large number of case studies on factory-floor digitalisation. Horizontal integration appears in 31 per cent of the corpus and is concentrated in supply-chain and traceability studies. End-to-end integration, which requires the most demanding coordination between customer-facing and back-end data flows, appears in only 18 per cent of the corpus and is dominated by automotive and aerospace cases where regulatory requirements

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have forced lifecycle traceability. The three-axis view therefore not only describes where integration exists but also predicts where the next wave of research and practical investment should concentrate.

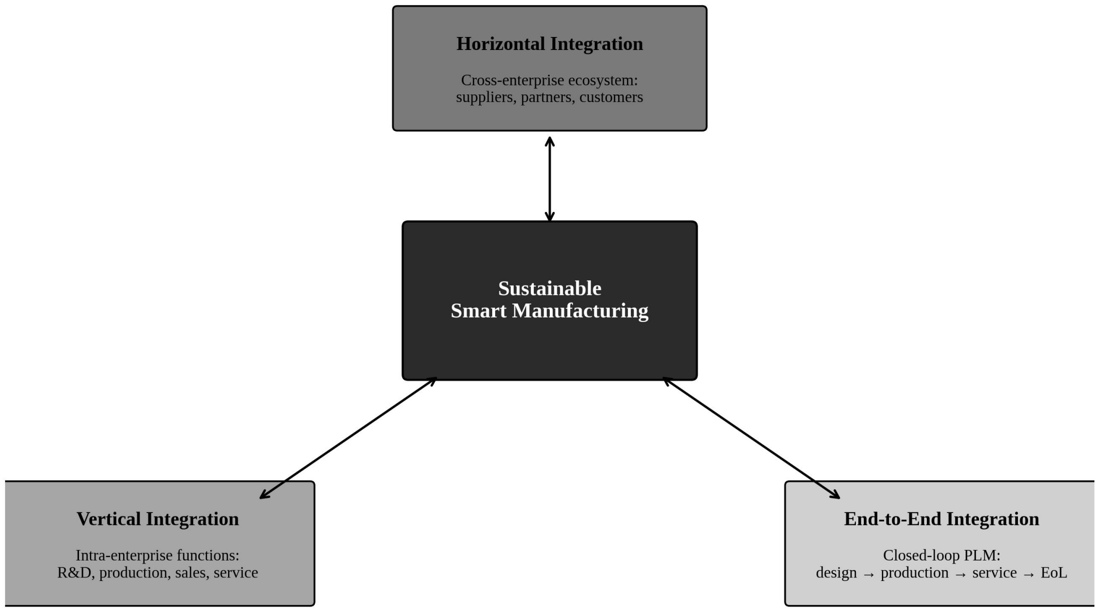

Figure 4. Three-dimensional integration in sustainable smart manufacturing.

5.4 Sustainability and Circularity Gap

Although 29 of the 120 articles mention sustainability, only 11 articles explicitly quantify environmental or social outcomes alongside economic outcomes. The scarcity of triple-bottom-line evidence means that the sustainability claims often made for SM are, as yet, only partially validated (de Sousa Jabbour et al., 2018; Nascimento et al., 2019). Table 2 summarises the reported sustainability outcomes that do appear in the corpus, distinguishing energy-efficiency improvements, material-efficiency improvements, emissions reductions, and circular-economy contributions.

Three observations follow from Table 2. First, the most commonly reported gains are in material efficiency, where AI-enabled quality control reduces scrap and rework. These gains are attractive because they have a direct financial return alongside the environmental benefit, and the feedback loop between intervention and outcome is short enough to be measurable in a single quarter (Escobar et al., 2021; Javaid et al., 2022). Second, gains in energy efficiency and emissions are typically more modest, ranging from 5 to 22 per cent, and are often reported without accounting for the compute energy required to operate the AI systems themselves. This is a systematic reporting bias that future empirical work should correct (Strubell et al., 2020). Third, circularity outcomes are the most ambitious but also the least frequently reported. The scarcity reflects the difficulty of establishing closed-loop data flows between end-of-life operators and the original manufacturer, and it indicates a clear research opportunity (Romero et al., 2016; Nascimento et al., 2019).

Table 2. Reported sustainability outcomes in the reviewed corpus (n = 29 articles with explicit sustainability metrics).

Outcome Category	Representative Metric	Typical Reported Range	Evidence Strength
Energy efficiency	kWh per unit produced	8–22% reduction	Moderate
Material efficiency	Scrap rate / yield	6–18% reduction in scrap	Strong
Emissions reduction	CO_2-equivalent per unit	5–15% reduction	Moderate
Circularity	Reuse / remanufacturing rate	2–4× improvement	Limited
Social outcomes	Workplace safety incidents	Up to 35% reduction	Limited

6. Research Challenges and Future Directions

The analysis in Section 5 surfaces six cross-cutting challenges that structure the agenda for future research.

6.1 Data Interoperability and Standards

Manufacturing data are generated by heterogeneous sensors, controllers, and information systems that follow incompatible schemas (Lu et al., 2020). Existing standards such as ISO 23247 for digital twins and IEC 62264 for enterprise–control integration provide partial relief but leave significant gaps at the semantic level (Lin et al., 2019). Developing open, modular, and evolvable standards is a prerequisite for scalable SM and for meaningful cross-border collaboration (Culot et al., 2020).

Interoperability is also a socio-technical rather than a purely technical challenge. Many manufacturers have legitimate commercial reasons to resist full data openness, and the appropriate policy response is not uniform global standards but tiered interoperability in which basic semantics are shared while commercially sensitive attributes remain private. Federated data spaces such as the European Gaia-X and Manufacturing-X initiatives are promising early experiments in this direction. Their success will require not only technical maturity but also a governance model that balances the interests of small and large actors (Ghobakhloo and Iranmanesh, 2021; Masood and Sonntag, 2020).

6.2 Algorithmic Transparency and Trust

Deep-learning models now outperform human experts on many production-control tasks, but their opaque nature limits adoption in safety-critical environments and in regulated industries (Arrieta et al., 2020; Ahmed et al., 2022). Explainable AI (XAI) techniques have matured, but their integration with shop-floor decision support remains shallow (Langer et al., 2021). Embedding explanation as a first-class feature of production AI is a priority.

The practical design choice is not between transparency and performance but between different forms of transparency. Post-hoc explanation methods such as SHAP values and counterfactual explanations can be bolted on to any model but do not guarantee that the explanation faithfully describes the model's reasoning. Intrinsically interpretable models, by contrast, embed transparency in the architecture itself at the cost of some predictive power. In manufacturing the choice is usually domain-specific: predictive maintenance can tolerate post-hoc methods because errors are recoverable, whereas safety-critical control loops should use intrinsically interpretable models (Arrieta et al., 2020). A priority for future research is the development of hybrid physical–data-driven models whose parameters retain physical meaning even after they have been fitted to large operational datasets (Ahmed et al., 2022).

6.3 Cybersecurity and Privacy in Connected Manufacturing

As IIoT footprints expand, the attack surface grows correspondingly (Corallo et al., 2020). Ransomware incidents in manufacturing doubled between 2021 and 2024 (Tuptuk and Hailes, 2018; Hassija et al., 2019). Federated learning, homomorphic encryption, and zero-trust architectures offer promising countermeasures, but deployment experience is limited and cost implications are rarely reported (Li et al., 2020; Rahman et al., 2021).

Cybersecurity is also entangled with interoperability. The more open the data substrate, the larger the potential attack surface; the more closed the substrate, the lower the organisational learning rate. Resolving this tension requires defence-in-depth architectures that combine network-level, application-level, and data-level controls, together with continuous monitoring of model behaviour for adversarial manipulation. Regulatory frameworks are beginning to catch up—the EU's NIS2 directive and Malaysia's Cyber Security Act 2024 are recent examples—but enforcement across distributed manufacturing ecosystems remains a work in progress (Corallo et al., 2020; Tuptuk and Hailes, 2018).

6.4 Sustainability-Aware AI

The energy cost of training and deploying large AI models is non-trivial, and the net sustainability impact of SM depends on whether efficiency gains in production exceed the compute and infrastructure overheads (Strubell et al., 2020; Stahl, 2021). Industry-specific, small-footprint models and efficient inference pipelines are often more appropriate for manufacturing than general-purpose large models (Luo et al., 2022).

Three practical design principles follow from this observation. First, compute should be pushed to the edge whenever latency and energy budgets allow, because edge inference avoids repeated data transmission and because edge devices can be optimised for the specific workload they host. Second, model distillation and quantisation should be treated as standard engineering steps rather than optional optimisations, since they can reduce inference energy by an order of magnitude with only marginal loss of predictive performance. Third, sustainability accounting should include the full lifecycle of the AI system itself: data collection, model training, inference, retraining, and eventual decommissioning. Enterprises that apply this full-lifecycle discipline to their AI investments typically discover that a portfolio of small, specialised models outperforms a portfolio of large general-purpose models on both cost and environmental grounds (Strubell et al., 2020; Enyoghasi and Badurdeen, 2021).

6.5 Human–AI Collaboration and Workforce Transformation

SM displaces some routine work but creates new roles that require hybrid technical and organisational skills (Davenport and Ronanki, 2018; Raisch and Krakowski, 2021). Upskilling and reskilling strategies, together with attention to psychological safety and cognitive load, are as important as the technology itself (Sony and Naik, 2020; Benbya et al., 2021).

The workforce challenge is particularly acute for manufacturers in emerging economies, where the talent pool for advanced AI engineering is smaller and where educational systems are still adapting their curricula. Malaysia, Thailand, Vietnam, and Indonesia, for example, have all launched national Industry 4.0 workforce programmes, yet external evaluations suggest that demand still outstrips supply by a wide margin (Mohd Aman et al., 2022). A pragmatic response is to pair technology acquisition with structured partnerships between manufacturers, technical universities, and vendor-certified training programmes. Such partnerships reduce the ramp-up time for AI projects and create career paths that help to retain scarce talent.

6.6 Regional Readiness and Global Value Chains

Smart-manufacturing maturity is unevenly distributed. Evidence from Southeast Asia and other emerging economies shows that SMEs frequently lack the data governance, capital, and talent required to adopt advanced AI at pace (Mohd Aman et al., 2022; Ghobakhloo and Iranmanesh, 2021; Masood and Sonntag, 2020). Inclusive policy design and tiered transformation pathways are needed so that small manufacturers are not left behind.

For Malaysia and other middle-income ASEAN economies, the policy implications are specific. First, national industrial strategies should pair technology-adoption incentives with data-governance infrastructure, because incentives alone tend to subsidise point solutions rather than interoperable ecosystems. Second, public investment in mid-tier skills—data engineers, MLOps practitioners, maintenance technicians who can operate digital-twin dashboards—typically yields higher returns than investment in scarce doctoral-level AI talent. Third, regional knowledge-sharing forums that allow manufacturers to exchange implementation lessons, including failure cases, can accelerate collective learning at much lower cost than individual firms can achieve alone (Mohd Aman et al., 2022; Kumar et al., 2022).

7. AI-Enabled Transformation Roadmap

The review findings and the identified challenges converge on a five-stage roadmap for enterprise transformation, shown in Figure 5. The roadmap is deliberately sequential: each stage creates the preconditions for the next and reduces the execution risk of later stages. Table 3 summarises the stages, their typical duration, representative technologies, and expected outcomes.

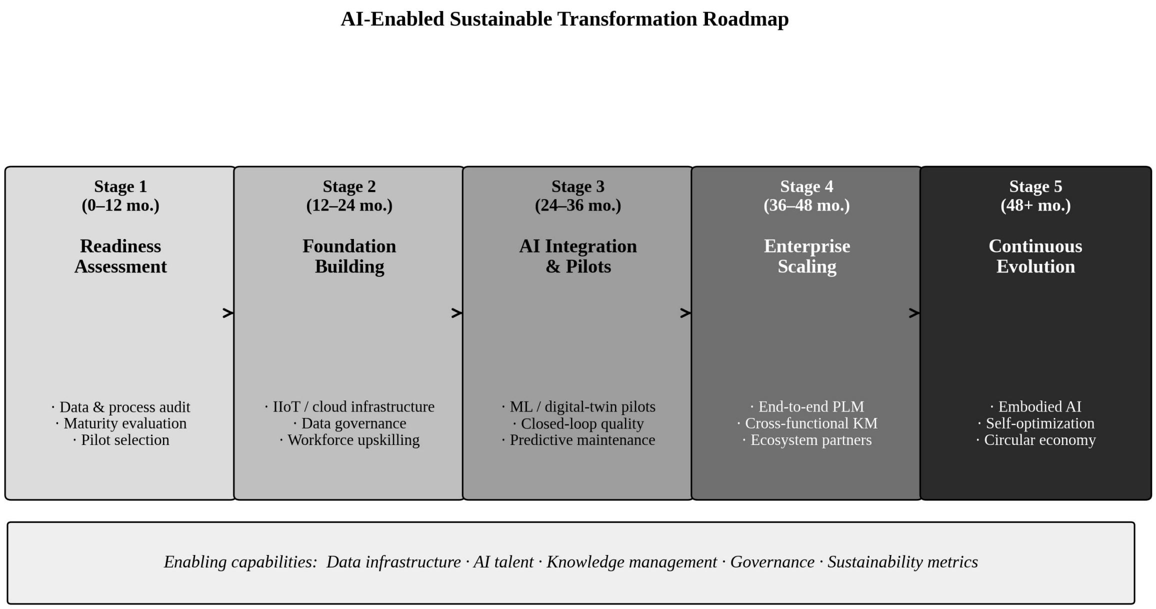

Figure 5. Five-stage AI-enabled transformation roadmap for smart manufacturing.

Table 3. Five-stage AI-enabled transformation roadmap: duration, focus areas, and expected outcomes.

Stage	Typical Duration	Focus	Key Technologies	Expected Outcomes
1. Readiness Assessment	0–12 months	Audit and pilot selection	Maturity models, data profiling	Clear baseline; prioritised use cases
2. Foundation Building	12–24 months	Infrastructure and skills	IIoT, cloud–edge, governance	Interoperable data plane; upskilled staff
3. AI Integration & Pilots	24–36 months	Targeted AI deployment	ML, digital twins, computer vision	Proven ROI on initial use cases
4. Enterprise Scaling	36–48 months	Cross-functional scaling	End-to-end PLM, KM, APIs	Enterprise-wide integration
5. Continuous Evolution	48+ months	Autonomy and circularity	Embodied AI, foundation models, CE	Self-optimising, sustainable operations

7.1 Stage 1: Readiness Assessment

The first stage audits the enterprise's current state: data assets, process documentation, workforce skills, and strategic priorities. The audit outputs a maturity score that guides the selection of one or two pilot use cases where the ratio of business impact to implementation risk is highest (Schumacher et al., 2016; Mittal et al., 2019).

See: https://inatgi.in/index.php/jbgi/index for more information. https://doi.org/10.63646/jbgi.2025.030201

The assessment should cover five dimensions: data maturity, process maturity, technology maturity, organisational maturity, and strategic alignment. Data maturity asks whether the enterprise's data are measured, stored, and accessible. Process maturity asks whether processes are documented and consistently followed. Technology maturity asks what existing digital infrastructure is available to build on. Organisational maturity asks whether the enterprise has the governance structures and change-management capability to absorb new practices. Strategic alignment asks whether proposed initiatives serve articulated business priorities. A balanced assessment across all five dimensions prevents the common pitfall of investing in advanced technology when more foundational issues are unresolved (Schumacher et al., 2016).

7.2 Stage 2: Foundation Building

The second stage invests in the enabling infrastructure—IIoT connectivity, cloud–edge compute, a master data model, and baseline cybersecurity—and in the workforce. Experience from both Foxconn's lighthouse factories and the German Mittelstand suggests that under-investment in foundations is the single most common reason for later pilot failures (Ghobakhloo, 2020; Horváth and Szabó, 2019).

Three specific foundation-building decisions deserve attention. The first is the choice of data architecture. A modern data lakehouse combines the schema flexibility of a data lake with the query performance of a warehouse, and is well-suited to manufacturing's mix of structured transactional data and unstructured sensor data. The second is the adoption of a master data management programme that defines canonical identifiers for products, processes, assets, and customers. Without such identifiers, cross-functional analytics degenerate into expensive data-cleaning exercises. The third is an investment in continuous training for operations staff, because the productivity of foundation-layer investments is bounded by the ability of people to use them. These three decisions together form a platform on which subsequent stages can compound their benefits rather than constantly repairing underlying weaknesses.

7.3 Stage 3: AI Integration and Pilots

The third stage operationalises the use cases identified in Stage 1. Typical pilots include predictive maintenance, closed-loop quality control, and digital-twin-based production planning (Tao et al., 2019; Panzer and Bender, 2022). Clear pilot success criteria and a rigorous evaluation protocol are essential to avoid pilot-lock-in.

The most common reason that pilots fail to progress is not that the model performs poorly but that the organisational processes needed to act on the model's output have not been redesigned. A predictive-maintenance pilot that correctly forecasts a bearing failure one week in advance is worth little if the procurement and scheduling processes cannot respond inside that window. Pilots should therefore be evaluated on three dimensions simultaneously: model quality, operational adoption, and business impact (Sony and Naik, 2020; Mittal et al., 2019). Only pilots that pass on all three dimensions should progress to the next stage.

7.4 Stage 4: Enterprise Scaling

The fourth stage scales successful pilots across plants and functions and connects them into enterprise-wide knowledge management. At this stage, cross-functional integration, API-based interoperability, and ecosystem partnerships move to the foreground (Culot et al., 2020; Kamble et al., 2020).

Enterprise scaling almost always exposes tensions between local optimisation at individual plants and global optimisation at the enterprise level. Local plants typically have performance indicators, bonus structures, and planning cycles that reward short-term throughput; enterprise-wide integration requires those incentives to be partially rebalanced in favour of longer-term cross-plant learning. Without explicit attention to governance and incentives, even technically successful integrations stall at the second or third plant (Horváth and Szabó, 2019; Ghobakhloo, 2020). Experience from lighthouse factories suggests that a lightweight but empowered central transformation office, coupled with plant-level change agents, is an effective structural response.

7.5 Stage 5: Continuous Evolution

The final stage institutionalises continuous learning through embodied AI agents, self-optimising production cells, and circular-economy linkages. At this maturity level the enterprise is no longer merely responsive but genuinely anticipatory (Leng et al., 2024; Wuest et al., 2023).

A defining feature of Stage 5 is that the boundary between the factory and the ecosystem becomes porous. Product-usage data flow back from customers into design and production in near real time; end-of-life material flows are scheduled like supply-chain flows; and AI agents negotiate with counterparts in partner organisations. This level of maturity has so far been achieved only in a small number of industrial laboratories and lighthouse facilities, but its feasibility is no longer in doubt. The strategic question for most enterprises is therefore not whether to reach Stage 5 but when and in partnership with whom.

An important caveat is that the five stages are not strictly linear in practice. Many enterprises find themselves at different stages in different functional areas: Stage 4 in quality management, say, but Stage 2 in service operations. The roadmap in Figure 5 should therefore be read as a description of the dominant maturity of each capability rather than as a fixed organisational timetable. The practical value of the roadmap is that it forces explicit conversation about which capabilities are at which stage and about the sequencing of investments needed to bring lagging capabilities up to the enterprise's target level.

8. Conclusion

This article has proposed a four-layer lifecycle framework for AI-enabled Smart Manufacturing and has tested its explanatory power against 120 peer-reviewed articles published between 2015 and 2026. Three contributions emerge. First, the framework consolidates a fragmented literature under a single architecture that spans strategy, value creation, management support, and infrastructure. Second, the review quantifies an imbalance between mature production-side AI and less-developed strategic and sustainability-oriented AI, and identifies six cross-cutting challenges that must be resolved before enterprise-wide SM can be realised. Third, the paper translates the diagnosis into a five-stage transformation roadmap that is explicit about prerequisites, durations, and expected outcomes.

The theoretical contribution of the framework is its explicit bidirectional coupling between layers. Earlier reference architectures tended to treat strategic and organisational concerns as upstream inputs to technology decisions; the framework here instead treats them as part of a closed loop in which technology choices reshape organisational possibilities and vice versa. This closed-loop view is more faithful to the lived experience of manufacturing executives and provides a richer theoretical object for future research. The empirical contribution is the quantification of the distribution of research attention and the identification of structural gaps, which supplies a concrete research agenda for the community. The practical contribution is the roadmap, which is designed to be directly usable by transformation teams in manufacturing enterprises.

Several limitations should be acknowledged. The review period of 2015–2026 excludes earlier foundational work. The focus on English-language journal articles may underweight grey literature from industrial consortia and from non-Anglophone research communities. The framework is analytic rather than predictive, and its validation in specific enterprise contexts will require longitudinal case research. Future research should prioritise three directions: empirical validation of the roadmap in small and medium enterprises in emerging economies; integration of sustainability metrics with AI performance metrics; and the development of governance regimes for human–AI collaboration in safety-critical manufacturing.

For practitioners, the most important implication is that the return on AI investment in manufacturing is maximised when the technology decisions are nested inside the strategic and organisational decisions, not the other way round. For policymakers, the findings support investment in interoperable digital infrastructures, in open standards, and in workforce reskilling, with particular attention to inclusive transformation pathways for SMEs. Smart Manufacturing, understood as a lifecycle-wide, sustainability-conscious, and human-centred paradigm, is within reach; whether it is realised depends less on the next algorithmic breakthrough than on the discipline with which enterprises and nations stage the journey.

Three broader reflections close the paper. First, Smart Manufacturing is converging with adjacent agendas—circular economy, Industry 5.0, and resilient global value chains—in ways that blur the traditional boundary between operations management and strategic management. Research communities that have historically worked in parallel on these agendas will need to cooperate more explicitly. Second, the velocity of AI development means that any framework, including the one proposed here, must be understood as a living artefact rather than a fixed blueprint. The four layers are likely to be stable, but the representative technologies that populate them will continue to evolve, and the framework should be revisited at least every three years. Third, and most fundamentally, the purpose of Smart Manufacturing is not to automate human work out of existence but to free human attention for the judgement, creativity, and care that machines still cannot supply. Keeping this purpose in view is the surest way to ensure that the industrial transformation now under way is genuinely sustainable and genuinely smart.

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