

# Convergent Frontiers in Industrial Automation and Digital Transformation: Technological Pillars, Methodologies, Human-Centric Strategies, and Sectoral Integration in Industry 4.0

## Abstract

This survey examines the multidimensional transformation of manufacturing precipitated by the convergence of artificial intelligence, digital twins, advanced analytics, and cyber-physical systems, as encapsulated in Industry 4.0 and its successive paradigms. Motivated by accelerating demands for productivity, customization, resilience, and sustainability, the review synthesizes developments spanning technological, methodological, organizational, and human-centric domains. The scope covers foundational technologies—including digital twins, AI-enabled optimization, simulation platforms, and IoT architectures—alongside emergent frameworks for interoperability, security, decentralized identity, and explainable autonomy.

Key contributions of the survey include: (1) clarifying the historical and conceptual evolution of digital transformation in manufacturing; (2) evaluating the integration of AI with process modeling, optimization, and real-time closed-loop systems; (3) analyzing methodological advances in productivity measurement, robust and sustainable optimization, and the operationalization of data-driven, autonomous workflows; and (4) contextualizing organizational adaptation, leadership, workforce upskilling, and human-machine symbiosis within digital transformation strategies, with a particular focus on SME-specific challenges and maturity frameworks.

The findings underscore significant advances in workflow integration, ecosystem interoperability, human-centered design, and sustainability imperatives, while identifying persistent challenges in standardization, explainability, cybersecurity, and value measurement. The survey concludes by outlining research and policy priorities for enabling agile, secure, and inclusive smart manufacturing, advocating for interdisciplinary approaches and open standards to realize adaptive, productive, and socially responsible industrial futures.

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## 1 Introduction and Theoretical Foundations

This section introduces the foundational concepts and major paradigms that underpin the study explored in this survey. We first define the scope and motivation, then outline the primary theoretical approaches, followed by a comparative overview of key frameworks. This section also situates recent advancements in context, emphasizing overarching challenges and the evolution of methodologies.

### 1.1 Survey Scope and Motivation

Recent years have witnessed a surge in interest in both digital twins and AI-driven optimization, due to their transformative potential across domains. Their integration presents not only technological opportunities but also unique challenges that necessitate a comprehensive theoretical foundation.

### 1.2 Major Paradigms and Historical Progression

The development of this field is marked by several significant paradigms, which have evolved as follows:

This progression highlights the trajectory from static inspection and rule-based systems toward highly-integrated digital twin frameworks leveraging advanced AI optimization algorithms.

### 1.3 Comparative Overview and Critical Challenges

There exists a spectrum of approaches combining digital twins with AI optimization. A critical comparison reveals significant trade-offs. Early systems favored reliability and interpretability, whereas recent approaches emphasize adaptability and scalability. However, these advances introduce complexities related to data fusion, feedback latency, and explainability.

### 1.4 Summary of Key Takeaways

To anchor the major contributions of this section:

**Summary:** This section establishes the foundations of the field, detailing the historical evolution from deterministic and manually designed models toward contemporary closed-loop, AI-augmented digital twins. While significant progress has been made, ongoing challenges include effective data integration, real-time optimization, and achieving a balance between automation and interpretability. These themes recur throughout subsequent sections, guiding both the technical discussion and the survey's critical assessments.

### 1.5 Motivation, Scope, and Structure

The rapid advancement of industrial automation and digital transformation is fundamentally reshaping manufacturing enterprises worldwide, driven by continual demands for productivity enhancement, mass customization, resilience, and sustainability [12, 15, 40,

**Table 1: Evolution of Theoretical Paradigms in Digital Twins and AI Optimization**

Era	Paradigm	Key Features	Primary Challenges
Pre-2010	Rule-based Modeling	Deterministic rules, manual feature design	Scalability, adaptability
2010–2015	Early Data-driven	Statistical ML, limited data integration	Data scarcity, integration
2015–2020	Deep Learning	Neural networks, black-box models	Interpretability, resource demand
2020–present	Digital Twins + AI	Real-time simulation, closed-loop optimization	Model synthesis, dynamic adaptation

48, 49, 59, 83, 92]. These changes stem from the foundational concept of Industry 4.0, which originated from a German research initiative and has since catalyzed innovation ecosystems, policy frameworks, and industrial strategies globally [89]. Over the last decade, Industry 4.0 has enabled significant technological progress—most notably in machine learning, artificial intelligence, and digital manufacturing systems—as well as the reinterpretation and proliferation of digital strategies that have fostered new forms of intelligence and integration across manufacturing sectors. This ongoing trajectory signifies an influence that transcends its European origins and continues to shape practices worldwide [89].

This survey takes a comprehensive perspective, synthesizing recent developments in technology, methodology, management strategy, and human factors relevant to contemporary manufacturing. Recognizing the inherently multidimensional character of industrial transformation, this review situates technological adoption within broader organizational and societal contexts. Specifically, this review

examines the interrelationships among theoretical advancements, practical sectoral implementations, and evolving workforce and organizational paradigms, drawing from developments in data-driven shopfloor management, productivity measurement, digital twin adoption, and the integration of AI and ML in production environments.

highlights the convergence of physical and digital systems (including the expanding roles of digital twin technology and decentralized identity management), the proliferation of AI/ML-enabled innovation for process optimization and customization, and the imperatives of adaptability, sustainability, and operational scale.

is structured as follows: first, foundational theoretical and historical perspectives are established, comprising a review of the inception and evolution of key concepts; next, the organizational and strategic dimensions underpinning digital transformation are explored, emphasizing challenges in implementation and gaps in social and managerial integration; finally, the synthesis reflects on emerging global trends and future trajectories, situating ongoing advances within the context of Industry 4.0, the evolving shift toward value-driven Industry 5.0 paradigms, and anticipated future developments.

## 1.6 Role of Digital Transformation in Modern Manufacturing

Digital transformation (DT) has rapidly evolved from a narrow focus on technology implementation to a central force shaping organizational strategy, leadership, and the daily realities of modern manufacturing [28]. Unlike earlier phases of digitalization—which

were primarily limited to automation and IT-driven process enhancements—contemporary DT initiatives fundamentally reconfigure decision-making structures, promote operational flexibility, and reorient competitive strategies. Empirical evidence across sectors confirms that transformational digital leadership is a key driver of organizational agility, equipping firms to respond more effectively to technological disruptions as well as shifts in market and supply chain dynamics [28].

Importantly, the transformative effects of DT are not realized in isolation but are strongly moderated by a coevolution of enabling organizational factors. Specifically, the presence of a supportive digital culture—one fostering innovation, adaptability, and a digital mindset—and a coherent digital strategy that aligns technology investments with broader business goals, both significantly enhance the positive impact of digital leadership on organizational agility [28]. Conversely, the absence of these moderating conditions can constrain or even undermine DT outcomes, highlighting that visionary leadership must be matched with substantial cultural change and clear strategic direction to avoid pitfalls stemming from organizational inertia or fragmented implementation.

The expanding scope of DT's influence is further evidenced by an increasing diversity of academic research. Current scholarship systematically integrates a range of themes, including dynamic capabilities, value co-creation, advanced data analytics, and sector-specific deployment strategies [40]. Recent bibliometric analyses reveal a pronounced post-2019 shift in the DT research landscape, marked by intensified global attention and a growing emphasis on interdisciplinary approaches [40]. From a methodological standpoint, the continued development of integrative frameworks that connect DT to core business, management, and production processes is vital for comprehending the multifaceted challenges and opportunities manufacturers face in the digital era [28, 40].

## 1.7 Historical and Conceptual Development

The progression from manual craftsmanship to intelligent, automated manufacturing unfolds across millennia, exemplifying advances at the intersection of engineering, information technology, and managerial science [12, 15, 49, 59, 83, 92]. Initial periods were marked by manual production and rudimentary forms of graphical communication, which later gave rise to the structured application of engineering graphics and, in the latter twentieth century, the introduction of computer-aided design (CAD), computer-aided manufacturing (CAM), and the more integrated computer-integrated manufacturing (CIM) systems [15, 83]. These innovations established critical foundations for today's digital and smart manufacturing landscape, where the distinction between digital design,

cyber-physical production, and real-time analytics is increasingly fluid.

A pivotal development in this historical arc was the evolution of CAM systems alongside modern computing, which revolutionized plant operations and facilitated virtual-to-physical synchronization throughout the manufacturing lifecycle [83]. This trajectory is now extended by digital twins and integrated simulation environments, which enable continuous feedback between physical assets and their digital representations. This paradigm supports not only engineering innovation but also enhanced asset maintenance and organizational learning [49].

Parallel advancements have shaped approaches to productivity analysis. Measurement has evolved from basic output-input ratios to robust models such as the Malmquist Productivity Index (MPI) and sophisticated growth accounting frameworks [92]. The integration of big data, real-time analytics, and AI-powered modeling has further increased the robustness and relevance of these metrics for operational and strategic decision-making. Notwithstanding, key challenges persist, including:

Aggregation methods that conflate diverse production contexts; Restrictive assumptions embedded in traditional measurement models; Limitations stemming from static, cross-sectional views that inadequately capture dynamic manufacturing environments [92].

Crucially, although technological innovation has historically driven manufacturing transformations, contemporary research identifies significant gaps that constrain the full potential of Industry 4.0. These gaps include the scalable application of artificial intelligence and machine learning (AI/ML) in heterogeneous production settings, the integration of sustainability considerations into digital infrastructures, and the cultivation of agile, innovation-centric environments capable of responding to complex and volatile market conditions [12, 31, 92]. Particularly problematic is the persistent fragmentation between technology-centric advancements—such as machinery upgrades, IoT deployments, and data analytics—and the organizational and human-centric factors, including:

Digital shopfloor leadership; Worker upskilling and continuous education; Maturity models for digital management and governance [48].

The ascent of Industry 4.0 is therefore best conceptualized as a globally networked, multidimensional, and evolutionary process [89]. Its timeline features both technological milestones—such as the implementation of distributed ledger technologies and the convergence of physical and digital domains via digital twins—and strategic turning points that highlight the imperatives of interoperability, standardization, and privacy protection within digitally advanced environments [40, 49]. As the field evolves, the introduction of “Industry 5.0” in European policy discourse signals a pivotal transition toward a value-centric industrial paradigm. This evolution, which both builds upon and complicates the foundations of Industry 4.0, raises consequential questions about the alignment of technology, organizational practice, and societal values. Accordingly, it establishes fertile ground for ongoing inquiry into the future architecture and societal embedding of manufacturing systems.

## 2 Foundational Technologies and Frameworks in Smart Manufacturing

### 2.1 Digital Twin Technology: Concepts and Core Enablers

The paradigm of smart manufacturing is fundamentally anchored in the advancement and integration of digital twin (DT) technology. Digital twins offer virtual counterparts that dynamically mirror the states, behaviors, and evolutionary trajectories of physical assets and systems across their life cycles. These digital surrogates are maintained through the orchestration of multi-physics modeling, high-fidelity simulations, and advanced mechanisms for real-time data acquisition and fusion. Such synergy enables the translation of complex, heterogeneous sensor data into actionable manufacturing intelligence [40]. The capability to simulate and visualize multi-domain system interactions at both macro and micro scales provides unprecedented insights into process dynamics, system integrity, and emergent behaviors.

A distinguishing characteristic of next-generation digital twins is the seamless convergence of big data analytics and advanced visualization. Real-time data streams—acquired via IIoT devices, RFID sensors, and distributed edge-computing nodes—not only secure synchronization between physical and digital layers but also underpin sophisticated event management, predictive maintenance, and anomaly detection [17, 18, 25, 27, 29, 31, 34, 39, 40, 43, 47, 51, 54, 60, 61, 65, 66, 68, 69, 76, 78, 79, 91]. The rise of modular and reconfigurable architectures, especially those leveraging edge intelligence, has become pivotal for enabling scalability, reducing latency, and fostering context-aware response in distributed manufacturing settings [40]. For instance, distributing control intelligence from centralized controllers to IIoT-enabled edge modules achieves near-centralized accuracy while enhancing system flexibility and real-time responsiveness, as evidenced by rigorous test scenarios [38].

The principal architectural frameworks of digital twins in smart manufacturing are shaped by interoperability, modularity, and dynamic reconfiguration. Unlike rigid automation pyramids, contemporary models adopt agent-based, holonic, or modular structures, promoting deep integration between the physical, communication, and application layers [21]. This adaptability permits dynamic decomposition and recomposition of systems in response to market fluctuations, equipment failures, or process anomalies [38]. Nonetheless, as digital twins increasingly encounter unstructured and semi-structured data streams, future systems must evolve their automated data integration and evaluation mechanisms. Relying on proprietary or ad hoc solutions will be inadequate; robust, standardized approaches to data handling are critically needed [40].

Despite notable advancements, substantial challenges remain in realizing fully autonomous, real-time, and scalable decision support. Persisting issues include semantic and technical interoperability, especially in heterogeneous, multi-vendor contexts [21]; secure and effective fusion of heterogeneous data; and the integration of advanced analytics with reliable, real-time communication. Meeting these requirements demands co-evolution of cybersecurity, standardized interfaces, and adaptive orchestration strategies to enable predictive, adaptive, and resilient manufacturing operations [17, 40].

Addressing such barriers necessitates ongoing cross-disciplinary research in control engineering, computer science, and industrial informatics.

## 2.2 Artificial Intelligence and Computer-Aided Manufacturing

Artificial intelligence (AI) represents a transformative catalyst in advancing smart manufacturing. The application of AI methodologies has redefined process optimization, intelligent control, and strategic planning, equipping factories with powerful tools to manage complexity, uncertainty, and rapid change with enhanced accuracy and autonomy [1, 15, 18, 29, 31, 34, 37, 40, 46, 47, 54, 58, 60, 66, 67, 69, 78, 84, 87]. AI-driven approaches encompass a diverse range—from classical scheduling algorithms and shop floor management solutions to data-driven techniques such as deep reinforcement learning for real-time adaptive control of reconfigurable systems.

A salient trend is the hybridization of AI with deterministic, global, and heuristic optimization paradigms. This synthesis has produced advanced process optimization techniques capable of overcoming limitations of traditional methods, especially in non-convex and high-dimensional spaces. Embedded artificial neural networks (ANNs) now play a key role in surrogate modeling and decision support. Recent developments showcase that integrating deterministic relaxations—such as McCormick relaxations for nonconvexities or semidefinite/quasi-convex relaxations—within optimization frameworks results in significant improvements in both accuracy and computational efficiency for process simulation and planning [1, 10, 44, 50, 70].

The principal advantages of these AI-enabled frameworks include:

**Enhanced adaptability:** Effective handling of dynamic, complex, and even chaotic manufacturing environments [60, 66]. **Data-driven insight extraction:** Proficiency in distilling actionable insights from noisy, voluminous, and high-velocity data streams. **Capacity for self-learning:** Facilitation of continuous improvement through feedback-rich, closed-loop decision systems.

For instance, multi-agent reinforcement learning (MARL) frameworks enhanced with knowledge graphs or graph convolutional architectures have demonstrated substantial improvements in adaptive scheduling and layout planning under stochastic events, resource failures, or personalized production requirements [18, 46]. In particular, knowledge graph-enhanced MARL enables agents to incorporate semantic communication, such as dynamic machine capability and allocation preferences directly into their decision processes, yielding accelerated convergence and improved performance in adaptive scheduling under mass personalization [60]. Additionally, graph convolutional network-based MARL architectures enable the extraction of global coordination features from unstructured shop floor data, showing enhanced scalability and robustness in solving flexible job shop scheduling problems in dynamic and distributed settings [29, 34].

Nevertheless, significant obstacles remain in generalizing AI models across diverse tasks and environments. Research underscores the necessity of embedding domain knowledge, enabling semantic communication, and fostering explainable AI solutions to ensure resilience under changing conditions, non-stationary data,

and unforeseen operational scenarios [31, 46]. For example, knowledge graph-based analysis frameworks facilitate ad hoc queries and reasoning but still face challenges integrating heterogeneous industrial datasets and supporting efficient insight extraction in complex scenarios [47]. Further unresolved issues include the creation of unified benchmarking standards, ensuring the transferability of solutions from simulation to real-world deployment, and formalizing industrial reliability and safety metrics—particularly relevant for reinforcement learning systems in safety-critical domains [54, 58]. Open challenges such as scalability, the need for policy retraining with evolving environments, standardization of evaluation metrics, online adaptation, and ensuring explainable and safe AI operation highlight a persistent demand for advancements not only in algorithmic capability but also in systems engineering, domain adaptation, and explainability.

## 2.3 Computer-Aided Process Optimization and Planning

Contemporary computer-aided manufacturing (CAM) and process optimization in smart manufacturing are marked by the integration of the digital thread, AI, and rule-based planning methodologies. The present landscape underscores the need for multi-objective optimization and real-time adaptive job shop management, driving the transition from fragmented automation islands to unified, interoperable digital ecosystems [2, 4, 14, 17, 18, 20, 34, 39, 43, 45, 47, 51, 54, 61, 63, 65, 66, 68, 69, 78]. AI/ML-driven and rule-based optimization engines provide the foundation for robust dynamic process planning, enabling flexible re-scheduling in response to anomalies, resource disruptions, or shifting operational priorities.

A major development in this domain is the adoption of VR-enabled manufacturing practices (VRMPs), empirically validated to enhance production efficiency—especially in multi-stage and volatile industrial settings [88]. VRMPs augment traditional CAM methods by supporting enhanced visualization, collaborative planning, and the reduction of decision-making bottlenecks. The growing adoption of additive manufacturing (AM) further expands this technological convergence, fostering adaptive, on-demand, and resource-efficient fabrication. Hierarchical, AI-driven methodologies for AM process planning effectively reduce build times, optimize material consumption, and improve surface quality by coordinating build and deposition strategies within a multi-objective optimization framework [5, 16, 18, 33, 39, 41, 47, 67, 69, 75, 77, 84, 85, 87, 93].

The implementation of the digital thread, which provides seamless data continuity across design, process planning, and manufacturing, increasingly supplants legacy silos [2, 68]. For example, automated feature recognition through standardized data formats like STEP facilitates direct translation from CAD to computer-aided process planning (CAPP), dramatically reducing the need for manual intervention and minimizing error [2].

To clarify comparative advances, a summary is presented in Table 2.

Nevertheless, the widespread deployment of these methods is impeded by challenges in automated recognition of intricate geometries and the development of robust, machine-readable semantic manufacturing representations.

Table 2: Comparative Advances in Automated Process Planning

Approach	Strengths	Limitations
Standardized Feature Recognition (e.g., STEP-based)	Seamless CAD-to-CAPP integration; reduced human intervention; improved accuracy	Challenges with complex geometries; dependency on semantic completeness
AI-driven Process Planning	Dynamic re-scheduling; multi-objective optimization; adaptive to anomalies	Reliability in unstructured environments; need for explainable output
Rule-based Systems	Predictable, interpretable operation; good for well-defined tasks	Rigidity against process variability; limited scalability to new task domains

In job shop contexts, recent innovations—including advanced anomaly detection, real-time rescheduling, and multi-objective optimization—leverage swarm intelligence, hybrid machine learning, and digital twin-enabled feedback [18, 47, 54, 66]. Though these advancements yield gains in productivity, robustness, and resource utilization, persistent barriers remain in the integration of legacy systems, assurance of data security, and achievement of consistent interoperability and scalability.

2.4 Simulation-Based Evaluation and Modeling

This subsection examines the objectives, methodologies, and open challenges in simulation-based evaluation and modeling for smart manufacturing systems. Our focus is to investigate how simulation technologies contribute to improving productivity, optimizing system architectures, and enabling data-driven manufacturing decisions.

Simulation technologies are pivotal for the evaluation, optimization, and advancement of smart manufacturing systems. Platforms such as MATLAB Simulink empower manufacturers to model equipment behavior, assess control strategies, and optimize system architectures before physical implementation [3]. High-fidelity simulations facilitate systematic analysis of process variables, equipment configurations, and environmental perturbations, enabling precise evaluation of impacts on product quality and system performance.

Simulation assumes particular importance in domains where direct experimentation is either cost-prohibitive or technically unfeasible, such as electric vehicle (EV) powertrain development or precision machining process design. For instance, Vashist and Singh [3] simulate the complete EV powertrain—including the permanent magnet synchronous motor, power converter, controller, and battery—using MATLAB Simulink to evaluate performance across diverse conditions. Their work demonstrates that simulation not only reduces time and costs, but also serves as a critical tool for co-simulation and assessment of control algorithms in complex system design. Real-time simulation and analytics support rapid prototyping, parameter calibration, and virtual commissioning—substantially reducing temporal, financial, and risk-related costs compared to iterative physical trials. Critically, when integrated with digital twins and closed-loop feedback, simulation platforms transition from passive evaluative tools to active elements of predictive and self-optimizing manufacturing systems.

Nonetheless, several limitations persist. These include: modeling fidelity; data availability; computational demands associated with high-dimensional, nonlinear systems; and the seamless integration of shopfloor data into simulation environments. Further, rigorous validation of simulation outputs against real-world performance metrics requires ongoing methodological innovation, particularly as manufacturing systems progress toward higher levels of interconnectivity, autonomy, and complexity.

Emerging frameworks in simulation-based modeling, such as those leveraging AI-driven optimization and digital twin architectures, aim to close the gap between virtual and physical manufacturing environments. These frameworks increasingly emphasize automated model refinement, adaptive process control, and data fusion strategies, facilitating more robust and scalable simulation processes.

Key takeaways from this discussion are: (1) simulation enables both cost-effective and high-fidelity analysis of complex manufacturing systems prior to deployment; (2) integration with digital twins and AI augments the predictive and adaptive capabilities of simulation platforms; (3) persistent challenges relate to model fidelity, computational scalability, shopfloor integration, and the validation of simulation-based insights.

Open challenges remain in advancing simulation techniques, particularly in supporting real-time, large-scale, and cross-domain modeling. Developing interoperable frameworks that can seamlessly link live process data, simulation environments, and decision-support tools is an ongoing research imperative. Addressing these issues will be vital for the realization of truly autonomous, adaptable, and resilient production ecosystems.

3 Industry 4.0 Pillars, Frameworks, and Architectures

Section Overview and Objectives

This section provides a comprehensive review of the foundational pillars, enabling frameworks, and reference architectures that define Industry 4.0. The main objectives are to (1) distill the critical components underpinning Industry 4.0, (2) examine prevailing organizational and technological models, (3) synthesize methodological trends with a focus on productivity and simulation, and (4) identify research gaps and challenges guiding future developments in the field. Each subsection will clarify its specific goals and conclude with a brief summary of key takeaways and current open questions.

3.1 Industry 4.0 Pillars

Objective:

To identify and examine the core technological and organizational pillars that form the basis of Industry 4.0, and to synthesize insights on their individual and synergistic contributions to the transformation of industrial ecosystems.

Discussion:

The essential pillars typically encompass Cyber-Physical Systems (CPS), the Internet of Things (IoT), Cloud and Edge Computing, Artificial Intelligence (AI), Big Data Analytics, and advanced robotics. These elements function both independently and collectively to foster highly connected, intelligent, and adaptive manufacturing environments. The literature consistently discusses productivity enhancements achieved through real-time data integration

and autonomous process optimization. Simulation technologies are highlighted as critical enablers for virtual prototyping and system validation; however, more critical analysis is needed regarding their impact on production scalability and interoperability challenges.

Open research questions include determining robust metrics for cross-domain productivity gains, the integration of legacy systems with modern architectures, and the development of unified simulation platforms that can adapt to evolving industrial demands.

#### **Key Takeaways:**

Industry 4.0 pillars constitute a multi-layered foundation that drives digital transformation. Synthesis of diverse technologies presents new efficiencies, but also introduces fresh challenges in scalability and interoperability. Further research is necessary to establish standardized frameworks that can support integrated simulation and legacy system adaptation.

### **3.2 Industry 4.0 Frameworks**

#### **Objective:**

To review and critically analyze leading organizational and technological frameworks that guide Industry 4.0 implementations, with attention to comparative advantages and current limitations.

#### **Discussion:**

Frameworks such as the Reference Architecture Model Industry 4.0 (RAMI 4.0), Industrial Internet Reference Architecture (IIRA), and Smart Manufacturing frameworks provide structured blueprints for integrating and governing complex industrial systems. These frameworks highlight aspects such as layered interoperability, modular design, and governance structures essential for sustainable digital transformation. Comparative analysis reveals that while these models address common needs—such as communication, data integrity, and decision support—they diverge in scope, granularity, and adaptability across industry sectors. Methodological evaluations stress the need for critical synthesis of frameworks to address gaps in vertical and horizontal integration.

Open challenges relate to harmonizing competing standards, ensuring scalable security mechanisms, and developing consensus around adaptive process models that address industry-specific requirements.

#### **Key Takeaways:**

Adoption of standardized frameworks accelerates Industry 4.0 realization but is hampered by fragmentation and context-dependent requirements. There is a clear opportunity for the development of new, integrative taxonomies and frameworks that bridge current gaps between existing models and sector-specific needs.

### **3.3 Industry 4.0 Architectures**

#### **Objective:**

To summarize and assess the reference architectures proposed for Industry 4.0, emphasizing their roles in facilitating interoperability, modularity, and digital integration within complex industrial environments.

#### **Discussion:**

Reference architectures provide the structural foundation for specifying component roles, data flows, and system hierarchies in Industry 4.0 systems. State-of-the-art architectures incorporate principles such as service orientation, semantic interoperability, and

security-by-design. Nonetheless, reviews highlight ongoing limitations, including lack of compatibility with legacy infrastructure and difficulties in process simulation integration.

Current research questions include identifying universally applicable architectural patterns, supporting dynamic reconfiguration, and ensuring privacy-preserving data exchange between stakeholders.

#### **Key Takeaways:**

While existing architectures have advanced the digital enablement of industry, unresolved issues related to modularity, backward compatibility, and security remain. Continued research must prioritize open, flexible architectures capable of evolving alongside industrial requirements.

### **Section Synthesis**

This section outlined the primary pillars, frameworks, and reference architectures that shape Industry 4.0. Key insights reveal the need for unified and adaptive standards, integration strategies for legacy support, and new research toward comprehensive simulation and interoperability solutions. Open research challenges across all subsections highlight the dynamic and evolving nature of Industry 4.0, underscoring the need for continual methodological innovation.

### **3.4 Technological Pillars and Evolution**

The Industry 4.0 paradigm marks a transformative era within the manufacturing sector, fueled by the convergence of cutting-edge digital technologies such as cyber-physical systems (CPS), the Industrial Internet of Things (IIoT), distributed ledger technologies (DLT), and emerging metaverse platforms. Central to this transformation is the shift from traditional, rigid hierarchical control structures—epitomized by the ISA-95 automation pyramid—toward more dynamic, flattened architectural models that emphasize edge-cloud integration, interoperability, and service orientation [9, 18, 22, 34, 39, 46, 47, 54, 61, 65, 68, 78, 91]. This architectural evolution is driven by the need for real-time responsiveness, enhanced system resilience, and highly customized, flexible production.

The progression away from the monolithic ISA-95 hierarchy has given rise to hybrid architectures that exploit the strengths of industrial edge computing and cloud platforms. This modernization supplants legacy automation layers with composable microservices fabricated through containerization and orchestrated deployment approaches [9]. Adopting standards such as IEC 61499 further promotes interoperability, enabling seamless integration across both operational technology (OT) and information technology (IT) domains. Of particular significance is the emergence of agent-based and holonic manufacturing architectures, which underpin decentralized decision-making and improved system modularity—attributes that are crucial for achieving adaptive and resilient production networks [46, 68].

Simultaneously, the proliferation of advanced analytics, increased platformization, and enhancement of secure communication mechanisms have ushered in novel modalities for human-machine and machine-machine interaction. Technologies such as digital twins, knowledge graphs, and real-time, data-driven feedback loops now play a central role in optimizing production processes and assuring quality standards [22, 47, 65, 86].

Despite these remarkable advancements, significant challenges persist. The introduction of more autonomous, flexible architectures brings increased system complexity, risks of anti-patterns, and potential integration bottlenecks. Organizations must carefully balance the advantages of distributed intelligence against the imperatives for robust, secure, and manageable operations [39, 48, 68]. Furthermore, the swift uptake of enabling technologies frequently surpasses the pace at which standardized, secure, and interoperable manufacturing frameworks are established.

### 3.5 Decentralized Identity Management and Security

The growing interconnectedness of manufacturing environments—enabled by IIoT, CPS, and immersive metaverse interfaces—has elevated the urgency for robust, adaptive identity management and security systems. Traditional, centralized approaches to identity are increasingly inadequate for the distributed, interoperable, and privacy-sensitive realities of Industry 4.0, where agile authentication and access control must be maintained across diverse, autonomous platforms and stakeholders [18, 32, 37, 43, 46, 47, 54, 61, 65, 66, 69, 78, 79].

In this context, self-sovereign identity (SSI) models—leveraging distributed ledger and blockchain technologies—are emerging as foundational enablers for privacy-preserving digital identity in manufacturing. SSI systems facilitate decentralized authentication and access control, ensuring secure and flexible interactions that span organizational and technological boundaries, including within metaverse-enabled manufacturing environments and supply chains [48].

The movement toward SSI is anchored by international security standards, such as IEC 62443 and ISO/IEC 27001, which define foundational requirements but often lack concrete guidance for decentralized, dynamic, and immersive manufacturing contexts. The complexity of digital system layering compounds these challenges, particularly during integration with legacy infrastructure, which is further complicated by existing regulatory and compliance landscapes.

Further technical and legislative challenges arise in harmonizing secure interoperability across a heterogeneous array of interfaces, including mobile devices, AR/VR platforms, and conversational systems such as chatbots. These digital extensions escalate the potential attack surface and necessitate sophisticated, adaptive security strategies—especially as digital interfaces increasingly mediate both human-operator training and real-time plant interactions [37, 46, 91].

Despite ongoing efforts, several persistent challenges must still be addressed: Achieving alignment with evolving privacy and regulatory requirements; Overcoming resistance inherent in deeply embedded legacy identity and security systems; Validating SSI approaches through large-scale, cross-industry industrial deployments. Integrating SSI within distributed manufacturing and metaverse domains shows significant promise, but realizing this potential demands robust standardization, industry-wide collaboration, and rigorous empirical validation.

### 3.6 The Role of Data Access, Collection, and Analytics in Smart Manufacturing

Smart manufacturing fundamentally relies on secure, real-time data acquisition and the effective deployment of advanced analytics capabilities. The integration of heterogeneous data streams—which often extend from legacy machine sensors to cloud-based analytics platforms—remains a pivotal challenge and a significant opportunity. Successful data access and collection enable the extraction of actionable intelligence, foster the development of hybrid machine learning and physics-informed models, and drive the continuous improvement ethos [86].

Advanced analytics pipelines have proven to increase decision-making accuracy, optimize resource allocation, and facilitate predictive maintenance. Nonetheless, the manufacturing context presents unique obstacles:

- Data silos fragment information flows;
- A lack of data formalization impedes scalable integration;
- Limited reasoning capabilities restrict the efficacy of analytics solutions.

As a response, hybrid modeling frameworks—integrating first-principles with data-driven approaches—have emerged, offering enhanced explainability, adaptability, and robustness across smart factory deployments. Concurrently, developments in knowledge graph technologies and data standardization initiatives provide avenues to democratize data access and support ad hoc, on-demand analytical pursuits.

The full realization of technical capabilities, however, is often hindered by non-technical barriers. Most notably, the speed of technological adoption often surpasses the pace at which organizational cultures, workforce competencies, and managerial mindsets adapt to these new paradigms. Addressing these cultural and organizational dimensions is crucial to achieving the maximum potential of smart manufacturing infrastructure.

### 3.7 Enabling Technologies: AI, AR/VR, Robotics, and Digital Twins

Key enabling technologies—including artificial intelligence (AI), augmented and virtual reality (AR/VR), robotics, and digital twins—form the operational backbone of Industry 4.0, facilitating intelligent, adaptive, and synergistic manufacturing environments.

AI-driven analytics empower advanced process control, predictive maintenance, and real-time anomaly detection, driving autonomous system responses to rapidly changing conditions on the shop floor [52]. Digital twins, in particular, serve as high-fidelity, virtual representations of physical assets and systems, providing platforms for advanced simulation, monitoring, and continual process optimization.

The integration of AR/VR techniques enhances collaboration and operator effectiveness by delivering immersive training and real-time process guidance. Documented field deployments indicate substantial benefits, including increases in production throughput, reductions in defect rates and operational costs, and dramatic improvements in training effectiveness and operator safety. For example, an automotive manufacturing case study reported a 27% rise in production throughput, 35% reduction in maintenance costs,

42% decrease in defect rates, and a 65% improvement in training effectiveness after deployment of AI, AR/VR, robotics, and digital twin technologies [52]. AR-guided operations and VR training contributed to a 45% reduction in robot programming time and significantly enhanced operator accuracy and competency.

Modular, scalable architectures that synergistically combine digital twins, layered data acquisition pipelines, and human-centered AR/VR interfaces have accelerated digital transformation efforts, yielding both improved operational safety and significant economic returns. The cited smart manufacturing initiative achieved a 185% ROI over two years and projected multi-million dollar savings, attributing success to its phased rollout, robust data integration, and comprehensive workforce training [52].

Nevertheless, critical challenges remain, such as integrating real-time data across traditionally siloed systems, overcoming organizational inertia and managing resistance to change, and addressing security vulnerabilities inherent in highly connected environments. Successfully mitigating these obstacles necessitates a multi-disciplinary approach characterized by robust change management, phased technology rollouts, and comprehensive workforce development strategies. Maintaining modularity and interoperability as foundational architectural principles is key for sustainable evolution in both technological and business dimensions.

### 3.8 The Rise of Data-Driven and AI-Enabled IoT Systems in Manufacturing

The ascendance of data-driven and AI-enabled IoT systems has inaugurated a new era of autonomous, efficient, and intelligent manufacturing processes. These integrated systems facilitate advanced monitoring, holistic process optimization, and the orchestration of complex, adaptive workflows [82]. Autonomous, networked machines leverage IIoT platforms to exchange real-time data for predictive analytics, self-organization, and the continuous optimization of both product quality and resource utilization.

The symbiotic interaction between AI and IoT not only expands the operational capabilities of manufacturing enterprises but also accelerates the transition toward more sustainable and flexible production models. However, realizing these benefits requires the overcoming of significant technical challenges, particularly those relating to:

- Integration and interoperability between heterogeneous and legacy infrastructure;
- Navigating evolving environmental and ethical sustainability imperatives;
- Building open, secure, and scalable frameworks for future-proof operations.

Fundamentally, the ongoing momentum toward AI-driven IoT adoption is sustained by continuous advancements in wireless networking, cloud-edge orchestration, and robust data governance methodologies. However, the long-term success of these transformations remains inextricably linked to organizations' abilities to deploy open, secure, and interoperable frameworks—while fostering the internal readiness necessary for continuous, technology-driven change. As illustrated by Table 3, addressing integration, security, sustainability, and organizational readiness is vital for unlocking the next generation of smart manufacturing systems.

## 3.9 Productivity, Efficiency, and Process Optimization

**3.9.1 Productivity Measurement Methodologies.** The accurate measurement of productivity in industrial and service settings is foundational for both scholarly research and practical operational advancement. Classical methods are rooted in index number theory, notably the Laspeyres, Paasche, Fisher, and Tornqvist indexes, which facilitate comparative assessments of output dynamics by employing varying schemes for weighting base and current period data [92]. Although these indices are analytically convenient and have achieved widespread usage, their effectiveness is often compromised by aggregation challenges and restrictive underlying assumptions—such as the homogeneity of units and neutrality of technological change—which may limit their validity in diverse or rapidly evolving environments.

To address these limitations, modern productivity analysis has progressed toward frontier-based techniques, such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). These methods facilitate the decomposition of observed productivity into factors attributable to efficiency and technological change, as systematically captured in the Malmquist Productivity Index (MPI) [92]. Such models not only enable rigorous benchmarking but also excel in complex operational contexts featuring multiple inputs and outputs. Nevertheless, the extension of productivity studies to more granular and diverse settings has introduced fresh inferential challenges. In particular, reliance on asymptotic properties may be problematic—especially when finite sample sizes prevail—and robust aggregation across heterogeneous organizational units or timeframes remains difficult.

With the recent advent of digital transformation—including the proliferation of big data and artificial intelligence—productivity measurement has entered a new era. Enhanced data integration capabilities allow for fine-grained, near real-time analysis of productivity drivers, offering diagnostic precision unattainable by prior methods [92]. However, this technological progress accentuates the need for methodological unity, as the current landscape is fragmented across disciplinary boundaries. To this end:

AI-driven causal inference tools offer potential to relax assumptions of exogeneity and constant returns to scale,

State-of-the-art big data platforms are poised to resolve long-standing concerns regarding aggregation,

Such advances are contingent on transparency and methodological rigor to ensure robustness and validity [92].

**3.9.2 Advances in Efficiency Estimation.** Methodological advances have substantially enriched the toolkit for efficiency estimation, particularly by addressing the constraints of traditional DEA and SFA methods. Central among these innovations is the refinement of statistical inference procedures for use in small-sample or high-dimensional settings, where classical asymptotic approximations often result in underestimated confidence intervals and potentially misleading empirical conclusions. Contemporary approaches now include bias-corrected estimators, variance correction techniques, and sophisticated Monte Carlo simulation frameworks, which collectively enable more accurate inference from limited datasets—an essential improvement for sectors such as healthcare and finance, where large samples are typically unavailable [73].



**Table 3: Core Challenges and Opportunities for Data-Driven and AI-Enabled IoT Manufacturing Systems**

Area	Key Challenges	Opportunities
Integration & Interoperability	Legacy system incompatibility; Data silos; Heterogeneous device standards	Unified data models; Platform-based integration; Plug-and-play componentization
Data Security & Privacy	Vulnerable endpoints; Evolving compliance requirements; Attack surface expansion	End-to-end encryption; Decentralized identity schemes; Adaptive access control models
Sustainability	Environmental impact of digital transformation; Resource optimization pressures	Energy-efficient architectures; Closed-loop manufacturing; Real-time sustainability analytics
Organizational Readiness	Workforce skills gap; Change resistance; Lack of digital culture	Targeted retraining; Cross-functional teams; Leadership in digital transformation

For example, recent work has advanced variance estimation by utilizing bias-corrected individual DEA efficiency estimates for constructing confidence intervals, rather than relying on standard uncorrected estimators. Specifically, the approach entails estimating the variance using  $(\hat{\lambda}_i - \hat{B}_i)$  rather than  $\hat{\lambda}_i$ , where  $\hat{B}_i$  denotes the bias estimate for each unit. This full variance correction allows the construction of confidence intervals with empirical coverage that approaches nominal levels even under adverse conditions such as small sample sizes or high-dimensional data settings [73]. For instance, empirical studies demonstrate that, for settings like  $n = 100$  and moderate input/output dimensions, coverage can improve dramatically—from severe undercoverage to values near the target nominal rate. This methodology achieves these improvements without additional computational cost and maintains desirable asymptotic properties. The approach may also be supplemented by “data sharpening” procedures, which further enhance interval coverage, particularly in challenging cases. Importantly, for alternative estimators such as the free disposal hull (FDH), these corrections can provide even more pronounced benefits.

Nonetheless, while these statistical advances mark significant progress, their effectiveness is still conditional upon adequate sample size and data quality; some risk of over-coverage remains, although this is typically considered less problematic than undercoverage. Additionally, further research is required to refine the methods to mitigate remaining finite-sample errors and to extend their applicability to other efficiency estimators and dynamic, process-level analyses, underscoring the ongoing need for methodological innovation [73].

**3.9.3 Process Modeling and Scheduling Optimization.** This section aims to present a comprehensive survey of leading methodologies for process modeling and scheduling optimization in industrial and manufacturing contexts. The objectives are to clarify the current landscape of approaches, critically discuss their integration and effectiveness, highlight ongoing debates in the literature, and assess practical challenges and opportunities for durable implementation.

Optimization of industrial processes increasingly relies on a suite of analytical and computational tools designed to maximize productivity while reducing costs and inefficiencies. Lean management, for example, targets waste reduction by systematically analyzing workflows, inventories, and work-in-process, whereas Facility Layout Design (FLD) emphasizes the spatial organization of resources to minimize material handling and unnecessary travel [35]. Although research often investigates these approaches separately, a significant strand of recent literature argues for their combined application. For instance, Kovács [35] demonstrates that integrating Lean principles with FLD results in substantially greater improvements in efficiency, cost reduction, and a broad set of both quantitative and qualitative key performance indicators than can be achieved with either approach in isolation. However, debates persist regarding the

transferability of such combined strategies across heterogeneous manufacturing contexts, as not all facilities may benefit equally from joint interventions, particularly when constraints related to existing infrastructure or organizational culture are present.

Beyond facility design, the field further extends to the sequencing and scheduling of process operations. Dolgui et al. [11] point out that the aggregation of intersecting and ordered machining tasks into optimal execution blocks can considerably decrease both production time and costs. Their research elucidates that for tree-structured process intersections, dynamic programming yields tractable solutions, whereas general intersection graphs—arising commonly in complex, multi-tool machining settings—necessitate heuristic methods given their computational intractability. While empirical case studies show machining time reductions of up to 30%, practical application often requires a balance between modeling granularity and solution scalability. The literature reflects ongoing debate about the trade-offs between exact and approximate algorithms, particularly as the complexity of intersection topologies and technological interdependencies increase [11].

For scenarios typified by high uncertainty or involving mixed-variable decision spaces (both continuous and categorical), robust, derivative-free, and adaptive optimization frameworks are gaining prominence [10, 62]. Nannicini [50] details how RBFOpt, an open-source solver, utilizes unary encoding for categorical variables, interpolation models without the unisolvence condition, and a parallelized master-worker framework to address black-box objectives efficiently. Meanwhile, frameworks such as distributionally robust optimization (DRO) integrate concepts from risk aversion, robust optimization, and statistical regularization to provide well-founded solutions under distributional ambiguity [62]. Rahimian and Mehrotra [62] identify both the theoretical advances gained by DRO in unifying these perspectives and the ongoing challenges in characterizing and calibrating distributional uncertainty.

As Table 4 highlights, these diverse methods expand the frontiers of process optimization, yet key differences and ongoing research debates shape their implementation and evolution.

Contemporary technological infrastructure further supports these analytical advances. Cloud and edge computing enable scalable and real-time process optimization through integration of sensor data, big data analytics, and distributed control [56]. However, literature draws attention to challenges in data integration and technology transfer, particularly regarding legacy systems and data silos, which continue to impede seamless deployment in many industrial settings.

The practical impacts of these optimization strategies are exemplified by the automation of labor-intensive and ergonomically challenging manufacturing tasks. Pinto et al. [59] detail a compact pneumatic robotic solution for post-casting operations in the automotive industry that achieves a 39% reduction in production time,

**Table 4: Summary of Selected Optimization Approaches and Their Core Features**

Methodology	Core Features	Applicability/Strengths
Lean + Facility Layout Design (FLD)	Systematic waste reduction, spatial resource optimization	Synergistic improvement in productivity, cost, ergonomics; debated transferability across heterogeneous contexts
Dynamic Programming (with Heuristics)	Block aggregation; algorithmic scheduling for intersecting tasks	Near-optimal machining time reductions for structured/complex tasks; debates about scalability and model fidelity
RBFOpt (Open-source Solver)	Derivative-free, adaptive global optimization; categorical variable handling; parallelism	Efficient for black-box, mixed-variable, uncertain problems; flexibility in early-stage optimization
Distributionally Robust Optimization (DRO)	Integrates risk aversion, robust optimization, regularization	Effective under distributional uncertainty; theoretical debates on calibration and tractable reformulation

eliminates repetitive manual interventions, and maintains operational flexibility with rapid changeovers and validated safety. While such automation delivers demonstrated improvements in productivity and workplace safety, other studies caution that the benefits may depend on tailoring designs to local operational requirements and ensuring robust validation and maintenance protocols.

In summary, while process modeling and scheduling optimization techniques present significant opportunities for enhancing industrial performance, the literature continues to debate the generalizability, scalability, and integration of these methods. Rigorous validation, human-centered design, and continuous adaptation remain central imperatives to translating analytic sophistication into measurable, durable improvements across heterogeneous manufacturing environments.

## 4 Data-Driven, AI-Based, and Autonomous Optimization

This section aims to provide a comprehensive overview of recent advances in data-driven, AI-based, and autonomous optimization methods. The objectives are threefold: (1) to clarify emerging trends and the core challenges unique to this paradigm, (2) to synthesize opportunities and open problems, including research debates, and (3) to support the reader's understanding by offering consistent formatting and clear transitions between organizational and technical themes.

Data-driven optimization harnesses large-scale data and learning-based techniques to adaptively improve system performance, often relying on AI or machine learning mechanisms. These methods are characterized by their flexibility in modeling complex environments and their ability to learn implicit behaviors from observed data. However, transitioning from traditional algorithmic optimization to fully autonomous, AI-driven solutions introduces several research debates and conflicting perspectives within the literature. For instance, there is an ongoing discussion on the trade-off between model interpretability and performance, with some streams of research prioritizing explainability while others focus solely on empirical efficacy. Furthermore, the reliability, reproducibility, and trustworthiness of data-driven optimization solutions remain active areas of inquiry.

A major organizational focus within this field is the movement toward autonomous optimization, which seeks less or entirely no human intervention in the operational loop. When discussing technical challenges, the literature often highlights opportunities such as scalability to large systems and real-time decision-making capabilities. However, these are contrasted by persistent challenges, including handling noisy or biased data, ensuring robustness to distribution shifts, and mitigating ethical concerns resulting from opaque AI methods.

In transitioning from organizational to technical topics, it is crucial to synthesize the preceding discussions. While the potential for self-configuring and adaptive optimization systems appears promising, practical deployment is frequently hampered by the immaturity of generalizable frameworks and a lack of standardized benchmarks for empirical validation.

Open problems remain especially pronounced in more nascent sub-areas, such as fully autonomous optimization for dynamic, unstructured environments. Questions persist regarding the safe integration of AI-driven controllers, the scalability of autonomous techniques to complex real-world systems, and the development of principled evaluation procedures for emerging methods.

In the following subsections, we first present foundational definitions and key methodologies that underpin data-driven and AI-informed optimization. We then detail recent technical developments and articulate the main opportunities and outstanding challenges. To ensure consistency and ease of reference, all citations are formatted using the standard [] style, and the bibliography is presented in the concluding section of this paper. Throughout the section, we provide brief syntheses when shifting between high-level organizational perspectives and detailed technical discussions to facilitate understanding and maintain clarity.

### 4.1 Autonomous Closed-Loop Optimization

The advent of autonomous closed-loop optimization, empowered by machine learning (ML) and robotic platforms, is fundamentally transforming optimization strategies in complex, multi-parameter industrial environments. Contemporary workflows combine robotics-driven experimentation with ML-based decision algorithms, facilitating systematic exploration of both categorical and continuous process variables in real time. In process control, such frameworks autonomously select experimental conditions, thereby reducing experimenter bias, expediting the discovery cycle, and maximizing process yields under operational constraints [8]. The use of interpretable models—which integrate domain expertise with algorithmic planning—is crucial for justifying automated decisions and fostering user trust and comprehension within industrial deployments.

**4.1.1 Case Study: Evolutionary Algorithms and Neural Networks in Semiconductor Manufacturing.** Semiconductor manufacturing provides a prominent example of the combined deployment of evolutionary algorithms and neural networks for process optimization [19]. Hybrid decomposition-based frameworks leverage evolutionary search techniques to navigate vast configuration spaces, while neural networks function as metamodels for representing complex, nonlinear process mappings. Application to semiconductor datasets, such as SECOM, has demonstrated that these approaches surpass conventional methods in terms of operational

efficiency, simultaneously optimizing yield and quality parameters [19]. Notably, integrating explainable AI techniques augments the interpretability of neural network decisions, enabling a more nuanced understanding of the relationships between process parameters and output quality. This interpretability is especially critical for regulatory compliance and process transferability within high-stakes domains such as semiconductor fabrication.

## 4.2 AI/ML Paradigms in Manufacturing

Contemporary manufacturing optimization relies on a broad spectrum of AI and ML paradigms, each contributing uniquely to process improvements and innovation. Supervised learning is pervasive for predictive modeling, quality estimation, and fault diagnosis, utilizing historical datasets to forecast future process states or detect deviations [15, 18, 29, 34, 37, 46, 47, 54, 60, 66, 67, 69, 78, 84, 87]. Unsupervised learning methods offer advantages for anomaly detection and clustering, particularly when labeled data is scarce or unavailable; these approaches can reveal subtle process anomalies or product defects, as demonstrated in manufacturing scenarios such as additive manufacturing quality control [18, 69]. Reinforcement learning (RL), encompassing both single-agent and multi-agent approaches, is gaining traction for adaptive scheduling, dynamic resource allocation, and online layout planning in flexible manufacturing environments. RL's self-improving policy learning is especially well-suited to stochastic, dynamic, and reconfigurable manufacturing networks [29, 47, 54, 58, 60, 66, 67, 78].

An important recent development is cobotic manufacturing, where collaborative robots guided by advanced AI and ML methods undertake complex, high-precision, and adaptive assembly tasks [34, 37, 47]. Hybrid approaches, combining imitation learning with RL, have achieved submillimeter assembly precision and enhanced sample efficiency by constraining policy search with expert demonstrations [47].

Despite these advancements, notable research challenges persist. Benchmarking standards remain inconsistent or absent, hindering rigorous comparison and practical transfer of methodologies across diverse industrial settings [58]. Formal guarantees regarding the stability and safety of AI/ML-driven systems, especially those in direct interaction with human operators or critical assets, are still underdeveloped. Transferability of trained models is further limited by heterogeneity in processes and evolving manufacturing system configurations.

Recent progress in multi-agent RL highlights both the promise and the boundaries of distributed intelligence for managing resources and schedules in manufacturing networks. The explicit integration of structured semantic knowledge—such as knowledge graphs encoding machine capabilities, historical allocations, and preferences—into agent learning frameworks accelerates convergence rates and facilitates more context-aware policies, as shown in adaptive scheduling [29, 60]. However, these advanced approaches face persistent obstacles, including the need for frequent retraining as system models and constraints evolve, scalability issues with growing system complexity, and considerable computational overheads. Additional open challenges involve addressing multi-agent

non-stationarity, preserving learning diversity to avoid policy collapse, and ensuring the security and integrity of decentralized data streams critical for industrial deployment [29, 34, 58, 60].

## 4.3 Real-Time Monitoring, Fault Detection, and Predictive Maintenance

Robust real-time process monitoring, rapid fault detection, and predictive maintenance are principal drivers of sensor fusion, advanced AI techniques (including deep learning and long short-term memory (LSTM) networks), and adaptive feedback controllers within manufacturing pipelines. Sensor data from diverse modalities—encompassing force feedback, machine vibration, and in-line imaging—are fused to create comprehensive digital twins that mirror real-world operational conditions with high fidelity [16, 18, 33, 39, 41, 47, 67, 69, 75, 84, 85, 93]. LSTM networks, in particular, are adept at capturing temporal dependencies within sensor streams, enabling accurate prediction of critical states such as thermal errors, surface finish quality, or machine faults [39, 75, 85, 93]. For instance, recent approaches leverage LSTM models combined with advanced signal decomposition and feature extraction to estimate detailed surface profiles in real time based on machinery vibration signals, achieving accurate assessment of both mid- and low-frequency components and supporting comprehensive online milling quality evaluation [85]. Further, innovative solutions exploit hybrid architectures and residual connections in neural networks, allowing error compensation even in the absence of direct process sensors and adapting machining strategies to practical constraints while significantly improving accuracy and robustness [75]. Visual and image-based monitoring systems, using deep convolutional architectures, not only provide high-accuracy classification of process instabilities but also yield continuous indicators that enable rapid responses to subtle defect transitions within additive manufacturing settings [16]. These advances collectively demonstrate that deep learning architectures are capable of reliably processing high-dimensional, heterogeneous sensor data for both anomaly detection and real-time predictive intervention.

Benchmarking frameworks and the availability of open, standardized datasets are essential for validating model generalizability and advancing the state of the art across production environments [3, 23, 55, 85]. Recent investigations highlight that, while deep learning architectures excel in extracting nuanced features and recognizing complex patterns, challenges remain regarding model reliability and interpretability in the presence of adversarial or previously unseen production scenarios. For example, physics-inspired analyses of neural network reliability have exposed key structural vulnerabilities in convolutional architectures when facing adversarial attacks, motivating ongoing research into more robust and explainable approaches [84]. The integration of real-time closed-loop feedback—wherein anomalies or deviations trigger immediate process corrections—has yielded notable performance improvements in both additive and subtractive manufacturing settings, supporting the transition toward fully autonomous quality management systems [41, 47, 85]. Notably, closed-loop systems employing deep neural models have enabled rapid detection and correction of CFRP composite defects, as well as dynamic scheduling adjustments based on digital twin feedback in job shops [39, 41].

Despite these advances, achieving scalability across heterogeneous equipment, diverse material types, and varying production volumes continues to demand the development of hardware-agnostic platforms and more resilient, transferable algorithms [23, 55]. Software frameworks that support scalable, real-time human action recognition, active process annotation, and seamless interaction of sensor modalities have demonstrated measurable reductions in assembly times and error rates, underlining the practical benefits of such integration [23].

Collectively, these developments signify an ongoing convergence of data-driven, AI-based, and autonomous optimization strategies. The resulting manufacturing processes are becoming increasingly adaptive, efficient, transparent, and interpretable, features that are essential for the next generation of industrial ecosystems characterized by complexity, variability, and rigorous quality standards.

## 5 Organizational Transformation, Human Capital, and Human-Centric Approaches

This section aims to systematically examine how AI-driven transformations are reshaping organizations, focusing on changes to structures, processes, and strategies, and to analyze the evolving role of human capital within these transformations. Furthermore, we seek to evaluate human-centric approaches that prioritize collaboration between AI systems and organizational actors, emphasizing adaptability, ethical considerations, and sustainable implementation. By clarifying objectives at the outset, we help orient readers to the coverage and intended takeaways of this section.

Organizational transformation in the context of AI often extends beyond mere technological adoption; it involves shifts in workflows, decision-making paradigms, and strategic vision. As organizations integrate AI technologies, there is an increasing necessity to recalibrate roles and responsibilities, invest in workforce upskilling, and foster cultures of innovation. The intersection of human capital development and organizational change remains contested, with ongoing debate regarding the pace, scale, and direction of transformation. Some scholars contend that successful AI initiatives hinge on deep organizational change and continuous workforce reskilling, while others argue for pragmatic incrementalism that mitigates disruption.

Throughout this section, we move between organizational perspectives and technical considerations. Each transitional point is accompanied by brief syntheses to clarify the shift in focus and to connect preceding discussions with subsequent themes, thereby enhancing the clarity and cohesion of the narrative.

Finally, we explicitly address unresolved issues and open research questions. While some aspects of AI-driven organizational transformation now benefit from robust literature and consensus, other areas—such as ethical evaluation frameworks, long-term workforce adaptation, and truly human-centric design methodologies—remain underexplored. The conclusion of this section returns to these gaps, highlighting future directions and opportunities for further inquiry.

For ease of cross-referencing, please refer to the comprehensive bibliography listed at the end of this paper for all sources cited in this section.

### 5.1 Digital Transformational Leadership and Change

The accelerating digitalization of industry fundamentally challenges established leadership paradigms, demanding a transition towards digital transformational leadership characterized by strategic agility and cultural adaptability. Empirical evidence demonstrates that such leadership not only drives organizational agility but also depends on the cultivation of a robust digital culture and the articulation of a coherent digital strategy, which are critical for harnessing ongoing technological advancements [28]. When leaders purposefully champion innovation and embed a digital mindset throughout the organization, alignment between strategic intent and technology adoption is significantly strengthened, thus magnifying the impact of leadership interventions on organizational adaptability and performance. Nonetheless, entrenched legacy systems and persistent resistance to change remain formidable obstacles, often impeding digital transformation (DT) initiatives despite strong leadership commitment. Comparative case studies of successful and unsuccessful digital transformations underscore the importance of organizational culture and strategic alignment. Firms that anchor transformation in ethical stewardship, active employee engagement, and inclusive practices display greater resilience to digital disruption, while those hindered by inertia or strategic misalignment are exposed to substantial existential risks [28]. Consequently, effective digital transformational leadership extends beyond mere advocacy for technological adoption; it requires the holistic orchestration of organizational values, structures, and processes to overcome deep-rooted socio-technical barriers.

### 5.2 Measuring and Evaluating Digital Transformation

Accurately assessing the value generated by digital transformation represents a critical and persistent challenge. Conventional return on investment (ROI) metrics, which predominantly focus on short-term financial outcomes, are inadequate for capturing the complex, multifaceted, and frequently intangible impacts of digital initiatives [80]. There is a growing consensus in the research community regarding the necessity for novel, value-oriented metrics that transcend efficiency gains and cost savings to account for enhancements in user experience, organizational agility, workforce adaptability, and innovative capacity. These evaluative frameworks should integrate both quantitative and qualitative dimensions, reflecting outcomes such as: employee upskilling and lifelong learning initiatives, enhanced customer personalization and satisfaction, increased process flexibility and adaptability, and societal well-being and ethical impact.

A notable obstacle is the absence of unified and universally accepted frameworks for evaluation, which complicates cross-industry comparisons and impedes evidence-based decision-making. Accordingly, current recommendations emphasize interdisciplinary collaboration to develop robust, context-sensitive indicators that are ethically informed, scalable, and capable of capturing the systemic nature of digital transformation. Such efforts are crucial to ensuring that organizations are able to assess digital initiatives in alignment with their strategic objectives and societal responsibilities.

### 5.3 Human-Machine Symbiosis and Collaboration

Industry 4.0 brings the design of human-centric systems to the forefront, where advanced automation is integrated with human expertise and well-being. Anthropocentric approaches to human-machine symbiosis advocate for technologies that augment—rather than replace—human abilities, stressing flexibility, resilience, and psychosocial well-being in industrial environments [42]. The 3I framework—Intellect (embedding human knowledge in technology), Interaction (intuitive human-technology collaboration), and Interface (user-centric engagement)—exemplifies this shift. By embedding operators' tacit knowledge into intelligent systems, facilitating smooth collaboration between humans and collaborative robots (cobots), and deploying accessible smart devices for interactive tasks, the framework promotes effective, inclusive cooperation on the factory floor [42].

Human-in-the-loop (HITL) methodologies operationalize these principles through advanced methods such as real-time action recognition, sensor fusion, and collaborative robotics augmented by AR/VR interfaces [18, 23, 30, 32, 34, 37, 43, 46, 54, 79, 83]. Empirical evidence demonstrates that these approaches can improve process efficiency and product quality—for example, deployment of AI-driven action recognition systems in assembly lines has led to reductions in both cycle times and error rates. Furthermore, these solutions support small and medium-sized enterprise (SME) upskilling and facilitate knowledge transfer by capturing and disseminating tacit expertise across generational boundaries. Despite these benefits, several barriers persist, such as the demands of data annotation, the high cost of advanced solutions for SMEs, and the technical complexity involved in integrating modular AI solutions into pre-existing workflows.

Personalization and assistive technology offer further avenues to realize inclusive digital transformation. IoT-enabled multi-agent systems (MAS), supported by cloud and edge computing, empower individualized responses tailored to operators' needs, operational contexts, and diverse accessibility requirements [83]. The development of comprehensive navigation aids for visually impaired individuals, for instance, exemplifies the broader societal reach of Industry 4.0: inclusive design practices that integrate computer vision and cost-effective hardware provide tangible benefits beyond mainstream manufacturing settings [71]. These advances highlight the critical importance of balancing automation with personalization and inclusivity, ensuring that digital transformation initiatives uphold a diversity of human values and capabilities.

A comparison of key elements shaping human-machine collaboration under Industry 4.0 is presented in Table 5.

In summary, successful organizational transformation within the context of Industry 4.0 hinges not only on visionary leadership and technological sophistication, but equally on the implementation of human-centric approaches that harmonize automation with personalization and well-being. Progress in this domain increasingly depends on interdisciplinary efforts to redefine measurement frameworks, align organizational culture and strategy, and foster effective human-machine symbiosis—each of which is essential for realizing the full promise and societal benefits of digital transformation.

## 6 Digital Transformation in SMEs: IIoT, HCI, Challenges, and Strategic Adoption

This section provides a comprehensive survey of digital transformation in small and medium-sized enterprises (SMEs), focusing on the integration of Industrial Internet of Things (IIoT) and Human-Computer Interaction (HCI), critical challenges, and effective strategic adoption. The primary objectives are to map the state-of-the-art, identify distinct characteristics and needs of SMEs compared to larger organizations, highlight research gaps, and propose a synthesized perspective to guide future inquiry. The scope includes technological enablers, organizational change, risk and optimization issues, and implications for sustainability, while emphasizing actionable barriers and research directions unique to SMEs.

### 6.1 Introduction and Section Objectives

Digital transformation is revolutionizing the operational landscape for SMEs, driven by technological advances including IIoT, next-generation HCI, and enhanced automation. This section aims to: (i) clarify how these technologies are shaping SME evolution; (ii) assess strategic and organizational challenges unique to SMEs; (iii) synthesize recent research developments; and (iv) explicitly identify ongoing research questions and actionable pathways to foster effective digital adoption in this sector.

### 6.2 IIoT Adoption in SMEs

SME engagement with IIoT technologies enables enhanced data collection, connected manufacturing, and process optimization. However, adoption is constrained by factors such as limited technical resources, cybersecurity concerns, and integration costs. SME-specific IIoT solutions often demand adaptable architectures and user-friendly interfaces to align with non-specialist workforce needs. Open research challenges include designing scalable IIoT systems that remain cost-effective, facilitating seamless interoperability across legacy infrastructure, and addressing data governance requirements under resource constraints.

**Open Research Directions:** Key research questions are summarized in Table 6. Practical adoption gaps include methodologies for affordable, incremental IIoT deployment and effective upskilling.

### 6.3 Human-Computer Interaction and Digital Enablement

The emergence of advanced HCI paradigms enhances the usability, acceptance, and ultimate value of digital tools in SME contexts. For SMEs, intuitive interfaces and adaptive interaction models are crucial to overcome resistance and digital fatigue, especially where workforce heterogeneity is significant. An area of open research remains the co-design of HCI systems tailored to SME workflows, balancing automation and human agency, and measuring long-term impacts on productivity and job satisfaction. Opposing views on the pace and desirability of automation, as well as concerns related to job displacement and digital fatigue, should be critically contrasted to foster a balanced perspective.

**Open Research Directions:** Future work should investigate participatory HCI design methodologies and longitudinal assessment frameworks for digital adoption efficacy, as detailed in Table 7.

**Table 5: Key Factors for Effective Human-Machine Collaboration in Industry 4.0**

Dimension	Human-Centric Approaches	Enabling Technologies/Practices
Knowledge Integration	Embedding operator expertise in systems	3I Framework, AI-driven action recognition
Collaboration	Intuitive, adaptive interaction between humans and technology	Collaborative robots (cobots), sensor fusion, AR/VR interfaces
Personalization	Tailoring workflows and interfaces to individual capabilities and contexts	IoT-enabled MAS, cloud/edge computing, inclusive navigation aids
Upskilling	Supporting continual learning and generational knowledge transfer	HITL methodologies, tacit knowledge capture systems
Accessibility	Ensuring inclusion of diverse operator needs	Assistive technology, cost-effective smart devices

**Table 6: Open Research Questions in IIoT Adoption for SMEs**

Research Gap	Description	Actionable Direction
Scalable, Cost-Effective IIoT Systems	Lack of affordable, SME-tailored IIoT platforms	Develop modular architectures for incremental integration
Interoperability	Difficulty integrating new IIoT with legacy systems	Standardize protocols for legacy connectivity
Data Governance	Limited resources to address security/privacy	Simplify compliance frameworks for SMEs
Workforce Enablement	Employees often lack IIoT expertise	Create targeted training and support materials

**Table 7: Open Research Questions in HCI for SME Digital Transformation**

Research Gap	Description	Actionable Direction
Participatory Design	Absence of co-design in most HCI tools	Develop SME-inclusive user testing protocols
Balance of Automation	Concerns about digital fatigue/job loss	Analyze sociotechnical impacts with inclusive metrics
Long-Term Acceptance	Limited study on sustained use	Deploy longitudinal studies of workflow evolution

## 6.4 Challenges, Risk, and Strategic Adoption

SME digital transformation is complicated by unique risk profiles, resource constraints, and regulatory uncertainty. Key challenges include financing digital initiatives, managing cybersecurity threats, and maintaining operational continuity during technological change. The optimization of digital investments—balancing risk, efficiency, and sustainability—remains insufficiently addressed and is a persistent topic in the literature.

Contrasting perspectives, such as skepticism regarding automation and concerns over loss of autonomy for SME operators, are critical to a holistic understanding of adoption barriers. Recent years also have seen growing discourse on sustainability, both in terms of environmental footprint and long-term socio-economic impact, demanding more nuanced strategies than one-size-fits-all approaches often proposed for larger corporations.

*6.4.1 Open Challenges and Future Research Directions.* Despite progress, several research challenges persist and constitute important avenues for scholarly and practical advancement. These include:

- Developing adaptable risk assessment frameworks responsive to SME realities.
- Identifying financing models tailored for SMEs' digital investments.
- Addressing regulatory uncertainty in rapidly shifting digital markets.
- Ensuring alignment of digital strategies with sustainability objectives.

Table 8 consolidates actionable open research questions for the domain.

## 6.5 Section Synthesis, Conceptual Framework, and Novelty

To provide conceptual clarity and organize the surveyed insights, we propose a high-level taxonomy of SME digital transformation, covering technological enablers (e.g., IIoT, HCI), organizational adaptation (e.g., skills, leadership), risk and optimization, and sustainability alignment. This taxonomy differentiates SME requirements and challenges from those of larger corporations, integrating critical and opposing perspectives such as resistance to automation and digital overload. The synthesis herein is novel in systematically linking open research questions with distinct SME constraints and in emphasizing participatory approaches and actionable pathways for practical adoption—points underexplored in prior surveys.

## 6.6 Transition and Research Questions

This section has articulated current advancements, open challenges, and future directions across IIoT, HCI, risk/optimization, and sustainability within SMEs. In transitioning toward the following sections on digital risks and operational strategies, our survey is thus guided by the following explicit research questions:

- What design principles and frameworks will empower affordable and sustainable digital adoption among SMEs?
- How can participatory HCI and IIoT systems be practically co-designed with SME stakeholders?
- Which risk/financing/regulatory models can accelerate digital transformation while safeguarding unique SME interests?
- What are the mechanisms for aligning digital transformation with long-term sustainability and human-centric values within SMEs?

**Table 8: Open Research Questions in SME Digital Transformation: Challenges and Strategies**

Research Gap	Description	Actionable Direction
Risk Assessment	Lack of SME-specific frameworks	Formulate adaptive, lightweight methodologies
Financing	Barriers to affordable digital investment	Propose scalable funding models targeting SMEs
Regulatory Compliance	Navigating complex, evolving standards	Study rapid compliance assessment tools
Sustainability Integration	Sustainability not systematically included	Develop tools for aligning digital and green strategy

**6.7 Barriers, Frameworks, and Adoption Strategies**

The pursuit of digital transformation among small and medium-sized enterprises (SMEs) is shaped by the interplay between technological potential and significant implementation challenges. Key barriers include issues related to flexibility, security, privacy, scalability, and workforce readiness. These factors, while enabling automation opportunities, also act as major constraints on SME progress. The Technology-Organization-Environment (TOE) framework has become a foundational analytical tool for interrogating such dynamics, offering a structured lens to identify drivers and impediments along the SME digital innovation trajectory. Recent findings from manufacturing sectors indicate that effective deployment of industrial internet of things (IIoT) solutions necessitates attention to lightweight flexibility in system implementation, the incorporation of advanced human-computer interaction (HCI) paradigms to optimize non-monotonous workflows, the facilitation of real-time executive decision-making, and the exploitation of new market opportunities [30]. These requirements extend beyond technical adaptation, demanding strategic organizational alignment across culture, leadership vision, and external factors.

Despite the analytical promise of the TOE framework, persistent obstacles remain. These include integration with legacy infrastructures, heightened security vulnerabilities—particularly those arising from third-party partnerships—and pervasive gaps in workforce digital skills. While the TOE model provides a comprehensive perspective, its application within SMEs often encounters practical limitations if not paired with adoption strategies that bridge overarching typologies with the nuanced realities of specific sectors and firms [30]. Consequently, robust digital adoption requires adaptive and context-aware frameworks capable of guiding SMEs through both strategic and operational transitions.

**6.8 Digital Maturity in Small and Medium-Sized Enterprises (SMEs)**

Achieving digital maturity continues to be an evolving challenge for SMEs, primarily due to heterogeneous organizational profiles and varying degrees of exposure to environmental pressures. Emerging research asserts that digital maturity encompasses more than internal capacity building and the digitization of processes, highlighting the moderating effect of environmental dependence on digital outcomes. Quantitative analysis reveals that digital maturity in SMEs is multidimensional, comprising factors such as technology, product innovation, organizational structure, workforce capability, strategic

orientation, and excellence in operations [53]. Among these, technology infrastructure and operational proficiency exert the most pronounced influence on digital transformation trajectories.

A notable advancement in digital maturity modeling is the integration of environmental variables—including regulatory shifts, dynamic markets, and competitive intensity—resulting in enhanced explanatory depth within empirical analyses. This mediation by external factors exposes the limitations inherent in standardized transformation approaches, emphasizing the importance of customizing investments in skills, processes, and digital infrastructure to the demands of the operative context. Existing maturity frameworks, however, frequently exhibit shortcomings in translating diagnostic assessments into executable transformation pathways. Addressing this gap requires adaptive, context-sensitive models that support SMEs as they progress from self-assessment to implementation, while accommodating ongoing technological change and regulatory evolution [53].

**6.9 Investment Patterns in Digital Transformation: Technologies and Managerial Focus**

Investment strategies in SME-driven digital transformation are dictated by the convergence of technological innovation, managerial objectives, and a shifting risk landscape. Recent trends indicate a marked acceleration of investment in artificial intelligence, cloud platforms, blockchain, and other data-centric technologies, reflecting efforts to harness value from analytics, automation, and enhanced digital connectivity [7]. However, this rapid technological adoption frequently outpaces the integration of robust cybersecurity and privacy protocols at the managerial level. Despite growing awareness among executives, SMEs often devote only a minimal portion of transformation budgets to security controls, leading to heightened vulnerability to threats such as data breaches, regulatory infractions, and emergent risks introduced by third-party systems.

This pattern is exacerbated by the tendency to relegate cybersecurity to a primarily technical function, rather than an integrated strategic imperative. The result is a failure to institutionalize cybersecurity as a shared organizational responsibility, with insufficient investment in skilled cyber personnel, cross-functional accountability, and comprehensive frameworks for risk and impact assessment. As digitalization expands organizational attack surfaces and regulatory expectations, reliance on isolated technical teams is increasingly inadequate for effective risk mitigation [7].

Investment dynamics across technologies and functions are summarized in Table 9. These patterns illustrate that effective digital transformation in SMEs requires a balanced approach, with risk

**Table 9: Key Investment Priorities and Associated Risks in SME Digital Transformation**

Technology Area	Investment Focus	Principal Risks
AI, Cloud Computing, Blockchain	Analytics, process automation, connectivity	Data breaches, privacy loss, regulatory compliance challenges
Cybersecurity	Reactive/incremental investment	Attack surface enlargement, systemic vulnerabilities
Digital Workforce Training	Limited allocation	Skills gap, low change readiness
Legacy System Integration	Minimal modernization	Operational disruption, incompatibility, exposure of outdated interfaces

management considered an integral component of broader strategic agendas.

### 6.10 Internet of Things Adoption and Application Landscapes

The adoption of the Internet of Things (IoT) across SMEs and manufacturing ecosystems underscores both the promise and complexity of contemporary digital innovation. Scientometric studies depict a robust and escalating trajectory of IoT research and real-world applications, signaling expanding sectoral influence and global reach [57]. Within manufacturing SMEs, IoT integration centers around a cluster of foundational technologies—artificial intelligence, blockchain, and advanced sensing—enabling diverse applications in precision agriculture, logistics, healthcare, and other domains.

Organizational readiness and technology assimilation have benefitted from increasingly sophisticated theoretical frameworks, including extensions of the TOE, the Technology Acceptance Model (TAM), and the Diffusion of Innovations paradigm. However, several core challenges persist: Security and privacy vulnerabilities, especially amidst interconnected devices and shared data environments remain major concerns. Interoperability deficits stemming from heterogeneous technology stacks continue to complicate IoT integration. A pronounced need exists for workforce upskilling in IoT and digital competencies to fully leverage the benefits of these technologies. Regulatory ambiguities and the absence of universal adoption standards disproportionately affect resource-limited SMEs, hindering consistent implementation across regions.

The evolution of IoT research from narrow technical inquiries to holistic, ecosystem-level questions reflects a maturing field oriented toward policy-informed and sector-integrative innovation. The central ongoing imperative is the translation of interdisciplinary insights into practitioner-ready, scalable solutions that empower SMEs to harness IoT not only for operational efficiency but also as a strategic lever for competitive differentiation and equitable growth [57].

## 7 Risk, Robust, Sustainable, and Energy-Efficient Optimization

This section aims to systematically review and synthesize optimization strategies with respect to risk, robustness, sustainability, and energy efficiency in the context of SME digital transformation. The primary objectives are to (i) elucidate leading optimization paradigms addressing uncertainty, energy constraints, and resilience; (ii) identify their unique challenges and research gaps pertinent to SME adoption; and (iii) propose a synthesized lens integrating these paradigms for future research directions. These topics are increasingly critical in light of recent technological shifts,

growing regulatory pressures, and the need for adaptive strategies among small and medium-sized enterprises.

In this section, we first examine risk-aware optimization frameworks, exploring how stochasticity, adversarial conditions, and unpredictable environments are modeled and mitigated. Next, robust optimization is discussed, with an emphasis on frameworks that can adapt to data imperfections and parameter uncertainties. The discussion extends to sustainable and energy-efficient optimization approaches, especially those aiming for environmental and operational sustainability within SMEs.

Transitions between macrotopics stress the importance of practical deployment within resource-constrained settings of SMEs. Notably, the intersection of digital transformation and SME constraints motivates the need for both theoretical advances and practically deployable solutions.

### 7.1 Open Research Challenges and Future Directions

The landscape of optimization in SME digital transformation is shaped by ongoing challenges. First, risk-aware methods often struggle with balancing model complexity against practical deployability, particularly when computational or domain expertise is limited. Robust optimization, while reducing sensitivity to uncertainty, can sometimes sacrifice optimality or scalability—challenges magnified in dynamic SME contexts. Sustainable and energy-efficient methods may face trade-offs with business performance metrics, raising both technical and cultural barriers to broad adoption.

There remains a critical need to develop unified frameworks that simultaneously address risk, robustness, and sustainability, specifically calibrated to SME constraints. Furthermore, despite substantial literature, research gaps persist regarding (i) actionable adaptation strategies to fast-changing regulatory landscapes, (ii) lightweight yet effective algorithms accessible to non-experts, and (iii) systematic methods to quantify and benchmark trade-offs among conflicting objectives.

To summarize these open challenges, Table 10 presents prominent research questions and future directions by subtopic.

Additionally, there is a growing discourse around opposing perspectives, such as concerns over excessive automation and digital fatigue, particularly among SME workforces. Future research should more holistically weigh the benefits of optimization against such critical views to inform more balanced and sustainable strategies.



**Table 10: Key Open Research Questions in Risk, Robust, Sustainable, and Energy-Efficient Optimization for SME Digital Transformation**

Subtopic	Open Research Questions	Actionable Directions	Adoption Barriers
Risk-Aware Optimization	How to simplify risk models for SMEs with limited data?	Develop modular, interpretable risk frameworks	Lack of technical expertise; limited historical data
Robust Optimization	How to ensure scalability and maintain optimality under uncertainty?	Design adaptive, resource-efficient robust algorithms	Computational resource constraints
Sustainable Optimization	How to quantify trade-offs between sustainability and business performance?	Create SME-oriented sustainability metrics and benchmarks	Resistance to change; unclear ROI
Energy-Efficient Optimization	How to enable real-time optimization with minimal overhead?	Explore lightweight, edge-computable solutions	Integration with existing legacy systems

7.2 Novelty and Synthesis Relative to Prior Surveys

Our synthesis explicitly integrates risk, robustness, sustainability, and energy-efficiency from the perspective of SME digital transformation—a context often underrepresented in existing surveys. By foregrounding actionable research directions and practical barriers, this section aims to extend beyond prior work that often isolates these optimization paradigms or overlooks SME-specific constraints.

Overall, the reviewed literature and open questions underscore an urgent need for interdisciplinary, SME-aware optimization models capable of fostering both resilience and sustainability in rapidly evolving digital ecosystems.

7.3 Distributionally Robust Optimization and Risk Awareness

The dynamic, uncertain nature of smart manufacturing environments demands advanced optimization methodologies that can reliably manage fluctuations in demand, supply, and operational parameters. Distributionally Robust Optimization (DRO) has become a foundational paradigm in this context, extending both robust and chance-constrained optimization by directly accounting for ambiguity in the underlying probability distributions that govern uncertainty. Instead of assuming precise probabilistic knowledge—a convention frequently invalidated in practical industrial settings—DRO seeks solutions safeguarded against the worst-case probability distributions confined within a statistically justified ambiguity set. This approach enhances resilience to model misspecification and data limitations, thereby bridging theoretical rigor and practical robustness. It stands as a sophisticated extension of classical risk-averse modeling, capable of addressing evolving challenges in process control and data-driven decision-making [62].

Contemporary research in DRO emphasizes sophisticated risk calibration and refined ambiguity management, often drawing on statistical learning theory to define ambiguity sets around empirically observed distributions or prior information. Key advantages of this approach include the explicit encoding of managerial risk aversion and operational priorities through risk-oriented metrics such as Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR), as well as the provision of quantifiable performance guarantees under diverse uncertainty conditions, aligning decision-making processes with industry demands.

Nevertheless, the deployment of DRO in industrial applications remains challenged by concerns related to computational tractability and the precise specification of ambiguity sets. As systems become increasingly complex—and as interactions between multiple layers of uncertainty, such as supply disruptions and machine failures, intensify—these difficulties grow more pronounced. As such,

ongoing research directions emphasize the development of scalable algorithms and domain-adaptive calibration strategies capable of preserving robust performance without introducing unnecessary conservatism [62].

7.4 Sustainable and Energy-Efficient Manufacturing

Optimization efforts within manufacturing are increasingly oriented towards sustainability and energy efficiency, converging with broader environmental imperatives and social mandates. Mathematical modeling and empirical analyses consistently demonstrate that integrating consumer environmental awareness (CEA) significantly reshapes optimal energy-saving strategies, particularly in energy-intensive industries. Notably, comparative models examining contract types—such as self-saving, shared-savings, and guaranteed-savings contracts—reveal that higher levels of CEA motivate manufacturers to pursue more ambitious energy conservation efforts. Profitability outcomes, however, can be sensitive to the nature of uncertainty in energy savings, whether it is deterministic or stochastic [56].

For clarity, the key impacts of contract types under varying uncertainty regimes are summarized in Table 11.

Empirical validation through simulation and real-world case studies substantiates that sustained environmental efficiency can be catalyzed via incentive-compatible contract design and technological innovation. Despite such potential, implementation barriers persist, including:

- Difficulty in quantifying the full spectrum of environmental impacts attributable to manufacturing adjustments.
- Organizational inertia rooted in legacy systems and processes.
- Heterogeneity in scalability and effectiveness, often contingent on firm size, industrial sector, or local regulatory frameworks.

Consequently, while anticipatory models and energy management strategies demonstrate promise, their adoption and efficacy hinge on context-specific factors and continued research into overcoming practical limitations [56].

7.5 Corporate Sustainability and Social Responsibility

Digital transformation—including digitization, digitalization, and holistic digital transformation—has emerged as a critical catalyst for advancing sustainability objectives and reinforcing corporate social responsibility (CSR) in manufacturing enterprises. The convergence of Industry 4.0 technologies with sustainability initiatives now constitutes a defining narrative in both academic and industrial spheres [61][65][6][18][43][81][31][37][79]. Pivotal technological advancements encompass cyber-physical systems and the Industrial

**Table 11: Impacts of Contract Type and Uncertainty on Manufacturer Energy-Saving Decisions**

Contract Type	Impact under Deterministic Savings	Impact under Stochastic Savings
Self-saving	Moderate ambition; higher autonomy	Ambition sensitive to risk aversion
Shared-savings	Higher ambition; shared risk and reward	Risk-sharing mitigates uncertainty
Guaranteed-savings	Most aggressive targets, contractually set	Strong risk mitigation required

Internet of Things (IIoT), which enable real-time energy and process monitoring; AI-powered analytics for predictive maintenance and life cycle management; and end-to-end digital integration that fosters transparency in reporting and resource optimization.

Recent empirical analyses illustrate that digital investment enhances environmental performance via two primary mechanisms: improvement in production efficiency and amplification of green innovation capabilities [31]. However, the distribution of these benefits is not uniform; they appear most pronounced among state-owned and heavy industrial firms, with private and light industry actors trailing—an indication of an entrenched digital divide linked to organizational structure and sectoral attributes.

Successful digital transformation in support of sustainability therefore demands deliberate alignment between technological upgrades, process reengineering, and explicit sustainability targets. Absent such alignment, digital investments risk yielding only incremental, rather than transformative, advances in CSR outcomes [79].

Despite evident synergies between digital technology and sustainability, practical implementation is frequently hampered by exposure to cybersecurity threats and insufficient data interoperability; organizational resistance to structural change; and persistent deficits in digital literacy and workforce upskilling [65][43][81].

Accordingly, the pursuit of sustainable manufacturing in the digital age remains as much a managerial and social undertaking as a technological one. Tensions between efficiency-oriented and ethically grounded digitalization further complicate these efforts, as productivity enhancements may inadvertently take precedence over sustainability and social responsibility considerations [90].

Current research agendas advocate for the development of interdisciplinary frameworks that unite digital transformation initiatives with systemic approaches to environmental and social governance. The integration of real-time data analytics, risk-aware optimization such as DRO, and transparent CSR metrics is essential. Such integration will support not only regulatory compliance and substantive reporting but also the realization of measurable triple-bottom-line impacts—economic, environmental, and social.

## 8 Sectoral, Spatial, and Cross-Industry Dynamics

This section examines the sectoral, spatial, and cross-industry dynamics that underpin the current landscape of AI and digital twin integration. Reiterating the primary objective of this survey, we aim to systematically map the interplay and comparative developments across industries, evaluate methodological convergences and divergences, and identify measurable outcomes germane to research, deployment, and policy. By anchoring the discussion in sector-specific and cross-sector frameworks, we clarify not only

technological progress, but also organizational, spatial, and implementation gaps that require further inquiry. This approach serves readers joining at this stage by restating our intent to inform both technical and strategic evaluation across diverse industrial contexts.

A structured comparative analysis is essential for highlighting the varied methodologies and frameworks in different sectors. For example, sectors such as manufacturing and logistics emphasize real-time optimization approaches, with substantial focus on computational efficiency, system scalability, and operational resilience. These strengths, however, may be counterbalanced by challenges in standardizing interoperability and integrating legacy systems. In contrast, sectors like healthcare and urban infrastructure often prioritize interpretability, regulatory compliance, and data privacy. This creates divergent methodological emphases and exposes trade-offs between explainability, performance, and the feasibility of cross-domain transfer.

Critical debates emerge around the competing standards and interoperability frameworks. Some methodologies advocate for strict adherence to widely accepted reference architectures, promoting modularity and standardized communication, whereas alternative schools of thought argue for more flexible, domain-adapted solutions that optimize for local performance at the expense of broader compatibility. This diversity highlights ongoing tensions in designing digital twin and AI systems that must operate reliably across both tightly coupled and distributed ecosystem settings.

The integration of digital twin and AI systems presents not only technical but also sociotechnical implications. While bridging data silos and enabling real-time multidomain analytics offer substantial efficiency gains, organizational adoption is frequently constrained by skill gaps, fragmented institutional incentives, and concerns about control and transparency. For instance, in sectors where human-in-the-loop decision frameworks remain critical, the full automation enabled by AI-driven digital twins may be resisted, necessitating hybrid interaction patterns and new roles for oversight.

To illustrate the spectrum of sector-specific challenges and the current state of methodological development, a comparative summary is provided in Table 12. This table draws attention to key differences in technical focus, standards adoption, organizational hurdles, and open research gaps, offering readers a high-level synthesis that informs subsequent, more granular analysis.

By explicitly mapping these sectoral nuances, this section underlines the breadth of technical and organizational landscapes encountered. In summary, understanding sectoral, spatial, and cross-industry dynamics is crucial not only for selecting appropriate methodologies, but also for anticipating structural barriers and emergent policy considerations as digital twin and AI solutions proliferate.

**Table 12: Comparative Summary of Sectoral Dynamics in Digital Twin and AI Integration**

Sector	Technical Focus	Key Methods	Organizational/Measurement Gaps	Standards Debate
Manufacturing	Real-time optimization, scalability	Model predictive control, agent-based simulation	Data interoperability, skill adaptation	Modular vs. bespoke architectures
Healthcare	Interpretability, compliance, privacy	Explainable AI, time-series analytics	Data privacy, regulatory alignment	Proprietary vs. open frameworks
Logistics	Resilience, multi-agent systems	Routing optimization, distributed ML	Inter-organizational trust, cost justification	Networked vs. siloed standards
Urban Infrastructure	Integration, heterogeneity	Semantic layers, federated learning	Stakeholder alignment, governance	Local adaptation vs. global consistency

**8.1 Sectoral Productivity and Cross-Industry Applications**

The interplay of sectoral productivity and spillover dynamics exhibits considerable heterogeneity, shaped by industry structural attributes and spatial context. In service-oriented industries, with tourism as a representative case, productivity emerges from a complex nexus of intra-sectoral efficiencies, cross-sectional linkages, and geographic interactions. Notably, a spatial econometric investigation of the Italian tourism sector reveals that productivity outcomes are significantly influenced by inter-industry interdependencies—encompassing accommodation, food services, creative arts, entertainment, and transport—and by spatial spillover effects among adjacent destinations. Applying a Cobb-Douglas framework at the Local Labour Market Area (LMA) scale, evidence supports the simultaneous presence of positive and negative externalities that transcend both spatial and sectoral boundaries, thus shaping local economic development trajectories.

An important insight is the observed heterogeneity in spillovers across tourism segments (e.g., urban, coastal, mountainous landscapes). This variation underscores the ineffectiveness of generalized policy measures and instead advocates for targeted, cluster-based interventions that amplify agglomeration benefits while ameliorating the risks of excessive competition or resource dilution. Moreover, persistent collaborative interactions among local tourism stakeholders emerge as pivotal mechanisms fostering both intra- and inter-sectoral synergies, which are instrumental for sustaining competitiveness in the long term. Nonetheless, current analytical approaches display limitations, notably in their aggregation of distinct spillover types and the assumptions underlying traditional production functions [13].

In contrast, advanced manufacturing sectors—such as hydrogen and chemical production—are increasingly characterized by the systematic integration of process-optimization methodologies, drawing on both process engineering advances and digital innovation. A paradigmatic example is found in hydrogen production via autothermal reforming using radial flow tubular reactors (RFTRs). Here, the fusion of experimental observations with theoretical models, coupled with the deployment of genetic algorithms, has facilitated the fine-tuning of operational parameters (including feed temperature and molar ratios). Such an approach yields substantial improvements in both hydrogen yield (an increase of 11%) and methane conversion (an increase of 5%). These findings highlight that spatial optimization within the reactor—particularly temperature management across the catalyst bed—exerts a substantial influence on overall productive efficiency, thus offering a spatial analogue to the externalities observed in service industries. However, it is important to note that such optimization processes are contextually bounded, with improvements geared toward specific

process efficiencies rather than broader techno-economic or environmental dimensions [72].

A further demonstration of cross-industry learning is evident in chemical manufacturing, where hybrid and metaheuristic optimization algorithms have been successfully applied to complex process systems, such as ethylene glycol production. Notably, comparative studies utilizing the multi-objective dragonfly algorithm (MODA), the multi-objective slime mold algorithm (MOSMA), and the multi-objective stochastic paint optimizer (MOSPO) have confirmed the capacity to optimize multiple, often competing, performance metrics—including yield, productivity, and energy consumption—under tightly constrained kinetic and process conditions. Among these, MODA offers the most balanced Pareto-front solution, achieving yields of up to 95.5% alongside strong economic performance (a productivity of RM41.3 million/year and an energy cost of RM0.1667 million/year). Sensitivity analysis further demonstrates the preeminence of reactor pressure in shaping output, thus underscoring the intersection between process engineering and resource economics.

A summary of the optimization strategies and their outcomes in ethylene glycol production is provided in Table 13. This structured comparison offers concise insights into their practical performance and evaluated trade-offs.

While these multi-objective optimization frameworks offer robust, cross-sector tools for navigating complex trade-offs, their practical utility is presently circumscribed by two principal limitations: limited integration of comprehensive sustainability (techno-economic-environmental) metrics, and continued reliance on idealized, rather than empirically grounded, process models. This signals the necessity for future research to focus on integrating real-world data and aligning optimization strategies with broader sustainability concerns. These challenges parallel gaps observed in service sector productivity analyses, where spillover identification, classification, and measurement remain evolving analytical frontiers [64].

In sum, convergences and divergences across sectoral domains highlight that the mechanisms underpinning productivity—whether via spatial, sectoral, or cross-disciplinary spillovers—warrant nuanced analytical and policy attention. Prevailing models, though increasingly sophisticated, still face considerable hurdles in encapsulating the dynamic, multi-scalar realities of modern economic landscapes. The emergence of hybrid optimization techniques, particularly those leveraging digital twins and integrated data streams, offers a promising avenue; nonetheless, substantive progress requires analytical frameworks that can reconcile empirical specificity with systemic generalizability. Only by tailoring tools and interventions to the multisectoral and interconnected reality of industrial landscapes can sustainable and adaptive productivity gains be fully realized [72][64][13].

Table 13: Comparison of Multi-Objective Optimization Approaches in Ethylene Glycol Production

Algorithm	Max. Yield (%)	Productivity	Energy Cost
MODA	95.5	RM41.3 million/year	RM0.1667 million/year
MOSMA	94.7	RM40.8 million/year	RM0.1675 million/year
MOSPO	94.2	RM40.5 million/year	RM0.1680 million/year

9 Key Challenges, Methodological Gaps, and Future Research Directions

To support readers and clarify the scope, we begin by reiterating the survey’s primary objectives: to synthesize the current state-of-the-art in digital twin and AI integration, critically evaluate prevailing methodologies across sectors, identify organizational and measurement gaps, and map out actionable future research directions.

9.1 Overview and Objectives

This section aims to: (1) systematically distill the major technical, methodological, and sociotechnical challenges facing the field; (2) provide a comparative and critical discussion of competing methodologies, including their known strengths and weaknesses; and (3) highlight future research priorities with particular attention to organizational and industry-wide measurement bottlenecks. The discussion is structured to enable readers joining at this point to anchor themselves in the motivations, scope, and intended measurable outcomes of the survey.

9.2 Current Challenges and Methodological Gaps

Current integration efforts between digital twin systems and AI methods reveal persistent challenges across interoperability, standardization, data governance, and meaningful validation. Interoperability remains hampered not only by technical heterogeneity and data silos but by disagreement across communities (e.g., model-driven vs. data-driven approaches) regarding interface definitions and platform-agnostic protocols. Standardization bodies have made progress, yet adoption lags due to competing priorities among stakeholders and legacy system constraints.

Methodological gaps exist in both the algorithmic power of AI for real-time digital twin operation and the scalability of simulation environments. For instance, optimization-based approaches may excel in structured scheduling scenarios but are less robust to stochastic disruptions, whereas reinforcement learning methods often struggle with sample inefficiency and domain adaptation. There remains an ongoing debate between deterministic versus probabilistic modeling schools, particularly concerning uncertainty quantification and transferability to real-world settings.

Despite advances, many studies lack rigorous comparative benchmarks. For example, when evaluating predictive maintenance or anomaly detection, reporting isolated performance metrics without context on system complexity or robustness can mask fundamental trade-offs between accuracy, scalability, and interpretability. The absence of industry-wide evaluation frameworks exacerbates these gaps.

**Case Example: Measurement Gaps in Smart Manufacturing.** In large-scale manufacturing, digital twins can simulate production line behavior under various operational strategies. However, measurement gaps often emerge when real-world sensor reliability fluctuates, resulting in partial or delayed data streams. This leads to uncertainty in both the fidelity of the virtual twin and the applicability of data-driven optimization methods, making it difficult to objectively compare predictive methods or to generalize across production settings.

9.3 Critical Comparison of Competing Methods

Our review indicates substantive methodological debates across sectors. Optimization-centric approaches are typically more interpretable and provide guarantees on solution quality, but frequently require precise modeling of the underlying system. By contrast, machine learning-based or hybrid approaches can better accommodate noisy or incomplete data, although they may sacrifice interpretability and require larger annotated datasets. Debates also persist regarding the adoption of open standards (e.g., OPC UA, Asset Administration Shell) versus proprietary solutions, particularly concerning long-term interoperability and vendor lock-in.

9.4 Sociotechnical and Organizational Gaps

While much attention focuses on technical hurdles, integration at scale is often limited by organizational inertia and sociotechnical misalignments. Differences in workforce expertise, unclear roles and responsibilities, and misalignment between IT/OT departments frequently slow adoption. The digital twin–AI interface frequently exposes hidden challenges in data stewardship, privacy, and regulatory compliance, emphasizing the need for a clear division of responsibilities and auditability.

**Case Example: Digital Twin Deployment in Healthcare.** The adoption of digital twins for patient-specific modeling often encounters organizational barriers such as unclear clinical workflows, resistance to automated decision support, and compliance-related constraints. Without robust mechanisms for stakeholder engagement and data governance, technical solutions may fail to gain traction.

9.5 Future Research Directions

Based on these identified gaps, several promising directions emerge: (1) the codification of comprehensive evaluation frameworks for benchmarking AI-digital twin methodologies across standardized metrics and representative settings; (2) development of modular, interoperable architectures guided by open standards; (3) sociotechnical research into workforce adaptation, human-AI collaboration, and cross-domain measurement standards; and (4) advancing robust

Table 14: Comparison of Key Methodologies for Digital Twin–AI Integration

Methodology	Strengths	Weaknesses	Typical Use Cases
Optimization-based	Interpretable; solution quality guarantees	Model accuracy dependence; poor adaptability	Planning, Scheduling
Reinforcement Learning	Adaptivity; handles sequential decisions	Sample inefficiency; opaque reasoning	Process control, Anomaly detection
Hybrid (Physics+ML)	Leverages domain knowledge; balances data/model	Integration complexity; propagation of modeling errors	Predictive maintenance, Simulation
Data-driven ML	Suited for noisy, large-scale data	Requires large datasets; may lack physical meaning	Pattern recognition, Forecasting

data governance, with special attention to privacy, accountability, and ethical deployment in sensitive sectors.

9.6 Section Summary

In summary, addressing the methodological, technical, and sociotechnical gaps in digital twin and AI integration requires a multidisciplinary approach and the active development of common benchmarks, organizational best practices, and standardized frameworks. These efforts will serve as the foundation for robust, scalable, and trustworthy digital twin systems capable of transforming diverse industries.

9.7 Standardization, Interoperability, and Data Governance

The advancement of digital manufacturing and Industry 4.0 initiatives is significantly impeded by enduring deficiencies in standardization and interoperability across platforms, devices, and data formats. The absence of unified protocols and data models complicates system integration and fragments innovation, limiting both composability and the scalability of solutions within heterogeneous industrial ecosystems [40, 48]. Liu et al. [40] highlight that digital twin technologies rely heavily on seamless integration of physical and digital systems, further underscoring the critical need for common data formats, real-time acquisition, and harmonized frameworks to enable effective synchronization and industrial deployment. However, despite substantial attention to technical standards, current harmonization efforts are outpaced by the rapid evolution of advanced digital and cyber-physical systems. The proliferation of vendor-specific solutions further exacerbates integration obstacles and generates persistent challenges for scalable interoperability.

Moreover, as data sharing expands into distributed and decentralized industrial environments, privacy and security considerations become increasingly multifaceted. Islam et al. [48] demonstrate that frameworks such as Self-Sovereign Identity (SSI) are promising alternatives to traditional centralized identity management by enabling improved privacy, personal autonomy, and compliance with evolving regulatory landscapes. Yet, the integration of SSI into industrial and metaverse scenarios faces considerable technical and governance hurdles, including the alignment with distributed ledger technologies and complex legislative requirements. This exemplifies the ongoing tension between maximizing data utility for innovation and ensuring rigorous data protection, especially as digital twins and the metaverse converge in Industry 4.0 contexts [48].

In summary, addressing the dual imperatives of interoperability and data governance demands continued research not only on the technical synchronization of complex systems, but also on advanced, privacy-preserving governance frameworks. Establishing

standards that balance openness with robust data protection remains a central goal for realizing scalable, secure, and innovative digital manufacturing ecosystems.

9.8 Fusion of Digital Twins with AI and Advanced Methods

The confluence of digital twin (DT) technologies and artificial intelligence (AI) represents a pivotal methodological evolution in smart manufacturing. Digital twins enable real-time, high-fidelity synchronization between physical assets and their virtual representations, thereby supporting predictive maintenance, performance optimization, and scenario-based simulation [40]. The fusion of DTs with AI extends decision-support capabilities, facilitating real-time, cross-domain adaptation such as automated system reconfiguration and complex optimization—areas traditionally hindered by data silos or modeling limitations [3].

Despite these opportunities, realizing the full potential of AI-enabled digital twins necessitates the seamless integration of multiphysics modeling, data fusion, big data analytics, and simulation platforms. Current research chiefly addresses isolated applications or theoretical formulations, with comparatively few examples of scalable, flexible architectures that span heterogeneous domains and operational constraints. Notable methodological gaps include:

- The absence of standardized digital twin interfaces conducive to broad interoperability
- Challenges in establishing real-time, reliable data pipelines
- The need for embedding explainable and robust AI into closed-loop industrial operations
- To address these limitations, future work must prioritize modular and interoperable digital twin ecosystems, capable of accommodating evolving data types and supporting resilient autonomy.

9.9 Organizational Adaptation and Digital Maturity

Although technological implementation garners significant focus, the importance of organizational adaptation and digital maturity must not be underestimated. Research demonstrates the criticality of digital culture and transformational leadership in enabling organizational agility and adaptation to rapid technological change [28]. In particular, Alakaş [28] found that digital transformational leadership directly enhances organizational agility, and its benefits are amplified when supported by a strong digital culture (fostering innovation and digital mindsets) and a coherent digital strategy. Such findings highlight that investments in leadership alone are insufficient—parallel advancement of culture and strategic clarity are essential components for achieving true agility during digital transformation.

Despite this, empirical findings point to a persistent gap between aspirational digital leadership and the realities imposed by legacy organizational structures, resistance to change, and pervasive skill shortages. Existing maturity models, while offering diagnostic frameworks for digital transformation, are predominantly designed to measure technical readiness, often overlooking the need for holistic alignment of people, processes, and cross-functional strategies [12, 36]. For example, Eichenseer and Winkler [12] show that while technology-centric approaches are well-represented in current literature and practice, organizational and human-centric aspects remain underexplored, resulting in conceptual and practical gaps in achieving full digital shopfloor integration. Moreover, there are very few models that simultaneously address technological, organizational, and people-related dimensions or provide an overarching maturity framework suitable for value-stream-oriented contexts.

The sustained adoption of data-driven shopfloor management remains further impeded by unresolved organizational and human factors; the literature rarely examines the sociotechnical interdependencies that underpin sustainable transformation [12]. In this regard, longitudinal studies that track the progressive, integrated alignment among leadership, digital culture, and strategic objectives are warranted. It is also necessary to develop new maturity models that integrate technological, organizational, and human capital dimensions, addressing the interdependencies and bridging the gap between technical advancement and effective organizational adaptation.

### 9.10 Measurement, Benchmarking, and Value Realization

The evaluation of digital transformation success within manufacturing settings remains an unresolved methodological issue. Traditional measures—such as return on investment (ROI) and efficiency benchmarks—often fail to account for the full spectrum of value created, particularly intangible or strategically significant outcomes attributable to digitalization [80]. This limitation constrains both investment decision-making and the iterative improvement of transformation initiatives.

Researchers increasingly advocate for multidimensional metrics, encompassing not only operational performance but also innovation capacity, resilience, workforce empowerment, and ecological sustainability. The challenge extends to the development of benchmarking frameworks that enable fair comparisons across organizations at varying stages of digital maturity, while factoring in contextual differences and shifting business models.

To support comprehensive and sound transformation, robust, multidimensional measurement systems must be developed and validated, ensuring organizations neither underestimate nor overstate the true value of their digital investments.

### 9.11 Cross-Domain Simulation and Real-Time Optimization

The integration of advanced simulation environments with real-time optimization algorithms remains a promising yet underutilized strategy for next-generation manufacturing [3]. The synthesis of cross-domain simulation platforms with real-time data enables

extensive digital experimentation, as demonstrated in domains such as electric vehicle engineering and agile shopfloor reconfiguration, without the material and temporal costs associated with physical prototyping.

However, the practical deployment of such comprehensive co-simulation tools is hindered by interoperability limitations that restrict cross-domain applicability. Additional challenges stem from the requirement for scalable communication interfaces between simulation modules and live operational systems, as well as the need for robust optimization mechanisms capable of accommodating real-world uncertainties. To address these gaps, future research should focus on the development of integrated frameworks that bridge disciplinary boundaries, facilitating multi-physics, multi-agent, and multi-objective analyses within dynamic industrial contexts.

### 9.12 Security Threats in Industrial Automation and Industry 4.0 Environments

Cybersecurity remains a continually evolving, critical challenge in Industry 4.0 environments, exacerbated by the increased attack surfaces resulting from automation, expanded connectivity, and digital transformation. Existing signature-based intrusion detection solutions are insufficient for countering advanced, rapidly adapting cyber threats, necessitating the adoption of machine learning-based approaches to enhance adaptability and detection accuracy within diverse and dynamic industrial contexts [7, 26].

Despite ongoing technical advancements, empirical research indicates that resource allocation for cybersecurity has not kept pace with broader digital investments—this is particularly apparent in scenarios involving third-party system integration and complex supply chains [7]. Organizational tendencies often relegate cybersecurity concerns solely to technical specialists, rather than embedding these issues within broader strategic planning. Major barriers include insufficient investment, lack of integration with digital culture, and the escalating sophistication of adversarial tactics [7]. The literature also points to critical methodological gaps in:

- Comparative risk assessment frameworks tailored to industrial automation
- The development of context-sensitive best practices
- Adaptive strategies for threats exploiting interconnected physical-digital systems [24]

Emerging innovations, such as unsupervised learning and anomaly-based detection for threat identification, exhibit promise but require extensive empirical validation and robust integration into real-world operations. Consequently, future research must focus on constructing holistic and adaptive security postures, formalizing investment-risk benchmarks, and aligning methodologies with international regulatory landscapes to maximize resilience in global Industry 4.0 environments.

## 10 Synthesis, Discussion, and Conclusion

At the outset, it is important to reiterate the primary objectives of this survey: to systematically review state-of-the-art developments at the intersection of AI and digital twin technologies, to critically examine competing methodologies and frameworks, and to highlight both technical and sociotechnical challenges while identifying

organizational and measurement gaps that persist across industry sectors. The intended outcomes of this survey are to clarify the current landscape, synthesize comparative insights, and delineate actionable future research directions.

This section synthesizes key findings from across the technical domains reviewed, focusing on comparative analyses, critical perspectives on alternative approaches, and the broader sociotechnical implications of integrating AI with digital twins.

A review of optimization methods (see Table 15) reveals a pronounced diversity in performance characteristics, both in terms of computational efficiency and adaptability. While traditional model-based optimization is favored for its interpretability and deterministic guarantees, it often struggles with real-time scalability and handling the high-dimensional data typical of digital twin environments. Conversely, data-driven and AI-enhanced optimization approaches offer substantially improved scalability and dynamic adaptation but may introduce challenges related to data quality, explainability, and transparency. The trade-off between speed and interpretability continues to fuel ongoing debates in both academic and industrial practice.

The evolving landscape of interoperability standards is another area marked by lively discourse. Industry-wide, there is no consensus on a single set of technical protocols, resulting in a proliferation of point solutions. While open standards enable ecosystem growth and vendor neutrality, they often lag behind proprietary solutions in providing cutting-edge features. This tension between openness and innovation raises important questions regarding future consolidation or heterogeneity among digital twin platforms.

Throughout this survey, a new taxonomy has been proposed that classifies integration strategies for digital twins and AI along technical, organizational, and sociotechnical axes. The taxonomy organizes reviewed methods into categories informed by operational scope (component, system, or enterprise level integration), degree of automation, and extent of stakeholder involvement. Distinctions between technologically-centered and human-centered approaches are made explicit. Referencing this taxonomy here emphasizes that successful digital twin and AI ecosystems demand not only robust technical solutions but also alignment with organizational culture, policies, and user expertise.

To further clarify typical practical challenges, consider the following illustrative case: In the energy sector, implementing a predictive maintenance digital twin must account for not just sensor and data fusion challenges, but also workforce training, regulatory compliance, and resistance to process change. Similar gaps emerge in healthcare, where data privacy regulations intersect with the technical difficulty of real-time patient model updating. These cases exemplify the intersection of measurement gaps, organizational inertia, and technical complexity highlighted in Sections X-Y.

Moreover, the integration of digital twin and AI extends well beyond technical architecture to encompass critical sociotechnical issues—ranging from user trust and transparency concerns to the need for cross-disciplinary teams and adaptive governance models. Policy, interoperability, and the development of open benchmarks remain pressing community needs.

In summary, this survey aimed to (i) map the state of the art in AI-powered digital twins, (ii) offer explicit comparative critique of competing technical approaches, (iii) introduce an organizing

taxonomy that clarifies integration strategies and gaps, and (iv) call attention to sociotechnical as well as organizational considerations. Key research challenges persist, particularly in balancing adaptability with explainability, integration with legacy systems, and ensuring that human and ethical factors are treated as first-class concerns. Looking ahead, sustained collaboration between technical, organizational, and policy stakeholders will be essential for fully realizing the transformative potential of AI-empowered digital twin solutions.

## 10.1 Summary of Convergent Advances

Over the past decade, the industrial landscape has been fundamentally reshaped by the convergence of artificial intelligence (AI), digital twins, simulation, optimization, and robotics, alongside the seamless integration of these technologies into holistic, productivity-driven workflows. Collectively, these developments are the bedrock of Industry 4.0 and its successors, where interoperability, adaptability, and intelligence are intrinsic, systemic properties of industrial ecosystems rather than isolated features.

Digital twins have matured from conceptual demonstrations into critical operational assets, facilitating real-time synchronization between physical and virtual spaces throughout the entire lifecycle of products and manufacturing systems. Modern implementations leverage high-fidelity sensor integration, dynamic multi-physics simulations, and AI-driven predictive analytics, resulting in markedly increased throughput, reduced maintenance costs, minimized defects, and enhanced workforce training—with these benefits substantiated by empirical evidence from large-scale deployments [54]. Digital twins now extend beyond monitoring, enabling prescriptive interventions in which anomalies are detected, processes are autonomously optimized, and corrective actions are executed in closed-loop configurations [31][79].

AI and machine learning, particularly those leveraging hybrid models that blend data-driven with physics-informed approaches, have driven significant progress in process control, scheduling, and quality assurance. These methods address the complexity and variability inherent in modern production environments [65][74][4]. The adoption of reinforcement learning and multi-agent systems has enhanced adaptive scheduling capabilities in dynamic, stochastic shop floors, supporting mass personalization and on-the-fly reconfiguration [66][89][20]. AI-enabled systems are delivering superior productivity, evidenced by faster convergence rates, greater operational robustness, and improved scalability and autonomy. However, deployment challenges persist, particularly regarding retraining requirements and adaptation to non-stationary conditions [89][20].

The integration of robotics, encompassing both fixed and mobile platforms, is now increasingly characterized by intelligent agent-based control, force-feedback, and collaborative human-robot interaction. AI techniques are overcoming the traditional limits of rule-based controllers in complex tasks such as deburring, flexible assembly, and adaptive layout planning. Furthermore, there is a discernible shift toward human-centric design, as evidenced by advances in human action recognition, symbiotic interaction models,

**Table 15: Comparative Summary of Optimization Approaches in AI-enabled Digital Twins**

Approach	Strengths	Weaknesses	Typical Domains
Model-based Optimization	Proven reliability, transparent, mathematically rigorous	Less flexible, computationally heavy for real-time, sensitive to modeling errors	Manufacturing, Process Control
Data-driven/Augmented AI	Adaptive, scalable, tolerant to noisy data	Opaque reasoning, data dependency, harder to validate results	Smart Cities, Autonomous Systems
Hybrid Methods	Balance of speed and accuracy, leverages domain knowledge	Implementation complexity, integration overhead	Energy Grids, Predictive Maintenance

and intuitive human-machine interfaces. These developments address not only performance and safety but also ergonomic and cognitive dimensions of human-robot collaboration [69][47][34][55][88].

Simulation and optimization have converged to create comprehensive frameworks for efficient, sustainable manufacturing, encompassing multi-objective, deterministic, and distributionally robust paradigms. These methods have proven transformative in resource planning, energy management, and chemical process design [56][5][90]. Additionally, methodological advances in productivity analysis enable multidimensional decompositions, improved sampling corrections, and integration of causal inference, ensuring accurate and actionable performance assessment amid increasingly heterogeneous, data-rich industrial environments [73].

The synergistic impact of these technological pillars is most apparent when viewed through the lens of end-to-end workflow integration. Standardized protocols and interoperable architectures now bridge the longstanding gaps among enterprise resource planning, shop-floor automation, and cloud or edge-based analytical services. This systemic integration is a prerequisite for realizing modular, reconfigurable, and scalable manufacturing as envisioned in contemporary reference architectures [38][43].

## 10.2 Research and Practical Implications

This subsection aims to articulate the central research and practical consequences of industrial digital transformation, reflecting on achievements, open questions, and areas of scholarly debate, while clarifying the alignment between the survey's objectives and the broader field context.

The rapid confluence of digital and physical domains has initiated not only technical transformation but also a broadening of interdisciplinary research, policy deliberation, and practical models for sustainable, inclusive industrial practice. The cross-fertilization of control engineering, computer science, operations research, and organizational studies is fostering integrative approaches to industrial intelligence, where methods across AI, optimization, and human-computer interaction are synthesized into cohesive solutions [31][92].

At the policy and governance interface, industrial digitization is inherently intertwined with issues of inclusiveness and sustainability. Comparative research into national and sectoral digitization strategies demonstrates that sustained value creation is contingent on coordinated policy, the establishment of standards, and targeted support for digital maturity—especially for small and medium-sized enterprises (SMEs) that encounter particular resource constraints [86][52]. Digital transformation strategies must therefore transcend narrow performance metrics to embrace equitable access, workforce upskilling, and proactive mitigation of digital divides [40].

Sustainability is an increasingly central theme, with AI and digitalization driving both immediate operational efficiency and long-term socio-environmental benefits such as emissions reduction and welfare enhancement [42]. Realizing the full range of sustainable outcomes depends on interdisciplinary collaboration and policy interventions that incentivize ecosystem-level innovation [13].

The practical deployment of digital technologies also exposes persistent challenges in security, privacy, operational resilience, and workforce transformation. The expansion of IoT and open architectures increases vulnerability to cyber threats, necessitating multi-layered security approaches. Adaptive, machine learning-based intrusion detection, coupled with a comprehensive security-by-design philosophy, has become indispensable to safeguarding industrial digital environments [24][48]. Furthermore, the success of digital transformation depends on agile change management practices, strategic alignment between digital initiatives and organizational objectives, and fostering a pervasive digital culture that prioritizes continuous learning and adaptability, all of which are critical to overcoming institutional inertia and ensuring organization-wide participation in transformation efforts [21][82][7].

Critical debate persists regarding the relative emphasis on technological infrastructure versus organizational and policy capacity. While robust digital architectures are foundational, evidence suggests that enduring transformation hinges equally on strategic leadership, the cultural integration of cyber risk management [7], and proactive regulatory alignment [40]. Further, unresolved tensions branch along the lines of measuring socio-environmental value beyond economic metrics [21], standardizing best practices across heterogeneous industries and national contexts [52], and achieving collaborative frameworks able to reconcile the rapid pace of technological development with human-centric approaches [42].

To align with the original aims of this survey, we explicitly restate that the key objectives were to: (1) synthesize interdisciplinary research on industrial digital transformation with an emphasis on sustainability and inclusiveness; (2) identify persistent challenges and unresolved debates at the intersection of technology, policy, and workforce adaptation; and (3) outline actionable opportunities and research priorities to guide future inquiry and practical implementation.

**Take-home messages:** The field of industrial digital transformation is advancing through complex interplay among technical, organizational, and policy innovations. Progress is marked by significant achievements in productivity, security, and sustainability, but persistent gaps remain—especially in integrating cybersecurity as a cultural artifact, supporting SMEs, and realizing ecosystem-level sustainability [21][7]. A recurring research imperative is to deepen cross-disciplinary integration, develop empirical frameworks for assessing long-term and non-economic value creation, and advance holistic approaches to security and workforce transformation.



**Table 16: Key Challenges, Opportunities, and Research Gaps in Industrial Digital Transformation**

Aspect	Main Trends	Persistent Challenges	Future Directions / Gaps
Interdisciplinary Integration	AI, HCI, and optimization convergence [31][92]	Siloed research traditions; Need for unified frameworks	Methodological synthesis; Cross-disciplinary collaboration
Policy and Governance	Support for digital maturity, standardization [86][52]	SME resource limitations; Uneven access	Comparative policy research; Policy frameworks sensitive to organizational scale
Sustainability	Socio-environmental benefits, efficiency gains [42]	Valuing long-term vs. short-term outcomes; Measuring impacts [21][13]	Integrative metrics; Empirical studies on long-run welfare
Security and Privacy	Security-by-design; ML-based detection [24][48]	Underinvestment in organizational cybersecurity [7]; Third-party risks	Holistic security frameworks; Organizational best practices
Workforce and Culture	Need for upskilling and digital culture [82]	Resistance to change; Skills gap, organizational inertia	Change management models; Adaptive training programs

In conclusion, navigating the path toward inclusive and sustainable industrial digitization requires a concerted, interdisciplinary effort—merging technological solutions, organizational change, and forward-thinking policy—so that digital transformation delivers broad-based, resilient, and responsible value creation.

**10.3 Concluding Outlook and Future Opportunities**

This section aims to synthesize key findings, map emergent trends and gaps, and explicitly address the core aims of this survey: to provide a critical overview of technological, organizational, and policy-driven advancements shaping the future industrial digital ecosystem; to highlight persistent challenges and unresolved tensions; and to suggest prioritized opportunities and directions for future research.

The forthcoming trajectory of the industrial digital ecosystem is expected to emphasize agility, human-centricity, security, and cross-domain standardization. Future operational architectures are anticipated to combine open, interoperable systems with robust mechanisms for privacy and security, facilitated by advancements in decentralized identity management, seamless platform integration, and compliance with evolving regulatory frameworks [31][92][28]. Modular and resilient system designs, inspired by principles of agility and rapid reconfigurability, will, in turn, empower manufacturers to respond efficiently to market shifts, supply chain disruptions, and technological innovations [38][36].

Human-centric approaches are poised to be vital enablers of future industrial progress. The relationship between humans and AI systems is expected to deepen, as future research expands explainability, enhances operator support, and systematically evaluates augmented cognition and safety in industrial contexts [34][88]. The emergence of unified frameworks for human-machine collaboration and interdisciplinary studies will maximize the practical impact of smart manufacturing, supporting both workforce retention and continuous upskilling [92][80].

Despite these prospects, several formidable challenges remain, including: technical and methodological limitations of current AI systems in industrial environments, especially regarding generalization, non-stationarity, and scalable adaptation to new tasks [66][69][83]; the imperative for universal adoption of open standards for data, knowledge, and interface specification to ensure a standardized, interoperable industrial ecosystem [60][92]; and the need for sector-driven and international collaboration to address fragmentation and promote universal access to digital innovation.

Ethical stewardship stands as a foundational concern in the next stage of digital transformation. This includes ensuring fairness, transparency, and equitable societal benefits of AI and automation; safeguarding privacy alongside productivity improvements; and fostering inclusive, regionally diverse industrial development [7][31][42]. As digital transformation progresses, there remains ongoing academic debate regarding the optimal balance between technical innovation, operator empowerment, and ethical responsibility. Unresolved tensions persist where rapid digital adoption may outpace regulatory adaptation, or where privacy and security are not fully integrated into organizational strategy [7][31].

To clarify prioritized gaps, we enumerate open research questions as focal points for future work: - How can AI systems in manufacturing overcome issues of generalization and scalable adaptation when faced with rapidly changing or non-stationary industrial environments [66][69][83]? - What frameworks and architectures will best facilitate open interoperability while preserving privacy, security, and regulatory compliance [60][92]? - In what ways can digital leadership, culture, and strategy be integrated to accelerate organizational agility without exacerbating fragmentation or resistance to change [28]? - How can human-AI collaboration and augmented cognition research translate into measurable improvements in operator well-being, safety, and upskilling [34][88]? - What are the comparative impacts of differing ethical and policy frameworks on the fairness, transparency, and inclusiveness of industrial digital transformation [7][31][42]?

In summary, this survey set out to delineate the intersecting technological, organizational, and policy trends that are shaping the contemporary industrial digital landscape. Integrating the findings across domains, it is clear that the pursuit of agile, intelligent, secure, and sustainable industrial paradigms must be fundamentally anchored in both rigorous research and practical innovation. Unresolved issues around AI adaptability, interoperability, human-machine integration, and ethical stewardship remain central to ongoing academic and practical debate. Addressing these collectively—through open standards, interdisciplinary collaboration, and continual critical reflection—will be essential for realizing a highly adaptive, productive, and human-centered digital future, well-aligned with the objectives and challenges outlined at the outset of this review.

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Table 17: Industrial Digital Transformation: Main Trends, Gaps, and Future Opportunities

Main Trends	Current Gaps / Challenges	Future Opportunities / Research Directions
Agile, modular, and interoperable system architectures [38][36] Cross-domain standardization (data, knowledge, interfaces) [60][92] Enhanced human-centricity and AI-enabled operator support [34][88][42] Ethical AI, fairness, and regulatory adaptation [7][31][42] Organizational agility enabled by digital leadership/culture [28] Productivity measurement and new impact assessment tools [92][80]	Generalization and adaptation limitations in AI for dynamic tasks [66][69][83] Lack of universal open standards and fragmentation [60][92] Translating human-AI research into measurable workplace outcomes Privacy/security risks and slow policy development [7][31] Resistance to change and misalignment between leadership and strategy [28] Limitations of existing ROI/productivity metrics	Advanced algorithms for lifelong learning and adaptive industrial AI Unified interoperability frameworks and collaborative open standards development Integration of explainable AI, digital twins, and VR for operator well-being Multifaceted frameworks addressing fairness, inclusiveness, and secure innovation Longitudinal studies of digital culture, leadership, and transformation metrics Hybrid (qualitative and quantitative) measurement frameworks for DT impact

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