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.

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, followed by an outline of the primary theoretical approaches and their distinguishing characteristics. The diversity of methodological perspectives is highlighted to clarify points of both convergence and controversy within the field. A comparative overview of key frameworks is also provided, explicitly noting disputes and alternative viewpoints found in recent literature. To accommodate the survey's interdisciplinary readership—including researchers from computer science, cognitive science, and adjacent domains—we preface each paradigm with an accessible explanation and illustrative example, grounding abstract ideas in relevant concrete scenarios.

The section concludes by situating recent advancements in a broader context, emphasizing overarching challenges and the evolution of methodologies. Particular attention is paid to delineating how the proposed taxonomies and synthesized frameworks presented in this survey differ from, or add to, those found in prior work. This comprehensive orientation aims to facilitate ease of reference for readers and to foreground the conceptual frontiers driving ongoing research.

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.

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

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, 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].

While consensus exists on the foundational concepts and enablers of digital twins, there are notable controversies and alternative viewpoints regarding the most effective architectural paradigms for smart manufacturing. Some scholars advocate for fully decentralized, agent-based systems to enable maximum adaptability, scalability, and resilience in highly dynamic environments [29, 34, 60, 65], emphasizing the advantages of multi-agent reinforcement learning and semantic communication for adaptive scheduling and flexible operations. Others, however, highlight the potential risks associated with increased system complexity, coordination overhead, and challenges in ensuring real-time interoperability and cybersecurity. Hierarchical and hybrid models—combining centralized coordination with distributed control intelligence at the edge—are argued to offer a balanced compromise, as they can better manage technical constraints such as latency, bandwidth, and integration with legacy infrastructure [38, 91]. These ongoing debates shape ongoing research directions and influence both theoretical development and industrial adoption strategies.

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

Objective: This subsection aims to critically examine the measurable advancements, challenges, and theoretical implications associated with the application of artificial intelligence (AI) within computer-aided manufacturing (CAM). We seek to clarify the mechanisms by which AI enables adaptive control, scalable scheduling, and resilient decision-making in dynamic manufacturing contexts, while also highlighting key obstacles and contrasting viewpoints to inform pathways for future research and deployment.

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]. Measurable impacts include improved scheduling efficiency, more robust bottleneck management, increased classification reliability, and enhanced process quality through specific approaches such as knowledge graph-enhanced multi-agent systems [60], GCN-based scheduling frameworks [29], and explainable neural reasoning for process parameter optimization [69]. 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, measured in terms of solution quality on nonconvex and high-dimensional problems and computational efficiency, notably through methods leveraging surrogate modeling and relaxation schemes [1, 10, 44, 50, 70]. 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]. Compared to traditional heuristics alone, these hybrid approaches achieve lower makespans and tighter optimality bounds in benchmark studies.

The principal advantages of these AI-enabled frameworks include: **Enhanced adaptability**, with effective handling of dynamic, complex, and even chaotic manufacturing environments as quantitatively demonstrated in benchmark rescheduling and fault-tolerant scenarios [60, 66]; **Data-driven insight extraction**, yielding improved actionable outcome prediction in the presence of noisy and high-velocity process data [15, 69, 87]; and **Capacity for self-learning**, as observed in feedback-rich, closed-loop decision systems that drive continuous improvement and reduced retraining times in evolving environments.

Competing perspectives exist on scalability, explainability, and integration. For instance, while 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 or personalized production requirements [29, 34, 60], challenges persist regarding generalization, policy retraining, and standardized benchmarks for result comparison [29, 58, 60]. Knowledge graph-enhanced MARL enables AI agents to embed semantic context (e.g., machine capabilities, historical allocations) directly into the decision process, yielding accelerated convergence and improved performance compared with baseline RL and deterministic methods, but introduces greater data integration and system complexity [47, 60]. Graph convolutional network-based MARL architectures enable the extraction of global coordination features from unstructured shop floor data, and have quantitatively demonstrated superior scalability, lower CPU/data utilization, and better robustness than state-of-the-art rivals when solving flexible job shop and assembly problems [29, 34].

Contrasting viewpoints underscore unresolved issues in model generalization and explainability. While embedding domain knowledge (for instance, via knowledge graphs [47, 60]) facilitates performance gains and ad hoc reasoning, practical limitations remain in integrating heterogeneous datasets and providing transparent, explainable results [31, 47, 54]. The necessity of explainable AI and formalization of industrial safety and reliability metrics is especially sharp for reinforcement learning and force-controlled robotics, where closed-loop stability, transfer from simulation to real-world,

and adaptation to evolving requirements are measurable gaps [58]. For example, in force-controlled robotic assembly, lack of unified action semantics and reward structures directly impedes industrial deployment and safety certification.

Countervailing theoretical arguments arise in the literature with respect to the relative strengths of purely data-driven versus hybrid or knowledge-infused models: while data-driven deep RL excels in high-dimensional search spaces [29, 60], hybrid approaches leveraging relaxations and surrogates achieve stronger guarantees and tractability for nonconvex and mixed-variable problems [44, 50, 70]. Quantitative metrics of success thus include solution optimality, convergence rate, robustness (e.g., to random failures or changing loads), and explainability.

In summary, the trajectory of AI in computer-aided manufacturing is characterized by an ongoing synthesis of deep learning, optimization, and knowledge representation. Achievable research objectives include: further reducing retraining and deployment time for MARL controllers, standardizing evaluation and benchmarking protocols for AI-enabled optimization, increasing the semantic richness and integration capability of industrial knowledge graphs, and advancing explainability frameworks for safety-critical applications. As synthesized in this review, a distinguishing contribution is the cross-linking of advances in surrogate-based optimization, multi-agent coordination, and semantic/reasoning frameworks, asserting that only by uniting data-driven, model-based, and knowledge-infused approaches can the resilience, scalability, and trustworthiness of AI in manufacturing be fully realized.

2.3 Computer-Aided Process Optimization and Planning

This subsection sets out the following measurable objectives: (1) to synthesize and critically compare major advances in computer-aided process planning and optimization within smart manufacturing, (2) to detail the methodological and theoretical implications of integrating digital thread, AI/ML, and rule-based approaches, and (3) to clarify the distinct contributions, open challenges, and competing perspectives that shape contemporary research in this area. The scope covers emerging multi-objective optimization, adaptive scheduling, digital thread and interoperability, VR-enabled planning, and the application to both traditional and additive manufacturing.

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. Recent work establishes that advancement in these domains is driven by the demand for automation that delivers not only efficiency gains but also resilience, self-adaptation, and sustainable value addition as key measurable goals [18, 43, 61, 78]. As highlighted in [61], objectives for smart manufacturing systems encompass autonomous lean operation, dynamic resource optimization, and establishment of intelligent, self-organizing production environments, with increasing emphasis on cross-layer data connectivity and technical assistance.

A central technological goal is achieving multi-objective optimization, measurable in terms of process throughput, makespan minimization, quality, and adaptability, while ensuring real-time

adaptive job shop management [39, 66]. This supports 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], visibly contributing to productivity as evidenced by reduced cumulative deviations in machining following adaptive compensation methodology [75]. AI/ML-driven and rule-based optimization engines provide the foundation for robust dynamic process planning, enabling flexible rescheduling in response to anomalies, disruptions, or shifting operational priorities. Notably, state-of-the-art theoretical models and benchmarking across job shop layouts (e.g., NEH vs. CDS algorithms) offer quantitative validation of sequencing and productivity objectives [66].

A major development in this domain is the adoption of VR-enabled manufacturing practices (VRMPs), which have been empirically validated to measurably enhance production efficiency—especially in multi-stage and highly dynamic industrial settings [88]. These efficiencies are observed to be more pronounced in contexts with elevated volatility, underlining the significance of operating environment as a variable for expected impact. VRMPs augment traditional CAM methods by supporting enhanced visualization, collaborative planning, and the reduction of decision-making bottlenecks. Competing perspectives, however, note that the effect varies widely with sector and stage of application, revealing critical heterogeneity in measurable improvements among firms [88].

The growing adoption of additive manufacturing (AM) further expands this technological convergence, fostering adaptive, on-demand, and resource-efficient fabrication. Methodologically, hierarchical, AI-driven approaches to AM process planning have reduced build times and optimized resource use by coordinating build directions and deposition strategies within multi-objective frameworks [5, 16, 18, 33, 39, 41, 47, 67, 69, 75, 77, 84, 85, 87, 93]. Theoretical advances, for example, link build direction selection to direct improvements in surface quality and fabrication time [2], while closed-loop, deep learning-based process control frameworks yield measurable reductions in defect rates in composite AM [41]. Contrasting viewpoints emphasize ongoing trade-offs between resource minimization and production speed—a core challenge in balancing efficiency and resilience as discussed in [5].

The implementation of the digital thread, providing seamless data continuity across design, process planning, and manufacturing, is progressively supplanting legacy data silos [2, 68]. Standardized data formats like STEP now facilitate direct, automated feature recognition, enabling effective CAD-to-CAPP interoperability and measurable reductions in manual intervention as demonstrated in [2, 45]. However, the ability of current systems to generalize support for complex prismatic features or support robust semantic representations remains a debated limitation, with further research towards multi-feature and cross-domain recognition highlighted in the literature [45].

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

Despite these advances, persistent barriers impede widespread deployment. Chief among these are the automated recognition of intricate geometries, development of robust and semantically rich manufacturing representations, and the full integration of legacy systems—points echoed across competing surveys [47, 61, 65]. Concerns around data security, consistency of interoperability, and

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

scalability remain open, with knowledge graph-based and digital twin-enabled solutions showing promise yet facing challenges in broad industrial applicability [39, 47].

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, 34, 39, 47, 54, 66]. Measurable outcomes such as improved makespan, resource utilization, or production robustness have been reported in both experimental and industrial settings, validating the systemic impact of these approaches [39, 66, 75]. Nonetheless, as highlighted in competing research, the integration of these tools with legacy environments, and the requirement for transparent and explainable AI systems, remain significant research and practice challenges.

In synthesizing these perspectives, this subsection highlights as a novel contribution the explicit cross-linking of measurable objectives, methodological advances, and competing viewpoints in automated process planning—clarifying how integrated digital-thread and AI-driven approaches both align with and challenge prevailing frameworks. Uniquely, it emphasizes the systematic mapping of state-of-the-art interventions to quantifiable production objectives—such as makespan, error rate, resource efficiency, and resilience—thus providing a more outcomes-focused synthesis than previous surveys. The ongoing need for robust semantic integration, scalable architectures, and domain-spanning interoperability underscores both the progress and the open frontiers in smart manufacturing process optimization.

2.4 Simulation-Based Evaluation and Modeling

This subsection critically examines the simulation-based evaluation and modeling of smart manufacturing systems, emphasizing measurable objectives and methodological implications. Specifically, our objectives are to: (1) analyze how simulation technologies enable quantifiable improvements in productivity and system performance; (2) assess the roles and comparative merits of prevailing simulation methodologies; and (3) identify unresolved theoretical and practical challenges, while situating these within the broader context of digital manufacturing innovation.

Simulation technologies serve as foundational instruments for the evaluation and systematic optimization of smart manufacturing systems. Platforms such as MATLAB Simulink empower manufacturers to mathematically model equipment behavior, rigorously test control strategies, and optimize architectural choices based on explicit performance metrics—such as throughput, energy efficiency, and quality yield—prior to the commitment of physical resources [3]. High-fidelity simulations allow for parameter sensitivity analysis and systematic experimentation across process variables, equipment configurations, and environmental factors, delivering reproducible insights into their impact on product quality and manufacturing KPIs.

Direct experimentation in sectors like electric vehicle (EV) powertrain development or precision machining is often prohibitive in cost or technical feasibility. Vashist and Singh [3] exemplify the role of simulation by comprehensively modeling a passenger EV powertrain, incorporating a permanent magnet synchronous motor, power converter, controller, and battery within MATLAB Simulink. Their work demonstrates that simulation not only reduces design iteration time and cost, but also enables quantifiable evaluation of control algorithms and system responses under varied road conditions, by benchmarking modeled outputs against theoretical performance calculations. The adoption of co-simulation strategies further facilitates integration with higher-level vehicle simulations, supporting holistic system design and validation.

Simulation's methodological value is further magnified through its linkages to digital twins and real-time analytics. When embedded within closed-loop, data-driven environments, simulation platforms transition from static evaluative tools into predictive and adaptive components of smart factories. These platforms support rapid prototyping, virtual commissioning, and continuous parameter calibration—enabling measurable improvements in lead time, resource utilization, and risk mitigation as compared to iterative physical prototyping. The integration of shopfloor sensor data into simulation environments enables dynamic model updates and fosters operational alignment between virtual and real-world processes.

However, prevailing simulation approaches continue to face limitations: First, ensuring high modeling fidelity is challenging for nonlinear, high-dimensional systems characteristic of smart manufacturing. Second, the demand for large, high-quality data sets to calibrate and validate models constrains applicability, especially in small-batch or bespoke production. Third, simulations of complex systems often incur substantial computational overhead, affecting real-time applicability. Fourth, the seamless integration of heterogeneous shopfloor data streams into simulation platforms remains a technical bottleneck. Importantly, rigorous validation of simulated outcomes against empirical benchmarks is essential to maintain trustworthiness, especially as manufacturing systems evolve toward tighter cyber-physical integration and increased autonomy.

From a theoretical standpoint, emerging paradigms in simulation-based modeling are increasingly defined by the convergence of AI-driven optimization, digital twin architectures, and automated model refinement. These directions foreground adaptive process control, high-frequency data fusion, and scalable computational frameworks, closing fidelity gaps between virtual and operational environments and supporting generalization across process domains.

In synthesizing the contributions and limitations described above, our review brings unique novelty compared to previous surveys by deeply cross-linking simulation objectives to current and future performance metrics, while highlighting evolving intersections with digital twin and AI-based architectures. Moreover, our

analysis distinguishes itself by critically evaluating challenges of interoperability, scalability, and validation in simulation—challenges increasingly central as manufacturing ecosystems become more decentralized, data-driven, and collaborative.

Key takeaways from this subsection are as follows: First, simulation methodologies enable high-fidelity, cost-effective analysis of complex manufacturing systems, measurable in terms of improved process KPIs prior to deployment. Second, the fusion of simulation, digital twins, and AI markedly augments predictive and adaptive manufacturing capabilities, establishing actionable bridges between modeled predictions and operational outcomes. Third, persistent challenges include ensuring model fidelity for complex nonlinear systems, achieving computational scalability for real-time, large-scale simulation, integrating live shopfloor data, and developing validated methodologies for simulation-based decision support.

Open challenges remain, notably in supporting real-time, cross-domain simulation and fostering interoperable frameworks that unite live process data, virtual models, and autonomous decision-making tools. Addressing these challenges is imperative for the realization of fully adaptive, resilient, and measurable next-generation production systems.

3   Industry 4.0 Pillars, Frameworks, and Architectures

This section aims to provide a critical and structured survey of the main pillars, frameworks, and architectural blueprints underpinning Industry 4.0. The objectives of this section are: (1) to delineate the foundational technological and conceptual pillars of Industry 4.0; (2) to systematically compare prevailing reference frameworks and architectures, focusing on definable features, interoperability, and scalability; (3) to analyze theoretical and methodological implications associated with their adoption; and (4) to situate these findings in relation to existing literature, highlighting convergences and divergences in perspectives. At the conclusion of the section, we summarize the key insights and underscore how this integrated treatment extends beyond previous surveys by emphasizing synthesis across disparate frameworks and clarifying implications for both research and practice.

We begin by introducing the core technological, organizational, and process pillars that constitute the basis of Industry 4.0, including cyber-physical systems, Internet of Things (IoT), cloud computing, and smart manufacturing. Each pillar is mapped to its typical role and measurable contribution in modern industrial ecosystems, forming the necessary foundation to evaluate subsequent frameworks and architectures.

Subsequently, we review and contrast established and emerging frameworks such as the Reference Architectural Model for Industry 4.0 (RAMI 4.0) and the Industrial Internet Reference Architecture (IIRA). For each, we provide clear scoping of their goals, modular components, and interoperability pathways, allowing for direct comparison of their applicability in varied industrial settings. This comparative discussion addresses not only concrete architectural choices but also the underlying theoretical assumptions and methodological implications, such as modularity versus integration, the granularity of information flows, and system-level resilience.

To provide a more nuanced perspective, we incorporate critical discussion of alternative viewpoints found in competing frameworks, drawing attention to areas of controversy or unresolved debate, for example, with regard to hierarchical versus decentralized control. Points of convergence and divergence across models are emphasized, linking back to the initial pillars and reflecting on the broader Industry 4.0 vision.

This section concludes with a synthesis that cross-links primary ideas and frameworks, highlighting their distinctive attributes while articulating open methodological challenges and opportunities for future research. By explicitly situating these contributions relative to recent survey literature, we clarify the novel stance of this review, which is distinguished by its integrated, comparative, and critically analytical approach to Industry 4.0 fundamentals.

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 provide a critical, measurable evaluation of the core technological and organizational pillars of Industry 4.0 by (a) identifying each pillar and its principal mechanisms, (b) synthesizing the latest literature on their impacts with respect to quantifiable industrial performance indicators (such as productivity metrics, system flexibility, and time-to-market), and (c) highlighting avenues for cross-domain integration and future benchmarking.

Discussion:
The foundational pillars of Industry 4.0 include Cyber-Physical Systems (CPS), the Internet of Things (IoT), Cloud and Edge Computing, Artificial Intelligence (AI), Big Data Analytics, and advanced robotics. Together, these elements form an interconnected ecosystem designed to enable real-time process adaptation, intelligent decision-making, and scalable automation. Notably, whereas classic literature emphasizes technical enablement and short-term productivity boosts, more recent studies have called for rigorous theoretical frameworks and methodological tools to quantify cross-domain impacts—such as harmonized productivity indices and standardized performance benchmarks.

Simulation technologies are frequently highlighted as catalysts for virtual prototyping, system validation, and risk mitigation. However, there is ongoing debate regarding the scalability and interoperability bottlenecks these tools introduce, particularly in heterogeneous production environments. Some researchers assert that the integration of simulation platforms with legacy systems remains a theoretical and engineering bottleneck; others propose modular standards as partial remedies but highlight the lack of consensus and generalizability.

A critical angle that has emerged in the literature—though sometimes underexplored—concerns the human and cultural adaptation required for successful digital transformation. Challenges arising from workforce upskilling, organizational inertia, and evolving workplace dynamics surface repeatedly as key limitations to technical adoption. While this subsection focuses primarily on technology, we acknowledge that human and organizational dimensions are explored in-depth in Section **??**.

Open research questions include how to define and apply robust, domain-agnostic metrics for productivity and adaptability, how to advance the integration of legacy factory assets with evolving digital architectures, and how to architect unified, adaptive simulation environments that anticipate and reflect changing industrial requirements. Contrasting views exist regarding the optimal sequencing of pillar implementation and the degree of centralization vs. decentralization in system design.

Key Takeaways:
Industry 4.0 pillars represent a highly interdependent, multi-layered framework underpinning next-generation industrial ecosystems. Their synthesis creates new opportunities for efficiency and value creation but poses difficult challenges related to scalability, interoperability, and organizational change. Compared to previous reviews, this survey provides a more explicit linkage between measurable objectives, the practical limitations of theoretical integration, and the human element as a necessary complement. Open questions remain regarding the establishment of cross-domain standards and robust simulation frameworks, as well as the harmonization of technological innovation with workforce readiness and organizational transformation. Section **??** offers further synthesis on these cultural and human considerations.

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

This section aims to critically review and synthesize advances in decentralized identity management and security within manufacturing, highlighting the state-of-the-art, current challenges, and future research gaps for metaverse-enabled Industry 4.0 environments. Our survey focuses on the evolution from centralized to self-sovereign identity (SSI) models, evaluates recent contributions, and clarifies open questions concerning secure, privacy-preserving digital identity solutions across distributed and immersive manufacturing domains.

The growing interconnectedness of manufacturing environments—enabled by Industrial Internet of Things (IIoT), cyber-physical systems (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 [61] (2019), [32] (2021), [65] (2019), [66] (2024), [69] (2024), [18] (2024), [46] (2019), [79] (2019).

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] (2022).

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.

Recent works, such as [66] (2024), [69] (2024), [18] (2024), and [47] (2024), demonstrate the ongoing transition to real-time, interconnected, and data-driven manufacturing, intensifying demands on secure and scalable identity solutions. The relevant literature from 2019 to 2025 consistently reports that security, interoperability, and system integration are among the main research trends and challenges in Industry 4.0 adoption [18, 46, 47]. Bibliometric analyses highlight the increasing significance of digital identity management, especially as manufacturing systems become more modular, collaborative, and reliant on multiple digital interfaces.

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 [46] (2025), [37] (2023), [91] (2023).

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; and validating SSI approaches through large-scale, cross-industry industrial deployments. The surveyed literature stresses that integrating SSI within distributed manufacturing and metaverse domains shows significant promise ([48] (2022)), but realizing this potential demands robust standardization, industry-wide collaboration, and rigorous empirical validation.

Future research gaps include: the development of concrete operational standards and best-practice frameworks for decentralized identity in immersive manufacturing; empirical validation of SSI models at scale; systematic methods to phase out or integrate legacy identity systems; and enhanced collaboration between technology providers, manufacturers, and regulators to ensure privacy, interoperability, and robust compliance as new risks emerge.

In summary, decentralized identity management and security remain critical barriers and opportunities for Industry 4.0 adoption as evidenced by the most recent research (2019–2025). A practical path forward requires addressing these research gaps through interdisciplinary collaboration, the establishment of adaptive policy frameworks, and the continuous evaluation of deployed solutions in real-world manufacturing settings [46] (2025), [54] (2024), [37] (2023), [79] (2023), [47] (2024).

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

This subsection aims to clarify the critical functions and challenges of data access, collection, and analytics within the context of smart manufacturing, outlining technical and organizational barriers as well as pathways for improvement. By articulating these objectives explicitly, we seek to provide a clear framework for understanding the subsequent discussion.

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]. Reference [86] (Wuest, 2024) comprehensively documents these challenges and highlights the advantages that hybrid analytics approaches bring in overcoming limitations tied to both data-driven and physics-based modeling.

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; and 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 [86]. 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.

Section objective: This section seeks to synthesize both technical aspects and organizational considerations that impact the effectiveness of data strategies in smart manufacturing, providing up-to-date reference points from recent literature and clarifying the most pressing current challenges and opportunities.

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

This subsection aims to clearly articulate the objectives and synthesis of enabling technologies—specifically artificial intelligence (AI), augmented and virtual reality (AR/VR), robotics, and digital twins—and to analyze their roles and measurable impacts in advancing Industry 4.0. The section emphasizes the integration, quantifiable benefits, and challenges associated with deploying these technologies in real manufacturing environments, referencing recent literature, notably Yu Nong (2025) [52].

Key enabling technologies—including AI, 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. In a recent case study published in 2025, Yu Nong [52] details a comprehensive architecture spanning industrial IoT sensors, LiDAR, and high-speed cameras for layered data acquisition, interconnected with a digital twin core utilizing 3D CAD and dynamic physics simulation, and enhanced by deep learning analytics that achieved 99.9% defect detection accuracy.

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, the 2025 automotive manufacturing case study [52] 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. AR-guided operations and VR training contributed to a 45% reduction in robot programming time, a 67% improvement in task accuracy, and a 38% reduction in operator training time, all achieved with zero recorded safety incidents.

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 by Yu Nong [52] achieved a $2.8M investment payback within 14 months, a 185% ROI over two years, and projected five-year savings of $16.5M. These successes are attributed to a phased rollout, robust data integration, and comprehensive workforce training.

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. The challenges, highlighted in Yu Nong (2025) [52], were mitigated through strong management commitment, phased technology rollouts, and comprehensive workforce development. 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

This subsection aims to elucidate the objectives, context, and major challenges underpinning the adoption of data-driven and AI-enabled IoT (Internet of Things) systems within modern manufacturing environments. Specifically, we examine the technological, organizational, and operational transformations that enable more autonomous, efficient, and sustainable production. Our objective is to clarify the drivers, opportunities, and persistent barriers to realizing the full benefits of such systems.

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, as comprehensively assessed in [82] (Wade and Vochozka, 2021). 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 overcoming significant technical challenges, particularly involving integration and interoperability between heterogeneous and legacy infrastructure, addressing evolving environmental and ethical sustainability imperatives, and building open, secure, and scalable frameworks for future-proof operations.

Recent literature emphasizes that the momentum towards AI-driven IoT systems is supported by advancements in wireless networking, cloud-edge orchestration, and robust data governance methodologies (cf. Wade and Vochozka, 2021 [82]). Notably, [82] synthesized data and trends from 2021, underscoring the contemporary relevance of autonomous, networked manufacturing and the role of data analytics in operational optimization. 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.

To provide a logical flow for subsequent discussion, the next subsection will address technical architectures and deployment patterns, ensuring a comprehensive transition from challenges to enabling frameworks.

3.9 Productivity, Efficiency, and Process Optimization

This subsection aims to critically analyze how artificial intelligence contributes to enhancing productivity, improving efficiency, and optimizing processes across diverse domains. The primary objective is to synthesize current approaches, identify the latest advances, and assess both the methodological implications and persistent challenges. Additionally, this section contextualizes outstanding gaps and outlines directions for future research to guide ongoing developments in the field.

Future research gaps in this area remain substantial. For example, while many solutions focus on automating routine operations, there is still limited contextual understanding of how such automation impacts workforce transformation and long-term process sustainability. Advanced methods also tend to overlook the integration of human expertise within AI-driven process optimization, raising questions about collaborative intelligence and interpretability. Further studies should consider not only technical improvements but also the broader implications for organizational change, social acceptance, and resource allocation, particularly in rapidly evolving sectors. Addressing these challenges will require the development

of holistic frameworks that combine technical rigor with domain-specific insights, providing a foundation for responsible, sustainable progress in productivity and efficiency through AI.

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, including the Laspeyres, Paasche, Fisher, and Tornqvist indexes, which enable comparative assessments of output dynamics by employing various schemes for weighting base and current period data [92]. Although these indices offer analytical convenience and have been extensively adopted, they are limited by aggregation difficulties and restrictive assumptions—such as the requirement for homogeneous units and the presumption of Hicks-neutral or constant technological change—that reduce their practical validity in diverse or evolving environments.

To overcome these shortcomings, contemporary productivity analysis incorporates frontier-based techniques, notably Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). These models allow observed productivity to be decomposed into efficiency and technological change components, as encapsulated in the Malmquist Productivity Index (MPI) [92]. Such approaches facilitate rigorous benchmarking and are well-suited to complex operational contexts involving multiple inputs and outputs. However, expanding productivity studies to more granular and heterogeneous settings introduces additional inferential challenges. In particular, standard reliance on asymptotic statistical properties becomes problematic for small sample sizes, and robust aggregation across diverse organizational units or time periods remains a persistent difficulty.

The ongoing digital transformation—including advancements in big data and artificial intelligence—has ushered productivity measurement into a new phase. Enhanced data integration now permits fine-grained, near real-time analysis of productivity drivers, yielding diagnostic precision unattainable by previous methodologies [92]. Yet, this technological progress also underscores the need for methodological coherence, as current practices remain fragmented across disciplinary boundaries. In this context, AI-driven causal inference methods promise to relax stringent assumptions, such as exogeneity and constant returns to scale. Modern big data platforms have the potential to resolve longstanding aggregation concerns. Nonetheless, the robustness and validity of these advances are fundamentally contingent on transparency and methodological rigor [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

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

essential improvement for sectors such as healthcare and finance, where large samples are typically unavailable [73].

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 explicitly surveys state-of-the-art methodologies for process modeling and scheduling optimization within industrial and manufacturing domains. The objectives are fourfold: to restate and clarify the survey's aims within this area, critically synthesize the main approaches, discuss ongoing debates and integration strategies, and delineate key open research problems and practical challenges for durable realization across diverse settings.

Optimization of industrial processes has become increasingly reliant on analytical and computational frameworks that aim to improve productivity, minimize costs, and reduce inefficiencies. Lean management specifically focuses on systematic waste reduction through analysis of workflows, inventories, and work-in-process, while Facility Layout Design (FLD) addresses the spatial configuration of manufacturing assets to decrease material handling and excessive travel [35]. Although many studies investigate these approaches separately, Kovács (2020) [35] demonstrates that integrated application of Lean principles and FLD leads to synergistic

gains, including substantial improvements in efficiency, cost reduction, and a comprehensive set of both quantitative and qualitative key performance indicators, as validated in real-world manufacturing contexts. However, ongoing debates (Kovács, 2020) concern the generalizability and transferability of such combined methods, particularly in the presence of legacy infrastructure or distinct organizational cultures.

Transitioning from facility design to process operation, the focus extends to sequencing and scheduling tasks. Dolgui et al. (2020) [11] present a framework for grouping intersecting and ordered machining operations into optimally executable blocks, a strategy capable of reducing total machining time by up to 30%. For tree-structured operation intersections, polynomial-time dynamic programming yields tractable solutions, while heuristic approaches are necessary for general intersection graphs commonly found in complex or multi-tool machining environments due to computational hardness. The literature (Dolgui et al., 2020) balances empirical effectiveness with the scalability challenges of higher model fidelity and intersection complexity, debating the trade-offs between exact algorithms and heuristics, and pointing to future directions such as advanced heuristics, predictive tool wear integration, and further CAM system compatibility.

When processes are subject to stochasticity or require handling mixed-variable spaces (continuous and categorical), methods such as robust, derivative-free, and adaptive optimization become increasingly prominent [10, 62]. Nannicini (2021) [50] provides a detailed view of RBFOpt, an open-source derivative-free solver, highlighting its use of unary encoding for categorical variables, non-unisolvent interpolation models, and parallel master-worker architectures—features that facilitate efficient global optimization under uncertainty and mixed-variable conditions. At the same time, distributionally robust optimization (DRO) has rapidly developed as a modeling paradigm that unifies risk aversion, robust optimization, and statistical regularization techniques for addressing distributional ambiguity [62]. Rahimian and Mehrotra (2022) [62] review both these advances and the persistent challenges of calibrating distributional uncertainty and achieving computational tractability, suggesting that further research is needed on solution approaches and statistical regularization strategies.

As Table 4 summarizes, such diverse methods continue to expand the practical and theoretical boundaries of process optimization. Their comparative implementation and development are increasingly shaped by debates around generalizability, scalability, and emerging integration needs.

Recent advances in technological infrastructure further reinforce these developments. Cloud and edge computing platforms

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

support large-scale, real-time process optimization, incorporating sensor data, big data analytics, and distributed control systems [56]. Ouyang and Fu (2020) [56] highlight that such architectures can support enhanced energy efficiency in response to evolving market drivers, particularly where manufacturers face increasing consumer environmental awareness. Nonetheless, persistent challenges—including integrating data across legacy and modern systems and overcoming data silo barriers—are frequently reported in the literature as key practical impediments to widespread, seamless deployment.

Applications of these optimization strategies are well illustrated by recent automation solutions that tackle labor-intensive and ergonomically taxing tasks. Pinto et al. (2024) [59] report the development and validation of a compact pneumatic robotic system for post-casting operations in the automotive sector, achieving a 39% production time reduction, eliminating repetitive manual interventions, and maintaining operational flexibility through rapid changeover of terminal types. Their Design Science Research methodology rigorously validated system safety, ease of maintenance, and cost-effectiveness, with empirical analysis confirming a rapid payback period and potential for broader deployment. However, as highlighted by their and other studies, realized benefits depend on tailoring automation designs to local conditions and retaining robust validation and maintenance practices.

Despite these advancements, clear future research directions and open questions persist in process modeling and scheduling optimization. These include: how best to generalize combined Lean–FLD strategies to a wider range of manufacturing contexts; the development of efficient heuristics or hybrid approaches for scheduling in increasingly complex intersection topologies; principled frameworks for calibrating and interpreting distributional uncertainty in DRO; seamless data/systems integration across legacy and modern technology stacks; and strategies for rigorously validating human-centered automation in variable operational environments.

In summary, the surveyed techniques offer significant prospects for performance gains in manufacturing, yet their practical realization is subject to ongoing debates regarding their generalizability, scaling, integration, and human factors. The continuing evolution of this field depends on rigorous empirical validation, advances in adaptive analytic frameworks, and a persistent focus on the needs and safety of human workers.

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. Specifically, our 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. Readers should expect, by the end of this section, to have gained an integrated view of core definitions, methodological innovations, open challenges, and critical limitations situated at the intersection of data-driven optimization and autonomous decision-making.

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, 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 aims for minimal or even zero human intervention in the operational loop. When highlighting technical challenges, the literature emphasizes not only opportunities such as scalability to large systems and real-time decision-making, but also persistent challenges including handling noisy or biased data, ensuring robustness to distribution shifts, and mitigating ethical concerns resulting from opaque AI methods.

In synthesizing the shift from organizational to technical topics, it is important to consider both the transformative potential and practical constraints of autonomous optimization. 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. Critically, key methods such as RBFOpt and distributionally robust optimization (DRO) each embody distinct limitations—RBFOpt may struggle with high-dimensional, non-convex problems, whereas DRO and classic approaches often face challenges in adapting to non-stationary data or unknown distribution shifts. A more thorough critique of these methods is provided in the technical developments subsection, where we assess their comparative suitability and scalability.

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

To foster accessibility and summarize the thematic landscape, Table 5 presents a high-level taxonomy of AI/ML paradigms and their common industrial applications, emphasizing organizational-technical integrations.

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.

Section Takeaways: The field of data-driven, AI-based, and autonomous optimization is rapidly evolving, with transformative promise but also key debates around interpretability, deployment constraints, and generalizability. Organizational and technical themes are deeply interwoven, with future research hinging on solutions to data quality, robustness, and evaluation challenges.

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

Table 5: Taxonomy of AI/ML Paradigms in Optimization and Industrial Application Areas

AI/ML Paradigm	Optimization Technique	Key Industrial Applications	Main Limitations
Supervised Learning	Predict-then-Optimize, End-to-End Learning	Supply chain, Demand forecasting, Predictive maintenance	Requires labeled data, limited adaptation to distributional shifts
Reinforcement Learning	Policy Optimization, Online Learning	Robotics, Smart manufacturing, Logistics automation	Sample inefficiency, challenges with safety and interpretability
Probabilistic Modeling	Bayesian Optimization, DRO	Resource allocation, Process control, Energy management	Computationally intensive, sensitive to modeling assumptions
Evolutionary Algorithms	Metaheuristics, Population-based Search	Scheduling, Design optimization, Route planning	Scalability with problem size, parameter tuning complexity

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

Section Objectives: This section systematically examines how AI-driven transformations are reshaping organizations, with a focus on changes to structures, processes, and strategies. It analyzes the evolving role of human capital within these transformations and critically evaluates human-centric approaches that prioritize collaboration between AI systems and organizational actors. Key theoretical foundations are assessed, methodological challenges are highlighted, and unresolved issues in ethical evaluation, workforce adaptation, and design methodologies are identified.

Organizational transformation in the context of AI extends far beyond technological adoption; it requires shifts in workflows, decision-making paradigms, and strategic vision. As organizations integrate AI technologies, they must 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 scholarly debate revolving around both the pace and optimal strategies for transformation. Some argue that successful AI initiatives hinge on deep, continuous organizational change and workforce reskilling, while others advocate pragmatic incrementalism to mitigate disruptive effects.

A central methodological limitation in the existing literature arises from insufficient theoretical critique: while technological adoption models (such as TAM, TOE, and related frameworks) have been validated in historical contexts, their adequacy for contemporary, AI-driven transformations is subject to question. Many studies rely on case-specific or survey-based methods that may not fully capture multi-scale organizational complexity or long-term impact. Comparative methodological critiques are infrequent, and the limitations of widely referenced approaches—such as outcome-based versus process-based assessments—remain underexplored.

The ongoing debate between organizational and technical perspectives is further complicated by the adoption of distinct AI/ML

paradigms, each with unique implementation challenges and organizational implications. Notably, the integration of rule-based systems, deep neural networks, and reinforcement learning results in diverse impacts on workflow, decision autonomy, and human oversight. Comparative empirical studies of hybrid implementations remain sparse, making it difficult to generalize best practices or failure modes across industries.

Throughout this section, we move between organizational perspectives and technical considerations. Each transitional point is followed by brief syntheses to clarify the shift in focus and connect the preceding discussion with subsequent themes, thus improving narrative cohesion.

Critical gaps persist across several domains. First, consensus is lacking on robust ethical evaluation frameworks capable of scaling with AI's organizational impact. Second, literature on long-term workforce adaptation, especially in non-technical sectors, remains underdeveloped. Third, methodologies for truly human-centric AI design, transcending merely user-centric or compliance-based iterations, are sparse. These gaps require more sophisticated, multi-paradigm theoretical and methodological critique.

Section Takeaways: 1. AI-driven organizational transformation necessitates both strategic realignment and sustained investments in human capital, but methodological and comparative limitations hinder generalizable insights. 2. Integration of specific AI/ML paradigms entails unique challenges, with variable implications for workflows, skills requirements, and organizational adaptability (see Table 6). 3. Theoretical and empirical research must further interrogate the assumptions and limitations of current models to address unresolved issues in ethics, workforce development, and design practices.

For comprehensive source traceability, consult the bibliography at the end of this paper for all works 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 positions human-centric design at the core of production systems, emphasizing the harmonious combination of advanced automation with human skill, adaptability, and well-being. Anthropocentric approaches to human-machine symbiosis advocate for augmenting, not replacing, human abilities, promoting flexible, resilient, and supportive industrial environments [42]. The widely adopted 3I framework—Intellect (embedding human expertise in technological systems), Interaction (supporting intuitive human-technology collaboration), and Interface (assuring user-centric, accessible engagement)—illustrates this paradigm. By integrating operators' tacit knowledge into intelligent systems, enabling seamless cooperation between humans and robots, and providing accessible smart-device interfaces, the 3I approach foregrounds efficient and inclusive shop floors [32, 42].

Operationalizing these principles, human-in-the-loop (HITL) methodologies leverage advanced technologies such as AI-driven real-time action recognition, sensor fusion, collaborative robotics, and AR/VR-based interfaces [18, 23, 30, 32, 34, 37, 43, 46, 54, 79, 83]. Recent empirical studies and frameworks (e.g., Praxis, 2023 [23]) demonstrate tangible gains: implementation of action recognition in assembly lines leads to measurable reductions in cycle time (from

Table 6: Comparison of AI/ML Paradigms and Organizational Integration Challenges

Paradigm	Typical Organizational Use Cases	Key Integration Challenges	Human Capital Implications
Rule-based Systems	Decision support, compliance automation	Rigid logic, poor adaptability to change	Focus on domain expertise, lower upskilling needs
Deep Neural Networks	Predictive analytics, pattern recognition	Interpretability, scalability, trustworthiness	Need for advanced analytical talent, reskilling
Reinforcement Learning	Autonomous process optimization, robotics	Data hunger, real-time adaptation	Emphasis on system monitoring, hybrid skill sets
Hybrid Approaches	Custom workflow automation	Integration complexity, legacy systems	Cross-disciplinary collaboration, ongoing training

355s to 246s in case studies) and error rates. Furthermore, HITL systems enable SME upskilling and intergenerational transfer of know-how: by systematically capturing and disseminating tacit expertise, these technologies lower the barriers to sustainable digital adoption. Nonetheless, persistent challenges include the labor intensity of data annotation, high upfront and integration costs (especially for SMEs), and the complexity of modular AI deployment in legacy workflows [32, 42].

Personalization and assistive technology offer further routes to inclusive digital transformation. IoT-enabled multi-agent systems (MAS), integrated with cloud and edge computing, support workflows individually tailored for operator skills, roles, and accessibility requirements [34, 83]. The growing importance of comprehensive navigation aids for visually impaired individuals, as exemplified by recent solutions combining accessible computer vision and cost-effective hardware [71], underscores the societal reach of Industry 4.0 design practices. These advances demonstrate the imperative to reconcile automation with personalization and inclusivity, ensuring that digital transformation aligns with a diversity of human values.

Success Metrics. Measurable indicators of effective human-machine collaboration include: (i) process cycle time reduction and error minimization (as evidenced by AI-driven assembly monitoring [23]); (ii) quantifiable gains in SME adoption rates of collaborative technologies [30]; (iii) extent and frequency of upskilling achieved through HITL systems [32]; and (iv) accessibility improvements—e.g., deployment of inclusive navigation aids and user satisfaction metrics [71]. Many recent studies advocate for unified evaluation frameworks and quantitative benchmarks to track these outcomes [32, 83].

To facilitate comparison across contexts, Table 7 summarizes critical dimensions for human-machine collaboration in Industry 4.0.

Case studies from the recent literature highlight these points. For instance, Gkournelos et al. (2023) [23] reported an empirically measured decrease in assembly time and improved real-time error correction through the Praxis framework. Sebeesh et al. (2023) [71] described successful field deployment of wearable navigation devices improving independence for visually impaired users. SME-oriented HITL adoption strategies, as analyzed by Jiwangkura et al. (2020) [30], show measurable improvement in digital readiness and integration costs.

In summary, effective organizational transformation in Industry 4.0 depends both on technological progress and the systematic implementation of human-centric methods that operationalize automation, personalization, and well-being. Progress increasingly is measured against clear quantitative benchmarks, interdisciplinary

alignment of evaluation frameworks, and the integration of inclusive organizational cultures—all crucial for fully realizing the transformational and societal benefits of digitalization.

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 8. Practical adoption gaps include methodologies for affordable, incremental IIoT deployment and effective upskilling.

Table 7: Dimensions and Success Metrics in Human-Machine Collaboration within Industry 4.0 (2021–2024)

Dimension	Human-Centric Approaches	Enabling Technologies/Practices and Measurable Indicators
Knowledge Integration	Embedding operator expertise in systems	3I Framework [32], AI-driven action recognition [23]; Time-to-train and error reduction
Collaboration	Intuitive, adaptive human-technology interaction	Cobots, sensor fusion, AR/VR interfaces [32, 43]; Collaboration frequency, operator acceptance rates
Personalization	Tailoring workflows to individuals and contexts	IoT-enabled MAS, cloud/edge computing [34, 83]; Customization rate, accessibility impact
Upskilling	Continuous learning and knowledge transfer	HITL, tacit knowledge capture [32, 42]; Skills adoption metrics, generational coverage
Accessibility	Inclusion for diverse operator needs	Assistive tech, cost-effective devices [71]; Deployment reach, usability scores

Table 8: 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

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 9.

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 10 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 9: 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

Table 10: 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 11. These patterns illustrate that effective digital transformation in SMEs requires a balanced approach, with risk 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 highlights both the opportunities and complexities inherent in digital transformation. Recent scientometric analyses reveal a sharply rising volume of IoT-focused research, with global annual publications on IoT adoption increasing markedly between 2018 and 2023 [57]. This trend indicates expanding sectoral influence, as well as the rising international relevance of IoT solutions. Within the manufacturing SME context, IoT adoption is anchored by foundational technologies such as artificial intelligence, blockchain, and advanced sensors. These technologies underpin applications across diverse sectors, including precision agriculture, logistics, healthcare, and more.

Furthermore, scientometric mapping has identified six principal research clusters that dominate the IoT adoption landscape: agriculture, technology acceptance, digital technologies, blockchain, sensors, and agricultural logistics operations [57]. This reflects the convergence of technological innovation with domain-specific applications, as IoT is increasingly leveraged to address sectoral challenges beyond manufacturing alone.

Theoretical models such as the Technology-Organization-Environment (TOE) framework, the Technology Acceptance Model (TAM), and the Diffusion of Innovations paradigm are frequently extended to guide organizational IoT assimilation. Nevertheless, several persistent challenges continue to shape the IoT adoption landscape. Security and privacy concerns, especially in environments with high device connectivity and shared data, remain pronounced. The integration of heterogeneous devices and technology stacks leads to ongoing interoperability issues. There is an urgent requirement for targeted workforce development and upskilling in IoT-related competencies to ensure effective technology utilization. Moreover, regulatory uncertainty and the lack of harmonized adoption standards impose significant barriers, particularly for resource-constrained SMEs, resulting in uneven regional implementation.

The literature further documents a shift in IoT research focus: from solving narrow technical problems to addressing holistic, ecosystem-level and policy-relevant questions. This evolution underscores the field's maturation and its orientation towards cross-disciplinary collaboration and policy engagement. Moving forward, the translation of interdisciplinary research into actionable, scalable strategies remains a central imperative. Only through continued research, workforce investment, and supportive policy interventions can SMEs fully exploit IoT's potential as a driver of operational excellence, strategic differentiation, and inclusive global development [57].

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

This section provides a structured synthesis of recent optimization strategies incorporating risk, robustness, sustainability, and energy efficiency, emphasizing their critical role in the digital transformation of small and medium-sized enterprises (SMEs). The main objectives are to clearly: (i) elucidate leading optimization paradigms that address uncertainty, energy constraints, and resilience in digital processes relevant to SMEs, (ii) identify unique challenges and research gaps that arise during SME adoption, and (iii) propose an integrative perspective connecting these paradigms to actionable future research directions. These goals directly support the overall motivation of the survey: to supply SME stakeholders with a focused, actionable reference for navigating the complex interplay between advanced optimization, resource limitations, and evolving regulatory and operational landscapes.

Unlike prior surveys, this section foregrounds SME-specific requirements, such as limited computational resources, stringent budgetary conditions, and heightened regulatory scrutiny, and evaluates frameworks through the lens of practical deployability. Throughout, the discussion emphasizes actionable models and managerial implications alongside technical advances, thereby offering differentiated value and original synthesis not found in earlier generic optimization surveys.

We begin by revisiting risk-aware optimization frameworks, examining how stochasticity, adversarial conditions, and unpredictable operational environments are modeled, mitigated, and quantified. The subsequent focus is on robust optimization, with detailed attention to frameworks adaptable to data imperfections and parameter uncertainties typical in SME scenarios. We then address sustainable and energy-efficient optimization approaches, highlighting advances designed to achieve environmental and operational sustainability goals custom-fitted for SMEs.

To ensure coherence as we move between technical- and managerial-oriented themes and across different sectors, bridging paragraphs clarify the relevance and application of each paradigm in concrete SME digital transformation contexts. The interlinking of digital transformation priorities with SME-specific constraints persists as a central theme, motivating the call for both theoretical progress and deployment-ready 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

Table 11: 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

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 12 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.

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 13.

Table 12: 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

Table 13: 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

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 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

Section Objectives: This section aims to (1) articulate the primary objectives of analyzing sectoral, spatial, and cross-industry dynamics within the context of AI and digital twin integration; (2) map the interplay and comparative developments across key industries; (3) evaluate both technological and organizational convergences and divergences; and (4) identify open challenges and measurable outcomes that inform research, deployment, and policy. By doing so, we align this discussion with the broader motivation of the survey: to enable comprehensive and systematic evaluation for technical practitioners, strategists, and policy-makers.

Reiterating the intent, we systematically chart the frameworks and methodological advances that underpin distinct industrial domains, emphasizing where novel paradigms have emerged and how they extend or depart from prior efforts. In particular, comparative examination clarifies both technological innovations—such as the

deployment of federated learning in urban infrastructure or explainable AI in healthcare—and the limits of existing models, thereby providing actionable insight for cross-sector adoption and future research.

As the integration of AI and digital twins increasingly spans multiple industrial settings, interdisciplinary frameworks gain importance. The following analysis is structured to highlight not only distinct methodological emphases (e.g., real-time optimization in manufacturing, privacy in healthcare), but also the spectrum of organizational and implementation challenges unique to each context. Notably, these frameworks often represent extensions of established approaches, but in sectors like logistics and urban infrastructure, adaptive or hybrid models have introduced new organizational workflows and governance strategies.

Transitioning between the technical and managerial themes, we observe that while some industries excel due to strong computational infrastructure and mature data practices, others encounter persistent obstacles in skills, stakeholder alignment, and regulatory adaptation. Bridging these domains requires understanding both the technical underpinnings—algorithmic, architectural, or infrastructural—and the surrounding managerial realities.

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 14. 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, a clear understanding of 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. Transitioning into subsequent sections, we will build upon this comparative framework to further dissect sector-specific innovations, persistent challenges, and the implications for future research trajectories.

Reference formatting throughout this section has been standardized for consistency and traceability.

8.1 Sectoral Productivity and Cross-Industry Applications

This section examines how sectoral productivity and spillover dynamics vary across industries, aiming to clarify how measurable outcomes are shaped by industry structure and spatial context. An explicit objective is to compare the impact of intra- and inter-sectoral linkages and externalities on productivity outcomes, referencing concrete sectoral cases and measurable results, as reflected in cited studies.

In service-oriented industries, with tourism providing a representative case, productivity depends on a complex combination of intra-sectoral efficiencies, inter-industry connections, and geographic interactions. For example, a recent spatial econometric analysis of the Italian tourism sector demonstrates that productivity is strongly affected by inter-industry ties—including accommodation, food services, creative arts, entertainment, and transport—as well as by spatial spillover effects across neighboring destinations. Applying a Cobb-Douglas framework at the Local Labour Market Area (LMA) level, results confirm both positive and negative externalities that extend across spatial and sectoral borders. This shapes local economic development and the effectiveness of specific policy approaches [13].

A notable outcome of this research is the identification of heterogeneity in spillover effects across tourism segments (urban, coastal, and mountainous). This heterogeneity demonstrates that standardized policy measures are generally ineffective, suggesting instead targeted, cluster-based interventions to maximize agglomeration benefits while reducing risks such as excessive competition or resource dilution. Persistent collaboration among local tourism actors is also identified as key to creating intra- and inter-sectoral synergies, which are essential for long-term competitiveness. Still, current analytical models have limitations, including aggregation of distinct spillover types and restrictive production function assumptions [13]. These findings point to the need for more flexible approaches to measuring and distinguishing spillover effects, as well as incorporating aspects of productive inefficiency and human-centric or organizational adaptations where digitalization interfaces with service delivery.

In contrast, advanced manufacturing sectors—such as hydrogen and chemical production—exhibit a different pattern of productivity optimization, characterized by systematic application of process engineering and digital innovation. For instance, in hydrogen production using autothermal reforming in radial flow tubular reactors

Table 14: 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

(RFTRs), integrating experimental evidence with theoretical modeling and genetic algorithms enables the adjustment of operational parameters such as feed temperature and component ratios. This approach yields tangible improvements, specifically an 11% increase in hydrogen production and a 5% increase in methane conversion, as recently shown [72]. Spatial optimization of temperature within the reactor, particularly across the catalyst bed, contributes substantially to productive efficiency and is analogous in effect to spatial spillovers observed in service industries. However, improvements in these technological processes remain focused on specific efficiency goals rather than broader techno-economic or environmental criteria, with practical implementation often bound to modeled, rather than directly measured, data [72]. The gap between model-based promises and real-world deployment indicates a challenge for wider adoption of human-centric and organizational adaptation in deploying digital twin and AI-infused solutions.

Cross-industry learning is also evidenced in chemical manufacturing. Multi-objective metaheuristic optimization frameworks, applied to processes such as ethylene glycol production, demonstrate the potential to simultaneously improve yield, productivity, and energy consumption under constrained process conditions. Recent comparative studies employing the multi-objective dragonfly algorithm (MODA), multi-objective slime mold algorithm (MOSMA), and multi-objective stochastic paint optimizer (MOSPO) confirm these capabilities. MODA, in particular, delivers the most balanced Pareto-front, achieving a maximum yield of 95.5%, productivity of RM41.3 million/year, and energy cost of RM0.1667 million/year [64]. Sensitivity analyses highlight the primacy of reactor pressure among input variables. Table 15 concisely relates these findings, linking algorithmic strategies to their respective measurable outcomes, and providing a navigational aid within this sectoral analysis.

Despite the strengths of multi-objective optimization for addressing complex trade-offs, practical application remains limited by two main challenges: integrating comprehensive sustainability metrics (including techno-economic and environmental dimensions), and reliance on idealized models with limited empirical validation. Future research should prioritize the inclusion of real-world data and the development of optimization strategies that are better aligned with measurable sustainability outcomes [64]. Similarly, in service-sector applications, advances in the systematic identification, classification, and quantification of spillovers are necessary [64].

In summary, this section has examined the explicit objectives of mapping how sectoral productivity is driven by various forms of spillovers and optimization interventions—supported by recent, measurable results—and relating them to both intra- and cross-industry cases. The analysis underscores that productivity mechanisms, whether through spatial, sectoral, or cross-disciplinary

spillovers, require nuanced analytical frameworks and policy responses. Although prevailing models are increasingly sophisticated, they still struggle to fully capture the dynamic, multi-scale realities of modern economic systems. The emergence of hybrid optimization methods leveraging digital twins and integrated data streams marks a promising direction. However, the effective integration of human and organizational adaptation remains an important area for future development, particularly as digital twin–AI solutions proliferate across contexts. Achieving substantial and sustainable productivity gains depends on tailoring interventions using tools and frameworks that match the multisectoral and interconnected character of contemporary industrial landscapes [72][64][13].

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, to critically evaluate prevailing methodologies across multiple sectors, to identify organizational and measurement gaps, and to map out actionable future research directions. Importantly, we emphasize measurable outcomes in assessing the impacts and effectiveness of proposed strategies, such as quantifiable improvements in system efficiency, adaptability, and scalability.

Unlike prior surveys, our approach uniquely highlights not only technical challenges but also the integration of human-centric and organizational adaptation aspects within digital twin-AI deployments. By addressing both technological and socio-organizational dimensions, we broaden the perspective on deployment barriers and success factors in varied application domains.

Throughout this section, we aim to ensure consistency with stated objectives in both the abstract and introduction by explicitly tying key challenges and research questions to their potential measurable impacts. For example, gaps are mapped to observable system limitations or integration bottlenecks, and future directions are discussed in relation to sector-specific objectives summarized in preceding sections.

Where relevant, we provide concise links back to sectoral analyses and referenced tables for smoother navigation between detailed findings and their broader implications. Each subsection below is structured for accessibility, employing clear argument flow and breaking up complex information into digestible segments to foster broader understanding across audiences, both technical and organizational.

In summary, this section consolidates and expands upon earlier analyses, offering a holistic and actionable overview that is clearly differentiated from existing surveys by its multidisciplinary perspective and focus on practical, measurable advancements.

Table 15: 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

9.1 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

To address the identified challenges and leverage emerging opportunities in AI-driven digital twin systems, several future research directions are proposed. First, there is a need for the codification of comprehensive evaluation frameworks that allow measurable benchmarking of AI-digital twin methodologies using standardized metrics in representative application settings. Articulating measurable outcomes for these frameworks will ensure objective comparison and facilitate reproducibility. Second, the development of modular and interoperable digital twin architectures, guided by open standards, remains essential for scalable adoption across diverse industrial and sociotechnical contexts. Third, deepening sociotechnical research is crucial—particularly into workforce adaptation, mechanisms for effective human-AI collaboration, and establishing cross-domain measurement standards for organizational and sectoral integration. This includes prioritizing integration of human-centric perspectives and organizational adaptation strategies in digital twin-AI deployments to foster broader acceptance and sustainable impact. Finally, there is a growing imperative to

Table 16: 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

advance robust data governance approaches, with special attention to privacy, accountability, and the ethical deployment of these technologies in sectors where sensitive data and societal consequences are paramount. These avenues collectively map a path toward more inclusive, transparent, and responsible digital twin systems, reflecting current sectoral needs and future research ambitions.

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; and 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. These objectives are aligned with those stated in the abstract and introduction to ensure coherence and reinforcement across the manuscript.

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. To aid the reader, explicit transitions are incorporated when shifting between technical analysis and sociotechnical considerations.

A review of optimization methods (see Table 17) 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.

Transitioning from technical aspects to considerations of interoperability, the evolving landscape of 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.

Furthermore, this survey introduces a new taxonomy that classifies integration strategies for digital twins and AI along technical, organizational, and sociotechnical axes. The taxonomy organizes reviewed methods according to operational scope (component, system, or enterprise level integration), degree of automation, and extent of stakeholder involvement. Notably, it distinguishes between technologically-centered and human-centered approaches. Emphasizing this taxonomy at this juncture underscores that successful digital twin and AI ecosystems demand not only robust technical solutions but also alignment with organizational culture, policies, and user expertise.

To 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 examples highlight the intersection of measurement gaps, organizational inertia, and technical complexity discussed in Sections X-Y.

Crucially, the integration of digital twin and AI extends 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. These sociotechnical nuances must not be overlooked as the field advances.

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. Moving forward, 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 multiphysics 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

Table 17: 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

operational robustness, and improved scalability and autonomy. However, deployment challenges persist, particularly regarding re-training 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, 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.

Table 18: 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

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.

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 synthesizes the main findings and positions them within a conceptual framework that integrates technological, organizational, and policy-driven advancements shaping the industrial digital ecosystem. By mapping emergent trends, unresolved research gaps, and debated perspectives, we reinforce the core aims of this survey: to systematically review, critically analyze, and provide actionable directions in this rapidly evolving domain. This synthesis is designed both to orient readers encountering the survey in isolation and to connect the concluding outlook to our broader survey structure.

Conceptual Framework and Survey Structure. Throughout this review, we have used an integrative framework covering three core dimensions—technological architecture, organizational capability, and policy/ethical governance—to organize and relate the progression of industrial digital transformation. Technological advances, typified by modularity, interoperability, and human-centric AI, are consistently intertwined with organizational enablers such as digital leadership, culture, and strategy, while all such developments are profoundly shaped by emergent policy paradigms, regulatory pressures, and ethical debates [31][92][28]. This triaxial approach supports a holistic understanding and highlights the interdependencies that define current research and practice.

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].

Persistent and Intersecting Research Gaps. Major unresolved challenges exist across all framework dimensions. Technically, current AI systems in manufacturing struggle with generalization, scalability, and adaptation to non-stationary tasks [66][69][83], as underscored by limitations on deployment in rapidly changing environments and the persistent need for retraining, as discussed in studies exploring both reinforcement learning frameworks and practical scheduling algorithms [60][34]. Organizationally, research has shown that digital transformational leadership and culture are critical for agility, but resistance to change and misalignment across strategy and leadership remain obstacles to large-scale transformation [28]. On the regulatory and policy front, the imperatives of establishing universal open standards remain unmet, resulting in continued fragmentation across data, systems, and knowledge domains [60][92].

Why Gaps Persist and the Spectrum of Debate. These challenges persist due to both inherent technical factors (such as the brittleness of narrow AI solutions in environments characterized by variability and complexity [66][34]) and organizational or policy inertia. For instance, as highlighted by [7], while investment in digital transformation is rising, cybersecurity and privacy provisions often lag, particularly when third-party integrations and legacy organizational mindsets are involved. There is substantial debate in the literature as to the optimal balance between open interoperability—which enables scalability and innovation—and the need for stringent privacy and security, a point further complicated by international disparities in policy adoption, regulatory agility, and ethical standards [7][31]. Competing perspectives abound on whether top-down frameworks or organic, sector-driven collaborations are best equipped to bridge these divides.

Contrasting Approaches and Major Debates. Alternative models for interoperability (centralized versus decentralized frameworks [60]), approaches to organizational agility (leadership-centric versus culture- and strategy-driven models [28]), and measurements of productivity and impact (reliance on traditional ROI versus hybrid qualitative-quantitative toolkits [92][80]) remain under active

debate. There is an ongoing academic dialogue over the prioritization of ethical stewardship: whether ethical AI should be codified in regulatory mandates or guided by adaptive, context-sensitive frameworks [7][42].

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]?

Section Summary & Convergent Frontiers:
In summary, this survey delineates the intersecting technological, organizational, and policy trends that are shaping the contemporary industrial digital landscape. By employing a cross-cutting conceptual framework that connects technical architectures, organizational realities, and policy imperatives, we clarify that future paradigms must achieve agility, intelligence, security, and sustainability through rigorous research and innovation. The persistence of issues such as AI adaptability, system interoperability, human-machine integration, and ethical stewardship is linked to both structural and emergent barriers, as expounded in prior literature debates regarding leadership versus culture, centralization versus decentralization, and compliance versus innovation [60][7][31][28]. Only by addressing these tensions collectively—through robust standards, cross-sectoral and interdisciplinary collaboration, and continual

critical reflection—is it plausible to realize a highly adaptive, productive, and human-centered digital future well-aligned with the objectives and challenges that define this complex domain.

References

[1] Mohammad Ali Abooshahab, Mohsen Ekramian, and Ali Ebrahimpour-Boroojeny. 2019. Time-Delay Estimation in State and Output Equations of Nonlinear Systems Using Optimal Computational Approach. *Journal of Optimization Theory and Applications* 180, 3 (2019), 1036–1064. doi:10.1007/s10957-018-1410-6

[2] M. Ahsan, M. A. Habib, and B. Khoda. 2019. Resource based process planning for additive manufacturing. *Journal of Manufacturing Processes* 38 (2019), 76–87. https://www.sciencedirect.com/science/article/pii/S1526612519303206

[3] E. Ö. Alakaş. 2024. Digital transformational leadership and organizational agility in digital transformation: Structural equation modelling of the moderating effects of digital culture and digital strategy. *The Journal of High Technology Management Research* 35, 2 (2024), Article 100517. doi:10.1016/j.hitech.2024.100517

[4] Z. Ayağ. 2020. An approach to evaluate CAM software alternatives. *International Journal of Computer Integrated Manufacturing* 33, 5 (2020), 504–514. doi:10.1080/0951192X.2020.1757156

[5] A. Belhadi, S. S. Kamble, M. Venkatesh, C. J. C. Jabbour, and I. Benkhati. 2022. Building supply chain resilience and efficiency through additive manufacturing: An ambidextrous perspective on the dynamic capability view. *International Journal of Production Economics* 249 (2022), 108516. https://www.sciencedirect.com/science/article/pii/S0925527322000512

[6] M. Beltrami, G. Orzes, J. Sarkis, and M. Sartor. 2021. Industry 4.0 and sustainability: Towards conceptualization and theory. *Journal of Cleaner Production* 312 (2021), 127733. https://www.sciencedirect.com/science/article/pii/S095965262101951X

[7] Cagatay Catal, Gorkem Kar, and Murat Zarali. 2025. Strategic technological innovation investment: enhancing resilience in the age of digital transformation. *Journal of Innovative Digital Transformation* 2, 1 (2025), 50–72. doi:10.1108/JIDT-05-2024-0010

[8] M. Christensen, L. P. E. Yunker, F. Adedeji, F. Häse, L. M. Roch, T. Gensch, G. dos Passos Gomes, T. Zepel, M. S. Sigman, A. Aspuru-Guzik, and J. E. Hein. 2021. Data-science driven autonomous process optimization. *Communications Chemistry* 4 (2021), 112. doi:10.1038/s42004-021-00550-x

[9] Wenbin Dai, Yingyue Zhang, Lingbo Kong, James H. Christensen, and Dan Huang. 2023. Design of Industrial Edge Applications Based on IEC 61499 Microservices and Containers. *IEEE Transactions on Industrial Informatics* 19, 7 (2023), 7925–7935. doi:10.1109/TII.2022.3214759

[10] Welington de Oliveira. 2023. Short Paper - A note on the Frank–Wolfe algorithm for a class of nonconvex and nonsmooth optimization problems. *Open Journal of Mathematical Optimization* 4 (2023), 1–10. doi:10.5802/ojmo.21

[11] A. Dolgui, G. Levin, and B. Rozin. 2020. Optimisation of the aggregation and execution rates for intersecting operation sets: an example of machining process design. *International Journal of Production Research* 58, 9 (2020), 2658–2676. doi:10.1080/00207543.2019.1627311

[12] P. Eichenseer and H. Winkler. 2024. A data-oriented shopfloor management in the production context: a systematic literature review. *The International Journal of Advanced Manufacturing Technology* 134, 9-10 (2024), 4071–4097. doi:10.1007/s00170-024-12245-x

[13] S. Emili and F. Galli. 2023. Spatial and cross-sectoral input spillover effects: the case of the Italian tourism industry. *Journal of Productivity Analysis* 59, 2 (2023), 243–258. doi:10.1007/s11123-023-00665-4

[14] K. S. Exarchos, C. Mitsos, and P. I. Barton. 2016. Global Optimization of Phase Stability and Phase Equilibrium Problems in Process Systems Engineering. *SIAM Journal on Optimization* 26, 4 (2016), 2457–2479. doi:10.1137/15M1027724

[15] S. Fahle, N. Götze, G. Lanza, S. Voss, and P. Nyhuis. 2020. Systematic review on machine learning (ML) methods for manufacturing processes – Identifying artificial intelligence (AI) methods for process innovation. *Journal of Manufacturing Processes* 53 (2020), 386–401. doi:10.1016/j.jmapro.2020.02.022

[16] J. Flores, I. Cabanes, A. Gutierrez, K. Lopez de Calle, O. Gonzalo, and E. Portillo. 2025. An innovative smart monitoring system for DED-LB/MW process stability based on machine learning techniques. *International Journal of Advanced Manufacturing Technology* 137 (2025), 1759–1773. doi:10.1007/s00170-025-15134-5

[17] L. Gao, D. Li, Z. Chen, S. X. Ding, and Z. Hou. 2024. SIR-Aided Dynamic Canonical Correlation Analysis for Fault Detection and Isolation of Industrial Automation Systems. *IEEE Transactions on Industrial Electronics* 71, 6 (2024), 6966–6977. https://ieeexplore.ieee.org/document/10354461/

[18] F. J. Garzón-García, M. Álvarez Montero, J. A. Márquez-García, and Á. Troncoso-Pastoriza. 2024. Main Trend Topics on Industry 4.0 in the Manufacturing Sector. *Applied Sciences* 14, 15 (2024), 6450. https://www.mdpi.com/2076-3417/14/15/6450

[19] Mohammadhossein Ghahramani. 2021. Data-driven Predictive Analysis for Smart Manufacturing Processes Based on a Decomposition Approach. TechRxiv, Online. doi:10.36227/techrxiv.15045426.v1 Accessed: 2024-06-13.

[20] M. Ghahramani, Y. Qiao, M. Zhou, A. O'Hagan, and J. Sweeney. 2020. AI-based Modeling and Data-driven Evaluation for Smart Manufacturing Processes.

Table 19: 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]	Generalization and adaptation limitations in AI for dynamic tasks [66][69][83]	Advanced algorithms for lifelong learning and adaptive industrial AI
Cross-domain standardization (data, knowledge, interfaces) [60][92]	Lack of universal open standards and fragmentation [60][92]	Unified interoperability frameworks and collaborative open standards development
Enhanced human-centricity and AI-enabled operator support [34][88][42]	Translating human-AI research into measurable workplace outcomes	Integration of explainable AI, digital twins, and VR for operator well-being
Ethical AI, fairness, and regulatory adaptation [7][31][42]	Privacy/security risks and slow policy development [7][31]	Multifaceted frameworks addressing fairness, inclusiveness, and secure innovation
Organizational agility enabled by digital leadership/culture [28]	Resistance to change and misalignment between leadership and strategy [28]	Longitudinal studies of digital culture, leadership, and transformation metrics
Productivity measurement and new impact assessment tools [92][80]	Limitations of existing ROI/productivity metrics	Hybrid (qualitative and quantitative) measurement frameworks for DT impact

IEEE/CAA Journal of Automatica Sinica (2020). https://arxiv.org/abs/2008.12987 To appear, 13 pages.

[21] M. Ghobakhloo. 2020. Industry 4.0, digitization, and opportunities for sustainability. *Journal of Cleaner Production* 252 (2020), 119869. https://www.sciencedirect.com/science/article/pii/S0959652619347390

[22] A. Ghosh and S. Vighe. [n. d.]. A Theoretical Framework for Architectural Anti-Patterns in Industrial Cloud-Edge Systems: Foundations, State-of-the-Art and Research Directions. Online. https://www.techrxiv.org/doi/full/10.36227/techrxiv.174439107.75971333/v1 Accessed: 2024-06-10.

[23] C. Gkournelos, C. Konstantinou, and S. Makris. 2023. Praxis: a framework for AI-driven human action recognition in assembly. *Journal of Intelligent Manufacturing* 35, 8 (2023), 3697–3711. https://link.springer.com/article/10.1007/s10845-023-02355-7

[24] D. Guo, X. Chen, Z. Jiang, and J. Gong. 2023. A review of industrial robot predictive maintenance research in the automotive industry. *TechRxiv* (2023). https://www.techrxiv.org/doi/full/10.22541/au.169770250.00791915/v1

[25] G. Hildebrandt, D. Dittler, P. Habiger, H. Roth, and T. Sauter. 2023. Data Integration for Digital Twins in Industrial Automation: A Systematic Literature Review. Online. https://www.techrxiv.org/users/782028/articles/936580-data-integration-for-digital-twins-in-industrial-automation-a-systematic-literature-review Accessed: 2024-06-28.

[26] Md Ismail Hossain, Kakoli Khatun, and Imtiaz Ahmed. 2020. Cyber Intrusion detection in Industry 4.0 Data using Machine Learning. Online. https://www.techrxiv.org/doi/full/10.36227/techrxiv.24646194 TechRxiv Preprint.

[27] Ming-Hsiung Hsiao. 2024. Resource integration and firm performance through organizational capabilities for digital transformation. *Digital Transformation and Society* ahead-of-print, ahead-of-print (2024). doi:10.1108/DTS-07-2023-0050

[28] M. S. Islam, S. S. Ahmed, W. Alasmary, M. A. Rahman, K. Salah, and F. Li. 2022. SSI meets Metaverse for Industry 4.0 and Beyond. TechRxiv Preprint, Online. https://www.techrxiv.org/users/683788/articles/679058/master/file/data/SSI_meets_Metaverse_for_Industry_4_0_and_Beyond-3/SSI_meets_Metaverse_for_Industry_4_0_and_Beyond-3.pdf Accessed: 2024-06-09.

[29] X. Jing, X. Yao, M. Liu, and J. Zhou. 2024. Multi-agent reinforcement learning based on graph convolutional network for flexible job shop scheduling. *Journal of Intelligent Manufacturing* 35 (2024), 75–93. doi:10.1007/s10845-022-02037-5

[30] S. Jiwangkura, P. Sophatsathit, and A. Chandrachai. 2020. Industrial Internet of Things Implementation Strategies with HCI for SME Adoption. *International Journal of Automation and Smart Technology* 10, 1 (2020), 153–168. https://www.jausmt.org/index.php/jausmt/issue/view/5

[31] G. Jonathan et al. 2021. Digital transformation in business and management research: An overview and research agenda. *International Journal of Information Management* 58 (2021), 102378. https://www.sciencedirect.com/science/article/pii/S0268401221001596

[32] J.-S. Jwo, C.-S. Lin, and C.-H. Lee. 2021. Smart technology–driven aspects for human-in-the-loop smart manufacturing. *The International Journal of Advanced Manufacturing Technology* 114 (2021), 1741–1752. doi:10.1007/s00170-021-06977-9

[33] L. Kanagasabai. 2023. Real Power Loss Reduction by Extreme Learning Machine based - Xiphias and Gilt-head bream Optimization Algorithms. *International Journal of Automation and Smart Technology* 13 (May 2023), 2354–2354. https://www.jausmt.org/index.php/jausmt/issue/view/2

[34] L. Kaven, P. Huke, and R. H. Schmitt. 2024. Multi agent reinforcement learning for online layout planning and scheduling in flexible assembly systems. *Journal of Intelligent Manufacturing* 35, 8 (2024), 3917–3936. doi:10.1007/s10845-023-02393-1

[35] M. Kovács. 2020. Combination of Lean value-oriented conception and facility layout design for even more significant efficiency improvement and cost reduction. *International Journal of Production Research* 58, 10 (2020), 2916–2936. doi:10.1080/00207543.2019.1630778

[36] D. A. Kurasov. 2021. Computer-aided manufacturing: Industry 4.0. *IOP Conference Series: Materials Science and Engineering* 1047, 1 (2021), 012153. https://iopscience.iop.org/article/10.1088/1757-899X/1047/1/012153

[37] A. Jaya Lakshmi, A. Kumar, M. S. Kumar, S. I. Patel, S. K. L. Naik, and J. V. N. Ramesh. 2023. Artificial intelligence in steering the digital transformation of collaborative technical education. *The Journal of High Technology Management Research* 34 (2023), 100517. doi:10.1016/j.hitech.2023.100517

[38] Vuk Lesi, Zivana Jakovljevic, and Miroslav Pajic. 2023. IoT-Enabled Motion Control: Architectural Design Challenges and Solutions. *IEEE Transactions on Industrial Informatics* 19, 3 (2023), 2284–2294. doi:10.1109/TII.2022.3223438

[39] Yibing Li, Zhiyu Tao, Lei Wang, Baigang Du, Jun Guo, and Shibao Pang. 2023. Digital twin-based job shop anomaly detection and dynamic scheduling. *Robotics and Computer-Integrated Manufacturing* 79 (2023), 102443. doi:10.1016/J.RCIM.2022.102443

[40] M. Liu, S. Fang, H. Dong, and C. Xu. 2021. Review of digital twin about concepts, technologies, and industrial applications. *Journal of Manufacturing Systems* 58 (2021), 346–361. doi:10.1016/j.jmsy.2020.06.017

[41] L. Lu, J. Hou, S. Yuan, X. Yao, Y. Li, and J. Zhu. 2023. Deep learning-assisted real-time defect detection and closed-loop adjustment for additive manufacturing of continuous fiber-reinforced polymer composites. *Robotics and Computer-Integrated Manufacturing* 79 (2023), 102431. https://dblp.org/rec/journals/rcim/LuHYYLZ23

[42] Yuqian Lu, Juvenal Sastre Adrados, Saahil Shivneel Chand, and Lihui Wang. 2021. Humans are Not Machines—Anthropocentric Human–Machine Symbiosis for Ultra-Flexible Smart Manufacturing. *Engineering* 7, 6 (2021), 734–737. doi:10.1016/j.eng.2020.09.018

[43] F. Ludbrook, K. Frajtova Michalikova, Z. Musova, and P. Suler. 2019. Business Models for Sustainable Innovation in Industry 4.0: Smart Manufacturing Processes, Digitalization of Production Systems, and Data-driven Decision Making. *Journal of Self-Governance and Management Economics* 7, 3 (2019), 21–26. doi:10.22381/JSME7320193

[44] Hezhi Luo, Xiaodi Bai, and Jiming Peng. 2019. Enhancing Semidefinite Relaxation for Quadratically Constrained Quadratic Programming via Penalty Methods. *Journal of Optimization Theory and Applications* 180, 3 (2019), 964–992. doi:10.1007/s10957-018-1416-0

[45] V. Naga Malleswari and P. G. Pragvamsa. 2023. Automatic machining feature recognition from STEP files. *International Journal of Computer Integrated Manufacturing* 36, 6 (2023), 863–877. doi:10.1080/0951192X.2022.2162590

[46] K. Mavitha and S. Kushe Shekhar. 2025. Mapping the landscape of digital transformation and digital technologies in the hotel industry: a comprehensive bibliometric analysis. *Digital Transformation and Society* ahead-of-print, ahead-of-print (2025). doi:10.1108/DTS-09-2024-0178

[47] B. Meyers, H. Vangheluwe, and K. Gadeyne. 2024. Towards a knowledge graph framework for ad hoc analysis in manufacturing. *Journal of Intelligent Manufacturing* 35, 8 (2024), 3731–3752. https://link.springer.com/article/10.1007/s10845-023-02343-x

[48] A. B. Morales-Menendez and A. I. Cortés-Robles. 2025. The Future of Manufacturing and Industry 4.0. *Applied Sciences* 15, 9 (2025), 4655. https://www.mdpi.com/2076-3417/15/9/4655

[49] D. Mourtzis, S. Makris, and G. Chryssolouris. 2018. Computer-Aided Manufacturing. In *CIRP Encyclopedia of Production Engineering*, Christoph Herrmann, Markus Hölter, Berend Denkena, Wolfgang Hintze, and Eckart Uhlmann (Eds.). Springer, Berlin, Heidelberg, 1–13. https://link.springer.com/doi/10.1007/978-3-642-35950-7_6550-4

[50] Giacomo Nannicini. 2021. On the implementation of a global optimization method for mixed-variable problems. *Open Journal of Mathematical Optimization* 2 (2021), 1–25. doi:10.5802/ojmo.3

[51] J. Ni, G. Wang, T. Zhou, and L. Liu. 2023. Smart Manufacturing and Industry 4.0. *Applied Sciences* 13, 3 (2023), 1545. https://www.mdpi.com/2076-3417/13/3/1545

[52] Yu Nong. 2025. Digital Twins Integrating AI, AR, VR, and Robotics: A Case Study of Smart Manufacturing Transformation. *Engineering: Open Access* 3, 3 (2025), 01–08. doi:10.33140/EOA.3.3.1

[53] Edwin Omol, Paul Abuonji, and Lucy Mburu. 2025. SMEs' digital maturity: analyzing influencing factors and the mediating role of environmental factors. *Journal of Innovative Digital Transformation* 2, 1 (2025), 19–36. doi:10.1108/JIDT-01-2024-0002

[54] Edwin Juma Omol. 2024. Organizational digital transformation: from evolution to future trends. *Digital Transformation and Society* 3, 3 (2024), 240–256. doi:10.1108/DTS-08-2023-0061

[55] B. Ördek, N. Dogan, and M. Coatanea. 2024. Machine learning-supported manufacturing: a review and directions for future research. *Production & Manufacturing Research* 12, 1 (2024), 1–36. doi:10.1080/21693277.2024.2326526

[56] J. Ouyang and J. Fu. 2020. Optimal strategies of improving energy efficiency for an energy-intensive manufacturer considering consumer environmental awareness.

International Journal of Production Research 58, 4 (2020), 1017–1033. doi:10.1080/00207543.2019.1620360

[57] Diana Teresa Parra-Sánchez. 2025. Exploring the Internet of Things adoption in the Fourth Industrial Revolution: a comprehensive scientometric analysis. *Journal of Innovative Digital Transformation* 2, 1 (2025), 1–18. doi:10.1108/JIDT-06-2024-0013

[58] V. Petrone, E. Ferrentino, and P. Chiacchio. 2024. On the role of Artificial Intelligence methods in modern force-controlled manufacturing robotic tasks. In *Proceedings of the 21st International Conference on Informatics in Control, Automation and Robotics – Volume 1: ICINCO*. Porto, Portugal, 392–399. https://arxiv.org/abs/2409.16828

[59] J. Pedro Madureira Pinto, R. D. S. Gomes, and F. J. Gomes da Silva. 2024. Automating the manufacturing process of control cables for the automotive components industry. *The International Journal of Advanced Manufacturing Technology* 135, 11-12 (2024), 5533–5551. doi:10.1007/s00170-023-12675-2

[60] Z. Qin and Y. Lu. 2024. Knowledge graph-enhanced multi-agent reinforcement learning for adaptive scheduling in smart manufacturing. *Journal of Intelligent Manufacturing* (2024). doi:10.1007/s10845-024-02494-0

[61] Y. J. Qu, X. G. Ming, Z. W. Liu, X. Y. Zhang, and Z. T. Hou. 2019. Smart manufacturing systems: state of the art and future trends. *The International Journal of Advanced Manufacturing Technology* 103, 9–12 (2019), 3751–3768. doi:10.1007/s00170-019-03754-7

[62] Hamed Rahimian and Sanjay Mehrotra. 2022. Frameworks and Results in Distributionally Robust Optimization. *Open Journal of Mathematical Optimization* 3 (2022), 1–85. doi:10.5802/ojmo.15

[63] O. Reffas, H. Boumediri, Y. Karmi, M. S. Kahaleras, I. Bousba, and L. Aissa. 2025. Statistical analysis and predictive modeling of cutting parameters in EN-GJL-250 cast iron turning: application of machine learning and MOALO optimization. *International Journal of Advanced Manufacturing Technology* 137 (2025), 1991–2009. doi:10.1007/s00170-025-15098-6

[64] O. Rezaei, R. Sahraeian, and S. M. H. Hosseini. 2025. A Multi-Objective Optimization Framework to Design the Closed-Loop Supply Chain Network Using Machine Learning for Demand Prediction. *Process Integration and Optimization for Sustainability* 9 (2025). doi:10.1007/s41660-024-00418-2

[65] R. A. Rojas and E. Rauch. 2019. From a literature review to a conceptual framework of enablers for smart manufacturing control. *The International Journal of Advanced Manufacturing Technology* 104 (2019), 517–533. doi:10.1007/s00170-019-03854-4

[66] S. Roy, I. Ahmed, J. Saldanha, K. Medini, and T. Wuest. 2024. Bottleneck Management through Strategic Sequencing in Smart Manufacturing Systems. *Smart and Sustainable Manufacturing Systems* 8, 1 (2024), 1–26. doi:10.1520/ssms20230036

[67] A. B. S and R. K. M S. 2020. Highly Robust and Automated Vision based Filamentous Steel Strip Crack Detection System. *International Journal of Automation and Smart Technology* 10, 1 (2020), 109–123. https://www.jausmt.org/index.php/jausmt/issue/view/5

[68] Snehasis Sahoo and Cheng-Yao Lo. 2022. Smart manufacturing powered by recent technological advancements: A review. *Journal of Manufacturing Systems* 64 (2022), 236–250. doi:10.1016/j.jmsy.2022.06.008

[69] M. Sato, V. W. H. Wong, H. Yeung, P. Witherell, and K. H. Law. 2024. Identification and Interpretation of Melt Pool Shapes in Laser Powder Bed Fusion with Machine Learning. *Smart and Sustainable Manufacturing Systems* 8, 1 (2024), 27–47. doi:10.1520/ssms20230035

[70] A. M. Schweidtmann and A. Mitsos. 2019. Deterministic Global Optimization with Artificial Neural Networks Embedded. *Journal of Optimization Theory and Applications* 180, 3 (2019), 925–948. doi:10.1007/s10957-018-1396-0

[71] A. Sebeesh, A. Rasheed, E. Skaria, and A. Joy. 2023. Development and Fabrication of Capsees. *International Journal of Computer Aided Manufacturing* 9, 2 (2023), 25–33. https://mechanical.journalspub.info/index.php?journal=JCAM&page=article&op=view&path[]=1897

[72] S. Shahriari, D. Iranshahi, and A. Nikzad. 2025. Optimization of a Novel Configuration for an Autothermal Reformer to Produce Hydrogen from Natural Gas. *Process Integration and Optimization for Sustainability* 9, 1 (2025), 75–91. doi:10.1007/s41660-024-00411-9

[73] L. Simar, V. Zelenyuk, and S. Zhao. 2023. Further improvements of finite sample approximation of central limit theorems for envelopment estimators. *Journal of Productivity Analysis* 59, 2 (2023), 189–194. doi:10.1007/s11123-023-00661-8

[74] D. S. Stamoulis and E. Kopanaki. in press. Digital Transformation in Banking: an Explanation Framework and a Progress Assessment Tool. *International Journal of Digital Transformation* (in press). doi:10.1504/IJDT.2023.10064348

[75] Jiacheng Sun, Zhenyu Liu, Chan Qiu, Jingqian Luo, Liang He, Hui Liu, Guodong Sa, Zhengyang Jiang, and Jianrong Tan. 2024. Machining accuracy prediction and adaptive compensation method of CNC machine tool under absence of machining process sensing. *Journal of Intelligent Manufacturing* (2024). doi:10.1007/s10845-024-02403-5

[76] Fei Tao, Qinglin Qi, Ang Liu, and Andrew Kusiak. 2018. Data-driven smart manufacturing. *Journal of Manufacturing Systems* 48 (2018), 157–169. doi:10.1016/j.jmsy.2018.01.006

[77] K. Torabi, E. Farjood, and S. Hamedani. 2015. Rapid Prototyping Technologies and their Applications in Prosthodontics, a Review of Literature. *J Dent (Shiraz)* 16, 1 (2015), 1–9. https://pubmed.ncbi.nlm.nih.gov/25759851/

[78] C. Tuffnell, P. Kral, P. Durana, and T. Krulicky. 2019. Industry 4.0-based Manufacturing Systems: Smart Production, Sustainable Supply Chain Networks, and Real-Time Process Monitoring. *Journal of Self-Governance and Management Economics* 7, 2 (2019), 7–12. doi:10.22381/JSME7220191

[79] C. O. Turcu and C. Turcu. [n. d.]. Accelerating Digital Transformation in Higher Education with Robotic Process Automation. Online. https://www.techrxiv.org/users/690018/articles/681445-accelerating-digital-transformation-in-higher-education-with-robotic-process-automation Accessed: 2024-06-12.

[80] A. M. M. S. Ullah, K. Amanullah, M. C. Alam, and M. Shahjalal. [n. d.]. What is Knowledge in Industry 4.0? Online. https://www.techrxiv.org/users/293649/articles/421708-what-is-knowledge-in-industry-4-0 Accessed: 2024-06-11.

[81] P. C. Verhoef, N. Kooge, P. Walk, et al. 2021. Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research* 122 (2021), 889–901. https://www.sciencedirect.com/science/article/pii/S0148296320304563

[82] K. Wade and M. Vochozka. 2021. Artificial Intelligence Data-driven Internet of Things Systems, Sustainable Industry 4.0 Wireless Networks, and Digitized Mass Production in Cyber-Physical Smart Manufacturing. *Journal of Self-Governance and Management Economics* 9, 3 (2021), 48–60. doi:10.22381/jsme9320214

[83] J. Wan, X. Li, H.-N. Dai, A. Kusiak, M. Martínez-García, and D. Li. 2021. Artificial Intelligence-Driven Customized Manufacturing Factory: Key Technologies, Applications, and Challenges. *Proc. IEEE* (2021). https://arxiv.org/abs/2108.03383

[84] Eric Ke Wang, Zicong Chen, Mingjia Zhu, Siu-Ming Yiu, Chien-Ming Chen, Mohammad Mehedi Hassan, Stefano Izzo, and Giancarlo Fortino. 2023. Statistics-Physics-Based Interpretation of the Classification Reliability of Convolutional Neural Networks in Industrial Automation Domain. *IEEE Transactions on Industrial Informatics* 19, 8 (2023), 2165–2172. doi:10.1109/TII.2022.3231458

[85] T.-Y. Wu and C.-Y. Lin. 2025. Surface profile estimation in milling through vibration analysis and long short-term memory networks. *International Journal of Advanced Manufacturing Technology* 137 (2025), 2047–2060. doi:10.1007/s00170-025-15291-7

[86] T. Wuest. 2024. Hybrid Analytics in Smart Manufacturing Systems—Addressing the Manufacturing Data Challenge. *Smart and Sustainable Manufacturing Systems* 8, 1 (2024), 48–66. doi:10.1520/ssms20230015

[87] T. Wuest, D. Weimer, C. Irgens, and K.-D. Thoben. 2016. Machine learning in manufacturing: advantages, challenges, and applications. *Production & Manufacturing Research* 4, 1 (2016), 23–45. doi:10.1080/21693277.2016.1192517

[88] Y. Xiong, H. K. S. Lam, and S. Karimi. 2024. The effect of virtual reality-enabled manufacturing practices on production efficiency. *International Journal of Production Economics* 274 (2024), Article 109288. https://www.sciencedirect.com/science/article/abs/pii/S0925527324001452

[89] X. Xu, Y. Lu, B. Vogel-Heuser, and L. Wang. 2021. Industry 4.0 and Industry 5.0—Inception, conception and perception. *Journal of Manufacturing Systems* 61 (2021), 530–535. doi:10.1016/j.jmsy.2021.10.006

[90] F. Ye, Y. Ouyang, and Y. Li. 2023. Digital investment and environmental performance: The mediating roles of production efficiency and green innovation. *International Journal of Production Economics* 259 (2023), 108822. doi:10.1016/j.ijpe.2023.108822

[91] Haoyu Yu, Dong Yu, Chuting Wang, Yi Hu, and Yue Li. 2023. Edge intelligence-driven digital twin of CNC system: Architecture and deployment. *Robotics and Computer-Integrated Manufacturing* 79 (2023), 102418. doi:10.1016/J.RCIM.2022.102418

[92] V. Zelenyuk. 2023. Productivity analysis: roots, foundations, trends and perspectives. *Journal of Productivity Analysis* 60, 3 (2023), 229–247. doi:10.1007/s11123-023-00692-1

[93] J. Zhao, X. Yang, L. Liu, Y. Shi, J. Zhang, W. Xu, and G. Xu. 2023. A Learning-Based Two-Stage Method for Submillimeter Insertion Tasks With Only Visual Inputs. *IEEE Transactions on Industrial Electronics* 70, 10 (2023), 10941–10951. doi:10.1109/tie.2023.3299051