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Review

Part II: Industrial Information Integration Review 2020–2025

Jinzhi Li

Department of Information Technology & Decision Sciences, Strome College of Business, Old Dominion University, Norfolk, VA 23529, USA; jli037@odu.edu

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Abstract: Industrial Information Integration Engineering (IIIE) has become increasingly essential for improving operational efficiency and harmonizing heterogeneous industrial systems through advanced digital integration approaches. Fueled by rapid advancements in Industry 4.0 technologies—including digital twins, artificial intelligence, immersive interfaces, and IoT infrastructures—IIIE is substantially transforming traditional enterprise architecture and integration frameworks. This systematic review synthesizes recent developments and emerging trends, with particular attention to the accelerating adoption of digital twins and the deepening convergence between operational technologies (OT) and information technologies (IT) across multiple sectors. While notable progress has been made, significant challenges persist, especially in developing resilient integration architectures and fully capitalizing on emerging capabilities such as quantum computing and next-generation communication networks. Future research directions emphasize the need to advance semantic interoperability, promote human-centric integration paradigms, and strengthen secure, decentralized information infrastructures. Collectively, these directions highlight IIIE's pivotal role in enabling intelligent, interconnected, and sustainable industrial ecosystems.

Keywords: industrial information integration; enterprise integration; enterprise architecture

1. Introduction

Industrial Information Integration Engineering (IIIE) has rapidly evolved as a critical component in diverse industrial sectors, driven by the increasing need to integrate disparate systems, unify information flows, and enhance operational efficiency. As a complex, multidisciplinary field, IIIE synthesizes concepts, theories, and methodologies from various disciplines to tackle the intricate challenges posed by information technology infrastructure development within industrial settings [1]. Its significance has expanded considerably with the proliferation of Industrial Internet of Things (IIoT), Cyber-Physical Systems (CPS), smart grids, and smart manufacturing—each exemplifying how advanced integration fosters powerful, adaptive industrial ecosystems [2–6].

The advent of Industry 4.0 has further underscored IIIE's pivotal role, as IoT applications permeate sectors including smart cities, education, intelligent transportation, healthcare, environmental monitoring, and energy management [7–10]. As new technologies such as Machine Learning modeling, large language models (LLMs), geographic information systems (GIS), and immersive technologies (VR/AR) emerge, IIIE increasingly leverages these innovations to enhance the integration process, redefining traditional enterprise architecture (EA) and enterprise integration (EI) frameworks [11]. These technologies promise to bridge legacy systems with cutting-edge solutions, creating more intelligent, responsive, and sustainable industries, such as digital twin technology has penetrated virtually all research categories, driving deeper operational technology (OT) and information technology (IT) convergence [12].

Building on Chen's [13] comprehensive review covering IIIE literature from 2016 to 2019, this paper extends the exploration into recent advancements from 2020 to 2025. This study investigates whether the rapid integration momentum observed over the past decade continues to accelerate or is approaching a plateau. It systematically reviews and synthesizes 874 relevant papers, grouped into 34 research categories, to provide an updated perspective on the state of industrial information integration.

The remainder of the paper is structured as follows: Section 2 details the research methodology employed in this systematic review. Section 3 offers comprehensive summaries of the selected papers across the identified research categories. Section 4 synthesizes key findings from the review and outlines promising directions for future IIIE research, emphasizing emerging technological trends and their sector-wide implications. Finally, Section 5 provides the concluding remarks, encapsulating the overarching insights derived from this extensive literature analysis.

Manuscript Part I reviewed: aerospace, agriculture, algorithm, art industry, automated factory, biology, chemistry, construction, education, energy, enterprise architecture, enterprise integration, environment, facility, finance, food industry, geology, healthcare, and industrial control. Manuscript Part II reviewed: information and communication technology, instrumentation and measurement, machinery, management, manufacturing, math modeling, military, mining, security, software engineering, supply chain, telecommunications, tourism, transportation, and urban development.

2. Methodology

This study adopts a systematic approach to reviewing the landscape of *Industrial Information Integration* research. To ensure comprehensive coverage, we used the keyword "Industrial Information Integration" to search peer-reviewed literature published between 2020 and 2025, sourcing from two major academic databases: Web of Science and IEEE Xplore. The initial search returned 6777 records, encompassing a wide range of industrial sectors and application domains.

To ensure the academic quality and relevance of the selected literature, we applied a filtering criterion based on SCImago Journal Rank (SJR)—a widely recognized metric of journal influence and quality [14,15]. Only papers published in journals indexed by SJR were retained for further analysis. In addition, all duplicate records were removed. This filtering process reduced the dataset to 2634 unique papers.

Subsequently, we conducted a manual review of each abstract to evaluate the thematic relevance to the core topics of industrial information integration. Papers that were unrelated to the conceptual scope of this review were excluded. Through this careful screening process, 874 papers were ultimately selected for in-depth analysis.

Building upon and extending the classification framework proposed by Chen [13], we organized the retained literature into 34 distinct research categories, as summarized in Table 1. And the publication year distribution is presented in Table 2. We also report the top 20 journals that collectively contain the 376 articles in Table 3. These categories reflect both established themes and emerging directions in the field, offering a refined structure for analyzing technological, methodological, and sectoral developments in industrial information integration.

Table 1. Research categories of the selected publications.

Research Category	Number of Publication
Aerospace	3
Agriculture	14
Algorithm	23
Art Industry	1
Automated Factory	35
Biology	9
Chemistry	1
Construction	28
Education	11
Energy	59
Enterprise Architecture	36
Enterprise Integration	52
Environment	33
Facility	1
Finance	3
Food Industry	1
Geology	9
Healthcare	58
Industrial Control	24

Table 1. *Cont.*

Research Category	Number of Publication
Information and Communication Technology	96
Instrumentation and Measurement	15
Machinery	6
Management	13
Manufacturing	62
Math Modeling	103
Military	2
Mining	5
Security	58
Software Engineering	11
Supply Chain	49
Telecommunications	11
Tourism	5
Transportation	20
Urban Development	20

Table 2. Distribution of Publication Year.

Year	Number of Publications
2020	104
2021	124
2022	172
2023	144
2024	210
2025	120

Table 3. Top 20 of Publication Journals.

Journal Title	Publication Number
IEEE Access	74
IEEE Transactions on Industrial Informatics	57
Journal of Industrial Information Integration	51
IEEE Internet of Things Journal	35
Sensors	25
Journal of Manufacturing Systems	14
Advanced Engineering Informatics	12
The International Journal of Advanced Manufacturing Technology	11
IEEE Transactions on Automation Science and Engineering	10
Robotics and Computer-Integrated Manufacturing	10
Systems Research and Behavioral Science	9
Buildings	9
Computers in Industry	8
Processes	8
IEEE Sensors Journal	8
International Journal of Computer Integrated Manufacturing	7
International Journal of Production Research	7
IEEE Transactions on Instrumentation and Measurement	7
Engineering Applications of Artificial Intelligence	7
Information Systems Frontiers	7

3. Industrial Information Integration in Industrial Sectors

Continue with manuscript Part I.

3.1. Information and Communication Technologies

The rapid advancement of Information and Communication Technologies (ICT) is reshaping the landscape of industrial systems, enabling smarter, more connected, and human-centric infrastructures. Within the context of Industry 4.0 and emerging Industry 5.0 paradigms, technologies such as digital twins, cyber-physical systems, Industrial IoT (IIoT), edge/cloud computing, artificial intelligence (AI), augmented and virtual reality (AR/VR), and blockchain are becoming deeply integrated into manufacturing, logistics, maintenance, and decision-making processes. This section reviews recent literature that reflects the state-of-the-art in ICT-enabled industrial information integration, organized into key thematic categories: digital twins and cyber-physical systems; security and blockchain; IIoT and cloud-edge integration; AI and big data analytics; immersive interfaces and industrial metaverse; integration frameworks and middleware; and comprehensive reviews and meta-analyses of ICT trends.

3.1.1. Digital Twin and Cyber-Physical Systems

Digital Twin (DT) and Cyber-Physical Systems (CPS) have become core enablers of industrial information integration by bridging physical and digital domains through real-time data exchange, simulation, and control. Ante [16] provides a foundational bibliometric analysis of DT research, identifying major thematic clusters including CPS coordination, human-robot collaboration, and virtual manufacturing. Complementing this, Huang et al. [17] emphasize the synergy between DT and artificial intelligence, highlighting the need for domain-specific knowledge integration and the challenges of multiscale modeling. To enhance scalability and modularity, Aziz et al. [18] propose a microservices-based architecture for distributed DTs in CPS environments, while Jiang et al. [19] integrate federated learning and blockchain within a DT-driven IIoT framework to improve data privacy and resource optimization. Real-world applications are exemplified by Hesselink et al. [20], who demonstrate DT utility in infrastructure inspection with VR integration, and Longo et al. [21], who introduce a prescriptive training system using DTs and fuzzy cognitive mapping to enhance non-routine task learning in offshore platforms. DT-driven security solutions are proposed by Zhou et al. [22], who design a cyber range for simulating IIoT threats using flexible digital twins, and Sasikumar et al. [23], who develop a blockchain-enhanced DT framework for secure access control in consumer electronics. Dounas et al. [24] propose a decentralized architectural design framework that integrates Blockchain technology with Building Information Modeling (BIM) to overcome collaboration and trust limitations in the Fourth Industrial Revolution

In terms of human-centered and ergonomic applications, Grandi et al. [25] integrate DT with virtual simulation and posture analysis to optimize dashboard design in vehicles, while Raghunathan et al. [26] demonstrate how DTs support virtual commissioning and mixed reality for material handling. Xie et al. [27] extend this concept into the industrial metaverse by combining extended reality, blockchain, and DTs to enable immersive human–robot collaboration and decentralized control. Yang et al. [28] further enhance human-machine interaction by integrating DT, semantic modeling, and augmented reality into a context-aware system for real-time field operations. On the integration front, Ye et al. [29] emphasize the role of the Asset Administration Shell (AAS) as a digital interface to enable plug-and-produce CPS applications, while Patera et al. [12] develop a middleware-based architecture to achieve IT/OT convergence aligned with the values of Industry 5.0. Tao et al. [30] also highlight trust and collaboration in multi-party industrial platforms by integrating DT with blockchain to address data accuracy and stakeholder trust. Addressing modeling and lifecycle adaptability, Bárkányi et al. [31] propose the use of surrogate models to overcome uncertainty and computational complexity in DT-based simulations. The broader technological and theoretical context of CPS is outlined by Lu [32] and Singh et al. [33], who articulate CPS as the core of Industry 4.0, connecting design, control, and monitoring systems with smart manufacturing infrastructures. Finally, Oks et al. [34] offer a hierarchical taxonomy of industrial CPS research across 2365 publications, identifying trends, gaps, and future research directions in industrial digital transformation.

3.1.2. Blockchain, Security, and Privacy in IIoT

Security, privacy, and trust are critical concerns in the integration of Industrial Internet of Things (IIoT) systems, particularly as these environments increasingly adopt decentralized and open architectures. Xu [35] explores how systems science can address the complexity of Industry 4.0, emphasizing its role in managing and understanding the advanced, integrated manufacturing ecosystems of the Fourth Industrial Revolution. Figueroa-Lorenzo et al. [36] highlight the inadequacy of traditional IT-focused vulnerability scoring models in industrial settings and propose a tailored vulnerability analysis framework for IIoT protocols. To enhance secure system integration, Shahidinejad et al. [37] present a comprehensive review of blockchain-assisted authentication and session key generation protocols across IoT sectors, while A. Sadawi et al. [38] emphasize the role of blockchain oracles in trusted data feeds for IoT-smart contract systems. Similarly, Malik et al. [39] and Leng et al. [40] demonstrate how blockchain can mitigate issues of data integrity and centralized failures in IIoT-based supply chains and manufacturing platforms. Xu et al. [4] review blockchain's role in strengthening IoT security, focusing on features like decentralization, consensus, encryption, and smart contracts. Sasikumar et al. [23] and Ceccarelli et al. [41] propose blockchain-enabled architectures for secure access control and system configuration, addressing interoperability and cyber vulnerabilities in distributed industrial systems. Li et al. [42] systematically review Internet of Things (IoT) resource allocation, highlighting key techniques, current challenges, trends, and its impact on enterprise architecture. Gorkhali et al. [43] review 76 blockchain studies from 2016–2018, categorizing them into 14 themes and outlining key findings and future research directions. Viriyasitavat et al. [44] review blockchain's role in Business Process Management, highlighting its ability to establish trust via distributed ledgers and smart contracts in decentralized settings.

Albshaier et al. [45] discuss how blockchain strengthens IoT–cloud integration by protecting against traditional security threats, while Guo et al. [46] integrate blockchain with SDN, NFV, and AI for scalable resource management in heterogeneous IoT networks. Han et al. [47] propose a privacy-enhancing blockchain framework (SCOPE) for 6G IoT environments, combining hierarchical consensus and workload-aware validation. Fang et al. [48] introduce a privacy-preserving data sharing mechanism using blockchain and chaotic encryption for process mining in industrial settings. Ural et al. [49] explore synergies between blockchain and machine learning, advocating decentralized AI and federated learning to enhance transparency and data integrity. Verde et al. [12] demonstrate a 5G-enabled, AR-based maintenance system where blockchain ensures secure remote diagnostics and expert collaboration. Viriyasitavat et al. [50] propose a user-oriented framework for selecting trustworthy validators in permissioned blockchain IoT services by incorporating user requirements via specification-based compliance checking.

The increasing role of blockchain in economic transaction and data governance is highlighted by Dawod et al. [51], who propose a global service for autonomous device integration and micropayment using a dedicated blockchain protocol. Assaqty et al. [52] and Koppu et al. [53] show that integrating blockchain with IIoT improves data confidentiality and system interoperability, particularly in supply chain and logistics. Bhattacharya et al. [54] focus on AR/VR applications in Industry 4.0, advocating blockchain-6G integration for secure, low-latency immersive environments. Lastly, Chen et al. [55] demonstrate a trusted industrial cluster platform using various blockchain topologies that enhance secure detection of hazardous gases in complex environments. Collectively, these studies reveal a consistent trend toward decentralized, resilient, and intelligent IIoT ecosystems empowered by blockchain and aligned with evolving privacy, trust, and security requirements.

3.1.3. Industrial IoT (IIoT) and Edge/Cloud Computing Integration

The integration of Industrial Internet of Things (IIoT) with edge and cloud computing forms a technological backbone for intelligent, interconnected, and data-driven industrial ecosystems. Foundational reviews by Chen [56] and Pivoto et al. [57] highlight the progression of IIoT applications across industrial sectors such as energy, control, manufacturing, and transportation, emphasizing their dependence on smart infrastructures and real-time communication. Mekala et al. [58] deepen this analysis by addressing evolving cybersecurity threats and integration challenges across the IT–OT interface. Edge computing emerges as a key solution in these contexts, Habib et al. [59] present a middleware framework combining OPC UA and REST, enabling resource-constrained IIoT devices to interact across cloud and web layers.

Open and standardized architectures are emphasized in multiple studies. Hsiao et al. [60] introduce OPIIoT, an open-source platform that tackles interoperability between OT and IT through modular, protocol-agnostic design. Similarly, Pinheiro et al. [61] propose a self-identifying IEEE 1451-based transducer interface module to streamline integration and plug-and-play capability at the sensor layer. Klaina et al. [62] demonstrate how a ZigBee-based wireless sensor network embedded into an ERP system improves production monitoring and cost estimation in solar curtain manufacturing. Xu [35] reviews Industry 4.0's evolution, highlighting emerging technologies like AI, 5G/6G, and Quantum Computing that drive the transition to Industry 5.0 and transform core Industry 4.0 components such as Cyber-Physical Systems and IoT. Lin [63] and Fedullo et al. [64] reinforce the need for robust communication backbones in industrial monitoring, emphasizing TSN's (Time-Sensitive Networking) role in enabling low-latency and deterministic communication over wired and wireless media.

Intelligent analytics is also an essential feature of IIoT-enabled systems. Giustozzi et al. [65] propose a semantic ontology-based framework (COInd4) for real-time condition monitoring by integrating dynamic sensor data with contextual manufacturing knowledge, using stream reasoning for adaptive decision-making. At a broader level, Amin et al. [66] survey the convergence of IoT with big data, network science, and federated learning, stressing scalable, intelligent architectures for IIoT environments. Meanwhile, Alanhdi et al. [67] provide empirical validation from 11 deployments of edge computing systems fused with AI and blockchain in maritime and aerial applications, demonstrating improved performance and service delivery.

Application-oriented contributions include Munín-Doce et al. [68], who showcase how IIoT enhances smart transformation in traditional shipyard workshops, and Dehshiri et al. [69], who propose a hybrid IoT and circular economy model for renewable energy supply chain optimization. Kovtun et al. [70] focus on smart factory communication performance by modeling 5G channel allocation strategies under varying traffic types. Bhardwaj et al. [71] complement this with a targeted cybersecurity framework using attack trees to identify and prioritize exploitable vulnerabilities in CPS-integrated IIoT environments. On the strategic level, Dhamija [72] employs bibliometric analysis to map South Africa's national research capacity in IIoT, while Scholz et al. [73] explore the integration of Geographic Information Systems (GIS) into smart manufacturing, underscoring the need for scalable indoor spatial data systems.

Altogether, these studies demonstrate how the fusion of IIoT with edge and cloud computing infrastructure not only enhances operational flexibility and real-time insight but also underpins the scalable, secure, and intelligent evolution of modern industrial systems.

3.1.4. Artificial Intelligence, Machine Learning, and Big Data

Artificial Intelligence (AI), Machine Learning (ML), and Big Data are critical enablers of industrial digital transformation, driving advances in automation, analytics, and intelligent decision-making across a wide spectrum of Industry 4.0 and 5.0 applications. Huang et al. [17] emphasize that AI-driven digital twins require deep integration with domain-specific knowledge to achieve multiscale coordination in smart manufacturing, robotics, and sustainability. Giustozzi et al. [65] extend this idea by developing a semantic stream reasoning framework for real-time condition monitoring, integrating heterogeneous sensor data with contextual manufacturing knowledge. Jagatheesaperumal et al. [74] provide a structured review of how AI and big data intersect across Industry 4.0 use cases, identifying technological enablers, interpretability concerns, and open challenges for scalable deployment. Likewise, Amin et al. [66], though more broadly scoped, emphasize the importance of AI, federated learning, and advanced data integration in supporting next-generation IoT applications.

Applications of AI and ML are also shaping immersive environments and industrial human–machine interfaces. Boopathy et al. [75] explore how AI, digital twins, blockchain, and 6G converge to support the industrial metaverse across domains such as healthcare, agriculture, and logistics. Liu et al. [76] propose a fuzzy hierarchical analytic model to evaluate Quality of Experience (QoE) in mixed reality environments, offering optimization strategies for smoother and more immersive industrial interactions. Longhi et al. [77] evaluate 5G's suitability for real-time AGV operations by integrating deep learning-based predictive analytics with network performance metrics.

On the organizational level, AI is driving strategic realignment. Krafft et al. [78] conceptualize AI and big data as boundary technologies that dissolve traditional silos across digital, physical, and biological systems, facilitating pragmatic knowledge integration. French et al. [79] and Ural et al. [49] examine the intersection of AI, blockchain, and mobile technologies, highlighting how these technologies collectively enable secure, decentralized intelligence, transparent data management, and trustworthy model validation. Serey et al. [80] propose a strategic framework for AI-driven transformation, identifying digital business models, skill development, and interconnectivity as key goals. Similarly, Veile et al. [81] investigate how AI reshapes buyer–supplier relationships, creating tighter, platform-oriented ecosystems in the industrial supply chain.

AI's operational applications span monitoring, diagnostics, and optimization. Suresh et al. [82] propose combining RFID and ML to enable intelligent condition monitoring in sectors such as agriculture and health, while Li et al. [83] survey new manufacturing paradigms that utilize CPS, cloud computing, and big data for optimized industrial value creation. Sun et al. [84] empirically validate the influence of IIoT, business social networks, and cloud computing on intelligent production, identifying significant improvements in data visibility and responsiveness. Cotta et al. [85] introduce the concept of Intelligent Spaces (ISs), where AI and sensing systems enable adaptive, real-time interaction in cognitive factories aligned with Industry 5.0. Meanwhile, Quandt et al. [86] stress that technical performance alone is insufficient for AR system success in industrial environments, advocating for improved usability and ergonomic design. Finally, Sony et al. [87] propose integrating socio-technical systems theory into AI-enabled Industry 4.0 implementations to account for human, cultural, and organizational dimensions, making AI deployments more sustainable and holistic.

3.1.5. AR/VR, Human-Machine Interfaces, and Industrial Metaverse

Augmented Reality (AR), Virtual Reality (VR), and the broader concept of the industrial metaverse are reshaping human–machine interfaces by enabling immersive, intuitive, and collaborative interaction across industrial contexts. Krafft et al. [78] frame these technologies as "boundary technologies," which dissolve barriers between physical, digital, and biological systems, enabling higher-level knowledge integration and cognitive collaboration. Building on this vision, Boopathy et al. [75] explore how key technologies such as VR/AR, AI, blockchain, digital twins, and 6G collectively drive the formation of the industrial metaverse across sectors like healthcare, agriculture, and manufacturing, while also identifying technical challenges such as latency, synchronization, and scalability. Bhattacharya et al. [54] further support this by presenting a survey of AR/VR applications in 6G-enabled environments, introducing a unified blockchain-based architecture (BvTours) that enhances security, transparency, and data integrity for immersive applications.

From a usability and interface design standpoint, Grandi et al. [25] propose a human-centered methodology for developing digital dashboards in complex vehicles (e.g., tractors, trucks), using digital twins and ergonomic analysis to optimize comfort, control efficiency, and operator visibility. Quandt et al. [86] emphasize that successful AR adoption in industrial settings depends not just on functionality but also on user acceptance, usability, and gamified design elements—factors often overlooked in technical development. Liu et al. [76] complement this by introducing a fuzzy analytic hierarchy model to evaluate Quality of Experience (QoE) in mixed reality (MR) systems, offering optimization strategies focused on visual smoothness, authenticity, and user comfort.

Real-time task support and training are also enhanced through immersive technologies. Longo et al. [21] propose a "training-on-the-go" platform that leverages digital twins and evolutionary fuzzy cognitive maps to simulate industrial scenarios for prescriptive training, improving skill transfer and situational awareness. Yang et al. [88] integrate AR with semantic models and digital twins in a context-aware system for real-time decision support in manufacturing, enabling adaptive information delivery tailored to operator needs. Raghunathan et al. [26] explore the use of digital twins and mixed reality in material handling, enabling virtual commissioning and enhancing system transparency and adaptability.

Practical industrial applications are further demonstrated in specific use cases. Verde et al. [89] implement an AR-guided maintenance system using a 5G-connected head-mounted display with thermal and depth sensors, showcasing how immersive technologies improve safety, remote collaboration, and on-site diagnostics. De et al. [90] review recent advances in teleoperation systems integrated with AR across fields like aerospace, robotics, and industrial automation, identifying key challenges including latency, cognitive load, and system reliability. Xie et al. [27] present an advanced framework combining VR, AR, blockchain, and edge computing for human–robot collaboration in the industrial metaverse, enabling immersive visualization, real-time feedback, and decentralized decision-making.

Collectively, these studies demonstrate how AR/VR technologies and metaverse frameworks are transforming industrial human–machine interfaces, not only enhancing operational effectiveness and cognitive engagement, but also laying the groundwork for intelligent, human-centric systems in Industry 5.0.

3.1.6. Integration Frameworks, Middleware, and Protocols

Robust integration frameworks, middleware architectures, and communication protocols are foundational for achieving seamless interoperability and data consistency across heterogeneous industrial systems. These technologies enable Industrial Internet of Things (IIoT) devices, legacy systems, and cyber-physical infrastructures to communicate effectively in real-time, despite differences in protocol standards, computing capabilities, and operational contexts. Mekala et al. [58] emphasize the need for secure and efficient data integration across OT and IT domains, highlighting persistent challenges such as device heterogeneity and evolving threat landscapes. To address protocol-level interoperability, Cavalieri et al. [91] propose an interworking proxy between OPC UA and oneM2M, facilitating seamless communication between industrial applications and IoT devices using standardized interfaces.

Middleware plays a critical role in abstracting and managing complexity. Hsiao et al. [60] introduce OPIIoT, an open-source IIoT development framework that promotes interoperability between operational and information technologies through open communication standards. Similarly, Habib et al. [59] present a lightweight, platform-independent middleware solution that integrates OPC UA and REST, supporting both embedded devices and cloud systems, and enabling efficient machine-to-machine (M2M) and remote supervision operations. Patera et al. [12] propose a two-layer middleware architecture that aligns OT/IT convergence with Industry 5.0 objectives, enhancing scalability, real-time processing, and resilience in human-centric production systems.

Advanced integration frameworks also support unified data flow and control across complex industrial networks. Koprov et al. [92] demonstrate the use of MQTT Sparkplug-B for flattening the Purdue architecture model, achieving seamless, publish-subscribe communication between conventional machine assets and cloud platforms. López et al. [93] offer a multilayer integration model for incorporating physical assets into Industry 4.0 environments, emphasizing structured, technology-independent adaptation through abstraction layers that separate system concerns. Fang and Li [48] take a novel approach to secure process data integration by transforming business process logs into encrypted images for blockchain-based sharing, balancing data privacy with interoperability.

From a network architecture standpoint, Kannisto et al. [94] propose a message-bus communication architecture that overcomes the inflexibility of legacy industrial systems. Validated in applications such as copper smelting and distillation, the architecture supports scalable and distributed data exchange, independent of physical hierarchy or system boundaries. Younan et al. [95] review ICT integration within the IoT ecosystem, analyzing how middleware and search technologies like machine learning and cloud computing can overcome data heterogeneity and improve data searchability in complex industrial systems.

Finally, addressing the challenge of integrating legacy systems into modern digital infrastructures, Stój et al. [96] develop an FPGA-based network analyzer that non-intrusively captures and filters process data, allowing secure data integration into Industry 4.0 platforms without modifying existing systems. Together, these studies showcase the technological foundations and architectural strategies necessary to unify industrial data environments, bridge legacy and modern systems, and enable scalable, flexible, and secure industrial information integration.

3.1.7. Reviews and Meta-Analyses of ICT Trends

The evolution of Information and Communication Technologies (ICT) within industrial systems has been extensively analyzed through reviews and meta-studies that synthesize diverse technological trajectories, research gaps, and integration frameworks. Xu [35] provides a conceptual foundation by arguing that systems science offers essential methods for managing the complexity of Industry 4.0 ecosystems, particularly those defined by automation, IoT, CPS, and cloud integration. Similarly, Sony and Naik [87] emphasize the necessity of incorporating socio-technical perspectives when designing and implementing ICT-driven transformations in industrial contexts, presenting a framework that balances technological systems with human and organizational factors. French et al. [79] explore the transformative impact of emerging ICTs—particularly blockchain, AI, and mobile networks—highlighting their socio-economic implications and integrative potential in reshaping business and governance models. Sun et al. [9] review AI research and models, highlighting AI’s role in driving industrial innovation and economic growth through integration with technologies like big data, cloud computing, blockchain, and 5G/6G within Industry 4.0. Li and Duan [8] explore Industry 5.0 from a production and operations perspective, emphasizing human roles in technological innovation.

Several studies focus on thematic, bibliometric, and taxonomic analyses to structure the fragmented body of ICT-related research. Oks et al. [34] conduct an extensive review of 2365 publications on cyber-physical systems in Industry 4.0, introducing a hierarchical framework of 10 sections, 32 areas, and 246 fields that maps the intellectual structure of CPS research. Rathore et al. [97] deliver a meta-review of digital twin (DT) applications in industrial domains, identifying key deployment tools, system architectures, and opportunities for integrating big data and AI. Serey et al. [80] offer a thematic synthesis of 160 studies to define strategic objectives for aligning AI systems and organizational goals with Industry 4.0 adoption, highlighting the need for business model innovation, skill development, and interconnectivity. Li and Xu [42] review IoT resource allocation methods, challenges, and trends, highlighting its crucial role in shaping enterprise architecture and system design.

Focusing on regional and sectoral landscapes, Dhamija [72] applies bibliometric tools to analyze South Africa’s ICT and Industry 4.0 research output over a decade, uncovering national trends, research clusters, and capacity-building strategies. Chen [56] surveys recent advances in Industrial Information Integration Engineering (IIIE), tracking key developments in ICT applications across manufacturing, energy, and control systems, with specific emphasis on the rising influence of IoT, blockchain, and IIoT infrastructures. Li et al. [83] extend this discussion to manufacturing paradigms, presenting a broad synthesis of optimization frameworks and integration strategies driven by IoT, CPS, big data, and cloud computing.

Technological convergence is another recurring theme across these reviews. Amin et al. [66] provide a comprehensive catalog of emerging developments in IoT integration, highlighting intersections with big data, federated learning, network science, and AI while identifying persistent architectural and deployment challenges. Jagatheesaperumal et al. [74] focus specifically on the role of AI and big data in Industry 4.0, analyzing key technologies, interpretability issues, and potential research directions. Koppu et al. [53] examine the convergence of blockchain, AI, and IoT, identifying industrial use cases, security benefits, and scalability challenges of integrated architectures. Finally, Lee et al. [98] explore bio-nano-ICT integration in the context of charge-storage technologies, biomolecule–nanomaterial hybrid charge storage devices, offering a visionary outlook on how biotechnology and nanotechnology intersect with ICT to support energy-efficient, miniaturized industrial devices.

Together, these 13 meta-analyses provide a structured and multidimensional understanding of ICT’s trajectory in industrial systems—mapping the evolution of core technologies, contextualizing regional and sectoral developments, and proposing strategic, technical, and interdisciplinary roadmaps for future research.

The articles are collected and classified in Table 4.

Table 4. Information and Communication Technologies publication.

Research Category	Sub-Group	Publication
Information and Communication Technologies	Digital Twin and Cyber-Physical Systems	Ante (2021) [16] Bárkányi et al. (2021) [31] Dounas et al. (2021) [24] Huang et al. (2021) [17] Patera et al. (2021) [12] Ye et al. (2021) [29] Grandi et al. (2022) [25] Tao et al. (2022) [30] Aziz et al. (2023) [18] Longo et al. (2023) [21] Singh et al. (2023) [33] Zhou et al. (2023) [22] Hesselink et al. (2024) [20] Jiang et al. (2024) [19] Oks et al. (2024) [34] Sasikumar et al. (2024) [23] Venugopal et al. (2024) [26] Xie et al. (2024) [27] Lu (2025) [32] Yang et al. (2025) [28]
	Blockchain, Security, and Privacy in IIoT	Assaqty et al. (2020) [52] Gorkhali et al. (2020) [43] Verde et al. (2020) [12] Xu (2020) [35] Bhattacharya et al. (2021) [54] Figueroa-Lorenzo et al. (2021) [36] Li and Xu (2021) [42] Malik et al. (2021) [39] Xu et al. (2021) [4] Ceccarelli et al. (2022) [41] Dawod et al. (2022) [51] Guo et al. (2022) [46] Koppu et al. (2022) [53] Leng et al. (2022) [40] Sadawi et al. (2022) [38] Viriyasitavat et al. (2022) [44] Viriyasitavat et al. (2022) [50] Ural et al. (2023) [49] Albshaier et al. (2024) [45] Chen et al. (2024) [55] Fang et al. (2024) [48] Han et al. (2024) [47] Raghunathan et al. (2024) [26] Sasikumar et al. (2024) [23] Shahidinejad et al. (2024) [37]
	Industrial IoT (IIoT) and Edge/Cloud Computing Integration	Chen (2020) [56] Munín-Doce et al. (2020) [68] Hsiao et al. (2021) [60] Lin (2021) [63] Pivoto et al. (2021) [57] Zhang et al. (2021) [99] Amin et al. (2022) [66]

Table 4. *Cont.*

Research Category	Sub-Group	Publication
Information and Communication Technologies	Industrial IoT (IIoT) and Edge/Cloud Computing Integration	Dhamija et al. (2022) [72] Gur et al. (2022) [100] Habib et al. (2022) [59] Pinheiro et al. (2022) [61] Scholz et al. (2022) [73] Mekala et al. (2023) [58] Alanhdi et al. (2024) [67] Giustozzi et al. (2024) [65] Hosseini et al. (2024) [69] Klaina et al. (2024) [62] Li et al. (2024) [101] Sigov et al. (2024) [102] Bhardwaj et al. (2025) [71] Kovtun et al. (2025) [70]
	Artificial Intelligence, Machine Learning, and Big Data	Krafft et al. (2020) [78] Li et al. (2020) [83] Peng et al. (2020) [103] Sony et al. (2020) [87] Huang et al. (2021) [17] Quandt et al. (2021) [86] Veile et al. (2021) [81] Amin et al. (2022) [66] Jagatheesaperumal et al. (2022) [74] Sun et al. (2022) [84] Suresh et al. (2022) [82] Cotta et al. (2023) [85] Liu et al. (2023) [76] Serey et al. (2023) [80] Ural et al. (2023) [49] Giustozzi et al. (2024) [65] Boopathy et al. (2025) [75] Longhi et al. (2025) [77]
	AR/VR, Human-Machine Interfaces, and Industrial Metaverse	Krafft et al. (2020) [78] Verde et al. (2020) [89] Vermesan et al. (2020) [104] Bhattacharya et al. (2021) [54] Quandt et al. (2021) [86] Yang et al. (2021) [88] Grandi et al. (2022) [25] Liu et al. (2023) [76] Longo et al. (2023) [21] Lumpp et al. (2024) [105] Venugopal et al. (2024) [26] Xie et al. (2024) [27] Boopathy et al. (2025) [75] Rosa-Garcia et al. (2025) [106] Yang et al. (2025) [28]
	Integration Frameworks, Middleware, and Protocols	Younan et al. (2020) [95] Cavalieri (2021) [91] Hsiao and Lee (2021) [60] Patera et al. (2021) [12] Yebenes Serrano and Zorrilla (2021) [107] Habib et al. (2022) [59] Kannisto et al. (2022) [94]

Table 4. *Cont.*

Research Category	Sub-Group	Publication
Information and Communication Technologies	Integration Frameworks, Middleware, and Protocols	Koprov et al. (2022) [92]
		Stój et al. (2022) [96]
		López et al. (2023) [93]
		Mekala et al. (2023) [58]
		Fang and Li (2024) [48]
		Zhang et al. (2025) [108]
	Reviews and Meta-analyses of ICT Trends	Chen (2020) [56]
		Lee et al. (2020) [98]
		Li et al. (2020) [83]
		Sony and Naik (2020) [87]
		Xu (2020) [35]
		French et al. (2021) [79]
		Li and Xu (2021) [42]
		Rathore et al. (2021) [97]
		Amin et al. (2022) [66]
		Dhamija (2022) [72]
		Fedullo et al. (2022) [64]
		Fortuna et al. (2022) [109]
		Jagatheesaperumal et al. (2022) [74]
		Koppu et al. (2022) [53]
		Serey et al. (2023) [80]
		AlShorman et al. (2024) [110]
		Oks et al. (2024) [34]
		Sun et al. (2024) [9]
		Li and Duan (2025) [8]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.2. Instrumentation and Measurement

Instrumentation and measurement play a foundational role in industrial information integration by enabling accurate, real-time sensing, intelligent monitoring, and seamless communication between physical and digital systems. [111] A key focus across recent works is the advancement of RFID-based sensor systems, which integrate wireless power, data collection, and identification to enhance Industrial Internet of Things (IIoT) capabilities. Meng et al. [112] and Zhang et al. [113] both propose dual-mode UHF-HF RFID sensor architectures using commercial components, facilitating flexible, unobtrusive sensing and communication without the need for additional infrastructure. These approaches are further supported by Maderböck et al. [114], who demonstrate the reliability of UHF RFID in overcoming industrial wireless communication challenges such as multipath propagation. Pacheco et al. [90] show how low-cost, open-source RFID solutions can be practically deployed for real-time production line monitoring, making smart manufacturing more accessible for resource-constrained settings.

Beyond identification, advanced sensor integration is driving progress in intelligent measurement systems and cyber-physical process control. Eifert et al. [115] present a forward-looking model for Process Analytical Technology (PAT) that combines physical and digital twins in a smart sensor framework for self-optimization and predictive process control. Similarly, Coito et al. [116] propose a sensor–business data integration system using a cloud–fog–edge architecture to improve scheduling, traceability, and quality control in highly regulated environments. Wang et al. [117] examine complementarity between tagging-to-trace and learning-to-trace practices in requirements tracing, revealing how they enhance each other's effectiveness. Chen et al. [118] address environmental complexity with the development of optical fiber-based chemical sensors that compensate for temperature and humidity, demonstrating the importance of robustness and selectivity in harsh industrial conditions.

Artificial intelligence is increasingly embedded in measurement systems to enhance monitoring, diagnosis, and safety. Li et al. [119] develop an AI-driven multispectral acoustic testing instrument that integrates thermal imaging, high-speed video, and acoustic sensors to monitor tribological behavior with high accuracy. Wang et al. [117] contribute a deep learning-based AMTCN model capable of detecting early-stage faults in industrial equipment using only normal operational data, enabling proactive maintenance. Qu et al. [120] focus on safety applications, introducing a real-time fire detection and response system that integrates deep learning, machine vision, and robotics to ensure rapid and precise incident response.

Advances in imaging and signal processing also support refined inspection and quality assurance. Koulountzios et al. [121] propose a triple-modality ultrasound computed tomography system that combines transmission and reflection imaging for enhanced spatial resolution in industrial process monitoring. Complementing this, Li and Hua [122] (in a separate study) introduce a data augmentation method—AFP-IA—that improves small defect detection in insulation pull rod imagery by enhancing foreground-background separation, boosting detection accuracy when integrated with mainstream neural networks.

Finally, targeted improvements in thermal management systems are addressed by Kalker et al. [123], who survey and evaluate real-time temperature sensing, estimation, and observation techniques. Their work outlines how next-generation temperature monitoring can be minimally invasive yet high-performance, particularly for reliability-critical components like power electronics. Collectively, these contributions illustrate a dynamic and interdisciplinary progression in industrial instrumentation and measurement—where sensor innovation, data integration, intelligent analysis, and real-time responsiveness converge to enable the next generation of smart manufacturing systems.

The articles are collected in Table 5.

Table 5. Instrumentation and measurement publication.

Research Category	Publication
Instrumentation and Measurement	Eifert et al. (2020) [115]
	Zhao et al. (2020) [124]
	Coito et al. (2021) [116]
	Koulountzios et al. (2021) [121]
	Meng et al. (2021) [112]
	Kalker et al. (2022) [123]
	Zhang et al. (2022) [113]
	De Jesus Pacheco et al. (2023) [90]
	Maderboeck et al. (2023) [114]
	Sun et al. (2023) [111]
	Chen et al. (2024) [118]
	Li and Hua (2025) [122]
	Li et al. (2025) [119]
	Qu et al. (2025) [120]
	Wang et al. (2025) [117]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.3. Machinery

Recent advancements in industrial information integration have significantly improved machinery operation, diagnostics, and simulation by leveraging digital twins, machine learning, and intelligent sensing technologies. Digital Twin (DT) models are playing a growing role in real-time state estimation and predictive maintenance. Ebadpour et al. [125] present a DT framework based on an Extended Kalman Filter (EKF) to estimate internal states of induction motors without physical speed sensors, using a realistic inverter model that enhances simulation fidelity. Similarly, Li et al. [126] propose a DT-assisted diagnostic method for rolling bearings that combines a dynamic simulation model with a stacked discrete wavelet-based transfer learning network, effectively overcoming the scarcity of labeled fault data in industrial applications. On a broader scale, Yang et al. [127] review the use of DT and emerging Metaverse technologies in fluid machinery, highlighting their utility in simulation, product design, and fault detection, while also noting practical challenges such as ensuring real-time responsiveness and data precision.

Complementing these twin-based approaches, data-driven diagnostic models continue to evolve toward better accuracy and interpretability. Wang et al. [128] introduce a physics-informed neural network for fault severity estimation in axial piston pumps, integrating physics-based pressure equations and volume efficiency metrics into a neural network framework. This hybrid approach enhances interpretability and links learned features directly to physical degradation indicators. Meanwhile, Ma et al. [129] propose a multimodal deep learning model for rotating machinery diagnostics that fuses 1D and 2D signal representations using wavelet transforms and symmetrized dot pattern graphs. Their model captures richer signal features and outperforms traditional CNNs in classification accuracy.

In parallel, intelligent sensing technologies are extending the capabilities of machinery systems beyond conventional boundaries. Huang et al. [130] review the use of tactile sensing in robotic systems—particularly in minimally invasive surgery—demonstrating how treating tactile data as images and analyzing them with AI techniques like deep learning and clustering can restore a sense of touch, improving surgical precision. Though focused on medical robotics, the study exemplifies how machinery-oriented tactile sensing can benefit from industrial AI and sensor integration strategies. Collectively, these contributions reflect a convergence of digital models, physics-informed intelligence, and advanced sensing that is reshaping the future of machine-centric industrial systems.

The articles are collected in Table 6.

Table 6. Machinery publication.

Research Category	Publication
Machinery	Huang et al. (2020) [130]
	Ma et al. (2022) [129]
	Yang et al. (2022) [127]
	Ebadpour et al. (2023) [125]
	Wang et al. (2023) [128]
	Li et al. (2024) [126]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.4. Management

Management within industrial information integration has undergone a profound transformation as organizations align strategic governance, operational efficiency, and digital technologies to adapt to Industry 4.0. A central theme is the strategic reconfiguration of traditional management domains to accommodate technological convergence. Stein et al. [131] advocate for Human-Automation Resource Management (HARM), a framework that blends human resource practices with automation oversight to promote synergistic human-machine collaboration in smart factories. Similarly, Govindan [132] proposes CSR 4.0, integrating digital technologies into corporate social responsibility to align industrial operations with the UN Sustainable Development Goals (SDGs), while Cheng et al. [133] develop an incentive mechanism—modeled as a Stackelberg game with deep reinforcement learning—to coordinate mobile data and e-commerce services for mutual benefit across digital ecosystems. Expanding beyond corporate domains, Zha [134] explores how IoT and big data support decentralized governance in community sports centers, illustrating how smart integration principles also enhance public service management.

Operationally, industrial firms are deploying digital tools to integrate predictive maintenance, asset management, and decision-making. Arena et al. [135] present a digital cockpit that synchronizes maintenance and production scheduling by fusing Remaining Useful Life (RUL) data with simulation via a digital twin, enabling cost-efficient coordination between operational units. Liu et al. [136] examine the evolution of safety management through three stages—Safety 1.0, 2.0, and 3.0—and propose a framework integrating Safety 3.0 with Industry 4.0. Kok et al. [137] identify organizational challenges in aligning IT and operational technology (OT) across physical asset lifecycles, emphasizing the need for integrated tools, standards, and governance frameworks. Vrana et al. [138] extend this operational view through the lens of NDE 4.0, showing how non-destructive evaluation, once limited to quality control, can be repositioned as a strategic information asset through its integration into Industrial IoT and cyber-physical systems.

Decision support and adaptive strategy are also increasingly data-driven and systemically informed. Chou et al. [139] propose a fuzzy analytic decision model for food processing machinery procurement, identifying key weighted criteria such as switching costs and after-sales service. Bauer et al. [140] explore how product development capabilities, when aligned with sales integration and market intelligence, drive superior business performance through international product adaptation strategies. Li [141] highlights the urgent need for workforce reskilling and upskilling to meet Industry 4.0 demands, noting that by 2025, half of employees will require new skills. The study outlines key industry priorities and advocates lifelong learning as a shared responsibility, emphasizing accessible and affordable education to build a future-ready workforce. Meanwhile, knowledge-driven planning is also advancing in design and construction. Al-Zubaidi et al. [142] review facility layout problem (FLP) literature, calling for integrated models that combine digital tools, layout optimization, and sustainability considerations. Complementarily, Locatelli et al. [143] highlight the role of Natural Language Processing (NLP) in enhancing Building Information Modeling (BIM) for compliance automation and semantic enrichment within the AECO sector, pointing to emerging opportunities at the intersection of AI and digital construction.

Together, these studies demonstrate how management strategies in industrial contexts are increasingly interwoven with digital infrastructure, data-driven insights, and system-level coordination—shaping a future where operational excellence, social responsibility, and intelligent integration converge.

The articles are collected in Table 7.

Table 7. Management publication.

Research Category	Publication
Management	Bauer et al. (2020) [140] Chou et al. (2020) [139] Liu et al. (2020) [136] Stein et al. (2020) [131] Al-Zubaidi et al. (2021) [142] Locatelli et al. (2021) [143] Vrana et al. (2021) [138] Arena et al. (2022) [135] Cheng et al. (2023) [133] Zha (2023) [134] Govindan (2024) [132] Kok et al. (2024) [137] Li (2024) [141]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.5. Manufacturing

Manufacturing lies at the heart of industrial information integration, serving as both a driver and a beneficiary of technological convergence. The emergence of Industry 4.0 has catalyzed a paradigm shift—where digital twin systems, artificial intelligence, additive manufacturing, and integrated cyber-physical architectures collectively redefine how products are designed, produced, and optimized. This section synthesizes current research efforts that demonstrate how these innovations reshape manufacturing workflows, decision-making, and value creation across industries.

3.5.1. Digital Twin, Simulation, and Virtualization

The Digital Twin (DT), simulation, and virtualization technologies form a central pillar in the advancement of industrial information integration, enabling enhanced monitoring, predictive analytics, and decision-making across diverse manufacturing domains [144,145]. Numerous studies illustrate the integration of DTs into complex systems to enhance process visibility and control. For instance, Mahdi et al. [146] developed a DT-based system for Wire Arc Additive Manufacturing (WAAM), incorporating CNN-based defect prediction and OPC UA-based secure communication. In fluid machinery, Yang et al. [127] reviewed the role of DT and emerging Metaverse applications in intelligent fault detection and simulation. Pombo et al. [147] designed a DT framework for the grinding industry, integrating material testing, modeling, and sensor feedback to support zero-defect manufacturing. Similarly, Ebadpour et al. [125] utilized an Extended Kalman Filter-based DT for induction motor drives, enabling real-time state estimation without physical speed sensors. The DT application also extends to sustainability, as shown by Li et al. [148], who proposed a DT-driven architecture for life-cycle-oriented sustainability assessment, and to consumer electronics, where Sai et al. [149] examined DT use in design and maintenance.

Expanding into cross-disciplinary applications, Rono et al. [150] presented a combined VR, IIoT, and DT framework to monitor chemical processes in real time, demonstrating strong cyber-physical system integration. Zhang et al. [151] proposed a blockchain-enhanced DT system for transformer coil manufacturing, ensuring secure and transparent traceability. To address system reliability and scalability, Saxena et al. [152] developed a self-healing, fault-tolerant cloud-based DT management model using federated learning. Torchio et al. [153] integrated AI-enhanced DTs in power electronics for thermal prediction and safe operation on embedded systems. Additionally, Paszkiewicz et al. [154] proposed a digital infrastructure for 3D printing in distributed manufacturing environments using virtualization to support remote incremental production.

At the architectural level, Binder et al. [155] incorporated DTs within the RAMI 4.0 framework using a model-based approach grounded in the Zachman framework, supporting interoperability in Industry 4.0 settings. Shi et al. [156] tackled Zero Defect Manufacturing by combining the Asset Administration Shell with large language models to automatically construct interoperable DT models for injection molding. In the aerospace domain, Li et al. [157] introduced a real-time multidisciplinary simulation framework based on DT principles to support hypersonic aircraft virtual testing. Complementing this, Zheng et al. [158] proposed a semantic tradespace framework that integrates ontologies and model-based systems engineering to optimize aircraft assembly during the design stage. Collectively, these works demonstrate that DTs, when coupled with simulation, blockchain, AI, and cloud technologies, are reshaping how industrial systems are designed, operated, and optimized.

3.5.2. AI, Machine Learning, and Data Analytics in Manufacturing

Artificial Intelligence (AI), machine learning (ML), and advanced data analytics have become foundational technologies driving innovation in manufacturing, enabling predictive intelligence, fault diagnosis, quality assurance, and process optimization across various industrial sectors. A growing body of literature demonstrates their integration into practical manufacturing systems. For instance, Ma et al. [159] proposed TFDFormer, a novel deep learning framework combining time-frequency features through CNN-Transformer architecture for robust fault diagnosis. Similarly, Du et al. [160] introduced LLM-MANUF, a large language model–driven decision support framework that enhances accuracy and reduces bias in industrial decision-making processes. In the additive manufacturing domain, Vaghefi et al. [161] developed an MLP-CNN model to accurately predict melt pool depth, addressing quality consistency in laser powder bed fusion.

Image-based defect detection is another prominent application. Zhao et al. [162] presented the Deep Parallel Attention CNN (DPACNN) for high-precision steel defect classification, while Shao et al. [163] introduced MLAD, a hybrid attention-enhanced autoencoder framework to detect both manifest and latent manufacturing anomalies. Zhou et al. [164] built SSNet, a hyperspectral imaging model tailored for real-time impurity detection in tobacco processing. Beyond vision tasks, Zhao et al. [165] proposed a multimodal CNN for machinery fault diagnosis using multimodal sensor inputs, and Feng et al. [166] applied a full graph autoencoder for anomaly detection in Industrial IoT environments by mapping multivariate time series into graph representations.

In IIoT-driven smart manufacturing, Wang et al. [167] leveraged multi-feature fusion and multi-kernel learning for enhanced image annotation, while Hussien et al. [168] proposed an AI-driven CSI compression model to enhance data transmission in cellular IoT systems. C. Ku et al. [169] addressed the deployment challenges of AI in factories by developing an AI model cloud platform that supports remote tuning, continuous integration, and multi-scenario operation. Meanwhile, Lin et al. [170] introduced the Intelligent Manufacturing Virtual Assistant (IMVA), combining large language models and AI agents to enhance yield analysis and defect detection in semiconductor production.

AI is also transforming additive manufacturing, with Pratap et al. [171] and Di Cataldo et al. [172] exploring deep learning and sensing integration to improve real-time quality control and defect prediction. In wood processing, Ji et al. [173] demonstrated how combining DL, automation, and machine vision leads to better material utilization and faster processing. Ou et al. [174] applied AI-driven soft sensors to predict semiconductor etching outcomes using multi-machine data aggregation. Lastly, Yu et al. [175] proposed a big data architecture that fuses industrial IoT, Apache Spark, NoSQL, and PCA-based analytics to detect faults in predictive maintenance systems. Together, these contributions underline how AI and data analytics are reshaping modern manufacturing, enabling smarter, more adaptive, and higher-quality production systems.

3.5.3. Additive Manufacturing and Process Optimization

Additive Manufacturing (AM) continues to evolve as a critical pillar of intelligent production, particularly under the Industry 4.0 paradigm. Recent research focuses not only on improving fabrication precision but also on enhancing traceability, real-time monitoring, data integration, and process optimization. Wang et al. [176] introduced a field-driven data compression framework to handle diverse AM data formats, significantly reducing data volume while preserving multi-information fidelity. Similarly, Yuan et al. [177] proposed a comprehensive motion planning system for Wire Arc Additive Manufacturing (WAAM), optimizing layer sequencing and collision avoidance for multidirectional builds. These contributions highlight the shift toward fully integrated AM environments.

Traceability and integration are also essential themes. Jarrar et al. [178] developed a knowledge-based traceability framework for AM value chains, while Poka et al. [179] proposed integrating Powder Bed Fusion—Laser Beam of Metals (PBF-LB/M) systems with Manufacturing Execution Systems (MES) through standardized

ETL pipelines. Complementing these efforts, Plotnikov et al. [180] designed a sensor suite combining infrared, optical, and acoustic emission sensing for in situ quality monitoring in LPBF processes.

Deep learning and machine learning further augment AM performance. Pratap et al. [171] and Di Cataldo et al. [172] demonstrated how AI can support real-time quality control, defect prediction, and process optimization. Vaghefi et al. [161] applied an MLP-CNN model to predict melt pool depth using hybrid numerical and image data, improving microstructure consistency. Similarly, Shao et al. [163] developed a hybrid anomaly detection framework (MLAD) to detect latent defects in manufacturing processes.

Framework-level innovation also features prominently. Paszkiewicz et al. [154] presented an integrated 3D printing framework tailored for distributed and remote manufacturing environments, and Mahdi et al. [146] proposed a WAAM digital twin system that integrates 3D visualization, CNN-based defect detection, and OPC UA communication. Jarrar et al. [178] also contributed to early-stage process planning through decision-support modeling. Additionally, Wang et al. [176] offered a modeling method to unify control fields in AM for efficient simulation and production integration. Beyond AM, Zhou et al. [164] addressed process diagnostics in blast furnace ironmaking by integrating PCA and ICA techniques to improve fault detection, bridging the gap between conventional metallurgy and modern data-driven optimization.

Altogether, these studies underscore a collective shift toward comprehensive, intelligent, and interoperable AM systems, where process reliability, traceability, and real-time responsiveness are core to future industrial competitiveness.

3.5.4. Industry 4.0 Integration and Smart Factory Architectures

The integration of Industry 4.0 technologies and the evolution of smart factory architectures are reshaping the manufacturing landscape across sectors. Core technologies such as IIoT, lean production, microservices, blockchain, AI, and cyber-physical systems are being combined to enable flexible, data-driven, and efficient manufacturing systems. Ferreira et al. [181] advanced this vision by integrating Lean principles with hybrid simulation in the furniture industry, while Guan et al. [182] proposed an improved genetic algorithm (MCO-GA) for optimizing scheduling in hybrid flow shops, showing measurable performance improvements in real factories. Sun et al. [183] review Industry 4.0 concepts and implementation to guide China's manufacturing transformation, identify key challenges, propose development strategies, and introduce a digital manufacturing ecosystem framework with theoretical and practical significance.

A recurring theme is the convergence of IIoT with intelligent frameworks. Guo et al. [184] proposed a self-organizing IIoT architecture using swarm intelligence to adapt to dynamic manufacturing needs. Similarly, Nounou et al. [185] combined Lean practices with IIoT for real-time smart value stream mapping. At the architectural level, Ibarra-Junquera et al. [186] developed a microservices-based Industry 4.0 framework using containerization and publish/subscribe models to ensure dynamic reconfigurability without downtime. Siahboomy et al. [187] tackled spatial logistics with a BIM-GIS hybrid approach for warehouse siting, enhancing factory layout and operations. Ge et al. [188] explore intelligent manufacturing by integrating cyber-physical systems, big data, IoT, cloud computing, and value chains, examining its role in supply and industry chains and discussing big data-driven integration.

Ensuring human-machine synergy is also critical. Walter et al. [189] proposed a safety-aware model for human-robot collaboration using voxel-based dynamic safety zones in aerospace manufacturing. In infrastructure modernization, Sverko et al. [190] addressed the evolution of SCADA systems to support continuous flow production in the steel industry, improving data integration and interoperability.

At the system analysis level, Li et al. [191] offered a network entropy-based framework to quantify the complexity of collaborative IIoT manufacturing networks, enabling better-informed system design. Blockchain also features in smart integration efforts: Deng et al. [192] proposed a dual-layer blockchain for secure industrial communication in chemical manufacturing, ensuring low-latency and trust across cyber-physical levels. Wicaksono et al. [193] applied AI and semantic middleware for industrial demand-response systems to align production with energy pricing, aiding renewable transitions. Sun et al. [194] reviews the key drivers and developments of IT-enabled service-oriented manufacturing (SOM), a strategy that integrates servitization with traditional manufacturing to enhance competitiveness.

Sector-specific innovations show the breadth of integration. Yuan et al. [195] empirically analyzed the impact of IT integration on textile industry competitiveness in China, while Yiyan et al. [196] proposed Industry 4.0 strategies to support circular economy adoption in post-pandemic garment manufacturing. Shi et al. [156] introduced AAS-LLM integration for standardized data modeling in zero-defect manufacturing, automating semantic alignment in quality control systems. Ji et al. [173] brought together machine vision, optimization algorithms, and industrial internet for intelligent wood structure processing, demonstrating increased utilization and efficiency. Finally, Gil-Martín et al. [2] enhanced acoustic testing in wood manufacturing with a computationally efficient ToF detection algorithm, bridging sensor design with real-world calibration needs.

Collectively, these works reflect the industrial shift toward modular, intelligent, and adaptive architectures that respond to operational complexity and sustainability demands through advanced integration strategies.

The articles are collected and classified in Table 8.

Table 8. Manufacturing publication.

Research Category	Sub-Group	Publication
Manufacturing	Digital Twin, Simulation, and Virtualization	Li et al. (2020) [148] Paszkiewicz et al. (2020) [154] Pombo et al. (2020) [147] Li et al. (2021) [197] Li et al. (2021) [157] Binder et al. (2022) [155] Ebadpour et al. (2023) [125] Rono et al. (2023) [150] Sai et al. (2024) [149] Shi et al. (2024) [156] Zheng et al. (2024) [158] Geng et al. (2025) [198] Mahdi et al. (2025) [146] Saxena et al. (2025) [152] Torchio et al. (2025) [153] Zhang et al. (2025) [151]
	AI, Machine Learning, and Data Analytics in Manufacturing	Yu et al. (2020) [175] Di Cataldo et al. (2021) [172] Zhou et al. (2021) [199] Feng et al. (2022) [166] Pratap et al. (2022) [171] Hussien et al. (2023) [168] Ji et al. (2023) [173] Zhao et al. (2023) [162] Zhao et al. (2023) [165] Ou et al. (2024) [174] Vaghefi et al. (2024) [161] Zhou et al. (2024) [164] Chen et al. (2025) [200] Du et al. (2025) [160] Ku et al. (2025) [169] Lin et al. (2025) [170] Ma et al. (2025) [159] Shao et al. (2025) [163] Wang et al. (2025) [167]
	Additive Manufacturing and Process Optimization	Paszkiewicz et al. (2020) [154] Plotnikov et al. (2020) [180] Di Cataldo et al. (2021) [172] Pratap et al. (2022) [171] Yuan et al. (2022) [177] Jarrar et al. (2023) [178] Wang et al. (2023) [176] Poka et al. (2024) [179] Vaghefi et al. (2024) [161] Zhou et al. (2024) [164] Mahdi et al. (2025) [146] Shao et al. (2025) [163]

Table 8. *Cont.*

Research Category	Sub-Group	Publication
Manufacturing	Industry 4.0 Integration and Smart Factory Architectures	Ge et al. (2020) [188] Li et al. (2020) [201] Longo et al. (2020) [202] Sun et al. (2020) [183] Asgari Siahboomy et al. (2021) [187] Carvalho De Souza et al. (2021) [203] Ibarra-Junquera et al. (2021) [186] Yuan et al. (2021) [195] Ferreira et al. (2022) [181] Nounou et al. (2022) [185] Sun et al. (2022) [194] Sverko et al. (2022) [190] Walter et al. (2022) [189] Yu et al. (2022) [204] Deng et al. (2023) [192] Guan et al. (2023) [182] Guo et al. (2023) [184] Ji et al. (2023) [173] Li et al. (2023) [205] Li et al. (2023) [191] Yiyan et al. (2023) [196] Sarivan et al. (2024) [206] Shi et al. (2024) [156] Gil-Martín et al. (2025) [2] Schuchter et al. (2025) [207] Wicaksono et al. (2025) [193]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.6. Math Modeling

Mathematical modeling plays a foundational role in industrial information integration by enabling the formal representation, analysis, and optimization of complex systems. Through methods such as physics-based modeling, statistical learning, hybrid AI frameworks, and semantic reasoning, mathematical models provide the analytical backbone for predictive maintenance, intelligent control, scheduling, anomaly detection, and secure information flow. This section reviews recent advances across six major themes—ranging from digital twin and cyber-physical systems to optimization algorithms and deep learning—highlighting how diverse modeling approaches are being tailored to meet the demands of smart, connected, and adaptive industrial environments.

3.6.1. Digital Twin and Cyber-Physical Systems

The integration of Digital Twin (DT) and Cyber-Physical Systems (CPS) has emerged as a foundational modeling approach for industrial information integration, enabling real-time synchronization between physical processes and virtual representations. Liu et al. [208] demonstrated a data-driven DT approach for machining quality control by coupling sensor data with intelligent algorithms to monitor tool wear. Similarly, Ruane et al. [209] developed a simulation-based DT framework tailored for medical device manufacturing, enhancing process transparency and control. Yin et al. [210] advanced a DT-enabled industrial service model integrating process knowledge graphs and deep learning for predictive decision support. In the context of real-time location tracking, Ruppert et al. [211] introduced a DT-based system using RTLS data and simulation to monitor industrial system performance. Complementing this, Zhuang et al. [212] proposed a smart shop-floor management platform based on DT and real-time data mapping for production coordination.

Sun et al. [213] presented a DT-IMS framework that utilizes multi-source integration for manufacturing service scheduling, while Park et al. [214] embedded a DT into a CPPS for lithium-ion battery production, enabling holistic process transparency through digital shadows. Uhlenkamp et al. [215] introduced a maturity model for DT development focused on structured industrial evaluation. Javaid et al. [216] designed a DT-enhanced scheduling optimization method for manufacturing using a hierarchical PSO algorithm and semantic BOM structure. In quality inspection, Liu et al. [217] utilized DT to enhance fabric defect detection, integrating image processing and production line data. Addressing parameter monitoring, Li et al. [218] proposed FL-DTPM, a federated learning-based DT predictive maintenance model that preserves privacy while achieving decentralized learning.

In vibration signal simulation, Hakam et al. [219] built a DT-based AI system that fuses empirical and simulated data for high-precision fault modeling. Similarly, Wang et al. [220] created a virtual CNC simulation platform integrating multiphysics and multivariate modeling to assist tool vibration analysis. From a theoretical lens, Villalba-Diez et al. [221] applied quantum modeling to CPSs, showing how digital shadows can encode causal structures to guide intelligent automation. Liu et al. [222] addressed microservice-based smart manufacturing by proposing an E^2MS migration strategy that leverages containerization and digital mapping. Montori et al. [223] contributed a modular toolchain to support DT-based structural health monitoring in bridges, facilitating predictive maintenance. Yahya et al. [224] combined DT and knowledge graph methodologies to model handcrafted football production lines, enhancing process traceability and semantic interoperability. Finally, Horváth [225] emphasized human-centric CPS and DT integration by formalizing model behavior ontologies, laying groundwork for hybrid modeling in cognitive manufacturing systems.

Collectively, these studies underscore DT and CPS as central enablers in industrial modeling, offering scalable, intelligent, and integrated solutions for monitoring, simulation, optimization, and predictive control across diverse domains.

3.6.2. Fault Detection, Predictive Maintenance, and Monitoring

Fault detection and predictive maintenance have become pivotal components of industrial information integration, driven by the increasing deployment of machine learning (ML), deep learning, and hybrid modeling techniques. Yan et al. [226] proposed DAMPNN, a dual-attention multi-scale probabilistic neural network for soft sensing of blast furnace burden level, combining temporal-spatial attention with probabilistic regression. Ali et al. [227] developed a hybrid model integrating LSTM and wavelet decomposition for early fault detection in rotating machinery, enhancing sensitivity to incipient failures. Naqvi et al. [228] advanced intelligent retrieval systems by coupling large language models (LLMs) with knowledge-based semantic indexing to support predictive maintenance knowledge sharing. In a similar predictive maintenance context, Jaenal et al. [229] introduced MachNet, a compact CNN-GRU model optimized for industrial-scale health monitoring with low computational cost.

Ruiz-Sarmiento et al. [230] leveraged sensor fusion and self-organizing maps for predictive maintenance in steel production, detecting wear and misalignment in real time. Al-Dulaimi et al. [231] proposed a noise-robust BiLSTM model that learns temporal degradation patterns for accurate remaining useful life (RUL) prediction. Wei et al. [232] presented an ensemble learning framework combining autoencoder and attention mechanisms to improve multi-scale RUL prediction in complex systems. Similarly, Ni and Li [233] integrated stacked broad learning systems with LSTM for adaptive fault prediction in chemical processes. Sun et al. [213] propose FedTDLearning, a distributed reinforcement learning framework for efficient order-driver matching in mobility-on-demand systems.

Jiang et al. [234] developed an unsupervised self-diagnosis system for sensor drift using kernel entropy-based similarity learning, enabling autonomous monitoring in sensor-rich environments. Goodarzi et al. [235] addressed distributional and domain shift detection in industrial monitoring via a multi-sensor AutoML ensemble framework, which reduces retraining costs while preserving accuracy. Liang et al. [236] proposed CVA-DisDAE, a combined canonical variate analysis and denoising autoencoder approach for enhanced process fault detection in multivariate systems. Huo et al. [237] extended this line with DiWCA, a dynamic weighted contrastive autoencoder model enabling interpretable diagnosis across changing operating conditions.

Further advancing interpretability and trust in monitoring systems, Gutierrez-Rojas et al. [238] applied explainable AI techniques to CPS fault classification using hybrid ML-physics reasoning. Pang et al. [239] utilized a variational quantization one-class SVM for anomaly detection in sensor networks, balancing generalization and detection sensitivity. Cerquitelli et al. [240] proposed UDaMP, a unified data mining platform supporting real-time equipment health analytics and trend prediction in smart factories. To improve accuracy in sequential anomaly recognition, Li et al. [241] introduced TIFN, a temporal interaction fusion network that models long-term dependencies using attention mechanisms.

Complementing algorithmic modeling, Jose et al. [242] surveyed the integration of LLMs in prognostics and health management, identifying their potential for reasoning over complex, sparse datasets. Zhang et al. [243] proposed a hierarchical attention-based temporal CNN for fault classification in high-speed railway systems. Guan et al. [244] constructed a lightweight CNN-RNN framework to support portable predictive maintenance systems for embedded devices. Finally, Cuentas et al. [245] demonstrated an optimized SVM approach using genetic algorithms to improve accuracy and parameter efficiency in condition monitoring of induction motors.

Collectively, these contributions reflect a shift toward intelligent, robust, and explainable fault modeling frameworks that can operate under uncertainty, heterogeneity, and dynamic conditions in industrial environments.

3.6.3. Optimization Models and Scheduling Algorithms

Optimization modeling plays a central role in industrial information integration, supporting intelligent decision-making across production scheduling, resource allocation, transportation, and architectural coordination. Wang et al. [246] proposed a digital twin-enabled deep reinforcement learning (DT-DRL) framework to enhance scheduling under dynamic shop-floor conditions, leveraging simulation feedback for iterative policy improvement. Similarly, Zhang et al. [247] developed KAiPP, an adaptive intelligent production planning system that integrates reinforcement learning and manufacturing KPIs for flexible scheduling. Zhao et al. [248] presented a CPS-oriented production optimization architecture for automobile painting systems, using multi-level models and data integration to optimize energy and material usage. Tan et al. [249] propose GoCC, a group-oriented crowdsensing approach that forms user groups based on real social connections to improve task coverage and cooperation quality in mobile crowdsensing.

Heuristic and metaheuristic optimization strategies are also prominent. Hu et al. [250] introduced HDSTA, a hybrid differential search and teaching–learning-based algorithm to solve large-scale engineering optimization problems efficiently. Guo et al. [251] applied multi-objective evolutionary algorithms for vehicle routing with integrated waste collection and recycling constraints, enabling sustainability-aware logistics planning. Psarommatis et al. [252] contributed a real-time cost modeling method that aligns production optimization with economic performance indicators in manufacturing execution systems. Zhao et al. [124] propose an evolutionary heuristic-based method to optimize resource allocation in crowd-based cooperative task allocation, balancing matching accuracy and collaboration quality cost-effectively.

Reinforcement learning continues to gain traction, as seen in Yang et al. [253], where RL was used to prioritize combinatorial test cases based on industrial contextual importance. In vehicular communication, Reshma and Sudha [254] optimized coordinated multipoint (CoMP) transmission scheduling in V2X networks using graph convolution networks to improve reliability and latency. Hu et al. [255] introduced an optimization strategy for low-humidity solar heat pump drying systems using mixed-integer nonlinear programming, balancing drying rate and energy consumption.

Factory-level scheduling was further enhanced by Jung et al. [256], who designed a GA-based digital twin simulator for garment production lines that enables layout planning and real-time scheduling optimization. Mishra et al. [257] proposed IF-CODAS, an intuitionistic fuzzy decision model for multi-criteria supplier selection, useful in cases where human judgment and vagueness are dominant. From a semantic modeling angle, Fang [258] developed a semantic hierarchical structure for design intent, facilitating the optimization of CAD-based product design workflows.

Herrera-Vidal et al. [259] focused on complexity-driven production planning by integrating complexity indices into an optimization framework to ensure adaptive scheduling under volatile environments. Liu et al. [260] introduced ST-EGAN, a spatial–temporal energy estimation model using generative adversarial networks to forecast energy consumption patterns for demand-side optimization. In the building domain, Andrich et al. [261] proposed a BIM-based automated checking mechanism that uses IFC constraints and NLP to optimize regulatory compliance and design validation.

Graph-based learning also contributes to combinatorial scheduling, as seen in Wang et al. [262], who designed ParSGCN, a parallel spatial–temporal graph convolutional network for multi-resource task scheduling in smart factories. Finally, Mu et al. [263] developed MS-STN, a multi-scale spatiotemporal neural network model tailored for dynamic workshop scheduling, capturing long-range task dependencies and resource interactions.

Together, these works highlight how optimization strategies—spanning deep reinforcement learning, heuristic methods, fuzzy logic, graph-based modeling, and semantic integration—can effectively address the complexity, uncertainty, and scale of modern industrial systems.

3.6.4. Deep Learning Models for Industrial Applications

Deep learning has become a cornerstone in industrial modeling, offering powerful capabilities for process representation, sensor fusion, anomaly detection, and intelligent recommendation. Liu et al. [264] laid the foundation by surveying the convergence of blockchain and machine learning (ML), highlighting how decentralized architectures and deep models can jointly enhance industrial security, scalability, and automation.

Wei et al. [265] proposed a Hessian semi-supervised scatter regularized classification model, improving generalization in complex industrial data environments. Li et al. [266] developed a novel subspace clustering algorithm that integrates label information to improve feature extraction and dimensionality reduction for process data classification.

Several works focused on surface defect detection and image processing. Li et al. [218] introduced IDP-Net, a multi-scale parallel dilated convolutional network for defect detection in industrial surfaces, combining fine-grained context learning with noise suppression. Similarly, Huang et al. [267] proposed NCE-Net, a dual-attention convolutional encoder-decoder framework that enhances spatial and channel features to detect PCB surface anomalies. Mustafaev et al. [268] combined Inception-CNN with GANs to detect surface defects under occlusion and illumination variation, showing superior performance in generalization.

Deep learning also supports physical modeling and parameter estimation. Wang et al. [269] presented SDDM, a sensor-driven deep learning model for gas turbine engine performance analysis, integrating sensor fusion and temporal learning. Lu et al. [270] developed a physics-informed neural network to model thermal drift in sensor systems, combining data-driven learning with physical constraints. Liu et al. [271] proposed TiTAD, a lightweight transformer-based model for time series anomaly detection in IIoT systems with high interpretability. Shi et al. [272] introduced TART, a temporal-aware recurrent transformer network capable of modeling irregularly sampled time series for predictive analytics.

Security and system management are also prominent applications. Khan et al. [273] utilized RNNs for efficient malware classification in industrial networks, addressing lightweight requirements of embedded systems. Ramathulasi et al. [274] introduced a deep learning-powered recommendation framework for industrial IoT APIs based on probabilistic matrix factorization and semantic embeddings. Wang et al. [275] proposed a cross-domain recommendation system using deep reinforcement learning to improve ad targeting in smart industrial applications.

Deep learning enables transfer learning and domain adaptation in low-data environments. Jiang et al. [276] demonstrated transfer learning using CNNs for optical character recognition on laser-engraved serial numbers, achieving high accuracy in metal surface applications. Ding et al. [277] modeled gas metal arc weld bead geometry using support vector machines optimized by artificial bee colony, capturing complex spatial interactions. Sun et al. [9] applied Gaussian process regression for centrifugal pump performance prediction, illustrating hybrid modeling in mechanical systems.

In manufacturing automation, Li et al. [278] developed a GAN-GRU hybrid model to estimate welding penetration and bead width from sensor data, enhancing robotic welding precision. Wang et al. [262] created a multimodal anomaly detection framework combining image, time series, and contextual data for cross-sensor fault analysis. Liu et al. [271] proposed a dual-branch deep saliency detection network tailored for PCB defect inspection, enabling robust object boundary enhancement in cluttered scenes.

Finally, Jose et al. [242] explored the use of large language models (LLMs) in predictive health management (PHM), discussing their capacity to interpret complex, multimodal industrial datasets for failure reasoning and decision support.

These contributions collectively showcase how deep learning facilitates accurate, scalable, and interpretable modeling across a wide range of industrial applications—from vision-based inspection and physical system modeling to intelligent diagnostics, recommendation, and cross-domain adaptation.

3.6.5. Mathematical Modeling, Statistical & Hybrid Models

Mathematical, statistical, and hybrid modeling techniques remain fundamental in industrial information integration, providing interpretable, physics-consistent, and computationally efficient models for control, diagnosis, and decision support. Xiang et al. [279] combined BiLSTM with physical feature selection to predict coke structural deterioration, illustrating the synergy between data-driven and physics-based approaches in complex material systems. Kovtun et al. [280] presented a multi-source Markov queuing model to estimate resource requirements and latency in industrial IoT, enabling real-time adaptive system provisioning.

Advanced control strategies were also explored. Cui et al. [281] proposed a model predictive control (MPC) scheme for hydrogen production via steam methane reforming, optimizing reactor dynamics under economic and safety constraints. Szega [282] introduced the DVR framework for dynamic thermal performance modeling in layered industrial systems, integrating numerical simulations and real-time feedback. Similarly, Farlessyost et al. [283] used the Sparse Identification of Nonlinear Dynamics (SINDy) method to identify governing equations in industrial processes, supporting simplified and explainable system modeling.

Metaheuristic optimization was addressed by Denimal et al. [284], who introduced the GMASA algorithm—a hybrid of moth-flame and simulated annealing—for vibration parameter tuning in rotating machinery. Ayoub et al.

[285] employed Bayesian updating in probabilistic safety assessment to dynamically revise industrial risk estimates under uncertainty. Xu et al. [286] coupled finite element modeling and response surface methodology (FEM-RSM) to predict mechanical bruise severity in postharvest processes, balancing accuracy and computational cost.

Alarm and fault sequence modeling were addressed by Manca and Fay [287], who developed a hybrid method combining kernel density estimation and distance metrics to detect dangerous alarm subsequences in manufacturing systems. Liang et al. [236] applied a CVA-DisDAE model—merging canonical variate analysis and denoising autoencoders—to detect process anomalies with improved robustness against non-Gaussian noise.

In structural health monitoring, Montori et al. [223] developed a modular toolchain combining physics-based diagnostics with digital twin frameworks for predictive maintenance of bridge structures. Rathee et al. [288] proposed a hybrid multi-criteria decision-making model combining Simple Additive Weighting (SAW) and Analytic Hierarchy Process (AHP) for optimal resource selection in IIoT environments. Josphineleela et al. [289] addressed industrial cybersecurity with a fuzzy-logic-based blockchain framework for secure node authentication in fog–cloud architectures.

From the education and knowledge modeling side, Chen et al. [290] used fuzzy AHP to evaluate the suitability of integrated industry–education frameworks, providing a structured methodology for stakeholder decision-making. Lastly, Contreras-Ropero et al. [291] modeled phycocyanin pigment production in cyanobacteria by combining mechanistic metabolic models with experimental validation, bridging biological processes with industrial biomanufacturing.

Collectively, these studies demonstrate the continued value of mathematically grounded models—often augmented with hybrid data-driven techniques—in addressing the interpretability, reliability, and domain-specific complexity challenges of industrial systems.

3.6.6. Knowledge Graphs, Semantics, IT/OT Integration & Security

The integration of semantic frameworks, knowledge graphs, and secure architectures is essential for advancing interoperability, traceability, and cybersecurity in industrial information systems. Arazzi et al. [292] introduced SemIoE, an ontology-driven semantic integration framework for Industry 5.0 that facilitates human-centric and intelligent interoperability across distributed industrial systems. Corradi et al. [293] developed a modular IT/OT integration platform leveraging semantic models to enable context-aware industrial applications, bridging the divide between operational technology and information systems.

Security remains a critical concern. Rathee et al. [294] proposed a hybrid anomaly detection model combining hidden Markov models and blockchain to detect cyber threats in circular economy supply chains, enhancing trust and transparency. In parallel, Kuhn and Franke [295] designed a graph-based traceability model for assembly systems that utilizes ontology structures to ensure flexible and accurate product lineage documentation. Yahya et al. [224] focused on knowledge graph generation for smart manufacturing, proposing a rules-guided ontology mapping (RGOM) approach to enable semantic reasoning in complex, handcrafted production lines.

Data quality in industrial monitoring was addressed by Gómez-Omella et al. [296], who proposed DQ-REMAIN, a framework integrating semantic rules and real-time analytics to maintain integrity and validity of IoT data streams. Lopez-de-Ipina et al. [297] introduced the HUMANISE framework, which enables context-aware risk management and information integration by aligning human factors with semantic models. Complementing this, Naqvi et al. [228] discussed the fusion of large language models with ontologies to enhance semantic retrieval and representation in predictive maintenance knowledge systems.

Cognitive interfaces also play a growing role. Wellsandt et al. [298] presented a semantic digital assistant embedded within maintenance operations, enabling intuitive interaction with production systems via a contextual knowledge graph backbone. Liu et al. [299] contributed a blockchain-based PLM integration architecture, ensuring tamper-proof product data across design, production, and supply chain stages.

Security architecture advances continue with Josphineleela et al. [228], who developed a fuzzy-rule-based blockchain framework for secure fog–cloud industrial IoT authentication, combining logic-based decision making with decentralized security. Zhang and Zheng [300] explored quantum-secure deterministic communication (QSDC) and time-sensitive networking (TSN), offering a secure and synchronized communication layer for smart manufacturing networks. Yang et al. [301] proposed a remote attestation mechanism for IIoT systems using trust anchors and cryptographic proofs to verify device integrity during system integration.

Finally, Ramathulasi and Babu [274] introduced DL-PMF, a deep learning-based probabilistic matrix factorization model for recommending secure and semantically relevant APIs in industrial IoT environments, enhancing software component reuse and integrity.

Together, these works illustrate how ontologies, semantic modeling, and hybrid AI-security techniques are converging to support trustworthy, intelligent, and interoperable information architectures for future industrial ecosystems.

The articles are collected and classified in Table 9.

Table 9. Math Modeling publication.

Research Category	Sub-Group	Publication
Math Modeling	Digital Twin and Cyber-Physical Systems	Ruppert and Abonyi (2020) [211] Horváth (2021) [225] Liu et al. (2022) [217] Ruane et al. (2022) [209] Uhlenkamp et al. (2022) [215] Villalba-Diez et al. (2022) [221] Montori et al. (2023) [223] Park et al. (2023) [214] Sun et al. (2023) [213] Li et al. (2024) [218] Liu et al. (2024) [222] Liu et al. (2024) [208] Yahya et al. (2024) [224] Yin et al. (2024) [210] Hakam and Benfriha (2025) [219] Javaid and Ullah (2025) [216] Wang et al. (2025) [220] Zhuang et al. (2025) [212]
	Fault Detection, Predictive Maintenance, and Monitoring	Al-Dulaimi et al. (2020) [231] Ruiz-Sarmiento et al. (2020) [230] Zhao et al. (2020) [124] Cerquitelli et al. (2021) [240] Cuentas et al. (2022) [245] Pang et al. (2022) [239] Tan et al. (2022) [249] Sun et al. (2023) [213] Zhang et al. (2023) [243] Ali et al. (2024) [227] Guan et al. (2024) [244] Jaenal et al. (2024) [229] Jose et al. (2024) [242] Liang et al. (2024) [236] Ni and Li (2024) [233] Goodarzi et al. (2025) [235] Gutierrez-Rojas et al. (2025) [238] Huo et al. (2025) [237] Jiang et al. (2025) [234] Li et al. (2025) [241] Naqvi et al. (2025) [228] Wei et al. (2025) [232] Yan et al. (2025) [226]
	Optimization Models and Scheduling Algorithms	Yang et al. (2020) [253] Mishra et al. (2021) [257] Andrich et al. (2022) [261] Ghidoni et al. (2022) [302] Guo et al. (2022) [251] Hu et al. (2022) [255] Mu et al. (2022) [263]

Table 9. *Cont.*

Research Category	Sub-Group	Publication
Math Modeling	Optimization Models and Scheduling Algorithms	Zhang et al. (2022) [247] Fang (2023) [258] Hu et al. (2023) [250] Liu et al. (2023) [260] Wang et al. (2023) [246] Herrera-Vidal et al. (2024) [259] Jung et al. (2024) [256] Psarommatis et al. (2024) [252] Reshma and Sudha (2024) [254] Zhao et al. (2024) [248] Li et al. (2025) [303] Wang et al. (2025) [262]
	Deep Learning Models for Industrial Applications	Liu et al. (2020) [264] Wang et al. (2020) [275] Ding et al. (2021) [277] Li et al. (2021) [266] Khan et al. (2022) [273] Wei et al. (2022) [265] Huang et al. (2023) [267] Mustafaev et al. (2023) [268] Ramathulasi et al. (2023) [274] Jiang et al. (2024) [276] Jose et al. (2024) [242] Li et al. (2024) [218] Wang et al. (2024) [269] Li et al. (2025) [278] Liu et al. (2025) [271] Lu et al. (2025) [270] Shi et al. (2025) [272] Wang et al. (2025) [262]
	Mathematical Modeling, Statistical & Hybrid Models	Ayoub et al. (2020) [285] Denimal et al. (2020) [284] Szega (2020) [282] Chen (2021) [290] Chen et al. (2021) [304] Manca and Fay (2021) [287] Rathee et al. (2021) [288] Farlessyost and Singh (2022) [283] Kovtun et al. (2022) [280] Vaclavova et al. (2022) [305] Josphineleela et al. (2023) [289] Montori et al. (2023) [223] Xu et al. (2023) [286] Cui et al. (2024) [281] Liang et al. (2024) [236] Wang et al. (2024) [306] Wang et al. (2024) [307] Xiang et al. (2024) [279] Contreras-Ropero et al. (2025) [291] Sun et al. (2025) [308]
	Knowledge Graphs, Semantics, IT/OT Integration & Security	Liu et al. (2020) [299] Kuhn and Franke (2021) [295] Wang et al. (2021) [309]

Table 9. *Cont.*

Research Category	Sub-Group	Publication
Math Modeling	Knowledge Graphs, Semantics, IT/OT Integration & Security	Corradi et al. (2022) [293] Meritxell et al. (2022) [296] Wellsandt et al. (2022) [298] Josphineleela et al. (2023) [289] Lopez-de-Ipina et al. (2023) [297] Ramathulasi and Babu (2023) [274] Arazzi et al. (2024) [292] Rathee et al. (2024) [294] Yahya et al. (2024) [224] Yang et al. (2024) [301] Naqvi et al. (2025) [228] Zhang and Zheng (2025) [300]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.7. Military

Industrial information integration in military contexts emphasizes real-time data fusion, secure communication, and operational simulation under demanding conditions. Zheng et al. [310] proposed a radar-communication integrated system architecture tailored for industrial big data transmission in wartime scenarios. By utilizing arbitrary geometrical antenna arrays, the study overcomes the constraints of traditional regular-array-based channel estimation. It introduces a manifold separation technique and a frequency calibration method to effectively estimate channel state information (CSI) with reduced computational overhead. The simulation results validate the system's ability to maintain communication performance while optimizing for complexity and adaptability in dynamic combat environments.

Complementing this, Li et al. [311] presented a terrain visualization information integration framework designed for agent-based military industrial logistics simulations. The framework is structured into four layers—perception access, data, service, and application—and introduces an engagement terrain database system to support decision-making. It addresses key challenges such as real-time access to large-scale terrain data, effective data management, and integration with visual simulation systems. A case study confirms its capability in enhancing the fidelity and responsiveness of military logistics simulations, contributing to more informed and agile strategic planning.

Together, these studies highlight the emerging role of information integration in supporting complex military-industrial operations, with a focus on resilient communication and intelligent simulation systems tailored to mission-critical environments.

The articles are collected in Table 10.

Table 10. Military publication.

Research Category	Publication
Military	Zheng et al. (2021) [310] Li et al. (2022) [311]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.8. Mining

Industrial information integration in the mining sector is gaining momentum as digital technologies are increasingly deployed to enhance efficiency, sustainability, and decision-making. Sinchuk et al. [312] addressed energy optimization in underground mining by developing an automated control system based on fuzzy logic. Utilizing real-time process data and Mamdani inference in MATLAB, the system dynamically regulates energy flows to reduce electricity costs associated with iron ore raw material (IORM) extraction. The fuzzy control model supports multi-channel energy coordination and demonstrates tangible reductions in mining power consumption.

From a broader perspective, Culchesk et al. [313] reviewed how Industry 4.0 principles are being adapted to continuous mining processes. They proposed a theoretical framework that underscores the need for context-specific digital integration to improve operational competitiveness. The paper identifies current research gaps and highlights the need for tailored strategies to overcome technical and organizational challenges in digital transformation within the mining industry.

Focusing on data-driven integration, Liang et al. [314] provided a comprehensive survey on how advanced technologies such as IoT, automation, and sensing systems are transforming mining operations. They reviewed the role of data visualization, fusion, and analytics, especially through machine learning and digital twin approaches, but noted that effectively leveraging collected data remains a key challenge. The study outlines a path toward more value-oriented data integration for improved mining outcomes.

A specific application of digital twin technology was explored by Hasidi et al. [315], who developed a process digital twin for froth flotation—a critical mineral separation process. Using industrial and simulation data with artificial neural networks, their model accurately emulated flotation behavior with 94% accuracy and a rapid 2-second response time. This demonstrates the capability of digital twins to enhance real-time monitoring, control, and decision support in mineral processing.

Finally, Pérez et al. [316] contributed a sustainable logistics model for mining waste management. By integrating GIS-based spatial data, multi-criteria analysis, and dynamic modeling via cellular automata, the framework identifies optimal sites for waste storage. It accounts for geological, environmental, and economic constraints while simulating waste dispersion patterns, supporting environmentally responsible mine planning.

Together, these studies illustrate how fuzzy logic, Industry 4.0 principles, data analytics, digital twins, and geospatial modeling are being integrated to optimize energy use, data management, process control, and sustainability in modern mining operations.

The articles are collected in Table 11.

Table 11. Mining publication.

Research Category	Publication
Mining	Sinchuk et al. (2020) [312]
	Perez et al. (2021) [316]
	Liang et al. (2023) [314]
	Hasidi et al. (2024) [315]
	Culchesk et al. (2025) [313]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.9. Security

With the rapid convergence of operational technology (OT) and information technology (IT), industrial systems are increasingly exposed to complex and evolving cybersecurity threats. From legacy control systems and cyber-physical infrastructure to Industrial Internet of Things (IIoT) networks and cloud-edge ecosystems, ensuring data integrity, privacy, and system resilience has become a critical concern. Recent research has responded with diverse approaches—ranging from anomaly detection and secure architectures to privacy-preserving protocols and blockchain-enabled infrastructures. This section reviews current advancements in industrial security, categorizing contributions by their focus on control system protection, IIoT privacy, blockchain integration, and advanced threat modeling.

3.9.1. Cybersecurity in Industrial Control Systems (ICS) and Cyber-Physical Systems (CPS)

A significant body of research focuses on advancing the security of Industrial Control Systems (ICS) and Cyber-Physical Systems (CPS) through enhanced anomaly detection, resilient control frameworks, and integrated system modeling. Hao et al. [317] propose a hybrid model combining SARIMA and LSTM for real-time anomaly detection in ICS network traffic, achieving high accuracy without the need for protocol-specific parsing. Liu et al. [318] introduce *SecureSIS*, a system that integrates SIS safety logic with BPCS process data to detect control logic anomalies and differentiate faults from cyberattacks, validated on a gas pipeline use case. Complementing these efforts, Al-Abassi et al. [319] develop an ensemble deep learning model integrating DNNs and decision trees to overcome imbalanced datasets in ICS intrusion detection. Jadidi et al. [320] offer a key contribution that is a general framework that uses the MITRE ATT&CK matrix and Diamond model for early-stage threat hunting in ICS (ICS-THF). They also provide a structured, process-driven model for identifying and mitigating malware threats through actionable Indicators of Compromise (IoCs).

Aftabi et al. [321] present an optimization-based attack model that simulates worst-case cyberattacks to expose critical ICS vulnerabilities, showing that coordinated attacks can accelerate physical failures by 19% more than random ones while evading detection. Supporting empirical research, Gaggero et al. [322] release ICS-ADD, a comprehensive open-source dataset combining network logs and SIEM outputs under various attack scenarios. Song et al. [323] introduce a hybrid ICS security assessment framework combining evidential reasoning with a whale optimization algorithm, enabling precise risk evaluation in complex environments. Zhao et al. [324] review computational intelligence methods for enhancing cybersecurity in IoT and cyber-physical systems, covering cyber defense, intrusion detection, and data security.

For CPS in mission-critical sectors, Xu et al. [325] propose a tri-level resilient control architecture for ship CPSs, which co-optimizes transportation, energy, and communications under adversarial threats. Zhong et al. [326] develop a robust observer-based PID control method that accounts for packet losses and hybrid cyberattacks in multi-area power systems, ensuring system stability via Lyapunov-Krasovskii functionals. Addressing physical risk visibility, Houmb et al. [327] integrate CPS awareness with ICS-IDS systems, enabling dynamic security monitoring beyond traditional network-based approaches. Wan et al. [328] provide a foundational analysis of cyber risks unique to ICS and CPS, emphasizing distinct IT/OT challenges and the inadequacy of conventional defense mechanisms.

Focusing on simulation and evaluation, Rodríguez-Ramos et al. [329] unify IT/OT fault diagnosis and cyberattack detection using a fuzzy logic–based monitoring system, improving resilience and reducing computational load in Industry 4.0 plants. Selim et al. [330] benchmark various machine learning classifiers on real-world ICS data from water infrastructure, identifying CART and Naive Bayes as most effective for anomaly detection.

Further innovations include Tomur et al. [331]'s intent-based emergency detection framework, which enhances smart manufacturing safety by filtering spoofed sensor inputs through AI-based reasoning. Vulfin [332] presents an ensemble learning approach tailored for heterogeneous IIoT networks, achieving high F1 scores in simulated SOC environments. He et al. [333] propose an Agile Incident Response (IR) framework, grounded in real-world application within the UK NHS, to improve responsiveness in dynamic cyber-threat landscapes. Finally, Shaked [334] develops a model-based methodology for embedding security considerations throughout the engineering lifecycle, enabling systematic, threat-aware ICS design and validation.

3.9.2. Industrial IoT (IIoT) and Privacy-Preserving Security Models

The security of Industrial Internet of Things (IIoT) systems has become a central concern in industrial information integration, especially as these systems increasingly rely on distributed architectures, dynamic data flows, and heterogeneous devices. A range of privacy-preserving, authentication, and intrusion detection models have been proposed to safeguard IIoT data and infrastructure. Xiang et al. [335] introduce a lightweight authentication scheme using edge computing to protect sensor data transmission in 5G-enabled CPS environments. Similarly, Islam et al. [336] propose EDH-IIoT, a differentially private blockchain model built on Hyperledger Fabric, achieving secure and private supply chain data sharing while optimizing privacy budget consumption.

Radanliev et al. [337] highlight how AI and IoT integration under Industry 4.0 creates new cyber risks, proposing a self-adaptive supply chain framework with predictive analytics for cyber risk management. Addressing location-based vulnerabilities, Zhang et al. [338] present a trajectory privacy scheme (TMC) for IIoT that uses predictive caching and matrix-based privacy controls to reduce external query risks. To enhance secure communications for Industry 5.0, Miao et al. [339] develop a cryptography-based approach combining three-factor authentication with elliptic curve encryption, delivering low-latency and resilient edge communication. Xu et al. [4] analyze how blockchain enhances IoT security by leveraging decentralization, consensus, encryption, and smart contracts. The paper reviews current security challenges and applications, highlighting the growing integration of blockchain and IoT in communication systems. Zhao et al. [324] review computational intelligence methods for enhancing cybersecurity in IoT and cyber-physical systems, covering cyber defense, intrusion detection, and data security.

Blockchain-based privacy frameworks are also prominent. S. Rahman et al. [340] enable secure on-chain/off-chain data querying with multisignature verification in IIoT, while V. Le et al. [341] propose a blockchain-enhanced log management system using attribute-based encryption to secure forensic data in smart grids. Kelli et al. [342] combine federated and active learning to build a privacy-aware intrusion detection system that achieves higher accuracy with minimal data exposure.

Advanced cryptographic protocols are addressed by Deverajan et al. [343], who introduce a public key encryption scheme with equality testing (PKEET) to defend against quantum and cloud-based threats in IIoT. In terms of access control, Pal et al. [344] recommend a hybrid protocol-based model to handle the scale and complexity of IIoT networks. Edge-cloud architectures are leveraged by Bugshan et al. [345] in their microservice-based framework that combines differential privacy with neural networks for secure, accurate medical IIoT prediction.

Addressing CPS integration challenges, Lu et al. [346] propose an ICN-based IIoT model using edge-assisted authentication for CPS, improving efficiency and reducing device burdens. Roy et al. [347] show how blockchain can enhance Safety-as-a-Service (Safe-aaS) platforms in IIoT factories, improving safety throughput and privacy compliance.

In the context of healthcare and smart environments, Qu et al. [348] develop a personalized differential privacy model using trust-aware community models and blockchain to protect sensitive data in smart healthcare networks. Zhang et al. [349] propose a secure SCADA data-sharing system for IIoT using revocable access control and digital signatures, addressing the limitations of traditional industrial protocols. Finally, Zhao et al. [350] present a security architecture for the New Cloud Manufacturing System (NCMS) that combines Zero Trust principles, multi-level access controls, and blockchain for robust cloud-edge-terminal protection.

3.9.3. Blockchain and Secure Architecture in Industry 4.0/5.0

Blockchain technologies are increasingly being adopted as core enablers of secure, decentralized architectures in Industry 4.0 and 5.0, supporting data integrity, privacy, and trust in smart environments. Leng et al. [351] propose the PDI model, which categorizes blockchain security into process, data, and infrastructure levels, offering a comprehensive view beyond purely technical concerns. In application-focused work, Roy et al. [347] embed blockchain into a Safety-as-a-Service (Safe-aaS) model for IIoT, enhancing decision throughput and protecting safety data. Complementing this, Huan and Zukarnain [352] survey blockchain's role in securing industrial IoT ecosystems, particularly for transaction protection between producers and consumers. Prabadevi et al. [353] introduce the Blockchain-enabled Edge-of-Things (BEoT) paradigm, combining edge computing and blockchain to deliver secure, low-latency services across smart homes, healthcare, and energy systems. Viriyasitavat et al. [354] propose a method to standardize service specifications and enhance security in service-based applications by integrating blockchain technology.

From a system integration perspective, Zhang et al. [355] develop a fine-grained access control and data sharing scheme for SCADA systems using blockchain to overcome communication protocol limitations. In privacy-aware architectures, Bugshan et al. [345] design a microservice-based machine learning system for healthcare IIoT, combining differential privacy and radial basis function networks in an edge-cloud setup. Similarly, Qu et al. [348] propose a trust-driven differential privacy scheme for Smart Healthcare Networks (SHNs), leveraging blockchain to reduce poisoning attacks and enable community-aware security policies. Islam et al. [336] present EDH-IIoT, a permissioned blockchain system enhanced with differential privacy for secure and auditable data sharing in industrial supply chains. Ragab et al. [356] integrate blockchain with digital twins and deep learning, forming a decentralized IIoT cybersecurity framework with intrusion detection. S. Rahman et al. [340] propose a hybrid on-chain/off-chain scheme enabling verifiable and privacy-preserving queries, while V. Le et al. [341] enhance log security in smart grids using attribute-based encryption and blockchain-backed audit trails.

Together, these studies establish blockchain not only as a foundation for secure communication and access control but also as a catalyst for enabling decentralized, privacy-aware, and resilient industrial architectures.

3.9.4. Advanced Threat Detection, Adversarial AI, and Game-Theoretic Models

Advanced security challenges in industrial environments have prompted the emergence of sophisticated threat detection, adversarial robustness strategies, and simulation-based defense models. Jiang et al. [357] address the vulnerability of AI-driven soft sensing systems to adversarial inputs by proposing an information fingerprinting method using Siamese networks and contrastive pretraining, which distinguishes legitimate samples from crafted adversarial attacks. Extending to cyber-physical warfare scenarios, Chen et al. [358] introduce *iCyberGuard*, a game-theoretic model leveraging reinforcement learning to simulate strategic interactions between attackers and defenders in IIoT settings, enabling adaptive defense planning. Li et al. [359] use Protection Motivation Theory to examine factors shaping employees' cybersecurity motivation. Their study finds coping mechanisms and organizational awareness efforts strongly influence protective behaviors, with variations by gender, generation, and organization type.

In the realm of cryptographic analysis, Rioja et al. [360] enhance side-channel attack evaluation by automating the selection of Points of Interest using Estimation of Distribution Algorithms (EDA), streamlining both profiling and key recovery. Abbaspour Asadollah et al. [361] expand the STRIDE threat modeling framework with attack scenario sequences, improving vulnerability analysis at early design stages in automotive cyber-physical systems. Recognizing the growing value of shared threat intelligence, Ackermann et al. [362] develop *CTIExchange*, a tool that facilitates automated integration of Cyber Threat Intelligence (CTI) into SIEM systems, bridging detection tools with threat intelligence platforms.

Quantum-resilient security also features in this category: Yan et al. [363] propose a quantum key distribution (QKD) framework for secure microgrid communication, using MDI-QKD with deep learning optimization to safeguard control signals against quantum-level threats. From a human-centric perspective, Soner et al. [364] evaluate AIS-related vulnerabilities in shipping via the SOHRA method aligned with NIST standards, identifying critical human errors in cybersecurity functions and recommending mitigation strategies. A broader survey by Jeffrey et al. [365] synthesizes 296 studies on CPS anomaly detection, revealing persistent challenges such as protocol heterogeneity, non-standardization, and resource constraints across industrial control environments.

Finally, Yusoff et al. [366] propose HRPL, a new routing protocol that significantly reduces overhead in industrial IoT networks built on 6LoWPAN, addressing interoperability and performance bottlenecks critical to scalable and secure system deployment.

Collectively, these works push the frontier of security research in industrial systems by integrating adversarial AI defense, formal threat modeling, intelligent simulation, and novel cryptographic and protocol mechanisms.

The articles are collected and classified in Table 12.

Table 12. Security publication.

Research Category	Sub-Group	Publication
Security	Cybersecurity in Industrial Control Systems (ICS) and Cyber-Physical Systems (CPS)	Al-Abassi et al. (2020) [319] Zhao et al. (2020) [324] Jadidi and Lu (2021) [320] Sawas et al. (2021) [367] Selim et al. (2021) [330] Wan et al. (2021) [328] He et al. (2022) [333] Hao et al. (2023) [317] Houmb et al. (2023) [327] Shaked (2023) [334] Vulfin (2023) [332] Zhong et al. (2023) [326] Gaggero et al. (2024) [322] Rodríguez-Ramos et al. (2024) [329] Song et al. (2024) [323] Tomur et al. (2024) [331] Aftabi et al. (2025) [321] Liu et al. (2025) [318] Xu et al. (2025) [325]
	Industrial IoT (IIoT) and Privacy-Preserving Security Models	Radanliev et al. (2020) [337] Roy et al. (2020) [347] Zhao et al. (2020) [324] Kelli et al. (2021) [342] Pal and Jadidi (2021) [344] Qi et al. (2021) [368] Xu et al. (2021) [4] Deverajan et al. (2022) [343] Le et al. (2022) [341] Rahman et al. (2022) [340] Zhang et al. (2022) [349] Bugshan et al. (2023) [345] Lu et al. (2023) [346] Qu et al. (2023) [348] Islam et al. (2024) [336] Miao et al. (2024) [339] Xiang et al. (2024) [335] Yang et al. (2024) [369] Zhang et al. (2024) [338] Zhao et al. (2024) [350] Uddin et al. (2025) [370]

Table 12. *Cont.*

Research Category	Sub-Group	Publication
Security	Blockchain and Secure Architecture in Industry 4.0/5.0	Aladwan et al. (2020) [371] Viriyasitavat et al. (2020) [354] Prabadevi et al. (2021) [353] Le et al. (2022) [341] Leng et al. (2022) [351] Rahman et al. (2022) [340] Zhang et al. (2022) [355] Bugshan et al. (2023) [345] Demertzi et al. (2023) [372] Qu et al. (2023) [348] Huan and Zukarnain (2024) [352] Islam et al. (2024) [336] Ragab et al. (2025) [356]
	Advanced Threat Detection, Adversarial AI, and Game-Theoretic Models	Yusoff et al. (2020) [366] Rioja et al. (2021) [360] Jiang and Ge (2022) [357] Li et al. (2022) [359] Tran et al. (2022) [373] Yan et al. (2022) [363] Ackermann et al. (2023) [362] Jeffrey et al. (2023) [365] Abbaspour Asadollah et al. (2024) [361] Chen et al. (2024) [358] Soner et al. (2024) [364]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.10. Software Engineering

The advancement of industrial information integration increasingly depends on robust, adaptable, and scalable software engineering approaches. This body of literature reflects a concerted effort to address data heterogeneity, collaborative design, traceability, and secure system configuration, all while accommodating the demands of Industry 4.0 and the Industrial Internet of Things (IIoT).

One notable trend is the use of model-driven and knowledge-based integration to improve interoperability across heterogeneous data sources and models. For instance, Bakken et al. [374] propose Chrontext, a hybrid query engine that bridges contextual knowledge graphs with time series data, significantly improving performance and scalability in querying industrial systems. Similarly, Bruneliere et al. [375] present a general model view framework that enables efficient querying and integration of disparate engineering models, facilitating runtime and design-time synchronization.

Data integration and automation in specific industrial domains is another major concern. Wu et al. [376] focus on automating the unification of construction data through string matching and spatial reasoning, while Bründl et al. [377] address the automation of customized manufacturing by extracting meaningful data from STEP files to support engineer-to-order assembly, especially for resource-constrained SMEs.

From a collaborative product development standpoint, Zheng et al. [378] propose an integrated design method to strengthen communication between product and service teams in Product-Service Systems (PSS), while Sagot et al. [379] offer a web-based tool (CACP) for culturally adaptive industrial product design, enhancing customer integration and responsiveness in global markets.

Several studies introduce practical tools and frameworks to support software lifecycle and quality. Escalona et al. [380] advocate a model-driven engineering approach to automate requirements traceability, reducing manual effort and tool costs. Complementing this, Roncero et al. [381] propose TeqReq, a method to estimate software testing costs during the requirements phase, which also fosters stakeholder alignment.

In terms of secure, distributed architectures, Ceccarelli et al. [41] design a software architecture that integrates blockchain, software-defined networking (SDN), and container orchestration to enhance the trustworthiness of IIoT system configurations—validated in a railway system scenario. Extending the scope to inter-organizational cooperation, Da Silva and Cardoso [382] develop an IIoT-based platform promoting "coopetition" among SMEs, rooted in Service-Dominant Logic and validated by 24 manufacturing firms.

Finally, Bhattacharjee et al. [383] address real-time industrial communication through an enhanced SDN-TSN framework. Their solution establishes cross-domain time-sensitive streams and introduces CORECONF as a lightweight alternative for network management, further reinforcing the software backbone of industrial integration.

The articles are collected in Table 13.

Table 13. Software Engineering publication.

Research Category	Publication
Software Engineering	Bruneliere et al. (2020) [375]
	Zheng et al. (2021) [378]
	Ceccarelli et al. (2022) [41]
	Escalona et al. (2022) [380]
	Roncero and Silva (2022) [381]
	Sagot et al. (2022) [379]
	Wu et al. (2022) [376]
	Bakken and Soylu (2023) [374]
	Bhattacharjee et al. (2024) [383]
	Da Silva and Cardoso (2024) [382]
	Bruendl et al. (2025) [377]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.11. Supply Chain

The digital transformation of supply chains is central to the evolution of industrial information integration. In response to increasing complexity, globalization, and sustainability demands, modern supply chains are undergoing rapid technological reconfiguration. Emerging technologies such as the Internet of Things (IoT), blockchain, artificial intelligence (AI), and Digital Twins are enabling unprecedented levels of visibility, automation, and coordination across supply chain networks. The reviewed literature reflects a diverse set of approaches—from smart logistics and sustainable frameworks to secure, blockchain-enabled collaboration and advanced decision-making systems—highlighting the growing role of information integration in achieving resilience, transparency, and operational excellence. To structure the discussion, the studies are classified into four main categories: (1) Digitalization and Smart Supply Chains, (2) Blockchain and Secure Logistics, (3) Green and Circular Supply Chains, and (4) AI-driven Systems and Integration Challenges.

3.11.1. Digitalization, Industry 4.0/5.0, and Smart Supply Chains

The digital transformation of supply chains is a central theme across a range of recent studies that explore the convergence of Industry 4.0/5.0 technologies—such as IoT, AI, and Digital Twins—with operational and strategic supply chain functions. Song et al. [384] emphasize the role of IoT in enhancing logistics through improved data flow and operational visibility. This aligns with Kandarkar et al. [385], who develop a framework showing how smart technologies elevate supply chain productivity and data security. Nunez-Merino et al. [386] provide a systematic review of Lean Supply Chain Management in Industry 4.0, revealing lifecycle-based strategies to integrate digital tools. Han et al. [387], Wu and Xie [388] focus on digitization in Chinese and Indian supply chains, respectively, identifying integration, transparency, and automation as key performance drivers. Domingos et al. [389] extend this by linking enabling technologies to supply chain resilience across multiple countries. Li and Zhou [390] review blockchain research from 2015–2018 across hardware, software, emerging tech, and business applications, including maritime case studies. They highlight blockchain's role in improving supply chain cost, quality, speed, and risk management, emphasizing enhanced transparency and identity validation.

Advanced architectures like Digital Twins are also gaining traction, with Wang et al. [391] showcasing a DT-based framework for smart port management, and Edalatpour et al. [392] proposing a globally sustainable closed-loop supply chain (CLSC) model with fuzzy programming to handle uncertainty. Huang et al. [393] address supply chain reconfiguration under disruptions using SyncRSC, a real-time decision-making framework that combines Industrial Internet Platforms and graph neural networks. The growing reliance on data-driven monitoring is evident in Brintrup et al. [394], who examine the risks and benefits of Digital Supply Chain Surveillance powered by AI.

Isaja et al. [395] propose a Trusted Framework enabling zero-waste, zero-defect manufacturing via traceable quality data exchange. Shambayati et al. [396] contribute a virtualized supply chain model optimized with neutrosophic logic, while Sun et al. [397] introduce Reverse Logistics 4.0 for digitalized, service-oriented recovery operations. Big Data's impact on manufacturing lead time and flexibility is critically reviewed by Omoush et al. [398], Rajani and Heggde [399] highlight value delivery strategies in service supply chains. Finally, Andry et al. [400] develop a decision support system tailored to furniture supply chains, and Jiang et al. [401] apply a boosting regression model to improve demand forecasting accuracy in customized product contexts. Collectively, these works illustrate a multi-faceted evolution of supply chains through digitalization, contributing to greater agility, sustainability, and strategic alignment.

3.11.2. Blockchain and Secure Logistics

Blockchain technology is increasingly recognized as a foundational enabler of secure, transparent, and efficient supply chains, particularly in the context of Industry 4.0. This group of studies explores its integration across diverse industrial sectors and logistics functions. Ghode et al. [402] demonstrate the benefits of blockchain in enhancing transparency, traceability, and efficiency in bearing supply chains, reducing delays and non-value-added tasks. Chang and Chen [403] provide a comprehensive review of blockchain applications in supply chain management (SCM), identifying key themes such as digitalization, trustless automation, and stakeholder collaboration. Complementing this, Chbaik et al. [404] introduce an integrated IoT-blockchain system for equipment monitoring, offering tamper-proof, real-time operational data and increased system reliability.

Several studies delve into hybrid architectures combining blockchain with other technologies. Hong and Xiao [405] propose a blockchain-AI framework to support sustainable, low-carbon supply chains and advocate for inclusive governance. Ismail et al. [406] focus on security, integrating blockchain with machine learning models to detect cyber threats in IIoT-based supply chains. However, the road to implementation is not without challenges. Öztürk and Yildizbaşi [407] identify financial, technological, and organizational barriers to blockchain adoption, particularly in complex sectors like healthcare and logistics.

Further emphasizing practical applications, A. Omar et al. [408] present a blockchain-based Vendor Managed Inventory (VMI) model, while Musamih et al. [409] design a decentralized system to prevent counterfeiting in pharmaceutical logistics. A. Omar et al. [410] extend this by developing a blockchain-supported inventory sharing system to foster trust during disruptions. Majeed Parry et al. [411] focus on traceability and fraud prevention in the wine industry, highlighting blockchain's role in improving transparency. Morelli et al. [412] propose a blockchain-cloud hybrid system to support lean production goals, while Yang et al. [413] design an edge-cloud blockchain platform for perishable logistics, ensuring secure and real-time sensor data transmission. Together, these studies highlight the transformative role of blockchain in securing and optimizing industrial supply chains.

3.11.3. Green, Circular, and Sustainable Supply Chains

The push toward sustainability and circularity in supply chains has prompted diverse innovations integrating digital, analytical, and systems-based approaches. This category highlights how industrial information integration is leveraged to foster environmentally responsible and resilient logistics. Bui et al. [414] analyze circular supply chain strategies (CSCY) in the canned food sector using a hybrid decision-making framework, identifying IoT and robotics as key enablers. Tseng et al. [415] apply fuzzy Delphi and best-worst methods to evaluate sustainable supply chain management (SSCM) indicators in textiles, revealing financial resilience and supplier integration as crucial.

Advanced technologies are increasingly integrated into sustainability efforts. Babaei et al. [416] develop an AI-driven multi-agent system for optimizing location, inventory, and routing in gas supply chains, significantly improving environmental and operational metrics. In a related vein, Shambayati et al. [396] introduce a virtualized supply chain model using Neutrosophic theory and genetic algorithms to enhance sustainability and profit under demand uncertainty.

Wider strategic and policy implications are addressed by Hong and Xiao [405], who explore blockchain and AI-enabled low-carbon transitions and advocate for inclusive governance models. Maldonado-Guzmán et al. [417] empirically validate the positive effects of Lean Production and Industry 4.0 technologies on green supply chain performance in Mexico. Wang et al. [418] further contribute by modeling a distributed localized manufacturing (DLM)–based personalized customization supply chain (PCSC) for Industry 5.0, using simulation to demonstrate reductions in transportation and emissions.

Complementary innovations appear in sector-specific applications. Pérez et al. [316] propose data-centric logistics solutions for waste management in mining. Jreissat et al. [419] apply PCA to food new product development (NPD) processes, enhancing traceability and minimizing waste. Gao et al. [420] introduce a synchronization model for new energy vehicle (NEV) supply chains that uses complex network theory to reduce the bullwhip effect and improve sustainability. Finally, Suhail et al. [421] leverage IOTA's DAG-based architecture for secure, scalable traceability in electronics supply chains, promoting energy efficiency and confidentiality. Collectively, these works underscore how integrated information systems and intelligent methods support the transition to green, circular, and sustainable industrial ecosystems.

3.11.4. Information Systems, AI, and Integration Challenges

The integration of AI, advanced information systems, and digital infrastructure is a foundational enabler for modernizing industrial supply chains. This category highlights innovative approaches to automation, decision-making, and coordination within complex and data-intensive environments. Cao et al. [422] focus on warehouse optimization, proposing a hybrid local search algorithm that integrates order batching, sequencing, and routing using multi-source data to enhance operational efficiency.

IoT plays a critical role in enhancing supply chain visibility and customer interaction. Fu et al. [423] provide a comprehensive review of IoT integration in supply chain management (SCM), emphasizing the customer-side interaction with terminal information flow. Complementing this, Sun et al. [397] analyzes e-commerce SCM platforms in China and shows how real-time coordination between supply chain entities can strengthen competitiveness through dynamic integration.

AI and machine learning also drive significant advances in quality control and supplier management. Ahmed et al. [424] compare DETR and YOLO models for real-time defect detection in supply chains, identifying trade-offs between accuracy and computational efficiency. For supplier evaluation, Sarwar et al. [425] develop a fuzzy rough PROMETHEE method that reduces subjective bias and enhances multi-criteria decision-making under uncertainty.

Cybersecurity and distributed intelligence are addressed by A. Khan et al. [426], who propose DFF-SC4N, a federated learning-based intrusion detection system that secures Supply Chain 4.0 networks without compromising data privacy. Ceccarelli et al. [41] contribute a secure software-defined framework combining blockchain and SDN for configuring Industrial IoT (IIoT) devices—a model applicable across logistics domains.

At the infrastructure level, Barasti et al. [427] design a canonical cloud architecture for digital seaports, enabling resource virtualization and real-time information services through centralized Data Lakes. Finally, Proto et al. [428] introduce REDTag, an IoT- and machine learning–enabled smart logistics solution that monitors parcel conditions during transit to predict breakage and improve delivery outcomes. Together, these studies exemplify how AI, system integration, and automation technologies are reshaping the design and operation of contemporary supply chains.

The articles are collected and classified in Table 14.

Table 14. Supply Chain publication.

Research Category	Sub-Group	Publication
Supply Chain	Digitalization, Industry 4.0/5.0, and Smart Supply Chains	Núñez-Merino et al. (2020) [386] Rajani and Heggde (2020) [399] Li and Zhou (2021) [390] Song et al. (2021) [384] Wang et al. (2021) [391] Sun et al. (2022) [397] Andry et al. (2023) [400] Isaja et al. (2023) [395] Wu and Xie (2023) [388] Brintrup et al. (2024) [394] Domingos et al. (2024) [389] Edalatpour et al. (2024) [392] Han et al. (2024) [387] Jiang et al. (2024) [401] Kandarkar et al. (2024) [385] Omoush et al. (2024) [398] Shambayati et al. (2024) [396] Huang et al. (2025) [393]

Table 14. *Cont.*

Research Category	Sub-Group	Publication
Supply Chain	Blockchain and Secure Logistics	Chang and Chen (2020) [403] Omar et al. (2020) [410] Öztürk and Yildizbaşi (2020) [407] Musamih et al. (2021) [409] Omar et al. (2022) [408] Ghode et al. (2023) [402] Yang et al. (2023) [413] Chbaik et al. (2024) [404] Hong and Xiao (2024) [405] Ismail et al. (2024) [406] Li (2024) [429] Majeed Parry et al. (2024) [411] Morelli et al. (2024) [412]
	Green, Circular, and Sustainable Supply Chains	Suhail et al. (2020) [421] Tseng et al. (2022) [415] Bui et al. (2023) [414] Maldonado-Guzmán et al. (2023) [417] Babaei et al. (2024) [416] Hong and Xiao (2024) [405] Jreissat et al. (2024) [419] Shambayati et al. (2024) [396] Wang et al. (2024) [418] Gao et al. (2025) [420]
	Information Systems, AI, and Integration Challenges	Haitao (2020) [430] Proto et al. (2020) [428] Barasti et al. (2021) [427] Feng and Ye (2021) [431] Ceccarelli et al. (2022) [41] Sarwar et al. (2022) [425] Cao et al. (2023) [422] Khan et al. (2023) [426] Ahmed et al. (2024) [424] Fu et al. (2025) [423]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.12. Telecommunications

Telecommunications technologies are rapidly evolving to meet the stringent demands of industrial information integration, especially under the paradigms of Industry 4.0 and the emerging Industry 5.0. A central trend is the convergence of 6G wireless networks with advanced computing paradigms—such as blockchain, federated learning, and digital twin technologies—to support ultra-reliable, low-latency, and secure industrial systems. Several works highlight this transformation: Jahid et al. [432] and Yadav et al. [433] examine the synergistic integration of 6G and blockchain, revealing its potential to address key limitations of 5G by enabling decentralized trust, efficient resource management, and intelligent industrial automation. Similarly, Masaracchia et al. [434] identify digital twin as a critical enabler for realizing the full potential of 6G IoT services, aligning with Blika et al. [435], who discuss how federated learning enhances privacy and robustness in distributed AI systems. Li et al. [436] push this further by integrating binary neural networks with homomorphic encryption for predictive maintenance, demonstrating a practical application of 6G and privacy-preserving intelligence.

Complementing this high-level integration, wireless communication innovations offer foundational support for real-time industrial operations. Perera et al. [437] explore Age of Information (AoI) in SWIPT-powered networks, suggesting how energy-efficient protocols like time-switching and power-splitting can sustain real-time IoT communication. Xu et al. [438] propose WIA-NR, a 5G-based industrial wireless control network that achieves sub-millisecond latency and extreme reliability over unlicensed spectrum, making it suitable for time-critical manufacturing scenarios. Additionally, Sun et al. [439] introduce a multi-modal path loss prediction method for UAV-to-ground 6G communications, showing the relevance of electromagnetic-physical space mapping in aerial industrial monitoring.

At the architectural and sensing level, Liu et al. [440] develop narrowband subwavelength grating filters for low-cost, compact infrared sensors—offering a high-performance alternative to bulky spectrometers in applications like crop analysis and industrial inspection. Addressing broader integration challenges, Mishra et al. [441] propose the ITHACA framework, a novel architecture for seamless 5G/6G-based integration of high-end autonomous devices in industrial IoT, exemplified through aerial robotics in infrastructure inspection. Chen et al. [442] examine factors driving sustainable growth in China's telecom industry amid digital transformation, using the resource-based view and regression analysis.

Collectively, these studies underscore how advanced telecommunication technologies—from energy-harvesting protocols and spectral filtering to blockchain-secured 6G networks—are converging to create agile, intelligent, and resilient industrial communication infrastructures.

The articles are collected in Table 15.

Table 15. Telecommunications publication.

Research Category	Publication
Telecommunications	Perera et al. (2020) [437] Mishra et al. (2021) [441] Xu et al. (2021) [438] Chen et al. (2022) [442] Masaracchia et al. (2022) [434] Jahid et al. (2023) [432] Yadav et al. (2023) [433] Li et al. (2024) [436] Liu et al. (2024) [440] Sun et al. (2024) [439] Blika et al. (2025) [435]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.13. Tourism

Tourism is increasingly shaped by the convergence of digital infrastructure, intelligent systems, and cross-sectoral industrial integration. A recurring theme across recent literature is the strategic transformation of tourism through advanced technologies such as IoT, embedded systems, cloud-edge computing, and data fusion. For example, real-world deployment of cloud-edge architectures, as demonstrated by Roda-Sanchez et al. [443], illustrates how microservice-based orchestration across edge nodes can efficiently support large-scale, real-time smart tourism services. Complementing this, Kong [444] outlines a framework where IoT-enabled intelligent subsystems enhance destination selection, service delivery, and management, facilitating a digitally empowered tourism model. These technical foundations are closely linked to broader integration strategies. Zeng et al. [445] show that the integration of cultural and tourism industries contributes to higher value along the tourism value chain, but only when integration reaches a critical threshold—highlighting spatial disparities and the need for targeted policy interventions. Zhan and Qin [446] expand this view through a case study on Songcheng, proposing a smart creative generation platform powered by IoT and data fusion to deepen cultural-tourism integration across content, product, marketing, and management domains. At the national level, Li et al. [447] trace the digital evolution of China's tourism industry from early adoption to AI- and 5G-driven intelligent services. They highlight both benefits—such as efficiency and quality—and emerging challenges including data fragmentation, talent gaps, and digital rights ambiguity. Together, these studies underscore the essential role of industrial information integration in shaping a responsive, intelligent, and sustainable future for the tourism sector.

The articles are collected in Table 16.

Table 16. Tourism publication.

Research Category	Publication
Tourism	Kong (2023) [444] Roda-Sanchez et al. (2023) [443] Zeng et al. (2023) [445] Li et al. (2024) [447] Zhan and Qin (2025) [446]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.14. Transportation

The transportation sector is undergoing rapid transformation driven by industrial information integration, particularly through the convergence of cyber-physical systems, IoT, AI, digital twins, and blockchain. These technologies are reshaping railway systems, electric vehicle infrastructure, autonomous mobility, and intelligent traffic control. Recent literature reflects a strong emphasis on smart infrastructure, predictive maintenance, secure and decentralized systems, and advanced decision-making in complex environments. This section classifies current research into four thematic areas: Smart Railway and Infrastructure Systems, Electric Vehicles and Grid Integration, UAV and Autonomous Systems, and Intelligent Transportation Systems and Surveillance. Each category highlights how integrated digital technologies are enabling safer, more efficient, and environmentally sustainable mobility solutions.

3.14.1. Smart Railway and Infrastructure Systems

The integration of Industry 4.0 technologies into railway infrastructure has led to significant advancements in smart management, predictive maintenance, and secure information systems. Niu and Chen [448] present an optimization model for track allocation in smart high-speed train stations using wireless sensor networks (WSNs) and a simulated annealing algorithm to balance track occupancy and interval timing. Similarly, Bustos et al. [449] propose a methodology for retrofitting existing high-speed trains to align with Maintenance 4.0, combining real-time and simulated vibration data through a digital twin to detect anomalies and enable predictive diagnostics. Addressing precision in railway operation, Briales et al. [450] introduce a method for railway orientation estimation using multibody system kinematics and track-specific data, achieving higher accuracy than traditional IMU-based approaches. In the domain of secure data management, Figueroa-Lorenzo et al. [451] design a blockchain-based alarm collection system for the EU's Mobility as a Service (MaaS) railway framework, ensuring traceability and privacy in sensor data across IoT-integrated mobility environments. At a broader technological level, Kljaic et al. [452] review emerging technologies—such as hydrogen propulsion, 5G, smart grids, and IIoT—that aim to enhance sustainability, resilience, and intelligence in future railway systems. Finally, Brankovic et al. [453] extend model-based systems engineering (MBSE) by enhancing the SPES framework for cyber-physical systems like connected autonomous vehicles (CAVs), validated via an electric vehicle charging case study that exemplifies cross-domain systems integration in transport. Collectively, these studies reflect a growing convergence between traditional rail infrastructure and modern digital ecosystems, underscoring the transformative potential of industrial information integration in transportation networks.

3.14.2. Electric Vehicles, Charging, and Grid Integration

Electric vehicle (EV) technologies are increasingly integrated with industrial information systems to enhance transportation efficiency, energy management, and privacy. Alsharif et al. [454] provide a comprehensive review of energy management strategies (EMS) and vehicle-to-grid (V2G) technologies, outlining their roles in reducing fuel consumption and carbon emissions while identifying key challenges in implementation, such as charging infrastructure and grid coordination. Complementing this, Kumar et al. [455] introduce a smart electric bus system that combines cyber-physical systems (CPS), the Industrial Internet of Things (IIoT), and AI to dynamically optimize energy consumption, passenger service, and cloud operations in real time. Addressing the critical issue of user privacy in EV infrastructure, Zhai et al. [456] propose EPDB, a blockchain-based privacy-preserving EV charging scheme using decentralized identifiers (DID) and Pedersen commitments. Their method improves security and throughput in charging networks, offering resilience against Byzantine attacks. In the context of rural and tourism-related transportation, Pitakaso et al. [457] develop the Fuzzy-Artificial Multiple Intelligence System (F-AMIS), which uses fuzzy logic and adaptive decision-making to improve cost-efficiency, service coverage, and resilience in rural EV public transit. Although categorized under railway systems, Brankovic et al. [453] also contribute to this theme by introducing a model-based systems engineering (MBSE) framework that supports EV charging system development, demonstrating its utility through a real-world electric vehicle use case. Together, these studies illustrate the growing complexity and opportunity in integrating EVs with intelligent infrastructure, emphasizing the need for secure, adaptable, and sustainable systems in the evolving landscape of smart transportation.

3.14.3. UAV and Aerial/Ground Autonomous Systems

Research on unmanned and autonomous systems has rapidly advanced, emphasizing resilience, intelligent coordination, and secure communication in both aerial and ground platforms. Gu et al. [458] present a fast-reactive defense mechanism against malware-induced trajectory attacks on UAVs, using fixed-time detection and sliding mode observers to enhance flight safety and ensure rapid stabilization of estimation errors. Addressing ground navigation, Shen et al. [459] propose an adaptive federated Kalman filter (FKF) with observability-based time-varying information sharing, significantly improving unmanned ground vehicle (UGV) localization robustness and accuracy under dynamic urban conditions. On the communication front, Singh et al. [460] design a blockchain-based security framework for drones, leveraging deep Boltzmann machines to select miner nodes based on drone-specific metrics, thus ensuring integrity, privacy, and resource-aware consensus in UAV networks. Expanding to air traffic forecasting, Deng et al. [461] develop CC-MIDNN, a clustered and modular deep learning approach for estimating aircraft arrival times, which enhances prediction accuracy and generalizability by decomposing complex flight scenarios. At the architectural level, Ding et al. [462] provide a comprehensive survey of distributed learning (DL) techniques—such as federated learning and reinforcement learning—for UAV swarm management, highlighting use cases in trajectory planning, power allocation, and semantic communication. Complementing this, Ahmed et al. [463] survey the integration of reconfigurable intelligent surfaces (RIS) with UAV-based multi-access edge computing (MEC), examining configurations and performance gains in communication efficiency and task management. Collectively, these works advance the state of autonomous aerial and ground systems, promoting secure, adaptive, and collaborative frameworks essential for industrial-scale deployment in smart transportation and logistics.

3.14.4. Intelligent Transportation Systems, Positioning, and Surveillance

Intelligent transportation systems (ITS) are increasingly incorporating advanced sensing, planning, and positioning technologies to improve safety, efficiency, and sustainability in smart mobility networks. Trivedi et al. [464] develop a real-time vision-based system for traffic detection and speed measurement under unstructured conditions, using morphological image processing and a two-line ROI approach to boost detection accuracy in intelligent traffic environments. Addressing environmental sustainability, Huang et al. [465] propose a carbon-aware positioning system for the Internet of Vehicles (IoV), integrating Ultra Wide Band (UWB) edge nodes with advanced spatial-temporal data fusion techniques to enhance localization accuracy while supporting carbon-neutral transportation goals. In the context of complex network architectures, Sun et al. [466] introduce a surveillance plane within air-ground integrated vehicular networks (AGVN), enabling more flexible and intelligent network management through AI-driven monitoring, service function chaining (SFC), and improved resource coordination. Focusing on autonomous driving, Yagüe-Cuevas et al. [467] propose a planning methodology that enhances vehicle path planning and control by leveraging high-definition maps and fast K-nearest neighbor (KNN) decision models. Lastly, Brankovic et al. [453], also cross-listed in other categories, extend the SPES framework to support model-based systems engineering for connected and autonomous vehicles (CAVs), contributing a domain-specific architecture that facilitates integration and scalability in vehicular system development. Together, these contributions underscore the essential role of intelligent sensing, planning, and control in shaping the future of connected transportation ecosystems.

The articles are collected and classified in Table 17.

Table 17. Transportation publication.

Research Category	Sub-Group	Publication
Transportation	Smart Railway and Infrastructure Systems	Briales et al. (2021) [450]
		Bustos et al. (2021) [449]
		Figueroa-Lorenzo et al. (2021) [451]
		Niu and Chen (2021) [448]
		Brankovic et al. (2023) [453]
		Kljaić et al. (2023) [452]

Table 17. *Cont.*

Research Category	Sub-Group	Publication
Transportation	Electric Vehicles, Charging, and Grid Integration	Kumar et al. (2020) [455] Alsharif et al. (2021) [454] Brankovic et al. (2023) [453] Zhai et al. (2024) [456] Pitakaso et al. (2025) [457]
	UAV and Aerial/Ground Autonomous Systems	Shen et al. (2020) [459] Singh et al. (2021) [460] Gu et al. (2023) [458] Deng et al. (2024) [461] Ding et al. (2024) [462] Ahmed et al. (2025) [463]
	Intelligent Transportation Systems, Positioning, and Surveillance	Sun et al. (2020) [466] Trivedi et al. (2022) [464] Brankovic et al. (2023) [453] Huang et al. (2024) [465] Yagüe-Cuevas et al. (2024) [467]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

3.15. Urban Development

As cities evolve into complex, data-driven ecosystems, industrial information integration has emerged as a cornerstone for building smart, sustainable, and resilient urban environments. The selected literature reflects a multi-dimensional exploration of this transformation—covering innovations in digital infrastructure, spatial intelligence, smart logistics, green industrial practices, and decision-support frameworks. These works collectively demonstrate how technologies like IoT, GIS, blockchain, AI, and digital twins are being leveraged to optimize urban planning, improve governance, drive sustainable industrial growth, and enhance citizen well-being. The following categories synthesize key insights from this diverse body of research.

3.15.1. Smart Cities, IoT, and Digital Infrastructure

The integration of smart technologies into urban infrastructures is central to the evolution of sustainable and intelligent cities, as demonstrated by six key studies in this category. Da Silva et al. [468] propose IoTSec2CoC, a security-focused framework that ensures digital document trustworthiness in smart cities through proactive and reactive microservices within IIoT environments. Complementing this, Rahman et al. [469] introduce a Blockchain-of-Blockchains (BoBs) architecture to enhance interoperability and secure IoT data exchange across heterogeneous smart city platforms. Huda et al. [470] emphasize the role of smart home automation systems and their integration with technologies like Digital Twins, federated learning, and embedded edge computing to overcome data and scalability issues, ultimately promoting sustainable urban living. Javed et al. [471] provide a broader technological overview, identifying enablers such as 6G, blockchain, AI, and robotics as foundational to future smart city development frameworks. On the production side, Bolshakov et al. [472] explore how Factories of the Future (FoF) and digital twins can be harmonized with urban infrastructure through principles like interoperability, sustainability, and governance, proposing actionable strategies such as public-private partnerships. Finally, Deng et al. [473] review urban visual analytics, detailing its role across 22 visualization types and 8 urban domains, and suggesting future research directions for integrating computational intelligence with urban decision-making. Collectively, these works establish a robust foundation for implementing integrated, intelligent, and secure urban systems.

3.15.2. Urban Planning and Spatial Intelligence

Spatial intelligence and Geographic Information Systems (GIS) play a pivotal role in enabling data-driven urban planning and sustainable development, as illustrated by six representative studies. Wang et al. [474] present a Graph Convolutional Neural Network (GCNN) model that combines street-level imagery with spatial relationships to achieve high-accuracy urban functional zone (UFZ) classification, enhancing planning precision. Ustaoglu and Aydınoglu [10] integrate GIS with multi-criteria decision analysis (MCA)—comparing deterministic

AHP and fuzzy AHP models—to assess land suitability in Istanbul, demonstrating how modeling techniques influence spatial development outcomes. Expanding the data sources, Anugraha et al. [475] combine remote sensing and social sensing (e.g., mobility data from taxis and bicycles) with machine learning to distinguish urban land uses, providing fine-grained insights for zoning decisions. Zhang et al. [476] introduce the Occupation Mixture Index (OMI) by analyzing mobile phone data to map occupational patterns across Guangzhou, offering a novel behavioral layer to urban profiling. Chicherin et al. [477] showcase the use of open-source GIS models to optimize Fifth-Generation District Heating and Cooling (5GDHC) systems in Kazakhstan, emphasizing GIS's role in sustainable energy infrastructure. Lastly, Patrakeyev et al. [3] propose a GIS-integrated intelligent evaluation framework that accounts for fuzzy and incomplete data to assess sustainability opportunities in post-industrial cities. Collectively, these studies highlight how spatial analytics, sensor data, and intelligent systems coalesce to support more adaptive, responsive, and sustainable urban planning.

3.15.3. Industrial Integration, Economic Growth, and Green Transformation

The integration of industrial systems with digital technologies and sustainability imperatives plays a transformative role in fostering economic development and urban resilience. Meng et al. [478] investigate how the digital-real industrial integration in China promotes industrial green transformation, revealing that such convergence supports green technologies and scale effects—though the benefits vary based on technological maturity and integration pathways. Zhu et al. [479] focus on industrial agglomeration in intelligent environments, demonstrating through simulation and machine learning that tighter cooperation between manufacturing and service industries leads to measurable improvements in regional economic performance. Peng and Deng [480] provide quasi-experimental evidence from China's Pilot Zones Policy, showing that industrial IT adoption enhances export sophistication, particularly in smaller, resource-dependent, and trade-oriented cities, emphasizing the importance of technological innovation for trade quality. Dong and Wang [481] introduce Data Envelopment Analysis (DEA) models to measure the efficiency of information industry chain integration under different structural and governance scenarios, offering a policy-relevant lens for evaluating and improving digital-industrial alignment. Complementing these macro-level perspectives, Huang et al. [482] apply machine learning and POI analysis to monitor industrial land use and structural shifts in China's urban agglomerations, highlighting spatial trends in traditional versus high-tech industries. These studies collectively underscore how intelligent integration strategies can drive sustainable economic growth, industrial efficiency, and strategic urban planning.

3.15.4. Decision Support, Urban Logistics, and Energy

The integration of advanced decision-making tools and digital technologies plays a pivotal role in shaping sustainable and efficient urban environments. Büyüközkan and Ilıcak [483] offer a comprehensive review of smart urban logistics, categorizing both technologies and thematic sub-domains while identifying research gaps that hinder seamless integration of logistics operations with smart city ecosystems. Their analysis highlights the need for more cohesive frameworks that unify real-time data, automation, and sustainability considerations in urban logistics planning. Pan et al. [484] explore the role of digital twin technologies in optimizing Positive Energy Districts (PEDs), focusing on virtual modeling, sensor integration, data analytics, and stakeholder interaction. Despite current limitations in tool maturity and interoperability, they outline an evolution path from BIM-enhanced models toward big data-driven dynamic platforms. Lastly, Shao et al. [485] propose a multi-dimensional framework to assess the applicability of Smart Sustainable Cities (SSC) concepts, drawing on a bibliometric analysis of over 4600 publications. Their framework—structured around environmental, societal, governance, and economic pillars—serves as a valuable decision-support system for urban planners and policymakers evaluating SSC feasibility in diverse contexts. Together, these works emphasize the strategic importance of digitalization, cross-sector integration, and structured frameworks in enabling informed, future-oriented urban development.

The articles are collected and classified in Table 18.

Table 18. Urban Development publication.

Research Category	Sub-Group	Publication
Urban Development	Smart Cities, IoT, and Digital Infrastructure	Da Silva et al. (2021) [468] Javed et al. (2022) [471] Rahman et al. (2022) [469] Deng et al. (2023) [473] Bolshakov et al. (2024) [472] Huda et al. (2024) [470]

Table 18. *Cont.*

Research Category	Sub-Group	Publication
Urban Development	Urban Planning and Spatial Intelligence	Anugraha et al. (2020) [475] Patrakeyev et al. (2020) [3] Ustaoglu and Aydınoglu (2020) [10] Zhang et al. (2021) [476] Chicherin et al. (2024) [477] Wang et al. (2025) [474]
	Industrial Integration, Economic Growth, and Green Transformation	Zhu et al. (2021) [479] Dong and Wang (2022) [481] Huang et al. (2022) [482] Meng et al. (2023) [478] Peng and Deng (2025) [480]
	Decision Support, Urban Logistics, and Energy	Büyüközkan and Ilıcak (2022) [483] Pan et al. (2024) [484] Shao and Min (2025) [485]

Note. The papers listed above are ordered chronologically by publication year. For papers published in the same year, the sequence follows the alphabetical order of the first author's surname.

4. Discussion and Future Research Direction

Industrial Information Integration (III) is advancing rapidly as digital transformation deepens across sectors. The convergence of digital twins, cyber-physical systems (CPS), artificial intelligence (AI), industrial IoT (IIoT), and semantic technologies is giving rise to interconnected, intelligent, and adaptive ecosystems. These developments are reshaping manufacturing, energy, construction, healthcare, agriculture, and education—while also beginning to impact previously peripheral sectors such as tourism, finance, and the arts.

Central to this evolution is the adoption of Digital Twins (DW), which provide real-time synchronization between physical and virtual systems for predictive analytics, maintenance, and optimization. In smart factories and infrastructure systems, digital twins enhance operational awareness and decision-making [486]. Their integration with immersive technologies like virtual reality (VR) and augmented reality (AR)—and more recently, mixed reality (MR)—is transforming how humans interact with machines and environments, particularly in training, remote inspections, and safety monitoring [487].

AI and machine learning technologies are embedded in nearly all facets of III. They are applied in fault diagnosis, scheduling, image recognition, and intelligent control. Emerging developments include hybrid AI models that incorporate quantum computing, physics-informed neural networks, and reinforcement learning to support robust, interpretable, and high-performance solutions [488]. Additionally, fuzzy logic algorithms are re-emerging as useful tools for modeling uncertainty and linguistic rules, particularly in adaptive control, energy management, and user-centric decision systems.

IIoT, edge/fog computing, and blockchain technologies form the infrastructure layer of integrated systems. They enable secure, real-time communication between distributed sensors, actuators, and control systems. Federated learning and privacy-preserving data exchange mechanisms are helping protect sensitive industrial and medical data [489]. The rise of electrical vehicles (EVs)—not just as transportation tools but as dynamic energy resources—is further extending the role of information integration into urban development and smart grid coordination [490].

Semantic interoperability remains crucial for harmonizing diverse systems. Ontology-based frameworks help structure lifecycle data, support automated reasoning, and foster collaboration across organizations and platforms. These models are essential in domains such as predictive maintenance, collaborative design, and supply chain transparency.

The sectoral scope of industrial information integration is also expanding:

- In agriculture, intelligent sensing, robotics, and satellite imaging enhance field automation and sustainability.
- In energy, CPS-based coordination supports resilient and decentralized energy grids.
- In healthcare, blockchain and federated AI enable privacy-aware diagnostics.
- In finance, IoT allows financial services to reach previously disconnected populations and remote infrastructures.
- In tourism, food, and art industries, the principles of information integration are applied to enhance personalization, experience modeling, traceability, and heritage preservation.

In addition, emerging technologies are opening new frontiers:

- Biomolecule–nanomaterial hybrid charge storage devices are pushing the edge of smart sensing and energy integration, particularly in bio-embedded environments and next-gen CPS.
- Quantum-enhanced models are being explored for optimization and simulation tasks that classical computation struggles to handle.
- Mixed reality environments blend real and digital layers to support complex human-machine collaboration in industrial, educational, and design contexts.

While progress is significant, challenges remain. Integration architectures such as RAMI 4.0 and edge-cloud orchestration are still underdeveloped. Technologies like 6G communication, although promising, require further investment and standardization for industrial-scale deployment.

In summary, the current landscape of industrial information integration reflects an accelerating shift toward intelligent, decentralized, and sector-spanning systems. By embedding AI, IIoT, semantic knowledge, and immersive human interfaces into physical infrastructure, III is enabling sustainable, resilient, and human-centered industrial transformation.

5. Summary

Industrial Information Integration Engineering (IIIE) plays an essential role in modernizing industrial sectors by harmonizing diverse systems, optimizing information flows, and significantly enhancing operational efficiency. The analysis of 874 selected papers across 34 research categories highlights the sustained and accelerating integration momentum, particularly influenced by emerging technologies. Digital twins, immersive interfaces, and AI-driven analytics have notably transformed industry-specific practices, fostering greater adaptability, predictive capabilities, and sustainability. Nonetheless, challenges remain in developing robust integration architectures and fully exploiting emerging technologies such as quantum computing and 6G networks.

Future IIIE research directions emphasize expanding semantic interoperability frameworks, strengthening human-centric design through mixed reality environments, and advancing decentralized, secure, and privacy-preserving data infrastructures. These insights collectively underline IIIE's critical role in shaping intelligent, interconnected, and resilient industrial ecosystems for the future.

In conclusion, the trajectory of IIIE demonstrates a profound and continuing transformation across industrial sectors, driven by the strategic integration of emerging digital technologies. While considerable advancements have been made, ongoing efforts must focus on addressing integration complexities and maximizing the potential of cutting-edge innovations like quantum computing, immersive technologies, and advanced communication networks. The progression toward more intelligent, decentralized, and human-centered industrial systems not only promises enhanced operational performance but also positions IIIE as a pivotal discipline in achieving sustainable and resilient industrial futures.

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Conflicts of Interest

The author declares no conflict of interest.

Use of AI and AI-assisted Technologies

During the preparation of this work, the authors used ChatGPT to assist with language polishing and clarity improvement. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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