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Review

Part I: Industrial Information Integration Review 2020–2025

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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

3.1. Aerospace

As space missions evolve in complexity, scale, and autonomy, the integration of advanced information systems becomes central to ensuring reliability and adaptability in aerospace operations. Shen et al. [16] contributed to this transformation by proposing a reactive planning framework that enhances spacecraft autonomy through context-aware computing. Their model identifies critical event triggers via evolution analysis and leverages a symbiotic computing paradigm, flexible inference engine, and agent-based architecture to refine decision-making in uncertain orbital environments. This work lays the foundation for intelligent spacecraft software capable of adapting to real-time anomalies and integrating mission-critical information dynamically.

Building on the increasing need for adaptive control in space systems, Wong et al. [17] investigated the application of cybernetic principles to space station operations and spacecraft guidance. By tracing the evolution from closed-loop feedback control in the Apollo missions to modern neural-network-like architectures, the study illustrates how cybernetics underpins robust, self-regulating systems. It further emphasizes the pivotal role of information flow in coordinating complex behaviors and managing nonlinear industrial processes, positioning cybernetics as a foundational framework for intelligent integration across space infrastructures.

At a more strategic and architectural level, Tang et al. [18] introduced the concept of "Space III"—a comprehensive vision for space industrial information integration to support deep space exploration. Their proposed framework organizes integration into three core architectures—data, technology, and application—and categorizes enabling space technologies across six domains. Central to this vision is the idea of an "Internet of Planets," in which IoT technologies facilitate planetary-scale connectivity and coordination. This conceptual roadmap offers a unified foundation for guiding long-term developments in space-based industrial systems.

The articles are collected in Table 4.

Table 4. Aerospace Publication.

Research Category	Publication
Aerospace	Shen et al. (2022) [16]
	Tang et al. (2024) [18]
	Wong et al. (2024) [17]

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. Agriculture

The integration of industrial information systems in agriculture has become essential for advancing sustainable, intelligent, and resilient food production. At the enterprise level, Ye et al. [19] addressed the long-standing fragmentation across arable farm systems by proposing IEMFAFE, a tailored enterprise modeling framework that aligns technological infrastructure with strategic farm goals. This enterprise-centric vision is further complemented by Almadani et al. [20], who developed a multimodal communication system based on DDS middleware to integrate heterogeneous production systems, enabling reliable, low-latency coordination in smart farming environments. Together, these works lay the groundwork for scalable, interoperable agricultural ecosystems.

On the operational side, automation and robotics are increasingly being applied to reduce labor costs and enhance precision. Chen et al. [21] introduced an Industrial Information Integration Engineering (IIIE) approach to optimize coverage path planning for unmanned agricultural formations, integrating multi-model systems with improved roadmap algorithms to enhance field efficiency. Similarly, Fuentes-Peñailillo et al. [22] proposed a mobile application based on computer vision to automate seedling counting in horticultural trays, while Milella et al. [23] highlighted the Horizon 2020 ATLAS project, which fosters an open architecture to integrate robotic and sensor systems across varied farm settings. These efforts demonstrate how intelligent automation is streamlining agricultural processes through real-time data fusion and robotics integration.

To support data-driven agriculture, satellite and sensor technologies are being combined with advanced analytics. Chaves et al. [24] leveraged MODIS satellite time series with Time-Weighted Dynamic Time Warping to detect crop phenology and rotation patterns in Brazil's Cerrado region, offering high-accuracy monitoring for field-level decision-making. This trend aligns with the broader Industry 5.0 vision reviewed by Victor et al. [25], where remote sensing plays a key role in augmenting human-machine collaboration for sustainable and resilient farming. Barbosa et al. [26] extended this paradigm by modeling smart agriculture systems using Stochastic Petri Nets, demonstrating how integrating IoT with Edge, Fog, and Cloud Computing can optimize throughput and system responsiveness under variable workloads.

Supply chain integration has also emerged as a critical component of agricultural information systems. Sharma et al. [27] empirically demonstrated that Industry 4.0 Technology Capabilities (I4TC), when paired with supply chain integration, significantly enhance Sustainable Agricultural Supply Chain Performance (SASCP). To strengthen traceability and transparency, Ameri et al. [28] developed a formal ontology based on the Basic Formal Ontology (BFO) and Industrial Ontologies Foundry (IOF) standards, enabling semantic integration across stakeholders in a bulk grain supply chain. Complementing this, Zúñiga et al. [29] reviewed recent traceability trends and emphasized the need for digital systems that integrate environmental, social, and productivity indicators to support holistic sustainability across agricultural networks.

Advances in artificial intelligence have further enabled automation in quality control. Figorilli et al. [30] developed a convolutional neural network (CNN) model that successfully classifies olives into quality grades based on RGB images captured in real-time on conveyor belts. This automated classification approach enhances industrial processing efficiency and reduces reliance on subjective human judgment.

Finally, energy efficiency and environmental sustainability are being advanced through intelligent device integration. Yao et al. [31] proposed a model that aligns solar insecticidal lamp operations with the phototactic rhythms of crop pests. By optimizing on/off schedules based on pest behavior, the approach reduces energy waste while enhancing pest control efficacy, exemplifying how smart agricultural systems can leverage biological models for sustainable management.

Together, these studies reflect a growing convergence of cyber-physical systems, enterprise modeling, and AI-driven analytics within the agricultural sector. From farm-level autonomy to global supply chain traceability, industrial information integration is reshaping the agricultural landscape into one that is not only smarter and more interconnected, but also more sustainable and responsive to future food security challenges.

The articles are collected in Table 5.

Table 5. Agriculture Publication.

Research Category	Publication
Agriculture	Almadani et al. (2021) [20]
	Ameri et al. (2022) [28]
	Barbosa et al. (2025) [26]
	Chaves et al. (2021) [24]
	Chen et al. (2024) [21]
	Figorilli et al. (2022) [30]
	Fuentes-Penailillo et al. (2023) [22]
	Krupitzer et al. (2021) [32]
	Milella et al. (2024) [23]
	Sharma et al. (2024) [27]
	Victor et al. (2024) [25]
	Yao et al. (2024) [31]
	Ye et al. (2023) [19]
	Zuniga et al. (2023) [29]

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. Algorithms

Algorithmic innovation is foundational to the advancement of industrial information integration (III), enabling intelligent systems to process, analyze, and act upon complex industrial data in dynamic environments. Across a broad spectrum of industrial contexts—from manufacturing and defect detection to space missions and IIoT networks—recent research has advanced both the diversity and sophistication of algorithms designed to improve accuracy, adaptability, and real-time responsiveness.

A major focus in recent years has been the development of robust and efficient deep learning architectures for fault diagnosis and defect detection in noisy or complex industrial scenarios. Xu et al. [33] introduced MF-DRCN, a multireceptive field denoising convolutional network that integrates adaptive feature extraction to maintain high diagnostic performance under extremely low signal-to-noise conditions. Similarly, various improvements to YOLO-based architectures have been tailored to detect defects in specialized manufacturing contexts. Liu et al. [34] presented CBS-YOLOv5, integrating coordinate attention, BiFPN, and Swin Transformers for accurate real-time detection of faults in copper electrode plates. To address underwater industrial scenarios, Cheng et al. [35] optimized YOLOv11 for embedded systems, achieving high-speed, energy-efficient target recognition using edge computing platforms. Zhou et al. [36] targeted fabric defect detection with their YOLOv5s-4SCK variant, enhancing sensitivity to small-scale anomalies using CARAFE and K-Means++-based anchor optimization. Complementing this, Vengaloor et al. [37] integrated a Feature Recalibration Network (FRN) into YOLOv5s to improve metal surface defect classification, while Xiao et al. [38] proposed an improved YOLOv7 with Wise-IoU and a global attention mechanism for detecting micro-defects in transparent industrial materials.

Chen et al. [39] propose a dynamic grouping and resource allocation algorithm to enhance Cooperative Coevolution for Large-Scale Multi-Objective Optimization Problems. Guan et al. [40] tackle dynamic multiagent vehicle routing by adapting DMPVRP for real factory conditions.

Beyond deterministic deep learning, emerging industrial scenarios demand greater adaptability and decision-making under uncertainty. Hybrid models such as the quantum-classical integration proposed by Geda et al. [41] exemplify this shift. Their use of the Quantum Approximate Optimization Algorithm (QAOA) for satellite imaging scheduling outperformed classical approaches, demonstrating the potential of quantum-enhanced algorithms in complex optimization tasks. In parallel, Xu et al. [42] applied reinforcement learning (RL) to co-design control and communication systems in IIoT environments, ensuring dynamic reconfiguration in response to evolving cyber-physical system states. Niu et al. [43] propose INDMF, a network embedding model combining structural and attribute information using influential node diffusion and matrix factorization. Miao et al. [44] also addressed adaptability through the SPMCTS algorithm, a Monte Carlo tree search variant for real-time robot scheduling in IoT-enabled workshops, offering efficient computation through progressive pruning and task adjacency modeling. Tan et al. [45] introduce TNSAR, a dynamic network embedding model that captures global topological features via graph decomposition, integrates node attributes with topology using GCN, and preserves temporal evolution. Zou et al. [46] propose a Twin Support Vector Machines (TWSVM) model to predict daily up/down movements of the Shanghai Securities Composite Index and S&P 500 using thirteen historical indicators. Their results show TWSVM outperforms Decision Tree, Naive Bayes, Random Forests, Probabilistic Neural Network, and traditional SVM models. Zhao et al. [47] tackle reliable user coverage in Mobile Edge Computing with the CR-BEAD optimization problem.

To support scalable and efficient data management, several studies have introduced innovative algorithmic frameworks for integrating and processing heterogeneous industrial data. Younan et al. [48] proposed a dynamic data reduction method using Dynamic Time Warping (DTW) to compress and summarize high-volume IoT streams, preserving similarity for indexing while reducing data size by up to 95%. In the domain of semantic integration, Zhao et al. [49] employed a MapReduce-based Apriori algorithm to extract machining knowledge from STEP-NC files, enabling the continuous self-learning of manufacturing ontologies for cloud-based systems. Addressing the growing need for secure and low-latency communication, Tian et al. [50] developed an audio information hiding algorithm to embed data within sound signals, achieving 98.3% accuracy with minimal delay in IIoT environments. Zhao et al. [51] address reliable user recruitment in mobile social networks for spatial crowdsourcing by formulating the NP-hard R-SAC problem.

Security and resilience have also become critical algorithmic priorities as interconnected industrial systems face increasing cyber-physical threats. Villegas-Ch et al. [52] responded to this challenge with a sensor anomaly detection algorithm designed to proactively identify sabotage in sensor data, integrating a responsive alert system validated in real-world industrial settings.

Finally, broader algorithmic strategies for optimizing information propagation and quality evaluation have been proposed. Kumar et al. [53] introduced the Community structure with Integrated Features Ranking (CIFR) algorithm to identify influential nodes in enterprise networks by evaluating a combination of local, gateway, and global metrics—improving system-wide information flow. Zhao et al. [54] address the NP-hard MEAD problem in Mobile Edge Computing, aiming to optimize service quality and deployment cost amid user interference. Wang et al. [55] addressed process quality evaluation using a deep generative model grounded in variational Bayesian learning and neural ordinary differential equations, offering both high accuracy and a principled probabilistic foundation for modeling uncertainty in industrial quality data.

Taken together, these contributions reflect the increasing algorithmic diversity in III, encompassing deep learning, reinforcement learning, quantum computing, probabilistic modeling, and real-time optimization. This multi-algorithmic ecosystem is essential for enabling next-generation industrial systems to be not only intelligent and autonomous but also secure, scalable, and adaptive across varied operational contexts.

The articles are collected in Table 6.

Table 6. Algorithm publication.

Research Category	Publication
Algorithm	Xu et al. (2020) [42]
	Younan et al. (2021) [48]
	Xu et al. (2022) [33]
	Zhao et al. (2022) [47]
	Zhao et al. (2022) [51]

Table 6. *Cont*.

Research Category	Publication
Algorithm	Zhao et al. (2022) [54] Zhao et al. (2022) [49] Zou et al. (2022) [46] Kumar et al. (2023) [53] Tan et al. (2023) [45] Tian et al. (2023) [50] Villegas-Ch et al. (2023) [52] Xiao et al. (2023) [38] Zhou et al. (2023) [36] Miao et al. (2024) [44] Niu et al. (2024) [43] Vengaloor et al. (2024) [37] Wang et al. (2024) [55] Chen et al. (2025) [39] Cheng et al. (2025) [35] Geda et al. (2025) [41] Guan et al. (2025) [40] Liu et al. (2025) [34]

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. Art Industry

Industrial information integration is increasingly permeating creative domains, with recent advances in generative artificial intelligence (Gen AI) catalyzing innovation in digital art and media production. Mohedas et al. [56] provide a compelling case study on the application of convolutional neural networks (CNNs) and generative adversarial networks (GANs) in the audiovisual post-production of La Mesias, a landmark project in Spain's art industry. Their analysis reveals how Gen AI was not merely a tool for automation but a transformative agent in visual effects and 2D/3D compositing workflows. The integration of these technologies contributed to a unique aesthetic that merged hyper-realistic imagery with surreal, dreamlike visual motifs. This study exemplifies how industrial information integration enables novel forms of artistic expression, bridging the gap between computational design and creative storytelling.

The articles are collected in Table 7.

Table 7. Art Industry publication.

Research Category	Publication
Art Industry	Mohedas et al. (2025) [56]

3.5. Automated Factory

The automated factory represents a central domain in industrial information integration, where digital technologies converge to enable intelligent, adaptive, and efficient manufacturing. Recent research spans a wide range of innovations—from digital twin and cyber-physical system integration to secure IIoT architectures, AI-driven decision-making, and ontology-based knowledge modeling. The following literature is categorized into four thematic areas to reflect the diverse strategies advancing automation in Industry 4.0 environments.

3.5.1. Digital Twin and Cyber-Physical System Integration

Digital twin (DT) and cyber-physical system (CPS) integration have become foundational strategies in advancing industrial information integration within automated factories. Harrison et al. [2] proposed the SIMPLE framework to ensure lifecycle-consistent integration between IT and OT systems in cyber-physical production systems (CPPSs), emphasizing digital continuity beyond design and deployment. Extending this paradigm to assembly processes, Yi et al. [57] introduced a three-layer DT framework combining physical entities, interactive interfaces, and virtual simulations, which was validated in satellite assembly. Aiming to optimize production operations, Mei et al. [58] developed a DT-enabled multi-objective optimization model for milling processes, integrating real-time sensor data and machine learning (Optuna-XGBoost) to enhance energy efficiency, cutting quality, and noise reduction. In the sustainability domain, Li et al. [59] presented a DT-driven green performance evaluation system for manufacturing, enabling accurate environmental assessments via physical-digital mappings. Zhang et al. [60] addressed the lack of structured DT modeling by proposing a multi-level modeling and fidelity evaluation method to build intelligent, responsive production equipment. Meanwhile, Geng et al. [11] proposed a modular DT system with bidirectional mapping between physical and virtual machines using socket communication and immersive interfaces via VR and AR, offering real-time machining validation. To strengthen operational resilience, Maia et al. [61] developed SMS-DT, a platform that integrates AI, IoT, and ML within a DT framework to enhance cyber situational awareness across smart factories. In terms of security for intelligent DT learning systems, Zhang et al. [62] proposed the MASTER algorithm, a multi-timescale deep reinforcement learning method to mitigate model poisoning risks in DT model training under 6G edge environments. Li et al. [63] explored resource efficiency in DT-enabled mobile edge computing (MEC) environments, proposing an ILP-based framework to jointly optimize synchronization and task offloading. For scalable and flexible deployment, -H. Hung et al. [64] introduced IF-DTiM, a container-based DT implementation framework supporting diverse DT types and external cloud-based intelligence. Shi et al. [65] analyze the shift from traditional to intelligent manufacturing through Industry 4.0, emphasizing smart factories that integrate physical and cyber technologies to improve production efficiency and customization. The paper outlines key challenges, necessary resources, and provides guidance for manufacturers adopting smart factories. [66] Zhang [67] further demonstrated CPS-level integration using industrial cloud platforms and big data to support smart robotic factories, validated via simulations and a LeNet-based recognition model. Finally, Shahbazi et al. [68] integrated DT with blockchain and edge computing into a unified smart manufacturing system, employing swarm optimization to enhance real-time task processing in complex production environments. Collectively, these studies reveal that DT and CPS technologies are not only pivotal for synchronized control and monitoring but also vital enablers of sustainability, security, and intelligent autonomy in Industry 4.0 factories.

3.5.2. Secure, Scalable, and Interoperable IIoT Architectures

Achieving robust, scalable, and interoperable architectures is central to the success of industrial information integration (III) in automated factories, especially as Industry 4.0 systems grow more connected and data-intensive. Seiger et al. [69] addressed integration at the operational-process level by proposing an architecture that enables bidirectional communication between IIoT hardware and Business Process Management (BPM) systems, thus enhancing automation and process intelligence in smart factories. Mourad et al. [70] evaluated the financial viability of transitioning from traditional manufacturing setups to interoperable cloud manufacturing platforms, highlighting that benefits are contingent on the characteristics of service providers and order profiles. Security and data integrity remain pressing concerns; to this end, Manogaran et al. [71] developed a Blockchain-assisted Secure Data Sharing (BSDS) model for IIoT environments, employing reputation-based learning and blockchain verification to improve communication integrity and resilience. Complementing this, Kim et al. [72] proposed a self-supervised network intrusion detection system (NIDS) tailored for 5G-enabled smart factories, using knowledge distillation to ensure lightweight yet accurate anomaly detection under constrained conditions. Godor et al. [73] reviewed the integration of 5G and Time-Sensitive Networking (TSN), emphasizing the role of ultra-reliable, deterministic communications in meeting the stringent latency and synchronization demands of IIoT systems. Similarly, Boudagdigue et al. [74] presented a hybrid architecture for IIoT trust management in automotive factories, proposing decentralized models to improve adaptability and resilience against malicious behaviors. To streamline secure and distributed manufacturing operations, Volpe et al. [75] combined blockchain with Docker containers in a cloud manufacturing platform, further enhanced by deep learning–driven task allocation for dynamic process efficiency. Xiao et al. [76] proposed a Hybrid-IoT (H-IoT) platform integrating business, production, and technology layers, featuring a crash recovery mechanism at the edge layer to ensure operational continuity. Tackling semantic interoperability, Bi et al. [77] introduced QOMOU, a semantic integration framework that transforms OPC UA server models into RDF graphs and enhances device classification through ontology-driven inference. In parallel, Shirbazo et al. [78] offered a comprehensive procedural framework for implementing the Reference Architectural Model for Industry 4.0 (RAMI 4.0), addressing gaps in system design, monitoring, and security integration. Together, these contributions form a foundation for resilient, standardized, and secure IIoT architectures, enabling scalable data integration [79], real-time control, and trustworthy industrial collaboration across heterogeneous smart factory environments.

3.5.3. AI, Learning, and Cognitive Automation

Artificial intelligence (AI), machine learning (ML), and cognitive frameworks are playing increasingly pivotal roles in enabling intelligent decision-making, adaptive control, and flexible automation in smart manufacturing environments. Park et al. [80] proposed an innovative human-robot collaboration (HRC) system that integrates an exoskeleton-based teaching interface with digital twin (DT) and virtual reality (VR) technologies, making robot task programming more intuitive and accessible to non-expert operators. Xia et al. [81] advanced the field of cognitive automation by introducing a CPS architecture that leverages semantic interpretation of image and sensor data to enable event detection, real-time control, and integration into manufacturing ontologies—bridging machine cognition and human supervision. A broader perspective on AI integration is provided by Tsanousa et al. [82], who reviewed data fusion methodologies used in smart manufacturing, particularly for early-stage analytics, highlighting how multimodal sensor integration supports predictive maintenance and real-time process optimization. Building on this, Huang et al. [83] developed a multi-scale spatiotemporal attention network for accurate Remaining Useful Life (RUL) prediction, which identifies complex dependencies among multidimensional sensor inputs and provides explainable diagnostics. From a foundational and philosophical perspective, Sandini et al. [84] proposed the Artificial Cognition (ACo) framework, emphasizing brain-inspired, embodied AI systems that promote bidirectional human-robot interaction, generalization, and trust in industrial environments—challenging the limitations of disembodied AI models. In the context of production customization, Wan et al. [85] explored how AI-driven architectures, combining IoT, cloud-edge computing, and adaptive decision-making, can support smart factories in achieving efficient, small-batch customized manufacturing, validated through a packaging case study. Finally, Kumar et al. [53] introduced the Community structure with Integrated Features Ranking (CIFR) algorithm, which identifies influential nodes in enterprise networks by integrating local, global, and inter-community metrics, thereby improving information propagation and network optimization in intelligent enterprise systems. Together, these studies illustrate how AI and cognitive automation are becoming central to the evolution of smart factories—enhancing interaction, perception, reasoning, and responsiveness in complex industrial settings.

3.5.4. Ontology, Lifecycle Data, and Knowledge Integration

Efficient industrial information integration in smart factories increasingly depends on robust knowledge modeling, semantic interoperability, and unified data handling across the product and process lifecycle. Kwon et al. [86] addressed the critical gap in linking design and inspection data by integrating STEP (ISO 10303) and QIF (Quality Information Framework) standards through an ontology-based digital thread. Their approach employs knowledge graphs to automate the mapping and querying of lifecycle data, thereby improving traceability, quality assurance, and decision-making. Similarly, Cao et al. [87] proposed an ontology-based holonic event-driven architecture (EDA) for distributed manufacturing systems, enabling personalized production through secure, interoperable service integration governed by semantically defined access rules. Ge et al. [88] offered a broader view of knowledge-driven manufacturing transformation, emphasizing the role of big data, cyber-physical systems, and lifecycle integration in driving intelligent industrial value creation. Lee et al. [89] contributed to this knowledge-centric vision by integrating edge computing and blockchain into a smart manufacturing architecture, using swarm intelligence to optimize task distribution, reduce latency, and enhance data reliability in edge environments. Finally, Miao et al. [44] introduced the SPMCTS algorithm for adaptive scheduling in IoT-enabled workshops, combining real-time state modeling with knowledge-driven heuristics to improve computational efficiency and scheduling precision. Collectively, these studies demonstrate that lifecycle-wide semantic modeling, ontology integration, and intelligent data coordination are essential for scalable, adaptive, and context-aware automation in next-generation manufacturing systems.

The articles are collected and classified in Table 8.

Table 8. Automated Factory publication.

Research Category	Sub-Group	Publication
Automated Factory	Digital Twin and Cyber-Physical System Integration	Runji et al. (2020) [66] Shi et al. (2020) [65] Harrison et al. (2021) [2] Shahbazi et al. (2021) [68] Yi et al. (2021) [57] Zhang (2021) [67] Geng et al. (2022) [11]

Table 8. *Cont.*

Research Category	Sub-Group	Publication
Automated Factory	Digital Twin and Cyber-Physical System Integration	Hung et al. (2022) [64] Li et al. (2022) [59] Maia et al. (2022) [61] Zhang et al. (2023) [62] Zhang et al. (2024) [60] Li et al. (2025) [63] Mei et al. (2025) [58]
	Secure, Scalable, and Interoperable IIoT Architectures	Boudagdigue et al. (2020) [74] Godor et al. (2020) [73] Mourad et al. (2020) [70] Xiao et al. (2021) [76] Manogaran et al. (2022) [71] Seiger et al. (2022) [69] Volpe et al. (2022) [75] Marek et al. (2023) [79] Kim et al. (2024) [72] Bi et al. (2025) [77]
	AI, Learning, and Cognitive Automation	Wan et al. (2021) [85] Xia et al. (2021) [81] Tsanousa et al. (2022) [82] Kumar et al. (2023) [53] Huang et al. (2024) [83] Park et al. (2024) [80] Sandini et al. (2024) [84]
	Ontology, Lifecycle Data, and Knowledge Integration	Ge et al. (2020) [88] Kwon et al. (2020) [86] Lee et al. (2020) [89] Cao et al. (2021) [87]

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. Biology

The integration of industrial information systems into biological research and biotechnology is enabling unprecedented advancements in biomanufacturing, bioinformatics, and molecular engineering. From predictive modeling and automated production platforms to multi-omics data integration and AI-assisted drug development, recent work demonstrates how data-driven approaches are accelerating innovation, enhancing precision, and supporting sustainability across the biological domain.

In biomanufacturing, integrated systems are driving innovation across the product lifecycle. Feidl et al. [90] demonstrated a fully automated continuous biomanufacturing platform for antibody production, combining perfusion bioreactors, polishing steps, and SCADA-based digital monitoring to maintain yield and robustness even under disturbance. Complementing this, Barberi et al. [91] employed machine learning to predict monoclonal antibody titers in micro-bioreactors by integrating metabolomics and process data, enabling early identification of high-performing cell lines. Addressing protein production efficiency, Madani et al. [92] developed DSResSol, a deep learning tool that accurately predicts protein solubility from amino acid sequences, outperforming previous models and aiding experimental design. In the context of sustainable bioresource utilization, Sharma et al. [93] reviewed advances in lignocellulosic biomass valorization, particularly xylanase production, highlighting how integrated technologies such as recombinant DNA, enzyme immobilization, GIS, LCA, and TEA support scalable, green biorefinery processes.

Metabolic modeling continues to play a central role in industrial biotechnology. Pearcy et al. [94] developed a genome-scale metabolic model for *Cupriavidus necator H16* linked to the BioCyc database, integrating experimental data from TraDIS and omics to predict gene essentiality and optimize CO_2-to-biofuel conversion—positioning this organism as a sustainable microbial chassis. Saranya et al. [95] further emphasized the expanding relevance of such genome-scale models by reviewing 237 in silico organisms across domains including biomanufacturing, bioremediation, and drug discovery, underscoring their role in experiment design, model-driven engineering, and even replacing animal testing.

Beyond manufacturing, industrial integration is advancing biological data infrastructure. Mansueto et al. [96] introduced a Tripal-based multi-omics platform for cannabis genomics, enabling researchers to integrate and explore genome assemblies, expression profiles, and SNP data through a unified API-driven portal. Similarly, Soares et al. [97] created a FAIR-compliant database of cyanobacterial bioactives and machine learning models for predicting therapeutic and environmental targets, supporting applications in drug discovery and bioremediation.

In the pharmaceutical domain, Neves et al. [98] applied deep learning to reaction optimization, developing the BERT Enriched Embedding (BEE) model, which incorporates chemical context into reaction encoding. Trained on 16 million reactions and deployed at Janssen, BEE significantly improved yield prediction accuracy and reduced low-yield experiments in drug development pipelines by over 34%.

Together, these contributions illustrate how industrial information integration is catalyzing transformation in biology—from molecular prediction and production system automation to sustainable bioprocess engineering and intelligent platform development—ushering in a new era of data-driven biological innovation.

The articles are collected in Table 9.

Table 9. Biology publication.

Research Category	Publication
Biology	Feidl et al. (2020) [90]
	Madani et al. (2021) [92]
	Barberi et al. (2022) [91]
	Pearcy et al. (2022) [94]
	Neves et al. (2023) [98]
	Mansueto et al. (2024) [96]
	Saranya et al. (2024) [95]
	Sharma et al. (2024) [93]
	Soares et al. (2024) [97]

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. Chemistry

The integration of Internet of Things (IoT) technologies into analytical chemistry is reshaping the discipline by enabling real-time data exchange, system miniaturization, and automation. Amirian et al. [99] provide a comprehensive review of how IoT-driven architectures and sensor-based modules are advancing sustainable and green chemistry practices across environmental, industrial, healthcare, and educational domains. The paper emphasizes the growing synergy between IoT and analytical methodologies, facilitating rapid, decentralized chemical surveillance—especially for environmental monitoring. By introducing DIY-based degradation tools and low-cost instrumentation, the study also highlights the educational potential of IoT in chemistry, offering scalable and accessible alternatives to traditional laboratory equipment. Ultimately, this work illustrates how IoT serves as a catalyst for modernizing analytical chemistry and expanding its reach through interdisciplinary collaboration and digital integration.

The articles are collected in Table 10.

Table 10. Chemistry publication.

Research category	Publication
Chemistry	Amirian et al. (2024) [99]

3.8. Construction

The construction industry is undergoing a digital transformation through the integration of industrial information systems, with technologies such as Building Information Modeling (BIM), Digital Twins (DT), Artificial Intelligence (AI), Internet of Things (IoT), and blockchain reshaping how projects are designed, managed, and maintained. These advancements aim to address longstanding challenges including fragmentation, inefficiency, and sustainability, while enabling data-driven decision-making across the entire building lifecycle. The following literature is grouped into four thematic categories that reflect the evolving landscape of industrial information integration in construction.

3.8.1. Digital Twin and BIM Integration for Smart Construction

The integration of Digital Twin (DT) technologies with Building Information Modeling (BIM) is revolutionizing the construction sector by improving collaboration, real-time monitoring, and lifecycle management of built assets. Moshood et al. [100] highlighted DT's transformative role in overcoming inefficiencies and fragmentation in construction by enabling coordinated, data-driven decision-making across project stages. Madubuike et al. [101] further emphasized DT's dynamic capabilities in planning, operation, and maintenance, comparing construction's adoption lag with other industries like aerospace. Addressing information complexity in infrastructure, Jiang et al. [102] proposed a Domain-Driven Ubiquitous Digital Twin model that organizes construction information across six structured domains, validated in nuclear infrastructure cases. Sepasgozar [103] positioned DTs as key enablers for real-time monitoring and automation in smart cities, emphasizing their distinctiveness from other digital models through bi-directional data exchange. Yitmen et al. [104] demonstrated how integrating AI with DTs improves indoor environmental quality and energy efficiency, enabling fault detection, comfort optimization, and smart maintenance in building systems. In civil infrastructure, Wimmer et al. [105] explored DT implementation for bridge condition monitoring using the Asset Administration Shell concept, revealing current integration gaps with BIM and proposing scalable solutions for structural health management. Gourlis et al. [106] proposed a hybrid simulation-based DT ecosystem that merges BIM-based building models with energy, logistics, and production systems to enhance industrial facility operations. Badenko et al. [107] emphasized the critical role of DT-BIM integration in the digital transformation of industrial facilities, highlighting the underdeveloped Operation and Maintenance (O&M) phase and proposing System Information Modeling (SIM) to manage digital assets. Lastly, Yoon [108] introduced the concept of Virtual Building Models (VBMs) to simulate a building's physical behavior, proposing new methodologies that extend the capabilities of BIM and DT for sustainability and performance tracking. Collectively, these studies demonstrate that the convergence of DT and BIM technologies is central to achieving intelligent, sustainable, and responsive construction systems within the Industry 4.0 framework.

3.8.2. BIM-Centered Integration with Emerging Technologies

The interoperability of Building Information Modeling (BIM) with emerging technologies such as augmented/virtual reality (AR/VR), artificial intelligence (AI), the Internet of Things (IoT), and blockchain is accelerating the digital transformation of the construction industry. Amin et al. [109] identified six core functions—positioning, interaction, visualization, collaboration, automation, and integration—central to BIM-AR platforms, and proposed an evaluation framework to guide future development, emphasizing the potential of AI for enhanced automation. Brandín et al. [110] advanced BIM integration by combining it with blockchain and IoT to enhance traceability, transparency, and automation in off-site manufacturing, addressing data fragmentation and centralized control limitations across the asset lifecycle. Selvanesan et al. [111] also explored BIM-blockchain synergy in construction supply chains, finding that blockchain can address trust, transparency, and sustainability issues in BIM-based SCM systems, despite practical challenges like cost and regulatory gaps. Khan et al. [112] reviewed immersive technologies—including VR, AR, and MR—within BIM workflows, providing a scientometric and SWOT analysis that reveals their potential for enhancing project sustainability and collaboration across eight construction domains. Kang et al. [113] conducted a comprehensive review of BIM and Computational Fluid Dynamics (CFD) integration, showcasing its utility in hazard analysis and sustainability applications, particularly for improving environmental functionality in buildings. Fonsati et al. [114] proposed a flexible framework for BIM-Geo integration using geotechnical and geological modeling (GeoBIM), tested through multiple workflows and evaluated with the Analytical Hierarchy Process, demonstrating potential for as-built documentation and cross-domain coordination. Pan et al. [115] offered a typology for integrating XR technologies with robotics in construction, highlighting how AR facilitates real-time human-robot interaction while VR supports simulation and teleoperation, though practical deployment remains limited. Finally, Nassereddine et al. [116] demonstrated the use of AR in enhancing the Production Strategy Process (PSP), showing that HoloLens-based visualization significantly improved collaboration, decision-making, and on-site safety over traditional 2D planning methods. Together, these studies illustrate how BIM acts as a central hub for harmonizing diverse digital technologies, enabling more intelligent, collaborative, and resilient construction processes.

3.8.3. Smart Construction, Industry 4.0, and System-Level Integration

The shift toward smart construction under the Industry 4.0 paradigm emphasizes integrated cyber-physical systems (CPS), real-time data exchange, and adaptive workflows to improve project delivery, sustainability, and resilience. You et al. [117] proposed a comprehensive CPS framework for integrating BIM, IoT, AI, cloud computing, and big data, demonstrated through a case study of the Xiong'an Citizen Service Center to showcase practical pathways toward intelligent construction ecosystems. Addressing emergency response and infrastructure resilience, Zhang et al. [118] reviewed the state of smart firefighting construction in China, identifying data integration, platform management, and geographic information interaction as critical barriers to advancing intelligent disaster response and urban safety within smart cities. Vrana [119] focused on integrating Non-Destructive Evaluation (NDE) technologies into Industry 4.0 architectures, advocating for semantic interoperability and IIoT-driven inspection workflows to elevate NDE from a passive cost center to a proactive value generator within digitalized construction. From a client-supplier interaction perspective, Wang et al. [120] introduced a cloud-based configurator for customizable single-family homes, merging parametric design with certified components and a web interface to bridge supply chain gaps and support regulatory compliance. In the Middle East context, Aburumman et al. [121] analyzed the integration of BIM and Lean Construction (LC) in Jordan, demonstrating their synergy in reducing waste and improving efficiency but also highlighting implementation challenges, including technical expertise and institutional support. Lastly, Yu et al. [122] conducted a systematic review on the role of Information and Communication Technologies (ICT) in enabling Circular Economy (CE) practices in construction, calling for a Circularity Information Platform and proposing a Smart Circular Construction Ecosystem that bridges technology, business models, and sustainability. Collectively, these studies demonstrate how system-level integration of digital technologies is essential for advancing smart construction, enabling industry-wide transformation across operational, environmental, and strategic dimensions.

3.8.4. Sustainability, Circular Economy, and Lifecycle Data Management

The integration of digital technologies in construction is increasingly driven by the need to enhance sustainability, enable circular economy practices, and manage data across the full lifecycle of buildings and infrastructure. Miatto et al. [123] demonstrated how combining Material Flow Analysis (MFA) with Building Information Modeling (BIM) can quantify the environmental impacts of clay bricks in Italy, revealing long-term declines in production and CO_2 emissions while emphasizing the challenges of recycling and the predominance of maintenance in material use. To support standardized data exchange and lifecycle monitoring, Bellon et al. [124] proposed an IFC-based framework for inspection and maintenance in facility management, ensuring semantic interoperability and improving asset monitoring and planning decisions. At the enterprise level, Junussova et al. [125] reviewed the integration of Enterprise Resource Planning (ERP) and BIM, particularly through cloud-based platforms, to support smart, data-driven sustainability practices across the economic, environmental, and social dimensions of construction. Focusing on project cost and resource efficiency, Yilmaz et al. [126] developed a BIM-centered cost management framework aligned with the PMBOK approach, demonstrating improved estimation, budgeting, and control, while noting limitations in subcontractor data and risk-based budgeting. Finally, Zhang et al. [118] provided a comprehensive bibliometric review of BIM integration in prefabricated construction (PC), highlighting trends, key research gaps, and the potential of BIM-PC synergy to reduce waste and enhance industrialized, sustainable building practices. Together, these studies reflect a growing emphasis on leveraging digital integration to address sustainability goals, optimize resource usage, and support circular thinking throughout the construction lifecycle.

The articles are collected and classified in Table 11.

Table 11. Construction publication.

Research Category	Sub-Group	Publication
Construction	Digital Twin and BIM Integration for Smart Construction	Badenko et al. (2021) [107]
		Sepasgozar (2021) [103]
		Gourlis et al. (2022) [106]
		Madubuike et al. (2022) [101]
		Jiang et al. (2023) [102]
		Moshood et al. (2024) [100]
		Wimmer et al. (2024) [105]
		Yoon (2024) [108]
		Yitmen et al. (2025) [104]
	BIM-Centered Integration with Emerging Technologies	Brandín et al. (2021) [110]
		Khan et al. (2021) [112]
		Kang et al. (2022) [113]
		Nassereddine et al. (2022) [116]

Table 11. *Cont.*

Research Category	Sub-Group	Publication
Construction	BIM-Centered Integration with Emerging Technologies	Amin et al. (2023) [109] Fonsati et al. (2023) [114] Selvanesan et al. (2023) [111] Pan et al. (2024) [115]
	Smart Construction, Industry 4.0, and System-Level Integration	Guowei et al. (2020) [127] You et al. (2020) [117] Vrana (2021) [119] Yu et al. (2022) [122] Aburumman et al. (2024) [121] Wang et al. (2024) [120]
	Sustainability, Circular Economy, and Lifecycle Data Management	Zhang et al. (2021) [118] Junussova et al. (2022) [125] Miatto et al. (2022) [123] Bellon et al. (2025) [124] Yilmaz et al. (2025) [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.

3.9. Education

As industrial information integration reshapes the educational landscape, a convergence of technologies—including digital twins, immersive environments, big data, and secure infrastructure—is redefining both pedagogy and institutional systems. Tong et al. [128] propose a Digital Twin Campus (DTC) model that merges physical and virtual learning environments through a double-layer collaborative filtering algorithm, enabling personalized, data-driven teaching and learning. Complementing this trend, Paulauskas et al. [129] and Izquierdo-Domenech et al. [130] explore immersive education: the former leverages VR for kinaesthetic learning in museum contexts, while the latter integrates large language models (LLMs) with retrieval-augmented generation (RAG) to deliver interactive, domain-specific educational experiences in virtual reality. These intelligent environments are mirrored in systemic reforms aimed at aligning education with Industry 4.0. Xiao et al. [131] introduces a curriculum reform framework for vocational training in electronic information engineering, closely tying instruction to industrial processes, certification standards, and emergent technologies like the Metaverse. Similarly, He et al. [132] develop an Inter-Technology Information Management (ITIM) system to enhance teaching quality and bridge gaps between academia and industry in business and technical disciplines. Li [7] explores the use of systems theory in higher education, introducing the "education supply chain" concept to examine how Industry 4.0 impacts graduate skills and workforce reskilling. The study links educational mobility and transnationalization to industrial revolutions and proposes a systems-thinking-based curriculum that promotes global resource sharing and talent mobility. Hu et al. [133] provide a decision-making framework to evaluate school-enterprise collaboration using a novel probabilistic linguistic multi-criteria model. In the domain of STEM and engineering education, Rostoka et al. [134] propose a transdisciplinary framework for scientific personnel training, integrating information-analytical systems to cultivate research competencies aligned with open science and Industry 4.0. Inchan et al. [135] further this direction with the PPED blended learning model, designed to foster active, hands-on learning in embedded systems courses. Finally, to safeguard the expanding educational ecosystems, A. Chen et al. [136] developed and tested a blockchain-based system for international student administration at a US public university, showing improvements in efficiency, transparency, speed, and security. Rahman et al. [137] offer a blockchain-based privacy-preserving architecture for educational microservices, enhancing data confidentiality, transmission integrity, and user trust. Collectively, these works demonstrate how industrial information integration is catalyzing the transformation of education into a smarter, more adaptive, and securely interconnected domain.

The articles are collected in Table 12.

Table 12. Education publication.

Research Category	Publication
Education	Li (2020) [7] Chen et al. (2022) [136]

Table 12. *Cont.*

Research Category	Publication
Education	Rahman et al. (2022) [137] Tong et al. (2022) [128] He et al. (2023) [132] Paulauskas et al. (2023) [129] Rostoka et al. (2023) [134] Hu et al. (2024) [133] Izquierdo-Domenech et al. (2024) [130] Xiao et al. (2024) [131] Inchan et al. (2025) [135]

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. Energy

The transformation of modern energy systems is driven by the convergence of digital technologies, renewable integration, and evolving market structures. As energy systems grow more complex, research has increasingly focused on intelligent control and optimization, renewable deployment and forecasting, digital twin and cyber-physical system applications, cybersecurity and privacy protections, and innovative market mechanisms. Together, these areas form a comprehensive framework for understanding how industrial information integration is shaping the future of energy infrastructure. The following sections synthesize key literature across these five thematic categories, highlighting emerging methodologies, technologies, and strategic insights that enable more intelligent, resilient, and sustainable energy systems.

3.10.1. Intelligent Energy System Control and Optimization

This category centers on advanced control and optimization strategies for intelligent energy systems, with emphasis on microgrids, energy hubs, smart grids, electric vehicle (EV) integration, and digitalization. A core concern across these works is improving coordination and resilience under uncertainty and complexity. Hui et al. [138] and Cui et al. [139] propose coordinated dispatch frameworks for multi-energy systems and regional integrated energy systems respectively, leveraging quickhull-based methods and bilevel optimization under 6G communication constraints to enhance efficiency and market coordination. Peng et al. [140] and Wu et al. [141] contribute real-time deterministic scheduling and multirate distributed control approaches to enhance communication reliability and power allocation in microgrids and distributed battery energy storage systems. Gharibi et al. [142] and Liu et al. [143] focus on optimizing energy hubs through robust Information Gap Decision Theory and closed-loop bilevel sharing contracts, while Zhong et al. [144] proposes a two-stage energy-computation coordination framework via EVs. Reinforcement learning (RL) is widely applied: Zhu et al. [145] applies RS-TRPO in microgrid alliance dispatch, while Li et al. [146] integrates deep RL with graph surrogate models for robust microgrid coordination.

Cyber-physical security and resilience are also addressed. Jadidi et al. [147] and Zhou et al. [148] propose integrated control and detection mechanisms against cyber threats targeting wind farms and thermal energy systems. Similarly, Park et al. [149] develops a blockchain-based authentication scheme to secure demand response in smart grids. Multiple studies explore intelligent prediction and data-driven models. Fu et al. [150] introduces GAN-based weather simulation for power flow analysis, and M. Fathabad et al. [151] offers a robust optimization framework for renewable generation planning. Yang et al. [152] discusses long-term clean energy transitions via AI and blockchain integration, while Yang et al. [153] (EV pricing) and A. Afsher et al. [154] (PV-battery systems) highlight economic optimization strategies through multiagent systems and real-time pricing. Tran et al. [155] and Komala et al. [156] further contribute segmentation models and PINN-enhanced IoT control to enable smart infrastructure, and Liu et al. [157] combines residual deep learning with LSTM and GATs to manage noisy prediction tasks in aerodynamic environments. Collectively, these studies advance a comprehensive view of intelligent, secure, and adaptable energy system control in industrial and urban contexts.

3.10.2. Renewable Energy Planning, Deployment, and Forecasting

This category encompasses advanced strategies for planning, deploying, and forecasting renewable energy systems, with a strong emphasis on spatial optimization, predictive analytics, and technology integration. Several studies focus on optimizing the siting and deployment of photovoltaic (PV) and wind systems. Lu et al. [158] and

Tran et al. [155] introduce deep learning-based methods—PV Identifier and S3Former—for accurately detecting distributed PV installations in complex environments using high-resolution remote sensing and aerial imagery. Getie et al. [159] and Romero-Ramos et al. [160] leverage Geographic Information Systems (GIS) and decision support tools such as the Analytical Hierarchical Process (AHP) and Genetic Algorithms to identify optimal PV system allocations and green hydrogen production sites, maximizing efficiency and proximity to infrastructure. Pelda et al. [161] evaluates the integration of solar thermal and industrial waste heat in German district heating systems, showing significant potential for decarbonization by 2050.

Forecasting and predictive modeling are critical themes. Fu et al. [162] introduces GAN-based stochastic weather generators (SWG) for simulating hourly weather data to improve PV-based power flow modeling, while Medina et al. [163] enhances wind power forecasting by incorporating multi-station weather inputs into neural networks. Li et al. combines satellite thermal data with carbon emissions modeling to estimate power plant emissions with high accuracy, introducing the TACEE-Model. Saadi et al. [164] develops an ANN-based hybrid renewable energy management model, linking historical weather patterns with adaptive energy control. Similarly, Zhang [165] integrates rough set theory with deep learning for accurate thermodynamic parameter estimation in complex systems.

System-level digitalization is another focus. Alabugin et al. [166] proposes a transactional energy platform that unifies hybrid energy sources using machine-to-machine communication and IIoT principles, improving diagnostics and control. Angizeh et al. [167] presents a decision framework using mixed-integer programming and Gaussian Process Regression to evaluate the integration of energy storage systems (ESS) and offshore wind into power grids. Raza et al. [168] highlights the role of smart meters in supporting Business Intelligence (BI) for smart energy systems, emphasizing data-driven decision-making. Zhu et al. [169] provides a novel detection framework for complex power quality disturbances, crucial for maintaining system stability amid renewable integration. Finally, Abazari et al. [170] explores cyber-physical threats posed by EV-based load-altering attacks on grid stability, presenting adaptive control mechanisms that mitigate these risks.

Together, these studies contribute a comprehensive toolkit for renewable energy system deployment and operation—blending AI, GIS, forecasting, and resilience technologies to support smart, data-driven energy transitions.

3.10.3. Digital Twin and Cyber-Physical System Applications

This section highlights the diverse and evolving applications of digital twin (DT) and cyber-physical systems (CPS) in industrial energy domains, focusing on predictive maintenance, asset management, resilience, and intelligent decision support. Several studies explore how digital twins enhance real-time monitoring, simulation, and operational intelligence. Priyanka et al. [171] proposes a DT framework for oil pipelines using IoT and machine learning to predict pressure anomalies and estimate remaining useful life (RUL), thereby improving maintenance and risk control. Similarly, Fernandes et al. [172] utilizes DTs for geometric quality assurance in pipe spools, applying sensitivity analysis to forecast assembly behavior and manufacturing precision. Arraño-Vargas et al. [173] presents a modular DT framework for power systems, demonstrating its applicability in scenario analysis and renewable integration using the Australian National Electricity Market as a case study.

In industrial hydraulic systems, Yan et al. [174] introduces a knowledge graph-based method that transforms sensor data into machine-readable models to support predictive maintenance. Komala et al. [156] integrates IoT with artificial intelligence in microgrid control via a hybrid CMPA-PINN model, improving power quality and operational reliability under both islanded and grid-connected conditions. Mishra et al. [175] provides a broader review of how Industry 4.0 technologies, including CPS and DTs, are transforming the electrical utility industry, emphasizing improvements in cost, security, and efficiency.

Smart urban and energy environments are also central to this category. Zhang et al. [176] reviews DT applications in Positive Energy Districts (PEDs), outlining implementation tools and key challenges in data integration and interoperability. Qin et al. [177] proposes a Spatiotemporal Decomposition Agent (STDA) for Unbundled Smart Meters (USMs), leveraging AI to offer personalized energy strategies and building-level coordination. Zhao [178] designs a cloud-based management information system for power enterprises, incorporating 3D visualization to enhance decision-making. Collado-Mariscal et al. [179] applies BIM as a digital modeling tool to assess electrical risks from overhead power lines in construction projects, aligning with Construction 4.0 and preventive safety design principles. Marino et al. [180] bridges ICT and physical infrastructures through a virtualized cyber-physical testbed, simulating and detecting cyberattacks in wind systems. This low-cost, flexible environment supports integrated analysis of both cyber and physical behaviors, serving as a foundation for secure, data-driven industrial systems.

Collectively, these works illustrate the centrality of digital twins and CPS in enabling intelligent, integrated, and secure industrial energy systems—facilitating real-time control, predictive analytics, and resilient infrastructure management.

3.10.4. Cybersecurity, Blockchain, and Privacy in Energy Systems

This category explores the critical roles of cybersecurity, blockchain technology, and privacy-preserving mechanisms in securing modern and decentralized energy systems. As the energy sector increasingly adopts digital platforms and distributed architectures, these studies highlight both emerging threats and innovative protection strategies. Abdel-Basset et al. [181] introduces Fed-SCR, a federated semi-supervised anomaly detection framework for fog-assisted industrial smart grids. By incorporating class-rebalanced learning and federated geometric median aggregation, the model improves detection accuracy and communication efficiency in resource-constrained environments. Nasiri et al. [182] proposes a blockchain-integrated distributed state estimation (DSE) framework using consensus-based Kalman filtering and cooperative trust mechanisms, enhancing both accuracy and security in decentralized power systems. Similarly, Jogunola et al. [183] reviews the integration of blockchain consensus algorithms and deep reinforcement learning in energy trading systems (ETS), identifying synergies and proposing a combined framework to support secure and intelligent market operations.

Expanding this focus, Al-Abri et al. [184] presents a comprehensive review of blockchain's role in modern decentralized energy systems, highlighting its potential to improve transparency, fairness, and stakeholder trust in smart grids, microgrids, and distributed generation contexts. Verma et al. [185] addresses load redistribution (LR) attacks—an advanced form of false data injection (FDI)—by surveying their evolution, impact, stealth mechanisms, and current defense strategies, while identifying critical research gaps for future grid resilience.

Technical detection strategies are further refined by Mokhtari et al. [186], who develop a machine learning-based fault detection method focused on operational technology and load frequency control, achieving robust performance without relying on traditional model-based assumptions. Complementing this, Yu et al. [187] introduces a spatiotemporal sequence analysis framework for FDIA localization, accounting for the variability of renewable energy sources to enhance detection accuracy in dynamic grid environments.

Zhou et al. [188] reviews the transformative potential of quantum computing in power system analytics, from optimization and control to stability and cybersecurity. The study identifies emerging quantum algorithms and networking protocols as promising solutions to escalating computational demands and security risks. Zhao et al. [189] presents the concept of Intelligent Power Equipment (IPE), which leverages real-time sensing, data fusion, and remote communication to support situational awareness and proactive maintenance in power systems, reducing single-point vulnerabilities and improving operational security.

Finally, Park et al. [149] proposes BPPS, a blockchain-based privacy-preserving authentication scheme for secure demand response in smart grids. It ensures mutual authentication, key agreement, and resistance to cyberattacks while achieving high efficiency and real-world applicability, validated through simulations using NS3 and Ethereum testnet.

Together, these works underscore the imperative for resilient, trustworthy, and secure infrastructures in modern energy systems. They demonstrate how blockchain, artificial intelligence, federated learning, and emerging technologies can address evolving threats and support privacy, transparency, and reliability in energy management and control.

3.10.5. Energy Market Mechanisms, Trading, and Economic Models

This category focuses on the evolution of market mechanisms, trading strategies, and economic models tailored to the complexities of modern energy systems, especially under the influence of electric vehicles (EVs), renewable energy integration, and digital transformation. Li et al. [146] introduces a robust coordinated control framework for multiple microgrids with integrated heat and electricity systems. Using graph neural networks and multi-agent deep reinforcement learning, the approach enhances market participation accuracy and resilience, particularly under anomalous data and imperfect physical models.

Yang et al. [153] models competitive pricing dynamics among fast-charging stations (FCSs) within integrated power and transportation networks. Employing a multi-agent proximal policy optimization framework augmented with attention mechanisms and Bayesian inference, the study addresses uncertainties in EV user behavior and renewable energy availability, promoting fair pricing and increased efficiency in both grid and traffic systems. Rimal et al. [190] presents a comprehensive framework for cloud-based EV charging coordination. It leverages hierarchical models to balance charging demand during peak hours, supports decentralized energy trading through blockchain, and reviews enabling technologies such as digital twins, AI, and intelligent charging protocols. This positions the Internet of Vehicles (IoV) as a pivotal integration point between power infrastructure and transportation systems.

Cui et al. [139] proposes a bilevel optimization model for electricity and energy storage trading across regional integrated energy systems. Integrating 6G network slicing and shared battery energy storage, the model simultaneously maximizes individual generation unit profits and system-wide social welfare. A custom global Levenberg-Marquardt algorithm enhances convergence and reveals the significant influence of communication costs on market outcomes.

Finally, Haces-Fernandez et al. [191] develops a GIS-based framework to evaluate the economic benefits of wind energy for rural U.S. communities. By mapping tax revenue, lease income, and public funding flows, the model supports transparent stakeholder negotiations and informed decision-making, ultimately enabling more equitable renewable energy development.

Collectively, these studies reflect a strong emphasis on designing adaptive, data-driven, and multi-agent economic models to optimize energy trading, market coordination, and stakeholder benefits in increasingly complex and decentralized energy environments.

The articles are collected and classified in Table 13.

Table 13. Energy publication.

Research Category	Sub-Group	Publication
Energy	Intelligent Energy System Control and Optimization	Fathabad et al. (2020) [151] Cesari et al. (2021) [192] Zou et al. (2021) [193] Liu et al. (2022) [143] Peng et al. (2022) [140] Wu et al. (2022) [141] Mujeeb et al. (2023) [194] Park et al. (2023) [149] Jadidi et al. (2024) [147] Liu et al. (2024) [195] Yang et al. (2024) [152] Yang et al. (2024) [153] Zhu et al. (2024) [145] Afsher et al. (2025) [154] Cui et al. (2025) [139] Fu et al. (2025) [150] Gharibi et al. (2025) [142] Hui et al. (2025) [138] Komala et al. (2025) [156] Li et al. (2025) [146] Liu et al. (2025) [157] Tran et al. (2025) [155] Zhong et al. (2025) [144] Zhou et al. (2025) [148]
	Renewable Energy Planning, Deployment, and Forecasting	Getie et al. (2020) [159] Pelda et al. (2020) [161] Velazquez et al. (2020) [163] Alabugin et al. (2021) [166] Angizeh et al. (2023) [167] Raza et al. (2023) [168] Zhang (2023) [165] Li et al. (2024) [196] Lu et al. (2024) [158] Saadi et al. (2024) [164] Zhu et al. (2024) [169] Abazari et al. (2025) [170] Fu et al. (2025) [162] Romero-Ramos et al. (2025) [160]
	Digital Twin and Cyber-Physical System Applications	Fernandes et al. (2021) [172] Marino et al. (2021) [180]

Table 13. *Cont.*

Research Category	Sub-Group	Publication
Energy	Digital Twin and Cyber-Physical System Applications	Zhang et al. (2021) [176] Collado-Mariscal et al. (2022) [179] Mishra et al. (2022) [175] Priyanka et al. (2022) [171] Qin et al. (2022) [177] Zhao (2022) [178] Arrano-Vargas et al. (2023) [173] Yan et al. (2023) [174] Komala et al. (2025) [156]
	Cybersecurity, Blockchain, and Privacy in Energy Systems	Jogunola et al. (2021) [183] Al-Abri et al. (2022) [184] Zhou et al. (2022) [188] Abdel-Basset et al. (2023) [181] Park et al. (2023) [149] Mokhtari et al. (2024) [186] Nasiri et al. (2024) [182] Verma et al. (2024) [185] Yu et al. (2024) [187] Zhao et al. (2024) [189]
	Energy Market Mechanisms, Trading, and Economic Models	Haces-Fernandez (2022) [191] Rimal et al. (2022) [190] Yang et al. (2024) [153] Cui et al. (2025) [139] Li et al. (2025) [146]

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. Enterprise Architecture

As industrial systems evolve toward greater complexity and digital maturity, enterprise architecture (EA) plays a critical role in aligning technological infrastructure with organizational strategy. EA enables structured integration across diverse domains—spanning physical assets, information flows, and cyber systems—while supporting scalability, interoperability, and resilience. Recent research in industrial information integration reveals five key thematic areas within EA development: ontology and semantic integration, architectural frameworks and digital twin implementation, data management and intelligent services, enterprise platforms and coordination mechanisms, and policy-driven integration and strategic transformation.

3.11.1. Ontology and Semantic Integration in Industrial Systems

Driven by the need for semantic interoperability and standardized knowledge exchange, industrial systems are increasingly embracing ontology-based architectures. Babaei et al. [197] developed a domain ontology to integrate energy and supply chain systems, enabling multi-layered interoperability aligned with Industry 4.0. Banerjee et al. [198] tackled reconfigurability in IoT and CPS by modeling machine capabilities through ontologies, reducing manual coding and enhancing adaptability. To bridge gaps in collaborative product development, Fan et al. [199] proposed a digital twin–ontology framework for smart manufacturing, enabling lifecycle modeling and cross-enterprise asset sharing.

The foundational role of semantic standards was emphasized by Fraga et al. [200], who reviewed key tools such as OWL, Protégé, and ISO frameworks to support interoperability in global manufacturing. Guo et al. [201] introduced MDOCO, a domain-specific ontology that formalizes maintainability knowledge across the lifecycle of complex products. Enhancing device-level integration, Li et al. [202] proposed automated OPC UA-based interoperability using machine learning and knowledge graphs for protocol translation. López et al. [203] addressed the operationalization of RAMI 4.0 by building an agent-based platform for I4.0 asset integration.

The comparative evaluation by Miny et al. [204] of device description standards (OPC UA, WoT, AAS) informed strategies for effective automation integration. For knowledge reuse in maintenance systems, Polenghi et al. [205] developed the AMODO methodology, highlighting the value of existing ontology resources. Sousa et al. [206] offered an integration framework for metrology and quality management systems using IEC and ISO standards to support zero-defect manufacturing. Targeting additive manufacturing, Xiao et al. [207] proposed OntoSTEP-NC to enable digital thread continuity and structured knowledge discovery.

Production-level semantic integration was advanced by Yang et al. [208] through the InPro ontology, which organizes data using a 5M model and supports SPARQL-based querying. Addressing modern safety concerns, Zhang et al. [209] extended STPA into MSTPA with multilevel flow modeling for hazard analysis in cyber-physical systems. Holasova et al. [210] focused on OT protocol classification and IT/OT convergence issues, emphasizing the need for better datasets and ML methods. Finally, Reinpold et al. [211] drew conceptual parallels between software agents and digital twins, arguing for their integration to achieve highly autonomous manufacturing systems.

3.11.2. Architectural Frameworks and Digital Twin Implementation

The transformation of industrial enterprises demands flexible, modular, and integrated architectures—many of which are shaped by digital twin technology. Wang et al. [212] introduced Ind-OS, a collaborative architecture for Industrial Internet Platforms that unifies metadata through digital threads and modular services. Extending this, Edrisi et al. [213] proposed the EA Blueprint Pattern for constructing digital twins of organizations, offering a modular and evolution-ready architecture applied in real-world scenarios.

To support real-time performance and adaptability, Rolle et al. [214] presented a digital twin architecture using lightweight protocols and open-source tools for predictive analysis and system optimization. Bridging design and execution, Bruno et al. [215] developed a framework linking PLM and MES systems for faster, more efficient product development. Liu et al. [216] explored a service-oriented digital twin framework to enhance infrastructure maintenance, addressing interoperability and data heterogeneity challenges.

In support of microservice-based automation, Pontarolli et al. [217] implemented the MOAI architecture, which repackages industrial services as microservices to meet Industry 4.0 demands. For resilient multi-site data exchange, Park et al. [218] proposed using Apache Kafka instead of centralized ESB architectures, improving scalability and latency across smart factories. Likewise, Zhang et al. [219] offered a cloud-edge collaborative model to integrate manufacturing data and support AI model updates at the edge.

Enhancing digital communication across ecosystems, Kannisto et al. [220] designed a digital information exchange architecture based on standard data formats and consortium protocols. For AI integration in smart manufacturing, Trakadas et al. [221] proposed extending RAMI 4.0 with cross-site federation and human-in-the-loop designs to ensure secure and explainable decision-making. The potential of Metaverse platforms in enterprise design was explored by Nateghi et al. [222], who proposed a metaverse-tailored EA model validated through three virtual enterprise case studies.

Finally, Giao et al. [223] advocated for a service-oriented middleware architecture to modularize IoT systems in manufacturing, while Wei et al. [224] applied BIM and Integrated Project Delivery to industrialized residential design, demonstrating successful collaboration across lifecycle stages.

3.11.3. Data Management, Interoperability, and Intelligent Services

As industrial systems become increasingly complex and data-intensive, new models for managing data interoperability, adaptive services, and intelligent integration have emerged. Abdellatif et al. [225] addressed performance challenges in DDS-based industrial IoT by proposing an Application-Driven Network architecture that tailors network provisioning through SDN and DPI techniques. Similarly focused on efficiency, Azad et al. [226] introduced a linear mixed model approach to enhance multi-type data transmission across distributed industrial domains, supporting Level 1 and Level 2 integration in Industry 4.0 networks.

To support smart factories and production networks, Bagozi et al. [227] developed a methodology for designing cyber-physical services around a multi-perspective data model, facilitating vertical and horizontal integration through data-centric service provisioning. Tackling collaborative data mining while preserving privacy, Jiang et al. [228] proposed Industrial Federated Topic Modeling (iFTM), enabling distributed parties to train topic models without exposing raw data. Their approach incorporates novel mechanisms for heterogeneity and privacy, suited for cross-enterprise applications.

Knowledge-driven and adaptive systems were also central to several studies. Krupitzer et al. [229] offered a taxonomy of self-adaptive system design patterns, guiding the development of resilient, context-aware industrial IoT systems. Qiu et al. [230] enhanced process monitoring with a semantic reconstruction framework for multimodal data, applying dual latent constraints to extract interpretable features for fault diagnosis. In support of lightweight, interoperable data exchange, Semenov et al. [231] proposed converting traditional EXPRESS-based PDM data into JSON format, enabling better integration of CAD/CAE tools with modern PDM systems.

Finally, Yu et al. [232] tackled system heterogeneity in semiconductor manufacturing through the Bidirectional Heterogeneous Synergistic (BHS) model, which integrates subsystem-level variations using mutual information-based attention mechanisms to improve fault detection accuracy.

Together, these studies form a robust foundation for realizing intelligent, secure, and scalable data integration services across cyber-physical industrial ecosystems.

The articles are collected and classified in Table 14.

Table 14. Enterprise Architecture publication.

Research Category	Sub-Group	Publication
Enterprise Architecture	Ontology and Semantic Integration in Industrial Systems	Fraga et al. (2020) [200]
		Fan et al. (2022) [199]
		Polenghi et al. (2022) [205]
		Sousa et al. (2022) [206]
		López et al. (2023) [203]
		Miny et al. (2023) [204]
		Yang et al. (2023) [208]
		Guo et al. (2024) [201]
		Holasova et al. (2024) [210]
		Li et al. (2024) [202]
		Xiao et al. (2024) [207]
		Zhang et al. (2024) [209]
		Babaei et al. (2025) [197]
		Banerjee et al. (2025) [198]
		Reinpold et al. (2025) [211]
	Architectural Frameworks and Digital Twin Implementation	Bruno et al. (2020) [215]
		Kannisto et al. (2020) [220]
		Rolle et al. (2020) [214]
		Trakadas et al. (2020) [221]
		Wang et al. (2020) [212]
		Wei et al. (2021) [224]
		Giao et al. (2022) [223]
		Zhang et al. (2022) [219]
		Nateghi et al. (2023) [222]
		Park et al. (2023) [218]
		Pontarolli et al. (2023) [217]
		Edrisi et al. (2024) [213]
		Liu et al. (2024) [216]
	Data Management, Interoperability, and Intelligent Services	Abdellatif et al. (2020) [225]
		Krupitzer et al. (2020) [229]
		Jiang et al. (2021) [228]
		Bagozi et al. (2022) [227]
		Semenov et al. (2022) [231]
		Azad et al. (2024) [226]
		Qiu et al. (2024) [230]
		Yu et al. (2025) [232]

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. Enterprise Integration

Enterprise Integration plays a central role in aligning diverse components of industrial systems—including architecture, data, knowledge, and digital technologies—to enable seamless communication, coordination, and optimization across organizational levels. As industries evolve toward smart, data-driven, and service-oriented models, integration strategies have expanded from traditional IT alignment to include cyber-physical systems, ontologies, digital twins, and intelligent decision support. The following literature is categorized into four key areas that collectively reflect current advancements in enterprise integration: enterprise architecture and frameworks; ontology, semantics, and knowledge integration; cyber-physical systems and digital twins; and data-driven intelligence and decision support.

3.12.1. Architecture and Frameworks for Enterprise Integration

To address the growing complexity of modern industrial systems, many studies have developed enterprise-level architectural models and integration frameworks that support system-wide coordination, digital transformation, and real-time control. Banerjee et al. [198] proposed a knowledge-driven architecture to automate software configuration in IoT and CPSs using standardized ontologies and IDE-based control logic generation. Ding et al. [233] developed a digital twin–based intelligent assembly paradigm for large-scale non-standard equipment, integrating real-time simulation and commissioning to improve transparency and accuracy. Similarly, Frizziero et al. [234] introduced the IDeS methodology to accelerate customer-driven product design through cross-departmental feedback and DFSS integration.

Ghodsian et al. [235] offered a framework for integrating mobile manipulators into Industry 4.0 environments across physical, digital, and functional dimensions. Jagatheesaperumal et al. [236] explored digital twins integrated with semantic communication and Metaverse technologies, improving industrial shopfloor management through task-oriented communication.

Kamali et al. [237] proposed a structured workflow for developing 3D digital twin models in legacy environments, while Latsou et al. [238] presented a unified digital twin architecture validated in naval infrastructure monitoring. Li et al. [239] discussed collaborative manufacturing services on industrial internet platforms and introduced a 3D printing-based implementation framework. Liu et al. [240] introduced a task-centric enterprise modeling method for complex, project-type processes like shipyard hoisting, improving integration across hierarchies.

Meng et al. [241] developed a decentralized, model-based industrial network to support collaborative automation in heterogeneous environments. Monti et al. [242] framed manufacturing actors as services, allowing dynamic synthesis and task allocation based on actor properties. Strimovskaya et al. [243] applied Industrial Information Integration to the Resource Allocation Problem, offering a multidimensional approach aligned with business process management. Sukhomlinov [244] emphasized a systemic architecture for production management, integrating economic and operational functions in real time.

Van et al. [245] introduced the Energy Synchronization Platform to support demand response via a modular, multi-sided architecture that enhances interoperability across vendors. Wu et al. [246] developed a cognitive thread ontology for model traceability in MBSE, enabling structured knowledge reuse. Finally, Zhou et al. [247] focused on timing and scheduling in Distributed Integrated Modular Avionics systems using hybrid optimization methods to retain determinism and reduce reconfiguration costs.

3.12.2. Ontology, Semantics, and Knowledge Integration

In advancing industrial information integration, ontology development and semantic technologies play a pivotal role in achieving standardized knowledge representation, semantic interoperability, and intelligent system behavior. Babaei et al. [197] proposed a domain-specific ontology to unify energy and supply chain systems, enabling multi-layered interoperability and cross-domain data integration. Similarly, Guo et al. [248] introduced a complex relational network model to optimize process planning and workshop scheduling, demonstrating how semantic modeling enhances intelligent decision-making in manufacturing. Hollerer et al. [249] conducted a comprehensive review of operational technology (OT) risk management ontologies, identifying their critical role in formalizing safety and security knowledge in converged IT/OT environments.

To address inconsistency in interdisciplinary engineering models, Ji et al. [250] developed an ontology-versioning approach for intralogistics systems, facilitating conflict detection and model harmonization. Jiménez et al. [251] designed the OMSSA ontology to support maintenance strategy selection by formalizing cross-source knowledge using the Basic Formal Ontology framework. Jagatheesaperumal et al. [236] integrated semantic communication with digital twins in Metaverse applications, enabling intelligent and context-aware information exchange. Pokojski et al. [252] enhanced knowledge-based engineering by aligning UML modeling with dynamic industrial contexts, contributing to the adaptability and quality of engineering knowledge systems.

Reinpold et al. [211] conceptually linked software agents and digital twins, arguing that semantic representation supports autonomous system integration. Strimovskaya et al. [243] emphasized the centrality of information integration in complex resource allocation problems, advocating for semantically driven decision-support frameworks in volatile industrial settings. Wu et al. [246] developed a cognitive thread ontology embedded in an MBSE toolchain to formalize traceability and improve model interoperability across stakeholder domains. Zhang et al. [253] reviewed recent AI developments from an information integration standpoint, recognizing the importance of semantic foundations for intelligent industrial applications. Finally, Zhao et al. [254] introduced a motion estimation method based on expectation-maximization, embedded in the broader Industrial Information Integration Engineering framework, showing how semantic awareness improves object tracking in vision-based systems.

3.12.3. Cyber-Physical Systems, IoT, and Digital Twin Implementation

The fusion of cyber-physical systems (CPS), IoT technologies, and digital twin (DT) architectures is driving a new era of simulation-enhanced design and operational intelligence across industrial domains. Foundational work by Colli et al. [255] proposed a framework combining process excellence and business process management to scope IoT solutions aligned with operational improvement. Addressing early-phase safety analysis, Dedousis et al. [256] integrated system-theoretic methods and fuzzy logic into material and information flow modeling to reduce risk in CPS environments. Fayos et al. [257] examined the interplay between digitalization, sustainability, and channel integration in industrial SMEs, highlighting the mediating role of IoT-enabled coordination in international performance. CPS integration was further explored by Ghodsian et al. [235], who presented a four-dimensional framework for autonomous mobile manipulators within smart manufacturing settings, aligning physical, operational, and digital layers.

Jagatheesaperumal et al. [236] linked semantic communication with digital twins in a Metaverse environment, showing how CPS can achieve intelligent, task-aware coordination. Kamali et al. [237] addressed the underexplored challenge of 3D modeling for DTs in existing industrial facilities, proposing a four-phase workflow from data capture to semantic integration. Khorasani et al. [258] emphasized the synergistic impact of IoT and additive manufacturing, arguing that this convergence enhances flexibility, customization, and sustainability. From a building management perspective, Kozlovska et al. [259] examined BEMS-BIM integration and demonstrated its potential for energy-efficient industrial infrastructure through data-driven coordination.

Latsou et al. [238] proposed a unified digital twin framework that leverages ontology and agent-based modeling for continuous monitoring and simulation, validated in a naval dockyard application. At a strategic level, Liu et al. [260] introduced a three-stage model to guide the transformation from Industrial Internet to Industrial Intelligence Internet using IoT-enabled value creation. Perez-Lara et al. [261] contributed a readiness assessment tool to support organizational transitions toward Industry 4.0, emphasizing horizontal and vertical CPS integration. Sukhomlinov [244] analyzed the architecture of integrated production management systems, aligning CPS data with economic and operational enterprise functions. Complementing this, Wang et al. [262] presented a comprehensive smart factory architecture for the injection molding industry, featuring MES integration [263] and digital twin deployment to enhance transparency and responsiveness.

3.12.4. Data Integration, Decision Support, and Industrial Intelligence

Driven by the growing complexity of industrial ecosystems, recent research has increasingly focused on intelligent integration of data and decision-making mechanisms to enable informed, adaptive, and sustainable operations. [264] Bajagain et al. [265] improve automation and monitoring in power distribution systems by integrating load and PV estimation through Gaussian mixture models. Bi et al. [266] survey the technical landscape of information integration in space informatics, proposing the digital-triad (DT-II) concept. Dong et al. [267] propose value-chain integration for servitizing construction enterprises. Hu et al. [268] present a task-driven data fusion framework for additive manufacturing, enhancing multi-source decision-making.

From a strategic modeling angle, Joanna et al. [269] propose a qualitological framework for marketing information quality management, while Lu et al. [270] explore the transformative potential of quantum computing for future information integration. Ma [271] leverages neural networks to model industrial convergence trends, supporting digital economic integration. Nafei et al. [272] enhance decision-making in automation system selection by combining neutrosophic logic with VIKOR methodology. Peng et al. [273] address equipment health management by identifying integration gaps in fault prognosis systems.

Stoykova et al. [274] review the application of AI in management information systems (MIS), highlighting automation, predictive analytics, and governance gaps. Yamada et al. [275] propose an integrated product and supply chain design method for sustainability assessment. Finally, Yin et al. [276] examine the role of industrial information networks (IINs) during the COVID-19 pandemic, revealing that improving betweenness centrality in key sectors can significantly enhance information flow and systemic resilience for epidemic response and innovation.

The articles are collected and classified in Table 15.

Table 15. Enterprise Integration publication.

Research Category	Sub-Group	Publication
Enterprise Integration	Architecture and Frameworks for Enterprise Integration	Li et al. (2020) [239]
		Meng et al. (2020) [241]
		Zhou et al. (2020) [247]
		Liu et al. (2021) [240]
		Bimpizas-Pinis et al. (2022) [277]
		Fabregas et al. (2022) [278]
		Slim et al. (2022) [279]
		Ding et al. (2023) [233]
		Frizziero et al. (2023) [234]
		Ghodsian et al. (2023) [235]
		Jagatheesaperumal et al. (2023) [236]
		Strimovskaya et al. (2023) [243]
		Kamali et al. (2024) [237]
		Karakoltzidis et al. (2024) [280]
		Latsou et al. (2024) [238]
		Monti et al. (2024) [242]
		Sukhomlinov (2024) [244]
		Wu et al. (2024) [246]
		Zhang et al. (2024) [281]
		Banerjee et al. (2025) [198]
		Van et al. (2025) [245]
	Ontology, Semantics, and Knowledge Integration	Zhang et al. (2021) [253]
		Pokojski et al. (2022) [252]
		Zhao et al. (2022) [254]
		Guo et al. (2023) [248]
		Jagatheesaperumal et al. (2023) [236]
		Mantravadi et al. (2023) [263]
		Montero et al. (2023) [251]
		Strimovskaya et al. (2023) [243]
		Hollerer et al. (2024) [249]
		Wu et al. (2024) [246]
		Babaei et al. (2025) [197]
		Ji et al. (2025) [250]
	Cyber-Physical Systems, IoT, and Digital Twin Implementation	Pérez-Lara et al. (2020) [261]
		Colli et al. (2021) [255]
		Dedousis et al. (2021) [256]
		Wang et al. (2021) [262]
		Khorasani et al. (2022) [258]
		Liu et al. (2022) [260]
		Fayos et al. (2023) [257]
		Ghodsian et al. (2023) [235]
		Jagatheesaperumal et al. (2023) [236]
		Kozlovska et al. (2023) [259]
		Nakhal et al. (2023) [282]
		Kamali et al. (2024) [237]
		Latsou et al. (2024) [238]
		Saba et al. (2024) [283]
		Sukhomlinov (2024) [244]
	Data Integration, Decision Support, and Industrial Intelligence	Dong et al. (2020) [267]
		Joanna et al. (2020) [269]
		Peng et al. (2020) [273]
		Yin et al. (2020) [276]
		Bi et al. (2022) [266]
		Ma, Nan (2022) [271]
		Zhang et al. (2022) [264]
		Hu et al. (2023) [268]
		Lu et al. (2023) [270]
		Stoykova et al. (2023) [274]

Table 15. *Cont.*

Research Category	Sub-Group	Publication
Enterprise Integration	Data Integration, Decision Support, and Industrial Intelligence	Bajagain et al. (2024) [265] Jun et al. (2024) [284] Nafei et al. (2025) [272] Yamada et al. (2025) [275]

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3.13. Environment

With growing environmental challenges ranging from pollution and land degradation to resource scarcity and climate vulnerability, industrial information integration has emerged as a critical enabler for sustainable environmental management. The reviewed literature demonstrates how advanced data analytics, sensor networks, geospatial technologies, and intelligent systems are being integrated to support real-time monitoring, predictive modeling, decision support, and ecological planning. These works collectively highlight the transformative role of digital technologies in addressing complex environmental issues across air, water, soil, and ecosystem domains.

3.13.1. Environmental Monitoring Systems and Sensor Integration

Environmental monitoring systems are undergoing rapid advancement through the integration of IoT technologies, sensor networks, and intelligent data platforms to support real-time and continuous assessment of ecological conditions. Nair et al. [285] introduced the Water Quality Nowcasting System (WQNS), combining satellite and buoy-based sensors for dynamic monitoring of Indian coastal waters. Similarly, Yang et al. [286] developed a cloud-based acoustic telemetry system that utilizes edge computing for low-power, real-time underwater environmental observation. Quevy et al. [287] contributed an open-source smart buoy system equipped with lab-grade sensors to continuously monitor aquatic environments with minimal ecosystem disturbance.

For terrestrial air and pollution monitoring, Kristiani et al. [288] proposed the iSEC cloud-edge architecture to support low-latency ML/DL applications, while Samuel et al. [289] combined YOLOv5 with large language models on Raspberry Pi to detect and explain water pollutants in real time. Chen et al. [290] adopted a user-centered design process for IoT environmental services, leading to refined prototypes for wastewater and household monitoring based on stakeholder feedback.

IoT-enabled integration was further emphasized in Bandara et al. [291], who reviewed GNSS-supported location-based services for urban water quality monitoring. Mutunga et al. [292] explored the potential of emerging technologies like electrochemical sensors, IoT, and ML to enhance pesticide detection in water systems. Gorka-Kostrubiec et al. [293] presented a method for using magnetic susceptibility (κ) as a proxy to track airborne iron-rich particulate matter, establishing protocols for integration into routine air quality monitoring. Amri et al. [294] developed a deep learning model using Sentinel-1 SAR and contextual data for detecting oceanic oil slicks with improved accuracy. Finally, Manikandan et al. [295] reviewed AI's growing role in optimizing carbon capture technologies, from failure detection to system control, thereby reinforcing AI's value in sustainability-driven monitoring systems. Together, these studies illustrate a growing convergence of sensor integration, intelligent computing, and real-time data analytics in environmental information systems.

3.13.2. Air and Water Pollution Modeling and Prediction

Air and water pollution modeling is increasingly leveraging machine learning, deep learning, and geospatial data integration to improve the accuracy, timeliness, and spatial resolution of environmental predictions. Zaman et al. [296] developed a machine learning framework—using Random Forest, SVR, and XGBoost—to estimate PM2.5 concentrations across Malaysia from satellite-derived data, demonstrating high predictive accuracy except in cloudy or monsoon conditions. Lu et al. [297] advanced PM2.5 prediction with a novel DSFA-LSTM-CBAM hybrid model, addressing nonlinearity and time lag issues in indoor air quality and achieving significant improvements over conventional LSTM-based models.

Focusing on carbon monoxide (CO) in congested urban areas, Etemadfard et al. [298] used artificial neural networks in combination with GIS layers such as traffic, land use, and meteorology to predict CO concentrations in Baghdad, achieving 79% model accuracy. For methane detection, Radman et al. [299] proposed a deep learning method based on Sentinel-2 data, combining realistic synthetic plumes and noise to train EfficientNet-V2L, which outperformed both traditional physical models and earlier learning-based methods in accuracy and generalizability.

At the operational level, Li et al. [300] presented a hybrid optimization and decision-support system for wastewater treatment plants using self-organizing soft sensors and a dynamic multi-objective immune algorithm to balance pollutant reduction and energy efficiency. Complementing this, Polizzi et al. [301] developed a continuous titrimeter and integrated it into plant-wide process modeling to optimize nitrification and reduce energy use in real-time. Lastly, Chakrabortty et al. [302] proposed an integrated Urban Environmental Quality (UEQ) index for Mumbai by combining air pollution, noise, green cover, and demographic data in a geospatial multicriteria framework. Together, these studies showcase how advanced modeling techniques can enhance pollution prediction and inform real-time, sustainable decision-making in complex urban and industrial contexts.

3.13.3. Land Use, Waste Management, and Contamination Analysis

Land use planning, waste management, and contamination analysis are critical areas of environmental information integration, where geospatial modeling, digital technologies, and multi-criteria decision methods play vital roles in supporting sustainable development. Several studies focused on optimizing landfill site selection through integrated GIS-based frameworks. Nguyen et al. [303] combined GIS with the Analytical Hierarchy Process (AHP) to incorporate geologic and environmental criteria for landfill siting in delta regions, producing a robust Land Suitability Index. Similarly, Sadhasivam et al. [304] used fuzzy AHP to identify suitable solid waste landfill zones in Tiruchirappalli district, classifying 40.7% of the area as highly suitable. Sinha [305] applied a GIS-TOPSIS approach for landfill prioritization in Patna City, enabling transparent, multi-factor decision-making in urban waste management.

For hazardous waste, Wu et al. [306] and Wang et al. [307] proposed a digital twin–based decision system to optimize multiunit operations in dynamic environments and conducted an environmental impact post-assessment of a hazardous landfill, validating risk mitigation strategies. Feng et al. [308] addressed environmental risks from tailing ponds by enhancing the DeepLabv3+ segmentation model with attention modules, improving classification accuracy in remote sensing images for industrial site monitoring.

Contamination and visualization were advanced by Tang et al. [309], who integrated high-density ERT and hydrogeological data to construct a 3D model of heavy metal pollution (Pb, Zn, As, Cd) at legacy industrial sites, providing a clear spatial understanding of contaminant pathways. Zhang et al. [310] developed a 5G-enabled intelligent data collection vehicle for remote pollution sites, enhancing real-time environmental monitoring in hazardous or inaccessible areas. Lastly, Yin et al. [276] applied gravity models and social network analysis to assess the structure of industrial information networks (IIN) during the COVID-19 pandemic, identifying how weak bidirectional information flows and sparse connectivity impaired environmental response, and highlighting the need to strengthen sectoral betweenness centrality for sustainable epidemic prevention. Together, these studies offer practical, scalable frameworks for integrating environmental risks into land use and waste management decisions.

3.13.4. Groundwater and Ecosystem Sustainability Modeling

Groundwater and ecosystem sustainability modeling has emerged as a vital area within environmental information integration, leveraging geospatial analysis, machine learning, and climate forecasting to support sustainable resource planning. Bulbula et al. [311] combined GIS, remote sensing, and the Analytic Hierarchy Process (AHP) to delineate groundwater potential and recharge zones in Ethiopia's Melka Kunture Watershed, producing validated and actionable maps for groundwater resource management. Similarly, Amponsah et al. [312] integrated nine geophysical and hydrological data layers using a fuzzy AHP (FAHP) model in Ghana's Voltaian basin, resulting in a highly accurate classification of groundwater zones, with validation metrics (NSE = 0.9996, IoA = 0.9999) confirming the model's reliability.

Saro et al. [313] conducted a systematic review of groundwater mapping techniques from 2015–2020, emphasizing the growing adoption of machine learning methods (e.g., random forest, SVM, boosting) in India, Iran, and China. The review highlighted that while these tools enhance precision, they should complement—rather than replace—traditional field investigations. In the context of deltaic ecosystems, Elmorsi et al. [314] demonstrated the effective use of Landsat satellite imagery and TRIX and Carlson indices to assess the trophic status of Suez Bay. Their integration of remote sensing with water quality metrics revealed eutrophic conditions and established a reliable method for coastal monitoring.

On the broader climate scale, Wang et al. [315] introduced Kernel Analog Forecasting (KAF), a nonlinear machine learning approach that significantly extended the lead time and accuracy of El Niño–Southern Oscillation (ENSO) predictions compared to linear benchmarks, offering vital foresight for ecosystem and agricultural planning. Lastly, Kaiser et al. [316] developed the SIRIUS inventory, a harmonized geospatial dataset mapping infrastructure across Alaska's rapidly thawing permafrost regions. By linking permafrost degradation with human infrastructure vulnerability, this work supports ecological risk assessment and sustainable adaptation strategies in Arctic environments. Collectively, these studies exemplify the critical role of integrated modeling in conserving groundwater and sustaining fragile ecosystems under climate pressure.

The articles are collected and classified in Table 16.

Table 16. Environment publication.

Research Category	Sub-Group	Publication
Environment	Environmental Monitoring Systems and Sensor Integration	Kristiani et al. (2021) [288]
		Amri et al. (2022) [294]
		Chen et al. (2022) [290]
		Yang et al. (2022) [286]
		Górka-Kostrubiec et al. (2023) [293]
		Quevy et al. (2023) [287]
		Balakrishnan et al. (2024) [285]
		Mutunga et al. (2024) [292]
		Samuel et al. (2024) [289]
		Bandara et al. (2025) [291]
		Manikandan et al. (2025) [295]
	Air and Water Pollution Modeling and Prediction	Etemadfard et al. (2021) [298]
		Li et al. (2021) [300]
		Polizzi et al. (2022) [301]
		Radman et al. (2023) [299]
		Lu et al. (2024) [297]
		Zaman et al. (2024) [296]
		Chakrabortty et al. (2025) [302]
	Land Use, Waste Management, and Contamination Analysis	Sadhasivam et al. (2020) [304]
		Zhang et al. (2021) [310]
		Nguyen et al. (2022) [303]
		Wu et al. (2022) [306]
		Tang et al. (2023) [309]
		Sinha, Subha (2024) [305]
		Wang et al. (2024) [307]
		Feng et al. (2025) [308]
	Groundwater and Ecosystem Sustainability Modeling	Saro et al. (2020) [313]
		Wang et al. (2020) [315]
		Elmorsi et al. (2021) [314]
		Amponsah et al. (2022) [312]
		Bulbula et al. (2024) [311]
		Kaiser et al. (2024) [316]

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. Facility

Infrastructure facilities such as water distribution systems present persistent operational challenges, particularly in areas like leak detection, which is critical for resource conservation and cost control. To address this, the study proposes an innovative integration of optical networks with water infrastructure to enable efficient leak identification. By embedding fiber-optic cables capable of detecting vibrations along water pipelines, the system uses intelligent algorithms to not only localize leaks with high precision—including those with minimal flow rates down to 0.027 L/s—but also assess their severity to prioritize maintenance actions. This approach represents a cost-effective, scalable method to improve real-time monitoring, enhance water resource management, and elevate operational efficiency in facility management through industrial information integration technologies.

The articles are collected in Table 17.

Table 17. Facility publication.

Research Category	Publication
Facility	Wu et al. (2024) [317]

3.15. Finance

In recent years, the integration of blockchain and Internet of Things (IoT) technologies has shown transformative potential in reshaping financial systems and accounting practices within industrial contexts. Liu et al. [318] conduct a comprehensive bibliometric analysis of 1,414 academic papers to map the emerging knowledge system of blockchain in accounting. Their findings highlight blockchain's role in enhancing transparency, traceability, and automation—particularly through smart contracts and AI integration—suggesting that workloads in financial recordkeeping could be halved through these innovations. Li et al. [319] review AI applications in finance, highlighting supervised and deep learning techniques primarily used in financial forecasting, protection, and decision-making. From a global finance and risk management perspective, Yen et al. [320] present an IoT-driven sensing framework that applies large-scale treasury bill data to forecast credit default risks and estimate credit default swap (CDS) spreads. Their results confirm that IoT-enabled data collection significantly correlates with key macroeconomic indicators, offering a proactive approach to international credit risk prediction. Collectively, these studies underscore how industrial information integration via blockchain and IoT can support intelligent, adaptive, and secure financial infrastructures aligned with dynamic industrial ecosystems.

The articles are collected in Table 18.

Table 18. Finance publication.

Research Category	Publication
Finance	Yen et al. (2021) [320] Li et al. (2023) [319] Liu et al. (2024) [318]

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.

3.16. Food Industry

With growing public concern about food safety and environmental impacts, the role of industrial information integration in food traceability systems has gained increasing importance. Lei et al. [321] emphasize that food safety is not solely dependent on the physical quality of food but also on the integrity, privacy, and reliability of food-related information. To address these challenges, the paper presents a systematic review focused on the integration of Privacy Preservation (PP) technologies into food traceability systems—a relatively underexplored area. The study identifies key technological enablers such as the Internet of Things (IoT), Artificial Intelligence (AI), Blockchain (BC), and PP, highlighting their roles in enhancing data collection, monitoring, decision-making, and secure information exchange across the food supply chain. It systematically analyzes the security needs at each stage of data flow in the traceability process and explores how the integration of PP technologies can mitigate privacy breaches while boosting trust and efficiency. Additionally, the paper discusses the limitations of current systems and offers insights into potential advancements in multi-technology integration to strengthen food safety governance and decision support.

The articles are collected in Table 19.

Table 19. Food Industry publication.

Research Category	Publication
Food Industry	Lei et al. (2022) [321]

3.17. Geology

In the field of geology, industrial information integration plays a pivotal role in advancing subsurface analysis, resource exploration, geohazard monitoring, and land management through digital technologies. The integration of machine learning, remote sensing, geophysical modeling, and intelligent systems enables more accurate, efficient, and collaborative geological decision-making.

To address geological hazards, particularly landslides, several studies highlight the fusion of deep learning and remote sensing. Li et al. [322] enhance landslide detection in the Three Gorges Reservoir Area using shipborne photogrammetry and transfer learning-based CNN models, offering improved accuracy in classifying small-slope events. Similarly, Tomás et al. [323] apply high-resolution SAR interferometry and geomorphological mapping to monitor an active landslide in Spain, supporting municipal risk mitigation. For in situ loess investigations, Li et al. [324] present an adaptive robotic platform capable of capturing high-fidelity borehole imagery for structural assessment, advancing digital geological diagnostics.

In hydrocarbon and subsurface resource exploration, Hu et al. [325] propose a federated learning-based data framework to securely integrate IIoT datasets from multiple stakeholders, improving neural network-based reservoir prediction in karst stratigraphy. Complementing this, Luo et al. [326] introduce a high-resolution well-seismic integration technique for evaluating tight gas sandstones, significantly refining stratigraphic alignment and subsurface imaging in the Luodai Gas Field.

Geospatial technologies are further leveraged for groundwater and landform modeling. Oguntoyinbo et al. [327] combine GIS and vertical electrical sounding to map groundwater potential in Nigeria, while Pérez-Hernández et al. [328] analyze over a century of coastal landform loss in Spain, using GIS to document 83.2% urban encroachment—informing heritage and planning efforts.

On the frontier of geotechnical innovation, Firoozi et al. [329] explore how Fourth Industrial Revolution (4IR) technologies like AI, IoT, and robotics are reshaping geotechnical engineering, emphasizing interdisciplinary collaboration, data ethics, and policy reform. Meanwhile, Huang et al. [330] propose a hybrid ResNet-50 and k-means clustering framework for rural land suitability assessment, supporting industrial diversification and rural development planning.

Together, these contributions illustrate how the convergence of intelligent technologies and geoinformatics fosters more secure, responsive, and sustainable geological practices.

The articles are collected in Table 20.

Table 20. Geology publication.

Research Category	Publication
Geology	Perez-Hernandez et al. (2020) [328]
	Huang et al. (2023) [330]
	Li et al. (2023) [322]
	Tomas et al. (2023) [323]
	Hu et al. (2024) [325]
	Luo et al. (2024) [326]
	Oguntoyinbo et al. (2024) [327]
	Firoozi et al. (2025) [329]
	Li et al. (2025) [324]

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.

3.18. Healthcare

Healthcare represents one of the most dynamic and critical domains for industrial information integration, driven by the need for secure, efficient, and personalized medical services. As digital technologies like IoT, AI, blockchain, and federated learning converge with biomedical engineering and health information systems, new frameworks are emerging to enhance clinical decision-making, data interoperability, patient monitoring, and healthcare delivery. This section categorizes and synthesizes recent advances across four thematic areas—healthcare infrastructure and systems integration, secure data management, intelligent diagnostics, and wearable health technologies—to showcase how industrial information integration is transforming the healthcare landscape.

3.18.1. Industrial Healthcare Infrastructure, Systems Integration, and Information Architecture

The transformation of healthcare infrastructure through digital integration has been a focal point across recent literature. Digital health ecosystems now incorporate Electronic Health Records (EHRs), Industrial Internet of Things (IIoT), and data governance frameworks to improve service efficiency and patient care. For instance, Ganasegeran et al. [331] emphasized GIS-enhanced public health policy planning based on neighborhood-level data, while He et al. [332] proposed a collaborative cloud-based model to optimize medical supply chain coordination under industrial interconnection. Uysal [333] advanced the field by applying Industrial Information Integration Engineering (IIIE) principles to hospital healthcare information systems (HEIS), identifying integration pain points and offering an enterprise integration framework. The role of big data in healthcare transformation is reviewed by Karatas et al. [334], highlighting the convergence of Industry 4.0 technologies in resource management and clinical processes. At the hardware level, Fang et al. [335] introduced a Ku-band FMCW radar platform for privacy-preserving health monitoring. Platform-centric approaches are illustrated by Lee et al. [336] with the Lifelog Bigdata Platform, enabling standardized lifelog and clinical data fusion, and Li [337], who assessed post-HITECH Act EHR adoption trends across U.S. institutions, noting reduced institutional gaps through digital integration. Fu et al. [338] propose a framework showing that Healthcare Information Systems (HIS) improve hospital performance by increasing both costs and revenues, with greater revenue gains. In Korea, Ha et al. [339] reviewed MyHealthWay's attempt to unify medical data while underscoring challenges in standardization and regulation.

Further advancing system architectures, Malik et al. [340] proposed a three-layer IIoT framework for Structural Health Monitoring, while Epizitone [341] examined Health Information Systems' (HIS) readiness for industrial transformation, advocating resilience in digital healthcare. On the frontier of patient empowerment, Kim et al. [342] proposed a blockchain-based Personal Health Record (PHR) platform to ensure patient ownership and secure interoperability. Gómez-Bocanegra et al. [343] discussed blockchain's role in transforming breast healthcare through improved transparency and interoperability, though ethical and digital divide concerns remain. Disease-specific advances include Liu et al. [344], who developed an AI-driven X-ray system for skeletal fluorosis diagnosis, and Guo et al. [345], who proposed a fog-based cryptographic system for real-time, privacy-preserving body area network processing. Complementing these, Ge et al. [346] introduced a keyword-searchable EMR encryption scheme balancing usability and data confidentiality. Al-Turjman et al. [347] contributed an identity-based public auditing model for cloud-based cyber-physical systems, supporting secure outsourcing and integrity verification. Finally, Kumar et al. [348] presented a Blockchain 3.0-enabled smart healthcare architecture incorporating IoT, AI, and smart contracts, emphasizing scalability and efficiency. Together, these studies highlight how digital integration, system interoperability, and secure data infrastructure are reshaping the foundations of modern healthcare systems.

3.18.2. Privacy, Security, and Blockchain in Healthcare Data Management

Ensuring data privacy, security, and integrity has become a cornerstone of industrial information integration in healthcare, particularly with the rise of blockchain, federated learning, and encryption-based systems. Das et al. [349] proposed a blockchain-enabled intelligent healthcare system powered by federated matrix meta-learning (MGN), combining data privacy with adaptive AI for personalized healthcare. Similarly, Khan et al. [350] introduced a blockchain and IIoT-based architecture, integrating advanced encryption and wireless sensor network optimization to ensure real-time patient data protection. Khan et al. [351] developed the Deep Collaborative Alert system using knowledge graphs and real-time COVID-19 data, demonstrating how federated knowledge models can support secure and personalized healthcare alerts. Enhancing network security, Adil et al. [352] proposed HOPCTP, a time-triggered, multi-channel protocol for Industrial Healthcare IoT (IHC-IoT) systems that safeguards against interception and ensures data resilience.

Privacy-preserving data access in wearable healthcare was addressed by S. Rajput et al. [353] through polymorphic encryption and secure transcryptor protocols. On a broader scale, Stephanie et al. [354] combined secure multiparty computation and federated learning within a blockchain-enabled Healthcare 4.0 framework, eliminating the need for centralized AI training. Wang et al. [355] further advanced federated learning by applying differential privacy and variational autoencoders in a disease diagnosis system for the Internet of Medical Things (IoMT), achieving robust protection against inference attacks. Gu et al. [356] found that undergraduate students overestimate their online health information literacy, scoring 65% accuracy in COVID-19 information searches.

Meanwhile, Reddi et al. [357] presented a secure EMR sharing system using fully homomorphic encryption (CKKS-FHE) integrated with the IOTA Tangle, highlighting end-to-end protection in patient-doctor communication. At the architectural level, Gao et al. [358] proposed a blockchain-integrated IoMT system with trusted execution environments (Intel SGX) to securely authenticate devices and analyze encrypted data. Expanding this vision, Ghayvat et al. [359] developed a decentralized sharing technique for cyber twin (CT) data using blockchain and Solid PoD, enabling transparent and resilient healthcare record management. Dhingra et al. [360] offered a systematic review on blockchain applications across EHRs, insurance, and supply chains, identifying theoretical dominance and the need for empirical validation. In a similar vein, Kim et al. [361] applied reinforcement learning to optimize Parkinson's medication through secure multimodal data integration. Finally, Jeon et al. [362] proposed a link prediction framework leveraging blockchain to reposition digital therapeutics

(DTx) by analyzing disorder networks, thereby facilitating secure, knowledge-driven health innovation. Collectively, these works underscore the growing maturity of privacy-preserving frameworks in healthcare and their critical role in enabling trustworthy and secure information systems.

3.18.3. AI and Big Data Applications in Diagnosis and Personalized Medicine

Artificial intelligence and big data analytics are playing transformative roles in advancing diagnostic accuracy, treatment personalization, and predictive healthcare modeling. Sagdic et al. [363] reviewed the integration of AI with smart materials in biomedical systems, illustrating applications in biosensors and drug design. Guedj et al. [364] described how high-throughput AI computing platforms enhance pharmaceutical R&D, especially in immunology and oncology. Supporting neurodegenerative disease diagnostics, Tanveer et al. [365] demonstrated how fuzzy deep learning improves Alzheimer's diagnosis through explainable multimodal data fusion, while Q. Wu et al. [366] proposed HMS-based brain wave indicators and a warped Gaussian mixture model to assess dementia severity. In the realm of surgical guidance, Tai et al. [367] introduced an AR-based lung biopsy navigation system with deep learning models for real-time, patient-specific assistance. Similarly, Nie et al. [368] reviewed AI advancements in automated melanoma detection using dermoscopic images.

Ethical and practical implications of large-scale AI models were explored by F. Du et al. [369], who analyzed foundation models in computational pathology and highlighted key concerns including algorithmic bias and hallucination. Meanwhile, A. Siddique et al. [370] introduced a federated learning framework for privacy-preserving pneumonia diagnosis. The application of digital twins in healthcare was critically reviewed by D. Xames et al. [371], revealing gaps in integration and implementation despite strong potential. For predictive maintenance and health monitoring, Deng et al. [372] proposed a self-supervised model for RUL estimation, and Wang et al. [98] developed a cyber-physical framework to improve pharmaceutical quality control using adaptive learning.

Personalized treatment planning was addressed by Palmal et al. [373], who combined multimodal data and graph contrastive learning to predict breast cancer survival, and Chen et al. [374], who introduced a deep radio sensing technique to monitor vital signs using ambient WiFi signals. In chronic care management, Zhang et al. [375] built an IoT and ML-based framework for remote heart disease risk assessment. From a broader perspective, Kotzias et al. [376] mapped the technological landscape of Healthcare 4.0, highlighting the role of big data, IoT, and cloud computing in diagnosis and monitoring. Assistive applications were developed by Son et al. [377], who proposed a real-time outdoor navigation system for the visually impaired using lightweight AI models. In pharmaceutical manufacturing, Privitera et al. [378] improved dosing precision via adaptive time-series models. Lastly, Kavasidis et al. [379] integrated multi-blockchain and federated learning for secure AI model training in regulated pharmaceutical environments. Together, these studies underscore how AI and big data are driving personalized, predictive, and secure transformation across modern healthcare.

3.18.4. Smart Healthcare Devices, Sensors, and Wearables

Smart healthcare devices, sensors, and wearables are reshaping how health data is captured, transmitted, and utilized, enabling continuous, real-time monitoring and improving patient engagement and clinical outcomes. Gaikwad et al. [380] reviewed the evolution of wireless body area networks (WBANs), highlighting their utility in physiological monitoring and rehabilitation while emphasizing the ongoing challenges in privacy, security, and system dependability. Dobson et al. [381] review the benefits of wearable devices for health tracking, emphasizing continuous, low-burden data collection. Fawad et al. [382] proposed an integrated structural health monitoring (SHM) framework using IoT, BIM, AI, and AR technologies to visualize infrastructure health data through digital twins and AR interfaces. Complementing this, R. Iman et al. [383] introduced a smart textile system embedded with LoRa-enabled sensors for remote heart rate and temperature monitoring, demonstrating robust signal transmission in indoor and outdoor settings.

From a large-scale infrastructure perspective, Gigli et al. [384] presented MAC4PRO, a sensor-to-cloud SHM platform that significantly reduces data transmission volume while maintaining high sensitivity for industrial and civil monitoring. In the domain of aerial healthcare logistics, Yazdannik et al. [385] developed an advanced quadrotor UAV stabilization method using feedforward-PID control, ensuring precise delivery of medical payloads in dynamic conditions. For assistive rehabilitation, Wang et al. [386] designed a digital twin-based automatic gait data control system to enhance interaction between patients and lower-limb exoskeletons. Lastly, Son et al. [377] developed a lightweight, vision-enhanced outdoor navigation system for visually impaired individuals, integrating semantic segmentation and depth mapping for real-time environmental awareness. Collectively, these studies exemplify how advanced sensor systems and wearables are revolutionizing healthcare delivery by increasing autonomy, safety, and accessibility.

The articles are collected and classified in Table 21.

Table 21. Healthcare publication.

Research Category	Sub-Group	Publication
Healthcare	Industrial Healthcare Infrastructure, Systems Integration, and Information Architecture	Kumar et al. (2020) [348] Malik et al. (2020) [340] Guo et al. (2021) [345] He et al. (2021) [332] Liu et al. (2021) [344] Al-Turjman et al. (2022) [347] Epizitone (2022) [341] Fu et al. (2022) [338] Ge et al. (2022) [346] Karatas et al. (2022) [334] Lee et al. (2022) [336] Uysal, Murat Pasa (2022) [333] Fang et al. (2023) [335] Ganasegeran et al. (2024) [331] Ha et al. (2024) [339] Kim et al. (2024) [342] Gómez-Bocanegra et al. (2025) [343] Li (2025) [337]
	Privacy, Security, and Blockchain in Healthcare Data Management	Gao et al. (2021) [358] Adil et al. (2022) [352] Khan et al. (2022) [351] Rajput et al. (2022) [353] Jeon et al. (2023) [362] Khan et al. (2023) [350] Stephanie et al. (2023) [354] Wang et al. (2023) [355] Dhingra et al. (2024) [360] Ghayvat et al. (2024) [359] Gu et al. (2024) [356] Kim et al. (2021) [361] Reddi et al. (2024) [357] Das et al. (2025) [349]
	AI and Big Data Applications in Diagnosis and Personalized Medicine	Chen et al. (2020) [374] Tai et al. (2021) [367] Guedj et al. (2022) [364] Nie et al. (2022) [368] Sagdic et al. (2022) [363] Wu et al. (2022) [366] Zhang et al. (2022) [375] Kavasidis et al. (2023) [379] Kotzias et al. (2023) [376] Privitera et al. (2023) [378] Deng et al. (2024) [372] Palmal et al. (2024) [373] Siddique et al. (2024) [370] Tanveer et al. (2024) [365] Wang et al. (2024) [387] Xames et al. (2024) [371] Du et al. (2025) [369] Son et al. (2025) [377]
	Smart Healthcare Devices, Sensors, and Wearables	Dobson et al. (2023) [381] Gaikwad et al. (2023) [380] Wang et al. (2023) [386] Fawad et al. (2024) [382] Gigli et al. (2024) [384] Iman et al. (2024) [383] Putra et al. (2024) [388] Yazdannik et al. (2024) [385] Son 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.

3.19. Industrial Control

The rapid evolution of industrial environments under Industry 4.0 and 5.0 has redefined control systems, demanding more intelligent, flexible, and integrated approaches. Modern industrial control extends beyond traditional automation to embrace cyber-physical systems, collaborative robotics, machine learning, and real-time data-driven decision-making. This section reviews recent advances in industrial information integration as applied to control systems, highlighting key themes such as human-robot collaboration, fault diagnosis, digital twins, machine vision, and safety-enhancing monitoring technologies.

3.19.1. Human-Robot Collaboration and Cognitive Interaction

Human-robot collaboration (HRC) in industrial control has evolved significantly with the integration of cognitive interaction models, tactile sensing, and advanced perception systems. Li et al. [389] establish a foundational paradigm for proactive HRC by enabling mutual understanding, predictive cooperation, and self-organized task distribution between humans and robots through cognitive computing and IIoT technologies. Enhancing perception in dynamic environments, Yang et al. [390] propose the ATD-GCN framework that combines tree-decomposition and hierarchical attention to accurately recognize human activities, improving robots' interpretive capabilities in collaborative manufacturing. Further supporting precise interaction, Yang et al. [391] present a human-machine fusion system using multi-sensor data and predictive control to ensure responsive and safe collaboration. In environments where visual cues are obstructed, Wang et al. [392] offer a vision-free robotic assembly strategy based on force/torque feedback, emulating human tactile behavior to ensure reliable connector insertion. Extending robotic dexterity, Aslam et al. [393] introduce DartBot, a system that leverages high-resolution tactile sensing and reinforcement learning to achieve accurate throwing of deformable objects in real-world conditions. Addressing the broader operational context, Grigore et al. [394] investigate collaborative robotic mobility in hazardous settings using multi-agent systems, revealing both promise and challenges due to the absence of unified analytical frameworks. Collectively, these studies demonstrate the increasing sophistication and safety of HRC systems, making them integral to smart and adaptive industrial environments.

3.19.2. Intelligent Fault Diagnosis and Process Control

Advancements in intelligent fault diagnosis and process control have become central to enhancing operational efficiency and resilience in industrial control systems. Dai et al. [395] propose an automatic model generation method based on IEC 61499 and OPC UA standards, enabling seamless cloud-edge collaboration and closed-loop optimization through flexible model transformations. Addressing the challenge of dynamic fault monitoring, Hu et al. [396] introduce the Joint Time-Serial Variation Analysis (JTSVA) method, which effectively extracts dynamic latent variables from time-series data to improve fault detection and reduce false alarms. Baek [397] extends this line of work by presenting a machine learning-driven fault recovery system that utilizes real-time sensor data for automated process adjustment, significantly minimizing downtime in complex manufacturing. Korodi et al. [398] apply predictive maintenance concepts using a decentralized LSTM-based historian in a wastewater treatment plant, achieving accurate forecasting of equipment failures and process parameters. Complementing these innovations, Liu et al. [399] investigate the security-performance trade-offs of deep reinforcement learning (DRL) in IIoT control systems, revealing heightened vulnerability to inverse reinforcement learning attacks as controller accuracy improves. Finally, Wang et al. [392] enhance mechanical fault diagnostics by integrating variational autoencoders with CNNs, producing robust and noise-tolerant models for rolling bearing fault identification. Together, these studies highlight the growing integration of AI, standardization, and security in building resilient and intelligent industrial control environments.

3.19.3. Robotics and Control System Integration

Robotics and control system integration is evolving toward more immersive, intelligent, and simulation-supported frameworks to improve precision and adaptability in industrial environments. Hu et al. [396] propose a Petri nets-based digital twin (DT) framework for dual-arm robotic systems, combining discrete event simulation with 3D modeling to manage the hybrid and complex nature of cyber-physical systems. In a complementary exploration, Kuts et al. [400] evaluate the usability and effectiveness of DT interfaces using virtual reality (VR), comparing them against conventional teach pendants for industrial robot control. Their findings show comparable performance, with DT-VR interfaces offering potential for enhanced interaction despite increased stress levels. Sartaj et al. [401] shift focus to avionics, introducing a model-based approach for automated testing of Cockpit Display Systems (CDS), demonstrating robust test generation and fault detection capabilities through domain-specific UML profiling. Elser et al. [402] address integration challenges in computerized numerical control (CNC) systems by analyzing the complexity of embedding process-level information into machine dynamics, offering insights for improving interaction fidelity in automated manufacturing. Santhosh et al. [403] contribute to process optimization through the integration of machine learning, virtual experimentation, and trajectory analysis in robot-assisted industrial painting, achieving superior surface quality and defect detection. Collectively, these studies demonstrate a growing emphasis on the integration of digital modeling, hybrid control logic, and immersive interfaces for next-generation robotic and automated systems.

3.19.4. Machine Vision, Quality Inspection, and Defect Detection

Machine vision technologies are playing an increasingly critical role in industrial quality inspection and defect detection, enabling more accurate, real-time, and automated analysis of manufacturing outputs. Mirbod et al. [404] propose a machine vision-based model for recognizing industrial part changes, designed to enhance online quality control and monitor critical component wear—such as in train wheels or brake discs—beyond the capabilities of traditional visual or sensor-based methods. Zhang et al. [405] introduce LGGFormer, a dual-branch architecture combining convolutional neural networks (CNNs) and Transformers, which leverages local-guided global self-attention and edge-aware decoding to accurately detect surface defects in manufacturing settings, particularly small or low-contrast anomalies. Similarly focused on precision and efficiency, Fu et al. [406] present a lightweight CNN model for high-precision inspection of USB component defects. Their system, built on SqueezeNet with progressive feature fusion and deep supervision, delivers robust real-time performance, supported by a custom dataset containing five specific defect types. Shen et al. [16] propose a context-awareness framework for spacecraft reactive planning that detects unexpected situations via event evolution analysis to enhance operational resilience. These works collectively underscore the value of integrating deep learning and vision-based systems for industrial defect detection, offering scalable solutions for smarter, more autonomous quality assurance processes.

3.19.5. Intelligent Monitoring, UAV, and Integrated Safety Systems

Intelligent monitoring and safety systems are increasingly essential in industrial control environments, where the integration of UAVs, sensor networks, and smart algorithms can enhance situational awareness and resilience. Yang et al. [407] develop an Intelligent Environmental Monitoring System (IEMS) designed for industrial safety and disaster prevention, combining sensor networks, centralized data management, and user interfaces to detect real-time threats such as gas leaks or fires. Gu et al. [408] propose an advanced UAV path planning algorithm, IRIME, that introduces biologically inspired mechanisms—such as frost crystal diffusion and lattice weaving—to optimize flight trajectories in complex urban environments, supporting industrial data collection and monitoring. In the realm of robotic navigation, Li et al. [409] enhance visual SLAM (vSLAM) performance under dynamic, unstructured conditions by fusing multi-modal semantic information to detect and filter moving objects in real time, thereby improving localization accuracy and robustness. Complementing these efforts, Zheng et al. [410] present the Process-Oriented and Coalescent Analysis (POCA) framework, which integrates functional safety and cybersecurity risk analysis in cyber-physical systems, with a case study on railway signal systems. Collectively, these works highlight the convergence of intelligent sensing, mobility, and safety analytics in advancing industrial system robustness and operational integrity.

Rest review of this section could be found in manuscript Part II.

The articles are collected and classified in Table 22.

Table 22. Industrial Control publication.

Research Category	Sub-Group	Publication
Industrial Control	Human-Robot Collaboration and Cognitive Interaction	Grigore et al. (2020) [394] Li et al. (2021) [389] Yang et al. (2024) [391] Aslam et al. (2025) [393] Wang et al. (2025) [392] Yang et al. (2025) [390]
	Intelligent Fault Diagnosis and Process Control	Baek, Sujeong (2021) [397] Liu et al. (2021) [399] Dai et al. (2023) [395] Korodi et al. (2024) [398] Wang et al. (2024) [411]

Table 22. *Cont.*

Research Category	Sub-Group	Publication
Industrial Control	Intelligent Fault Diagnosis and Process Control	Hu et al. (2025) [396]
	Robotics and Control System Integration	Sartaj et al. (2021) [401] Kuts et al. (2022) [400] Hu et al. (2023) [412] Elser et al. (2024) [402] Santhosh et al. (2024) [403]
	Machine Vision, Quality Inspection, and Defect Detection	Mirbod et al. (2022) [404] Fu et al. (2023) [406] Zhang et al. (2025) [405]
	Intelligent Monitoring, UAV, and Integrated Safety Systems	Yang et al. (2020) [407] Li et al. (2024) [409] Gu et al. (2025) [408] Zheng et al. (2025) [410]

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. [58] 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. [80]

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. [41] 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. [71] 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. [144]

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

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