

Systematic Review

Digital-Twin Technology Across Manufacturing, Healthcare, Smart Cities, and Energy Systems: A Systematic Review and Experimental Validation

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Abstract

Digital-twin (DT) technology has evolved into a fundamental paradigm for integrating physical assets, processes, and systems with their dynamic digital counterparts, enabling real-time monitoring, simulation, prediction, optimization, and intelligent decision-making. This study presents a systematic review of 230 peer-reviewed articles published between 2018 and 2026, examining the evolution, application domains, enabling technologies, implementation challenges, and emerging research directions of DTs across manufacturing, healthcare, smart cities, and energy systems. The review synthesizes the growing convergence of DTs with artificial intelligence (AI), the Internet of Things (IoT), blockchain, edge computing, cloud computing, and cyber-physical systems, highlighting their role in developing intelligent, interconnected, and data-driven environments. Across the four domains, the principal challenges identified include heterogeneous and distributed data integration, cybersecurity and privacy, physical-virtual synchronization, interoperability, scalability, model fidelity, and computational and communication constraints. The review further identifies eight emerging research directions, including AI-enabled autonomous DTs, blockchain-assisted trust and security mechanisms, federated learning, 6G-enabled DT networks, adaptive and self-learning architectures, and sustainable and energy-efficient DT infrastructures. To complement the literature synthesis with practical evidence, two experimentally validated DT prototypes developed at the Laboratory of Advanced Electronic Systems (LSEA) and the Laboratory of Applied Automation and Industrial Diagnostics (LAADI), Algeria, are presented. The first integrates CIROS Studio, VGG16, and Node-RED for drilling-operation quality control, achieving an accuracy improvement from 98.63% to 99.83% following fine-tuning. The second combines Factory I/O, MobileNet, fuzzy logic, and a Gradio-based human-machine interface for conveyor-belt sorting, achieving true-positive and true-negative rates of 99.90% and 99.10%, respectively. The combined



Academic Editor: Jin Huang

Received: 18 August 2026

Revised: 12 September 2026

Accepted: 21 September 2026

Published: 8 October 2026

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findings demonstrate that the integration of DTs with AI, industrial automation, and simulation can substantially enhance monitoring, prediction, quality control, and intelligent decision-making. At the same time, they emphasize the need for interoperable, secure, scalable, computationally efficient, and energy-aware architectures to enable reliable real-time deployment of DTs across heterogeneous application domains.

Keywords: digital twins; Industry 4.0; artificial intelligence; Internet of Things; cyber–physical systems; smart manufacturing; real-time synchronization; edge computing; predictive analytics; intelligent automation

1. Introduction

Digital-twin (DT) technology has emerged as an important paradigm within Industry 4.0 for integrating physical assets, computational models, sensing technologies, and data-driven intelligence. A DT establishes a dynamic digital representation of a physical system and enables continuous monitoring, analysis, simulation, and decision support throughout the system life cycle. The concept can be traced to early aerospace applications, including NASA-related spacecraft simulation and modeling activities, and was subsequently formalized through influential definitions of the DT concept. Since then, DT technology has evolved beyond its initial aerospace context and has been increasingly adopted in manufacturing, healthcare, smart cities, energy systems, transportation, construction, and agriculture [1]. This cross-domain expansion reflects the growing need for intelligent systems capable of connecting physical processes with their digital counterparts and supporting data-driven operational decisions.

The rapid development of enabling technologies has significantly expanded the capabilities of DT systems. In particular, the Internet of Things (IoT) provides continuous sensing and data acquisition, while AI and machine learning techniques support prediction, anomaly detection, optimization, and intelligent decision-making. Cloud and edge computing provide complementary computational infrastructures for large-scale data processing and low-latency applications, while advanced modeling and simulation techniques facilitate the representation and analysis of complex physical processes [1]. The integration of these technologies has progressively transformed DTs from relatively static digital representations into interconnected cyber–physical systems capable of continuous data exchange, dynamic model updating, real-time monitoring, and bidirectional interaction with physical assets [2]. Consequently, DTs are increasingly considered an enabling technology for predictive maintenance, process optimization, intelligent quality control, resource management, and autonomous system operation.

Despite this rapid development, the implementation of reliable and scalable DT systems remains associated with significant technical and operational challenges. The integration and interoperability of heterogeneous data sources can affect the consistency and reliability of digital representations, while the continuous exchange of sensitive data between physical and digital environments increases exposure to cybersecurity and privacy risks. In addition, maintaining accurate real-time synchronization between a physical asset and its digital counterpart becomes increasingly challenging as system complexity, model fidelity, data volume, and computational requirements increase. These challenges become particularly important when DTs are deployed across heterogeneous application domains with different requirements for reliability, latency, safety, scalability, and data governance. More recent research has also increasingly considered the sustainability implications of DT deployment, including energy consumption, computational efficiency, resource utilization,

and the role of DTs in supporting the transition from Industry 4.0 toward human-centered and sustainable Industry 5.0 systems [3].

Although the DT literature has expanded rapidly, important limitations remain in the existing review literature. In particular, many previous reviews adopt a predominantly single-domain perspective, focusing on DT development within a specific sector such as manufacturing, healthcare, smart cities, or energy systems. These domain-specific reviews provide valuable and detailed insights into sector-specific applications and requirements, but their isolated treatment makes it difficult to determine whether reported architectural patterns, enabling technologies, implementation challenges, and validation practices are genuinely transferable across domains or are primarily domain-specific characteristics. Consequently, the existing review literature provides limited evidence on the common technological foundations of DTs across major application sectors and on the extent to which DT architectures and enabling technologies evolve similarly or differently across these sectors.

A second limitation is that even when previous reviews consider multiple applications, cross-domain comparisons are often not performed using a common extraction and analytical framework. Architectural layers, enabling technologies, application functions, and implementation challenges may therefore be classified differently across studies, making direct comparison difficult. Similarly, the maturity of experimental validation is not consistently compared across domains. Conceptual studies, simulation-based investigations, laboratory prototypes, pilot-scale implementations, and industrial deployments are often discussed separately rather than within a unified evidence-level framework. This limits the ability to assess where DT research has progressed from conceptual development toward experimentally validated and operationally deployed systems.

These limitations are particularly important because DT adoption is influenced by substantially different requirements across application domains. Manufacturing systems typically emphasize real-time control, quality, productivity, and predictive maintenance; healthcare applications place greater emphasis on safety, privacy, reliability, and clinical validation; smart-city DTs must address large-scale integration, heterogeneous infrastructure, and scalability; while energy systems require high reliability, resilience, and secure operation. A cross-domain review is therefore necessary to distinguish the technological characteristics that are common to DT systems from those that arise from domain-specific constraints.

Building on these observations, this review addresses the identified gap by systematically examining DT research across four major application domains—manufacturing, healthcare, smart cities, and energy systems—using a common analytical framework. The review simultaneously considers the evolution of DT architectures and modeling approaches, enabling technologies, application functions, communication and data integration mechanisms, synchronization and interoperability, AI-enabled decision-making, validation approaches, implementation challenges, and emerging research directions. This approach enables findings from different application domains to be compared using consistent analytical categories rather than treating each domain as an isolated research stream.

The present review therefore does not aim merely to provide a larger bibliographic collection of DT studies. Instead, it seeks to establish a structured and reproducible basis for identifying cross-domain convergences and domain-specific differences in DT development. Particular attention is given to whether common architectural patterns can be identified across the four domains, which enabling technologies are most widely integrated with DTs, how validation maturity varies between domains, and which technical and organizational challenges continue to limit large-scale DT deployment. The review

also examines emerging research directions associated with AI, advanced communication, interoperability, cybersecurity, sustainability, and human-centered DT development.

Accordingly, the principal contribution of this review is a cross-domain systematic synthesis rather than another single-sector review. It provides a common framework for comparing DT architectures, technologies, applications, validation evidence, and implementation challenges across manufacturing, healthcare, smart cities, and energy systems. The analysis is subsequently used to identify convergent architectural patterns and research gaps, while the laboratory-scale LSEA case studies presented later in the paper provide illustrative evidence of how some of these architectural and AI-enabled principles can be implemented in a manufacturing environment.

The article is organized as follows. Section 1 introduces DT technology, identifies the research gap, and defines the review objectives and research questions. Section 2 presents the materials and methods used for the systematic literature review, including the search, selection, and analysis procedures. Section 3 reports the main review results and their initial synthesis. Section 4 provides a thematic and technological synthesis covering DT architectures, enabling technologies, application domains, AI integration, validation, interoperability, and the proposed five-layer architecture. Section 5 presents two LSEA laboratory-scale DT case studies for industrial quality control. Section 6 discusses key DT implementation challenges, while Section 7 presents future research directions for 2025–2032. Section 8 addresses the study's limitations and threats to validity. Section 9 provides direct answers to the seven research questions, and Section 10 concludes the article by summarizing its main findings and contributions.

2. Materials and Methods

2.1. Review Design and Reporting Framework

This study presents a systematic review of DT technology across four major application domains—manufacturing, healthcare, smart cities, and energy systems—complemented by an experimental validation component. The review was designed to systematically identify, evaluate, classify, and synthesize the available scientific evidence concerning DT architectures, enabling technologies, applications, modeling and simulation approaches, data integration mechanisms, AI and ML techniques, real-time monitoring, prediction, diagnosis, optimization, decision support, and experimental or industrial validation.

The systematic review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. PRISMA 2020 (Figure 1) was selected to improve the transparency and reproducibility of the identification, screening, eligibility assessment, and inclusion of relevant studies. The PRISMA 2020 framework comprises a 27-item checklist and a flow diagram for reporting the study-selection process.

The literature search and identification of relevant studies commenced in January 2025. From that point onward, relevant scientific publications were systematically searched, examined, screened, and evaluated according to the predefined eligibility criteria.

The review was structured around seven research questions (RQ1–RQ7), defined in Section 1. These questions guided the literature-search strategy, screening and eligibility assessment, data extraction, thematic classification, and final synthesis. The review considered peer-reviewed research published between 2018 and 2026 in order to capture both the historical development of DT technology and recent advances related to Industry 4.0, Industry 5.0, AI, the IoT, edge computing, cloud computing, cybersecurity, and sustainable digitalization.

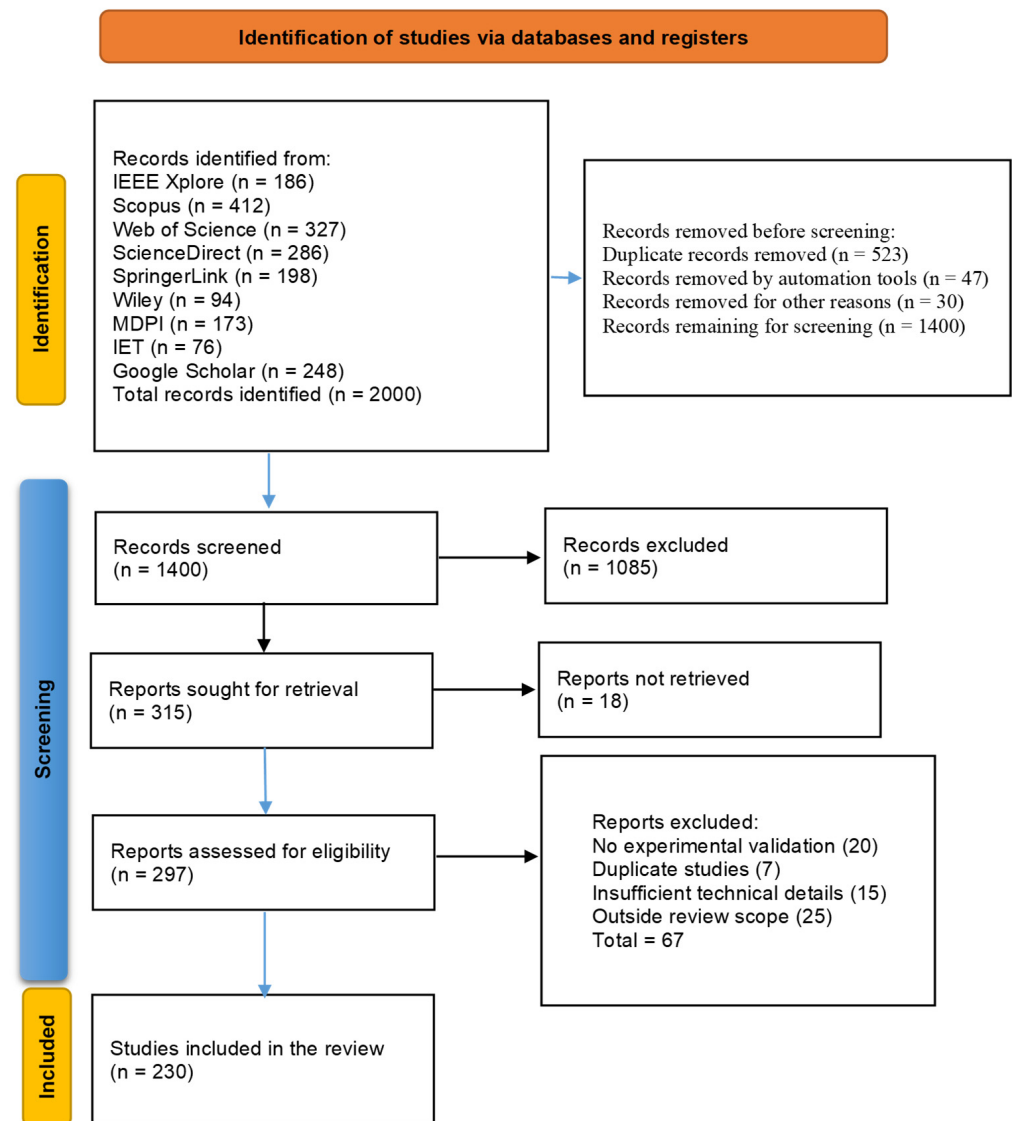


Figure 1. PRISMA 2020 flow diagram illustrating the systematic literature identification, screening, eligibility assessment, and study selection process adopted in this review.

The literature search was conducted between January 2025 and July 2026 using four sources: ScienceDirect, SpringerLink, IEEE Xplore, and the MDPI publishing platform. The search identified 368 records, including 219 records from ScienceDirect, 54 from SpringerLink, 62 from IEEE Xplore, and 33 additional records from MDPI. Web of Science and Scopus were not included in the search strategy. As MDPI is a publisher comprising multiple independent journals, similar to Elsevier and Springer, it was treated as an additional literature source within the same search period.

During the screening stage, 42 duplicate records were removed, leaving 326 unique records for title and abstract screening. Subsequently, 109 records were excluded because they were off-topic or not directly related to DT technology, resulting in 230 studies proceeding to the next stage. Full-text assessment was then conducted according to the predefined eligibility criteria. After this assessment, the eligible studies were retained for the final review corpus. The included studies were classified according to publication source, application domain, technological focus, and research theme. This methodological workflow provided the basis for addressing the seven research questions and for identifying common patterns, domain-specific characteristics, persistent challenges, and opportunities for future research.

The first stage of the review focused on the systematic identification and preliminary screening of scientific publications addressing DT technology. The literature search was conducted between January 2025 and July 2026 using four sources: ScienceDirect, SpringerLink, IEEE Xplore, and the MDPI publishing platform. The search covered peer-reviewed publications published between 2018 and 2026. Web of Science and Scopus were not included in the search strategy. The search strategy was designed to identify studies addressing key aspects of DT technology, including DT concepts and architectures, enabling technologies, industrial applications, implementation approaches, performance evaluation, challenges, and future developments.

The retrieved records were initially screened for relevance based on their titles, abstracts, keywords, and publication characteristics. Duplicate records were removed, followed by the exclusion of publications that were not directly related to DT technology or did not address the scope of the review. Studies were considered eligible when DT technology represented a substantive component of the research and when the publication provided sufficient information relevant to at least one of the predefined research questions.

In total, 368 records were identified across the four literature sources. Following the removal of 42 duplicate records, 326 unique records remained for title and abstract screening. At this stage, 109 records were excluded because they were off-topic or not sufficiently related to DT technology, leaving 230 studies for further assessment. Following the application of the predefined eligibility criteria, the 230 peer-reviewed papers were retained as the final review corpus. These publications were distributed across seventeen distinct journal titles, comprising eight primary journals identified through the main database search and nine additional MDPI-published journals. The selected studies covered major research areas associated with DT technology, particularly manufacturing systems, industrial informatics, advanced manufacturing, sustainable production, intelligent manufacturing, measurement, and industrial computing.

As illustrated in Figure 2, the distribution of the 230 selected papers across the seventeen journal titles is heterogeneous. For presentation and readability, the nine MDPI-published journals are aggregated into a single “MDPI Journals” category, while the eight primary journals are presented individually. The largest contribution comes from the *Journal of Manufacturing Systems* ($n = 71$; 32.7%), followed by *Computers in Industry* ($n = 39$), *IEEE Transactions on Industrial Informatics* ($n = 33$), *Journal of Cleaner Production* ($n = 15$), *Journal of Manufacturing Processes* ($n = 14$), *Journal of Advanced Manufacturing Technology* ($n = 13$), *Measurement* ($n = 11$), and *Journal of Intelligent Manufacturing* ($n = 6$). The nine MDPI-published journals collectively contributed 15 papers. Together, these publications constitute the 230-paper corpus analyzed in this systematic review.

Figure 2 presents the distribution of the selected publications across the eight primary journals and the aggregated MDPI category, while also highlighting the main thematic relationships within the reviewed literature. These themes include smart manufacturing, process-level DTs, cybersecurity and AI, DT frameworks and architectures, sustainability, advanced manufacturing, and sensing and calibration. The resulting classification provides a structured overview of the publication landscape and supports the subsequent analysis of the principal research themes, technological trends, challenges, and research opportunities identified in the review.

Keyword analysis was conducted to characterize the principal concepts, enabling technologies, standards, and application domains represented in the DT literature. The analysis was performed on the final corpus of 230 peer-reviewed papers published between 2018 and 2026. To improve the consistency and interpretability of the results, extracted keywords and related terms were normalized to account for differences in terminology, abbreviations, spelling, and synonymous expressions. The resulting terms were subsequently

organized according to their conceptual relationships with DT architectures, enabling technologies, industrial applications, data management, simulation, automation, connectivity, and emerging digital technologies.

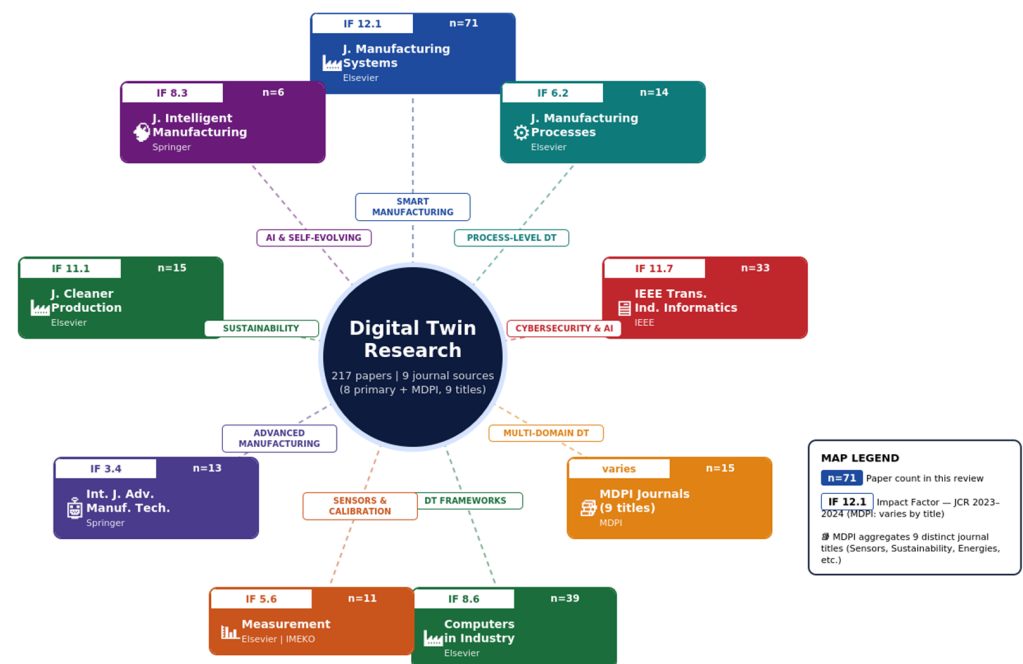


Figure 2. Journal coverage of the DT systematic review corpus (2018–2026, $n = 230$ papers, eight primary journals plus MDPI journals).

The frequency analysis revealed a strong concentration of terms associated with DTs, Industry 4.0, the IoT/Industrial Internet of Things (IIoT), AI, ML, predictive maintenance, real-time data, simulation, cyber-physical systems (CPS), smart manufacturing, cloud computing, edge computing, data analytics, automation, remote monitoring, and system integration. Other frequently represented concepts included blockchain, cybersecurity, and the digital thread, indicating the increasing integration of connectivity, data-driven intelligence, and secure information exchange within DT-enabled systems.

Figure 3 presents the frequency-based keyword word cloud generated from the analyzed corpus. The visualization provides a qualitative representation of keyword prominence, with larger terms corresponding to higher occurrence frequencies. Beyond the established DT and Industry 4.0 vocabulary, the analysis also reveals a growing presence of emerging concepts, including Generative AI, federated learning, Industry 5.0, 6G networks, digital thread, interoperability, OPC UA, MQTT, and AI-based architectures and algorithms such as Long Short-Term Memory (LSTM), CNN, and Physics-Informed Neural Networks (PINNs). The coexistence of these established and emerging terms suggests a progressive broadening of DT research from conventional simulation, monitoring, and predictive applications toward intelligent, interconnected, interoperable, secure, and increasingly autonomous cyber-physical systems.

Overall, the keyword distribution indicates that contemporary DT research is characterized by the convergence of AI-driven analytics, IoT/IIoT connectivity, edge-cloud infrastructures, real-time data processing, interoperability standards, and advanced learning methods. This convergence reflects a shift toward more intelligent and distributed DT architectures capable of supporting real-time decision-making, predictive operations, system integration, and adaptive manufacturing environments. The identified keyword

patterns therefore provide a basis for examining the technological evolution and emerging research directions of DT systems in the subsequent thematic analysis.

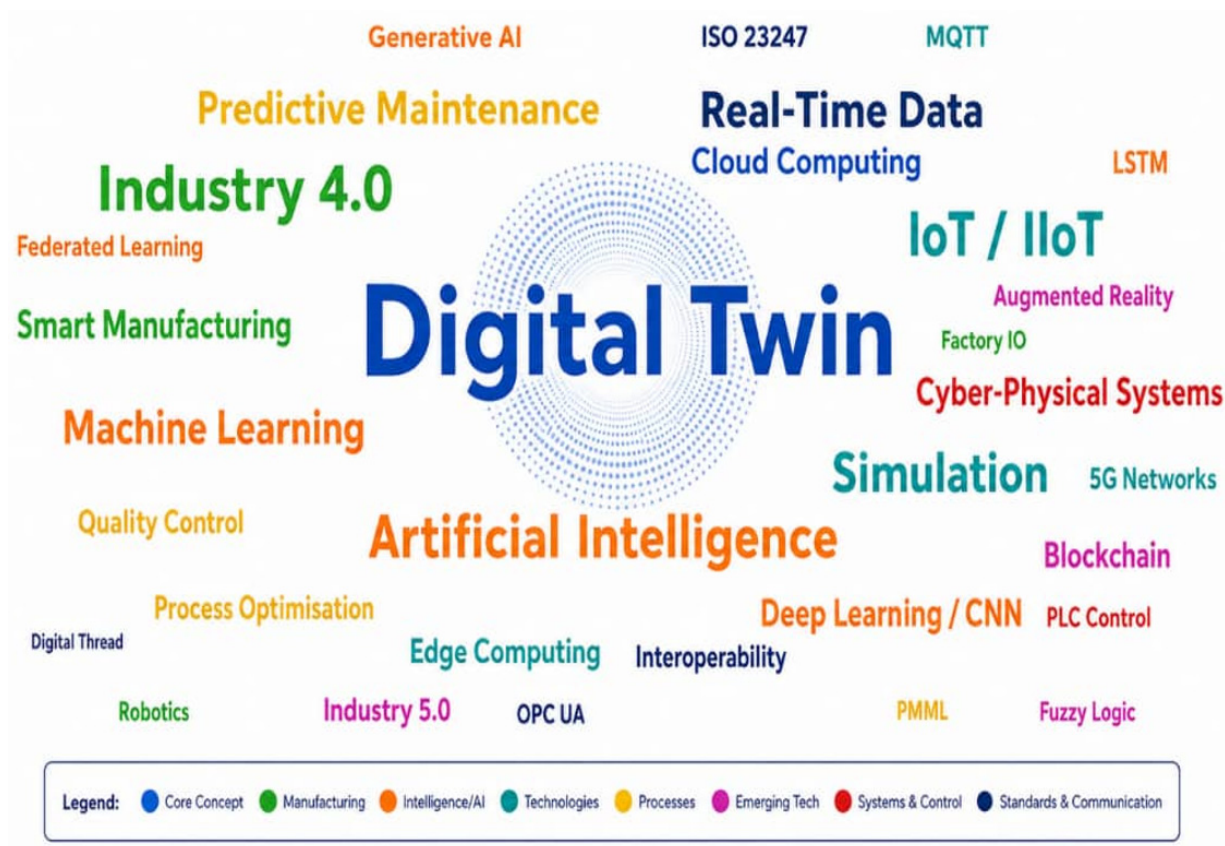


Figure 3. Keyword frequency word cloud of the DT research corpus (2018–2026, n = 230 papers).

PRISMA compliance and registration. This systematic review was conducted and reported in accordance with the PRISMA 2020 statement. A completed PRISMA 2020 checklist is provided in Supplementary Material S1, while the study-identification and selection process is presented in Figure 1. The literature search identified 368 records across the selected sources. After the removal of 523 duplicate records, 1400 unique records remained for screening. Of these, 1085 records were excluded during title and abstract screening because they were outside the scope of the review or were not sufficiently related to DT technology. Consequently, 230 peer-reviewed studies were retained for the final review corpus.

The literature search was conducted between January 2025 and July 2026 and targeted peer-reviewed studies published between 2018 and 2026. Searches were performed in ScienceDirect, SpringerLink, and IEEE Xplore, complemented by a search of the MDPI publishing platform. Database-specific search strategies were developed to identify studies addressing DT technology and its applications across relevant domains, including manufacturing, healthcare, smart cities, and energy systems. Web of Science and Scopus were not included in the search strategy. The complete database-specific search strings, search dates, and corresponding search procedures are provided in Supplementary Material S2.

Registration and protocol. The review was not prospectively registered in PROSPERO, OSF, or another systematic review registry. In addition, no separate publicly accessible review protocol was prepared or registered before the commencement of the literature search. This registration status is explicitly reported in accordance with PRISMA 2020 Item 24, which requires authors to state the registration and protocol status of the review.

2.2. Review Objectives and Research Questions

The primary objective of this systematic review is to provide a comprehensive and cross-domain assessment of DT technology and to examine its evolution from conceptual models and architectural frameworks toward increasingly intelligent, interconnected, data-driven, and experimentally validated systems. The review focuses on four major application domains—manufacturing, healthcare, smart cities, and energy systems—and systematically examines their architectural characteristics, enabling technologies, functional applications, validation approaches, implementation challenges, and emerging research directions.

To maintain a consistent analytical framework throughout the review, the study is guided by the following seven research questions:

RQ1: How has DT technology evolved in terms of architectures, modeling approaches, data integration, communication, synchronization, and interoperability?

RQ2: What are the principal applications of DT technology in manufacturing, healthcare, smart cities, and energy systems?

RQ3: Which enabling technologies are being integrated with DTs?

RQ4: How are DTs being employed for real-time monitoring, anomaly detection, prediction, diagnosis, optimization, maintenance, decision support, and control?

RQ5: What experimental, simulation-based, laboratory, pilot-scale, or industrial validation approaches have been reported?

RQ6: What are the principal challenges associated with DT implementation?

RQ7: What research gaps and future research directions can be identified from the existing literature?

These research questions provide the common analytical framework used for the systematic literature screening, extraction, thematic synthesis, cross-domain comparison, and identification of research gaps presented in the subsequent sections. RQ1–RQ6 primarily address the evolution, applications, technologies, functions, validation approaches, and implementation challenges of DTs, while RQ7 synthesizes the identified gaps into future research directions. The answers to all seven questions are consolidated in Section 9, where the findings are explicitly linked to the evidence synthesized throughout the review.

2.3. Contributions of the Review

This review makes four main contributions. First, it provides a cross-domain synthesis of digital-twin research across manufacturing, healthcare, smart cities, and energy systems using a consistent analytical framework. Second, it identifies common architectural patterns and enabling technologies and synthesizes them into a five-layer DT reference architecture. Third, it characterizes the reported validation maturity of DT studies by distinguishing conceptual, simulation-based, laboratory, pilot/field, and industrial evidence. Fourth, it identifies persistent implementation challenges and emerging research directions, including interoperability, cybersecurity, AI integration, sustainable DTs, and autonomous DT systems. The two LSEA case studies are considered laboratory-scale illustrative implementations of selected findings from the literature and are not used as evidence of cross-domain generalization.

2.4. Literature Search Strategy

The literature search was conducted systematically to identify publications relevant to DT technology and its applications across manufacturing, healthcare, smart cities, and energy systems. The search was initiated in January 2025 and covered the information sources specified in Supplementary Material S2.

The search strategy was developed iteratively around the central concept of “digital twin” and its synonyms, combined with application-domain and technology-related terms.

The principal DT-related terms included “digital twin”, “digital twins”, “digital twinning”, “virtual twin”, and “digital replica”. These terms were combined with domain-specific terms, including manufacturing, industrial, healthcare, health care, smart city, smart cities, energy, power systems, and renewable energy, as well as technology- and function-related terms such as Internet of Things (IoT), artificial intelligence (AI), machine learning, deep learning, anomaly detection, monitoring, prediction, diagnosis, optimization, simulation, interoperability, cloud computing, edge computing, real-time systems, cybersecurity, and digital transformation.

The search strategy was structured as a combination of three conceptual blocks: (1) digital twin terminology, (2) application-domain terminology, and (3) enabling technologies and functional terms. Synonymous terms within each block were connected using the OR operator, while the conceptual blocks were combined using AND operators. For example, a representative domain-oriented search structure was:

(“digital twin” OR “digital twins” OR “digital twinning” OR “virtual twin” OR “digital replica”) AND (manufactur OR industr OR healthcare OR “health care” OR “smart cit” OR energ OR “power system” OR “renewable energy”)

Additional combinations of DT terminology with specific technological functions and enabling technologies were used to identify relevant studies that might not explicitly mention the target application domain in their titles or abstracts. These combinations included DT terminology with concepts related to AI, machine learning, IoT, edge computing, cloud computing, blockchain, cybersecurity, simulation, optimization, monitoring, prediction, and predictive maintenance.

The search strategy was adapted to the syntax, indexing structure, and search functionality of each information source. In particular, search fields, Boolean operators, phrase searching, truncation symbols, and available filters were adjusted where required by the individual database interfaces. The complete database-specific search strings, exact search dates, search fields, language restrictions, document-type restrictions, and other applied limits are reported in Supplementary Material S2.

The search was not restricted to a single application domain, thereby facilitating the identification of DT studies across manufacturing, healthcare, smart cities, and energy systems. Retrieved records were subsequently consolidated and processed for duplicate removal, screening, and eligibility assessment according to the predefined inclusion and exclusion criteria described in Section 2 and Supplementary Material S2.

2.5. Information Sources

The literature search included major scientific databases and publisher platforms relevant to engineering, computer science, manufacturing, healthcare, energy, and interdisciplinary DT research.

The principal information sources included:

- IEEE Xplore;
- ScienceDirect;
- SpringerLink;
- MDPI (<https://www.mdpi.com/>).

In addition to database and publisher-platform searches, the reference lists of relevant publications were examined to identify additional studies. Forward and backward citation searching was also used where appropriate to identify relevant publications that might not have been retrieved through the initial search queries.

The systematic search and identification of relevant publications were conducted between 2018 and 2026, in accordance with the PRISMA 2020 reporting recommendations.

2.6. Eligibility Criteria

Eligibility criteria were established to ensure that the studies included in the systematic review were directly relevant to the objectives of the study.

2.6.1. Inclusion Criteria

Studies were included when they satisfied the following criteria:

- The study was published in a peer-reviewed scientific journal or peer-reviewed conference proceeding.
- The study addressed DT technology as a primary or substantial component of the research.
- The study presented a DT architecture, framework, methodology, model, algorithm, implementation, application, case study, simulation, or experimental validation.
- The study addressed at least one of the four principal domains considered in this review: manufacturing, healthcare, smart cities, energy systems.
- Studies addressing general DT architectures or enabling technologies were also considered when their contribution was directly applicable to one or more of the target domains.
- The publication contained sufficient technical or methodological information for data extraction and analysis.
- The full text was available.
- The publication was written in English.

2.6.2. Exclusion Criteria

Studies were excluded when they:

- Did not substantially address DT technology;
- Were outside the scope of the research questions;
- Were editorials, letters, news items, book reviews, patents, theses, dissertations, or other non-peer-reviewed materials;
- Were duplicate records;
- Were journal or publisher webpages rather than individual research publications;
- Did not provide sufficient information for meaningful analysis;
- Did not have accessible full text; or addressed only conventional simulation or virtual modeling without a substantive DT component.

The distinction between individual scientific publications and journal-level webpages was particularly important during the screening process. Records corresponding solely to journal homepages or publisher pages were excluded and were not counted as scientific studies.

2.7. Study Selection Process

The study-selection process consisted of four principal stages: identification, duplicate removal, screening, and eligibility assessment.

First, records retrieved from the different information sources were collected and consolidated into a reference database. Duplicate records were subsequently identified and removed.

Second, the titles and abstracts of the remaining records were screened against the predefined eligibility criteria. Publications that were clearly unrelated to DT technology or to the scope of the review were excluded at this stage.

Third, the full texts of potentially eligible publications were retrieved and assessed in detail.

Finally, studies satisfying all inclusion criteria were included in the systematic review and evidence synthesis.

The numbers of records identified, duplicates removed, records screened, records excluded, full-text reports assessed, full-text reports excluded with reasons, and studies finally included are presented in the PRISMA 2020 flow diagram (Figure 1). PRISMA 2020 recommends reporting the complete study-selection process and presenting it preferably using a flow diagram.

2.8. Data Extraction

A structured data-extraction framework was used to collect information consistently from the included publications.

The extracted variables included:

- Publication year;
- Authors;
- Publication venue;
- DT application domain;
- Physical asset or system;
- DT architecture;
- Level of DT representation;
- Data acquisition mechanisms;
- Sensing technologies;
- Communication technologies;
- IoT integration;
- Cloud/edge/fog computing;
- AI and ML techniques;
- DL and reinforcement learning;
- Modeling and simulation techniques;
- Data integration and interoperability;
- Ontology and knowledge-representation techniques;
- Blockchain and cybersecurity mechanisms;
- Monitoring and anomaly-detection capabilities;
- Prediction and diagnosis;
- Optimization and decision support;
- Maintenance applications;
- Real-time synchronization;
- Experimental methodology;
- Datasets;
- Validation environment;
- Evaluation metrics;
- Principal findings;
- Limitations;
- Identified research gaps.

For experimentally validated studies, additional information was extracted regarding the experimental setup, physical system, virtual representation, data sources, validation procedure, comparison methods, and quantitative performance measures.

2.9. Data Synthesis and Classification

Because the included studies cover multiple disciplines and employ substantially different methodologies, the evidence was synthesized using a qualitative and descriptive approach rather than a statistical meta-analysis.

The included publications were classified into four major application domains:

- Manufacturing and industrial systems;
- Healthcare and biomedical systems;
- Smart cities and built environments;
- Energy and power systems.

Within these domains, the studies were further categorized according to their principal DT functions:

- Monitoring;
- Anomaly detection;
- Prediction;
- Diagnosis;
- Simulation;
- Optimization;
- Maintenance;
- Decision support;
- Intelligent control;
- Real-time synchronization.

The technological dimension of the synthesis considered the integration of DTs with AI/ML, DL, RL, IoT, edge/cloud computing, blockchain, computer vision, ontologies, and other enabling technologies.

The evidence was subsequently compared with respect to technological maturity, validation level, application domain, reported benefits, limitations, and unresolved research challenges.

2.10. Experimental Validation

The experimental validation presented in this section complements the systematic-review findings by providing practical evidence for selected DT technologies and research directions identified in the literature synthesis.

The experimental component was designed to examine the practical behavior and applicability of DT technology beyond the conceptual findings identified through the literature review. The validation considered the relationship between the physical system and its corresponding virtual representation, including data acquisition, synchronization, modeling, prediction, and performance evaluation.

Where applicable, the experimental evaluation considered quantitative indicators such as prediction error, accuracy, computational performance, latency, synchronization quality, and other domain-specific measures.

The experimental findings were subsequently compared with the characteristics and validation practices identified in the systematic literature to determine the extent to which the experimental implementation supports the broader conclusions of the review.

2.11. Quality Assessment and Risk of Bias

Given the substantial heterogeneity of the included engineering and technology studies, including conceptual frameworks, simulation studies, computational methods, industrial case studies, and experimental implementations, a single clinical risk-of-bias instrument was not considered appropriate.

Instead, the methodological quality of the included studies was assessed according to the following dimensions:

- Clarity of research objectives;
- Transparency of the proposed DT architecture;

- Adequacy of data and system descriptions;
- Methodological completeness;
- Reproducibility of the proposed approach;
- Adequacy of validation;
- Appropriateness of evaluation metrics;
- Comparison with baseline or alternative approaches;
- Clarity of limitations.

The assessment was used during the synthesis to distinguish between conceptual proposals, simulation-based studies, experimental demonstrations, and real-world industrial implementations.

2.12. Protocol and Registration

This systematic review was not prospectively registered in PROSPERO, OSF, or another systematic-review registry. No formal review protocol was publicly registered before the commencement of the literature search.

The literature identification and search process commenced in January 2025 and concluded in July 2026, and the review methodology was subsequently structured and reported in accordance with the PRISMA 2020 reporting guideline. No registration number is therefore applicable.

This statement is provided explicitly to satisfy PRISMA 2020 Item 24a, which requires authors to provide registration information or state that the review was not registered. PRISMA 2020 also requires authors to indicate where the review protocol can be accessed or to state that no protocol was prepared.

2.13. Reporting According to PRISMA 2020

The present systematic review follows the reporting recommendations of PRISMA 2020 for the elements that could be retrospectively documented. The PRISMA checklist is provided in Supplementary Material S1 with the applicable items marked as not available, and the simplified identification and inclusion diagram is provided as Figure 1.

The checklist documents the location of each applicable PRISMA item within the manuscript. The search methods, information sources, eligibility criteria, study-selection process, data-extraction procedures, synthesis methods, registration status, and availability of Supplementary Materials are reported in Section 2.

The PRISMA framework also recommends reporting the exact dates of searches and the full search strategies for the information sources used. Accordingly, the database-specific search strings and search dates are provided in Supplementary Material S2.

2.14. Publication Sources and Distribution of the Review Corpus

The *Journal of Manufacturing Systems* was the most represented publication source, accounting for 71 of the 230 papers included in the review. The relatively high representation of this journal reflects the substantial maturity and publication volume of DT research in manufacturing and Industry 4.0. This concentration was not imposed as an inclusion criterion and did not result from restricting the search to the manufacturing literature. The search strategy covered manufacturing, healthcare, smart cities, and energy systems using the same overarching DT concept, with domain-specific terms applied to ensure coverage across the four application areas. In addition, a supplementary targeted search of selected MDPI journals was conducted to enhance the coverage of relevant DT literature.

2.15. Relationship Between the Systematic Review and Experimental Case Studies

The experimental case studies were included as a complementary validation component of the systematic review rather than as independent case reports. The systematic review identified several recurring technological trends in DT research, particularly the integration of DTs with artificial intelligence, computer vision, simulation environments, real-time monitoring, intelligent decision-making, and automated control. The experimental cases were therefore selected to provide practical evidence of how these technologies can be integrated into DT-enabled systems and to illustrate the transition from the concepts and research directions identified in the literature to experimentally validated implementations.

The two experimental cases build upon research activities previously developed by the authors; however, they are not presented as new literature contributions within the systematic-review corpus. Previously published methodological and implementation elements are explicitly acknowledged and referenced, while the present manuscript uses the cases as experimental validation and illustrative evidence in relation to the findings synthesized from the reviewed literature. Where applicable, previously reported configurations and results are distinguished from the experimental analyses and interpretations presented in this study.

Accordingly, the role of the case studies is complementary to the systematic review: the review provides the evidence-based synthesis of the state of the art, while the experiments demonstrate how selected findings—particularly AI-enabled DTs, simulation, real-time monitoring, intelligent classification, and automated decision-making—can be implemented and evaluated in practical environments.

3. Results and Synthesis

3.1. Definition and Evolution of DT Technology

The analysis of the selected literature indicates that the concept of DT has undergone a substantial evolution from simulation-oriented representations of physical systems to dynamic, interconnected, and intelligent cyber-physical systems. Early definitions primarily emphasized the representation and simulation of physical assets and their lifecycle behavior, whereas subsequent studies increasingly incorporated real-time sensing, communication, data analytics, AI, and bidirectional interaction between physical and digital environments.

As summarized in Table 1, the evolution of DT definitions reflects a gradual expansion in both scope and functionality. Early conceptualizations focused mainly on simulation and lifecycle representation [4]. With the emergence of IoT-enabled systems, DTs increasingly became associated with connected virtual representations capable of communicating with their physical counterparts [5]. Subsequent developments extended the concept toward dynamic modeling, real-time monitoring, prediction, optimization, and operational decision-making [6–8].

More recent interpretations consider a DT not simply as a static digital replica, but as an integrated system that continuously connects physical assets, sensing infrastructure, computational models, data-processing mechanisms, and intelligent decision-support functions. This evolution is particularly evident in manufacturing and industrial applications, where DTs are increasingly combined with AI, machine learning, IoT, cloud and edge computing, and advanced simulation technologies.

The evolution identified in the reviewed literature can therefore be characterized by three major transitions: (i) from static representation to dynamic simulation, (ii) from isolated digital models to connected cyber-physical systems, and (iii) from monitoring and simulation toward prediction, optimization, and intelligent autonomy. These transitions

provide the conceptual foundation for the architectural and application-level analysis presented in the following sections.

Table 1. Evolution of DT definitions (2010–2023).

Year	Definition and Key Reference
2010	Multi-physics probabilistic simulation mirroring the physical system lifecycle through sensor updates and fleet history. [4]
2016	DTs as virtual substitutes of real-world objects with communication capabilities, acting as intelligent nodes in the IoT [1]
2018	Evolution of modeling and simulation beyond traditional methods with limited capabilities for evaluating dynamic system performance [5]
2021	Software representation of a physical asset designed to detect, prevent, predict, and optimize through real-time analytics to deliver business value [6]
2022	A digital replica of an existing physical entity, encompassing assets, processes, and complete operational systems [7]
2023	Virtual replica of a physical asset used to simulate scenarios, monitor performance, and optimize operations in real time [8]

The evolution summarized in Table 1 indicates three broad transitions in DT research. First, early DT concepts emphasized simulation and lifecycle representation. Second, the emergence of IoT and connected sensing expanded DTs toward real-time monitoring and bidirectional communication. Third, recent developments increasingly incorporate AI, real-time analytics, optimization, and human-centered approaches, positioning DTs as intelligent components of next-generation cyber–physical and Industry 5.0 systems.

3.2. Publication and Research Trends

The temporal and bibliographic analysis of the 230 selected studies reveals a progressive expansion of DT research between 2018 and 2026. The distribution of publications indicates that DT research has evolved from a relatively specialized topic into a multidisciplinary research area involving manufacturing, industrial informatics, AI, IoT, simulation, healthcare, smart cities, and energy systems.

The journal distribution presented in Figure 3 demonstrates a particularly strong concentration of DT research in manufacturing and industrial computing. The *Journal of Manufacturing Systems* represents the largest contribution with 71 papers (32.7%), followed by *Computers in Industry* with 39 papers and *IEEE Transactions on Industrial Informatics* with 33 papers. This concentration reflects the historical relationship between DT technology and Industry 4.0, particularly in smart manufacturing, predictive maintenance, process optimization, industrial automation, and cyber–physical production systems.

At the same time, the literature demonstrates an increasing diversification of research themes. Recent studies increasingly address AI, machine learning, edge computing, blockchain, cybersecurity, interoperability, sustainability, Industry 5.0, and advanced communication technologies. This transition suggests that DT research is moving beyond the traditional objective of virtual representation toward intelligent, connected, secure, and increasingly autonomous systems.

The publication trends also indicate a shift from technology-oriented research toward application-driven and multidisciplinary investigations. While early studies primarily

focused on DT definitions, modeling, simulation, and architecture, more recent research emphasizes measurable operational outcomes, including predictive maintenance, quality control, resource optimization, real-time monitoring, anomaly detection, and intelligent decision-making.

3.3. DT Architectures and Components

The synthesis of the reviewed studies shows that DT architectures generally consist of several interconnected layers that establish a continuous information and control loop between the physical system and its digital counterpart. Although terminology and architectural configurations vary across application domains, the reviewed literature commonly identifies five functional components: (i) the physical layer, (ii) the data acquisition and communication layer, (iii) the digital/modeling layer, (iv) the analytics and intelligence layer, and (v) the application and decision layer.

The physical layer represents the actual asset, process, machine, infrastructure, patient-related system, energy installation, or urban environment being modeled. Sensors and controllers associated with the physical layer generate operational data that describe the current state and behavior of the physical system.

The data acquisition and communication layer provides the mechanisms required to collect, transmit, and synchronize information between the physical and digital environments. IoT and Industrial IoT technologies, communication protocols, gateways, and edge devices play a central role at this level. Technologies such as MQTT and OPC UA are particularly relevant to industrial environments where interoperability and low-latency communication are required (see Table 2).

Table 2. Common components and functions of DT architectures.

Component	Main Function	Typical Technologies
Physical Layer	Represents physical asset/process	Sensors, PLCs, actuators
Data Acquisition	Collects operational data	IoT/IIoT, gateways
Communication	Transfers and synchronizes data	MQTT, OPC UA, industrial networks
Digital Model	Represents physical behavior	Simulation, 3D/model-based systems
Intelligence	Prediction and optimization	AI, ML, CNN, LSTM
Computing	Data/model processing	Edge, cloud
Application	Visualization and decisions	HMI, dashboards, Gradio
Control/Feedback	Closes physical–digital loop	PLC, actuators, automated control

The digital/modeling layer contains the virtual representation of the physical entity. Depending on the application, this representation may involve mathematical models, simulation environments, 3D models, process models, system models, or hybrid modeling approaches. This layer enables the digital counterpart to reproduce, analyze, and predict the behavior of the physical system.

The analytics and intelligence layer transforms acquired data into actionable information through data analytics, machine learning, deep learning, optimization, and AI. The reviewed literature demonstrates increasing use of CNNs, LSTM networks, predictive mod-

els, and other AI techniques for anomaly detection, quality control, predictive maintenance, forecasting, and optimization.

Finally, the application and decision layer translates analytical results into operational actions, visualization, recommendations, or automated control. Human–machine interfaces, dashboards, decision-support systems, and automated controllers can therefore close the loop between the digital model and the physical system.

The synthesis indicates that the defining characteristic of a DT architecture is not simply the existence of a digital model, but the continuous interaction and synchronization between the physical and digital domains. Consequently, interoperability, data quality, communication latency, cybersecurity, and model updating are fundamental architectural requirements rather than independent technical considerations.

3.4. *DT Applications Across Major Application Domains*

3.4.1. Manufacturing

Manufacturing represents the most extensively investigated application domain in the reviewed corpus. DTs are widely employed to support smart manufacturing, predictive maintenance, production optimization, quality control, process monitoring, anomaly detection, and production planning. The integration of DTs with IoT sensors, PLC-based control systems, simulation platforms, and AI algorithms enables continuous observation and analysis of manufacturing processes.

3.4.2. Healthcare

In healthcare, DT applications extend the concept from industrial assets to patients, medical devices, healthcare processes, and hospital infrastructures. The reviewed literature highlights applications in patient monitoring, personalized healthcare, disease prediction, treatment planning, medical-device simulation, and hospital resource management. Unlike manufacturing DTs, healthcare applications introduce additional requirements related to privacy, safety, data governance, interoperability, and clinical reliability.

3.4.3. Smart Cities

In smart-city environments, DTs provide digital representations of urban infrastructure and interconnected services. Applications include traffic management, energy optimization, building management, environmental monitoring, infrastructure planning, and emergency-response support. The large scale and heterogeneity of urban systems make interoperability, scalability, real-time data integration, and cybersecurity particularly important.

3.4.4. Energy Systems

DT technology is increasingly applied to energy generation, transmission, distribution, storage, and consumption systems. The reviewed studies identify applications in predictive maintenance, renewable-energy forecasting, grid monitoring, asset management, fault detection, and energy optimization. The combination of DTs with IoT, AI, edge computing, and cloud platforms supports more responsive and data-driven energy management.

3.4.5. Cross-Domain Comparison

The comparative analysis of the reviewed literature reveals that DT applications share a common technological foundation while exhibiting distinct objectives, architectures, operational requirements, and performance priorities across application domains. As summarized in Table 3, manufacturing applications primarily focus on production optimization, predictive maintenance, quality control, and real-time process monitoring, whereas healthcare applications emphasize patient monitoring, personalized care, treatment support, and medical-device management. In smart-city environments, DTs are

predominantly employed for infrastructure management, traffic optimization, environmental monitoring, and resource allocation, while energy-system applications focus on asset monitoring, fault detection, renewable-energy forecasting, grid optimization, and energy efficiency. Despite these domain-specific differences, IoT, AI, simulation, cloud computing, and edge computing represent common enabling technologies across the four domains. The comparison also indicates that the principal implementation challenges vary according to application requirements: manufacturing is strongly affected by interoperability and real-time control requirements; healthcare places greater emphasis on privacy, security, safety, and data governance; smart cities face challenges related to scalability, heterogeneous data integration, and interoperability; and energy systems require high reliability, synchronization, and accurate prediction. These findings demonstrate that DT architectures cannot be treated as universally identical solutions and should instead be adapted to the operational, technological, and regulatory characteristics of each application domain.

Table 3. Cross-domain comparison of DT applications across manufacturing, healthcare, smart cities, and energy systems.

Dimension	Manufacturing	Healthcare	Smart Cities	Energy Systems
Primary DT Object	Machines, production lines, processes	Patients, medical devices, healthcare processes	Buildings, infrastructure, transportation, urban services	Power plants, grids, renewable-energy assets
Main Applications	Predictive maintenance, quality control, process optimization	Patient monitoring, diagnosis support, personalized healthcare	Traffic management, infrastructure monitoring, resource optimization	Fault detection, forecasting, grid optimization, asset management
Key Technologies	IoT/IIoT, AI, PLCs, simulation, edge/cloud	AI, IoT, data analytics, cloud/edge	IoT, AI, GIS, cloud/edge	IoT, AI, simulation, edge/cloud
Main Operational Objective	Productivity, quality, and efficiency	Safety, personalization, and clinical support	Sustainability, efficiency, and urban management	Reliability, efficiency, and energy optimization
Major Challenges	Interoperability, synchronization, real-time control	Privacy, cybersecurity, safety, data governance	Scalability, interoperability, heterogeneous data	Reliability, synchronization, prediction
Typical Benefits	Reduced downtime, higher productivity, improved quality	Improved monitoring and personalized decision support	Better resource utilization and infrastructure management	Improved efficiency, reliability, and predictive maintenance

The cross-domain comparison demonstrates that although DT architectures share common technological foundations, their implementation priorities differ substantially according to the characteristics and risks of each application domain. Manufacturing emphasizes real-time control, process optimization, and production quality; healthcare places greater emphasis on privacy, safety, and personalized decision-making; smart cities require large-scale interoperability and heterogeneous data integration; and energy systems prioritize reliability, forecasting, synchronization, and operational efficiency. These differences demonstrate that DT architectures cannot be considered universally identical and must instead be adapted to domain-specific operational, technological, and regulatory requirements.

Application-Domain Classification. Application-domain classification was based on the primary physical system and operational context addressed by each study rather than on individual keywords appearing in the title or abstract. In particular, terms such as “health monitoring” were not interpreted as healthcare unless the study concerned patients, clinical systems, medical devices, or healthcare infrastructure. Industrial applications, including mining, metallurgical, subsea, and engineering-system monitoring, were classified according to their underlying industrial or energy context. This classification criterion was applied consistently across the reviewed corpus to reduce ambiguity and avoid assigning studies to healthcare or smart-city domains solely on the basis of terminology.

4. Systematic Literature Review: Thematic and Technological Synthesis

This section presents a thematic and technological synthesis of the 230 peer-reviewed DT studies included in the systematic review corpus. The studies were published between 2018 and 2026 and were analyzed according to their architectural approaches, modeling methods, enabling technologies, application domains, operational functions, communication and data-integration mechanisms, artificial intelligence techniques, validation approaches, and reported research gaps.

Unlike a journal-by-journal organization, the present section synthesizes the literature according to the major conceptual and technological themes that emerged from the reviewed corpus. This organization is intended to provide a more coherent interpretation of DT development and to directly support the research questions defined in Section 2.2. Detailed study-level information extracted from the reviewed publications is retained in the corresponding tables, while the narrative below focuses on cross-study patterns, technological evolution, and research trends.

The quantitative distribution of the reviewed studies by publication venue and application domain is presented in Figure 4. Although the literature is synthesized thematically in the present section, the journal distribution remains useful for characterizing the composition of the review corpus and for identifying the publication venues in which DT research is most strongly represented.

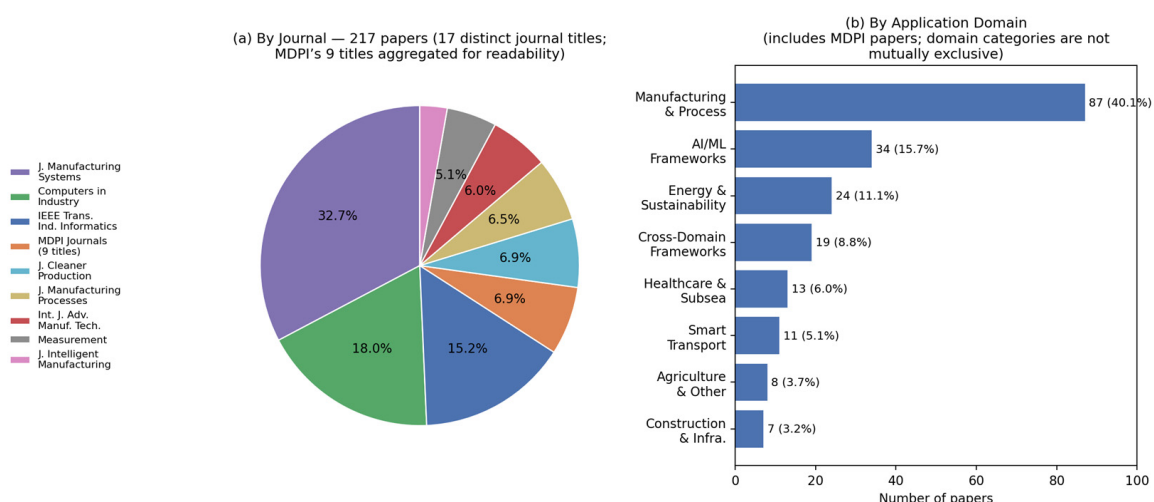


Figure 4. Research distribution of the 230 DT papers by journal and application domain.

The quantitative mapping presented in Figure 4 shows a pronounced concentration of DT research within manufacturing and industrial systems. The *Journal of Manufacturing Systems* represents the largest contribution, with 71 papers (30.9%) on the evolution of DT technology from relatively static virtual representations toward dynamic, interconnected, data-driven, and increasingly intelligent cyber–physical systems. Early DT implementa-

tions were primarily concerned with representing physical assets and processes through virtual models and simulation environments. Subsequent developments introduced continuous data acquisition, bidirectional communication, real-time synchronization, and integration with industrial information systems. More recent studies increasingly combine these capabilities with artificial intelligence, edge computing, semantic models, and autonomous of the total corpus, followed by *Computers in Industry* with 39 papers (17.0%) and *IEEE Transactions on Industrial Informatics* with 33 papers (14.3%). Together, these three journals account for 143 papers, corresponding to approximately 62.2% of the complete corpus. This concentration confirms the strong historical and technological association between DT research and smart manufacturing, industrial informatics, cyber–physical production systems, predictive maintenance, and intelligent process optimization.

The remaining publications are distributed across journals addressing manufacturing processes, sustainable production, intelligent manufacturing, advanced manufacturing technologies, measurement and calibration, as well as broader technological and multidisciplinary applications. This distribution demonstrates that although manufacturing remains the dominant research environment, DT research is increasingly extending toward healthcare, energy, smart cities, sustainability, infrastructure, and other application domains.

4.1. Evolution of DT Architectures and Modeling Approaches

The reviewed literature demonstrates a progressive evolution of DT technology from relatively static virtual representations toward dynamic, interconnected, data-driven, and increasingly intelligent cyber–physical systems. Early DT implementations were primarily concerned with representing physical assets and processes through virtual models and simulation environments. Subsequent developments introduced continuous data acquisition, bidirectional communication, real-time synchronization, and integration with industrial information systems. More recent studies increasingly combine these capabilities with artificial intelligence, edge computing, semantic models, and autonomous decision-support mechanisms.

At the architectural level, the literature does not converge on a single universally accepted DT architecture. Instead, different studies employ different numbers of layers and terminology depending on their application domain, modeling requirements, and technological implementation. Nevertheless, recurring functional components can be identified across the corpus. These components generally include physical assets and sensing infrastructure, communication and data-management studies increasingly consider multiple machines, production lines, and cyber–physical production systems rather than individual assets alone. Similar developments can be observed in healthcare, energy, and smart-city mechanisms, digital modeling and simulation, analytics and services, and user-facing applications or human–machine interfaces.

The architectural evolution is also reflected in the transition from isolated asset-level twins toward system-level and networked DT ecosystems. Manufacturing studies increasingly consider multiple machines, production lines, and cyber–physical production systems rather than individual assets alone. Similar developments can be observed in healthcare, energy, and smart-city applications, where DTs must integrate multiple physical entities, heterogeneous data sources, and distributed computational resources.

Modeling approaches have similarly evolved from conventional geometric and simulation-based representations toward hybrid and data-driven models. Physics-based modeling remains important in applications requiring high physical fidelity, while machine learning models are increasingly used where large volumes of operational data are avail-

able. Hybrid approaches seek to combine the interpretability and physical consistency of knowledge-based models with the adaptability of data-driven methods.

The reviewed studies also demonstrate increasing interest in dynamic model updating. Rather than maintaining a fixed digital representation, newer DT implementations attempt to continuously update the virtual model according to changes observed in the physical system. This evolution is particularly relevant to predictive maintenance, process optimization, condition monitoring, and autonomous manufacturing.

The evidence summarized in Table 4 shows that DT architectures have progressively incorporated greater levels depends on the integration of multiple enabling technologies rather than on a single technological component. The reviewed corpus identifies IoT/IIoT, simulation, artificial intelligence and machine learning, cloud computing, edge computing, industrial communication protocols, sensing technologies, and data-management platforms as the principal of connectivity, computational intelligence, and dynamic adaptation. However, the diversity of architectural definitions remains a challenge for interoperability and comparison between implementations. Future work should therefore investigate reusable architectural patterns, standardized interfaces, and formal methods for evaluating the fidelity and maturity of DT architectures across different application contexts.

Table 4. Evolution of DT architectures, modeling approaches, principal contributions, and identified research gaps.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2020	DT Enhanced Dynamic Job-Shop Scheduling [9]	Meng Zhang, Fei Tao, A.Y.C. Nee	Dynamic job-shop scheduling enhanced by DT technology, introducing DT to bridge physical and virtual job-shop spaces, utilizing DT for machine availability prediction.	Enhanced convergence between physical and virtual spaces via DT for dynamic scheduling, illustrated through a case study: Further explore DT applications in complex scheduling environments and enhance DT model adaptability.	Manufacturing
2022	A bibliometric review of research on digital identity [10]	Lennart Ante et al.	The research project studies digital identity development through bibliometric methods, which demonstrate different research paths and connections between study areas in digital identity research.	Comprehensive overview of digital identity research streams and influential publications; visualization of interrelations: Explore emerging research topics within digital identity streams; investigate cross-disciplinary intersections.	Cross-domain
2022	A consistency evaluation method for DT models [11]	He Zhang, Qinglin Qi, Fei Tao	The proposed framework evaluates DT model consistency through its established process.	The project needs to evaluate complete DT modeling scenarios because there is no existing framework for assessing all aspects of DT modeling in complex shop-floor operations. The project needs to enhance the AHP methodology for consistency evaluation, which requires more precise measurement methods, and the research team needs to investigate all potential uses of the developed framework.	Cross-domain
2020	A DT approach based on a nonparametric Bayesian network for complex system health monitoring [12]	Jinsong Yu et al.	The DT method establishes its health monitoring system through the use of a nonparametric Bayesian network. The DT model construction process establishes a Bayesian network system that enables adaptive real-time updates through its built-in updating mechanism.	Improved model adaptability through real-time updating; validation through experiments in electro-optical system monitoring; Explore scalability of the approach across different monitoring scenarios; investigate further applications in complex system health management.	Manufacturing/Industrial Systems

Table 4. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2022	A DT-based framework for detection, diagnosis, and improvement of throughput bottlenecks [13]	Mahesh Kumbhar et al.	The DT framework detects production bottlenecks, which it uses to enhance manufacturing operations. The system employs DT technology to identify bottlenecks through real-time monitoring while it provides diagnostic capabilities and simulation tools for potential operational enhancements.	Novel approach utilizing DT and process mining for bottleneck management; demonstrated throughput improvements in a real factory setting; Extend the framework to optimize multiple manufacturing objectives concurrently; integrate with predictive maintenance.	Manufacturing
2022	A DT dosing system for iron reverse flotation [14]	Dingsen Zhang, Xianwen Gao	The DT system provides intelligent dosing solutions through its application in iron reverse flotation. The flotation process uses DT and machine learning for real-time monitoring and intelligent dosing operations.	Development of DT system for reagent dosing optimization; industrial validation and economic benefit analysis: Investigate scalability of the dosing system across different mineral beneficiation processes; integrate adaptive control strategies.	Manufacturing/Industrial Systems
2023	A DT system of reconfigurable tooling for monitoring in aerospace assembly [15]	Jie Jin et al.	The development of a DT system for aerospace assembly, reconfigurable tooling monitoring, and evaluation testing. The development of a reusable DT system creates operational models that include geometric patterns and physical properties, behavioral patterns, and rule-based systems.	Verification of DT system accuracy and generalizability through assembly experiments; further refinement of DT system for broader tooling applications; explore integration with predictive maintenance.	Manufacturing
2020	A DT to train deep reinforcement learning agents for smart manufacturing plants [16]	Kaishu Xia et al.	Utilizing DT for training deep reinforcement learning agents in smart manufacturing. Integration of DT with deep reinforcement learning for automated manufacturing control.	Demonstration of DRL-based smart agent for industrial control; application of trained algorithms in manufacturing tasks: Investigate scalability of DRL-based control methods; optimize integration between DT and manufacturing systems.	Manufacturing
2020	A DT-based Approach for Geometrical Deviations during Assembly Processes [17]	Jean-Loup Grégorio et al.	Management of geometrical deviations in assembly processes, hybrid representation of the product, updating virtual component models, and integration of assembly data.	Integration of physical assembly data into virtual models, optimizing assembly operations: Implementation of more advanced tools for updating virtual representations.	Manufacturing
2020	A DT -based Big Data Virtual and Real Fusion Learning Reference Framework [18]	Pei Wang, Ming Luo	Fusion of virtual and physical spaces using DT and big data, Synthesis of DTs and big data for smart manufacturing, supported by Industrial Internet.	Enhanced virtual–real fusion, iterative optimization, and closed-loop feedback in the product lifecycle: Implementation of advanced analytics for real-time decision-making	Manufacturing
2020	A DT-based Flexible Cellular Manufacturing for Optimization of Air Conditioner Line [19]	Hongfei Guo et al.	Optimization of air conditioner production line using DT-based flexible manufacturing, flexible manufacturing based on DT for quick production line updates.	Significant production capacity increase, decreased WIP, improved balance rate: Integration of AI for real-time production line optimization.	Manufacturing
2023	A DT-based On-site Quality Assessment Method for Aero-engine Assembly [20]	Li Jinyue et al.	Quality assessment for aero-engine assembly using DT, Development of an analysis DT platform, dynamic modeling for quality assessment.	Enhanced quality analysis during assembly, prototype system for on-site assembly assessment: Integration of advanced measurement techniques for more precise quality assessment.	Manufacturing

Table 4. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2020	A DT-enhanced System for Engineering Product Family Design and Optimization [21]	Kendrik Yan Hong et al.	The DT technology enables organizations to design and improve entire product families through its DT technology. The team created a generalizable DT architecture framework that enables manufacturers to design their entire product family system according to specific environmental conditions.	Situational recognition, self-correction, and decision-aiding capabilities in product family management: Integration of context-aware optimization algorithms for enhanced decision support.	Cross-domain
2021	A Digital-twin Visualized Architecture for Flexible Manufacturing System [22]	Yepeng Fan et al.	Visualization of flexible manufacturing systems using DT, development of a DT visualization architecture for FMS lifecycle services.	Visualization of high-value information throughout the lifecycle planning, design, and service stages: Further development of lightweight architectures for broader adoption.	Manufacturing
2020	A Knowledge-based Digital Shadow for the Machining Industry in a DT Perspective [23]	Asma Ladj et al.	Machining industry data management and analytics using digital shadow, integration of expert knowledge into a digital shadow for improved decision-making.	Continuously enriched behavior model, improved shop-floor performance: Application of advanced unsupervised learning techniques for enhanced analytics.	Manufacturing
2022	A New Quantitative DT Maturity Model for High-end Equipment [24]	Weifei Hu et al.	The development of a DT maturity framework for high-performance equipment. The research study assessed two different methods to measure DT maturity in highly advanced equipment systems.	Comparison and assessment of different DTs, proposal of maturity levels, and improvement advice: Further refinement of maturity assessment metrics based on industry feedback.	Evaluation/Maturity
2021	Bi-level dynamic scheduling architecture based on service unit DT agents [25]	Jian Zhang et al.	Dynamic workshop scheduling using DT agents, bi-level distributed scheduling architecture utilizing workshop and service unit DTs.	Local, simple, and robust scheduling; coordinated scheduling for multiple units; divide-and-conquer strategy: Implementation of real-time data exchange and feedback loops for enhanced scheduling.	Cross-domain
2020	Blockchain-based data management for the DT of the product [26]	Sihan Huang et al.	Blockchain technology enables secure data management for DT systems through its capability to control access and authenticate data while safeguarding data storage and sharing processes.	Improved data management efficiency and security; demonstration through a case study: Exploration of scalability and performance considerations for blockchain implementation in large-scale product networks.	Smart city
2021	Building the right DT with model engineering [27]	Lin Zhang, Longfei Zhou, Berthold K.P. Horn	The process of creating an accurate DT requires appropriate model engineering methods, which need to be defined first. The introduction of model engineering principles and associated metrics, together with the evolutionary concurrent modeling method (ECoM4DT), which serves as a modeling framework for DT development, will be presented.	Clear definition and systematic approach for building effective DTs; avoidance of unnecessary complexities: Application of ECoM4DT across diverse industry domains.	Construction
2023	Characterization and evaluation of identity for DTs for the manufacturing domain [28]	Shuo Su, Aydin Nassehi, Ben Hicks, Joel Ross	Evaluating DT quality ('identity') for manufacturing, Development of an evaluation framework based on completeness, trueness, precision, and latency.	A comprehensive method for assessing DT quality tailored to manufacturing scenarios; use of manufacturing ontology: Integration of real-time monitoring capabilities and adaptive twin synchronization.	Manufacturing

Table 4. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2020	Conceptual DT modeling based on an integrated five-dimensional framework and TRIZ function model [29]	Chunlong Wu et al.	Modeling a multidimensional DT at the conceptual level for an intelligent vehicle, a five-dimensional DT framework to represent complex relationships, and TRIZ function model integration.	Method for conceptual modeling of DT objects and attributes, bridging material and virtual worlds: An effective method for multidimensional DT modeling.	Transportation
2020	Consistency retention method for CNC machine tool DT model [30]	Yongli Wei et al.	Retaining consistency in updating DT models for CNC machine tools, framework for consistency retention method, addressing performance attenuation update.	Method for updating DT model with performance attenuation; case study on rolling guide-rail verification: An effective method for maintaining the accuracy of DT models for CNC machine tools.	Cross-domain
2021	The construction method of shop-floor DT based on MBSE [31]	Juan Liu et al.	Construction of a structured DT for shop-floor systems, A method based on Model-Based Systems Engineering (MBSE), MagicGrid modeling, and V model application.	Hierarchical and modularized framework for shop-floor DT construction, example of NC machining shop-floor subsystems: Structured approach for developing shop-floor DTs, enhancing system scalability and maintenance.	Manufacturing
2020	Data Construction Method for the Applications of Workshop DT System [32]	Tianxiang Kong et al.	Construction of stable and efficient data support for the manufacturing workshop DT, framework for data construction based on functional requirements analysis.	The module implements data representation and organization together with data management functions. The research examined how workshop DT systems used stable and efficient data to improve their operational performance and precise measurement of application outcomes through cutting-tool wear prediction.	Manufacturing
2023	Deep active-learning-based model-synchronization of digital manufacturing stations [33]	Clint Alex Steed, Namhun Kim	Modeling human performance in virtual manufacturing systems using active learning and VR, an active learning framework for modeling human assembly duration in VR experiments.	Efficient modeling of human performance using VR-based active learning; reduction in experimental trials: Enhance the modeling of human performance in virtual systems.	Manufacturing
2020	Deep learning-empowered DT for visualized weld joint growth monitoring [34]	Qiyue Wang et al.	Monitoring and controlling welding processes using DT, Integration of deep learning for weld joint monitoring and control.	Use of deep learning for accurate weld joint monitoring and control, decision-making strategy for welding penetration control: Improve welding process control using deep learning in the DT framework.	Energy
2022	Digital thread-based modeling of DT framework for the aircraft assembly system [35]	Qiang Zhang et al.	Modeling complex assembly environments using digital thread-based DT, establishment of a DT framework with five modules.	Improved data management, controllability, and traceability in the aircraft assembly process: A DT framework enhances efficiency and traceability in the aircraft assembly process.	Manufacturing
2020	DT and blockchain-enhanced smart manufacturing service collaboration [36]	Fei Tao et al.	The research introduces a framework that uses DTs and blockchain technology to improve manufacturing service partnerships. The research introduces a framework that uses DTs and blockchain technology to improve manufacturing service partnerships.	The collaborative manufacturing service between individuals from different organizations and their ability to trust each other and adapt to changes has improved, but the production process needs proper management for its successful operation. The current study investigates the implementation of DT-BC to enhance manufacturing service collaboration through its dedicated framework.	Manufacturing

Table 4. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2021	DT and cloud-side-end collaboration for intelligent battery management system [37]	Yujie Wang et al.	Leveraging DT and cloud-side-end collaboration for battery management, establishment of a four-layer networked architecture for the battery management system.	Enhanced management of batteries throughout their lifecycle; introduction of DT model and key technologies: Utilize DT and cloud collaboration for refined battery management throughout the cycle.	Energy
2020	DT-Based Real-time Production Logistics Synchronization System [38]	Y.H. Pan et al.	Real-time monitoring and synchronization of the production logistics system; multi-level cloud computing enabled a DT system for production logistics synchronization.	The optimization model for production and storage introduces real-time monitoring and dynamic decision-making capabilities. The system needs better monitoring tools and decision-making processes for its production logistics operations.	Smart city
2021	DT-enhanced fault prediction for the autoclave with insufficient data [39]	Yucheng Wang et al.	Fault prediction for complex equipment with limited data using DT, construction and verification of DT model for autoclave, application in fault prediction.	Effective fault prediction using simulated and historical data; application of CNN for fault prediction in autoclave: Enhance fault prediction for complex equipment with limited data using DT technology.	Construction
2023	DT model-based smart assembly strategy design for PCB kit-box build [40]	Xurui Li et al.	Precision assembly of PCBs inside enclosures using DT, utilizing a DT model for accurate perception of object pose and real-time monitoring.	Development of a DT model for intelligent PCB kit-box assembly, including pose optimization and quality prediction: Further refine the DT model to achieve higher assembly success rates and minimize errors.	Manufacturing
2022	DT Technology—A bibliometric study of top research articles [41]	Tang Ji, Huiyue Huang, Xun Xu	Bibliometric analysis of top research articles on DT in smart manufacturing, identifying and summarizing the top 100 most cited DT studies in smart manufacturing.	Summary and discussion of important DT studies in terms of publication year: Provide insights into key areas and trends in DT technology development.	Manufacturing
2020	DT-based designing of the configuration, motion, control, and optimization of a flow-type smart manufacturing system [42]	Qiang Liu et al.	Designing a flow-type smart manufacturing system using DT, introducing a quad-play CMCO design architecture for DT-based smart manufacturing	Presentation of key enabling technologies and methodologies, and development of a DT-based manufacturing system design platform: Verification of the proposed design approach through a case study demonstrating feasibility and efficiency.	Manufacturing
2020	DT-based industrial cloud robotics: Framework, control approach and implementation [43]	Wenjun Xu et al.	The cloud computing system will be integrated with industrial robots through DT technology. The DT-based industrial cloud robotics framework will be established through this proposal.	The research work establishes a bidirectional connection between digital infrared systems and physical infrared systems to enable precise control of sensing operations through the developed systems. The research work demonstrates the successful implementation of the DTICR system through the execution of a case study, which showed its operational capabilities and system flexibility.	Manufacturing
2020	DT-based smart assembly process design and application framework for complex products [44]	Yang Yi et al.	Designing smart assembly processes for complex products using DT, presenting a DT reference model and application framework for DT-based smart assembly.	Detailing the application framework with three layers: physical space, interaction, and virtual space. Verification of the proposed framework through a case study involving assembly process design for a satellite.	Manufacturing

Table 4. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2023	DT-based structural health monitoring by combining measurement and computational data [45]	Xiaonan Lai et al.	Structural health monitoring framework using DT, combination of measurement and computational data.	MCC-DT framework, load identification, MFS models, online rain-flow counting algorithm, 3D visualization: Applicability and effectiveness verification.	Healthcare
2020	DT modeling method based on biomimicry for machining aerospace components [46]	Shimin Liu et al.	Modeling machining processes of aerospace components using DT based on biomimicry, proposing a DT modeling method that adaptively constructs multi-physics DT models of machining processes.	Development of multiple DT sub-models interacting to represent the physical machining process accurately: Further validate and refine the DT modeling method for broader applications in aerospace manufacturing.	Manufacturing
2023	DT-driven centering process optimization for high-precision glass lens [47]	Shiau-Cheng Shiu et al.	Centering process optimization for glass lens manufacturing, DT-driven optimization system.	DOE-GA optimization, virtual process model, industrial implementation: Reduced process development time, sampling inspection, and improved yield rate.	Manufacturing
2021	DT-driven machining process for thin-walled part manufacturing [48]	Zexuan Zhu et al.	Machining process optimization for thin-walled part manufacturing, DT-driven framework.	Real-time interaction, process management, case study: Faster start-up phases, accurate machining, real-time interaction.	Manufacturing
2021	DT-driven online anomaly detection for an automation system based on edge intelligence [49]	Huiyue Huang et al.	Anomaly detection for automation systems using edge intelligence DT-driven anomaly detection framework.	Edge-based DT, real-time monitoring, case study. Future: Early-stage anomaly detection, real-time monitoring.	Cross-domain
2020	DT for cutting tool: Modeling, application, and service strategy [50]	Yang Xie et al.	Cutting-tool DT development and services, DT-driven data flow framework.	Cutting-tool lifecycle management, virtual testing platform: Continuous improvement, virtual testing platform.	Cross-domain
2020	DT-driven optimization of gas exchange system of 2-stroke heavy fuel aircraft engine [51]	Zheng Xu et al.	Optimization of gas exchange system for aircraft engines, DT-driven optimization method.	Real-time feedback, virtual-physical integration, iterative optimization: Improved engine performance, smart manufacturing development.	Manufacturing
2023	DT-enabled automated anomaly detection and bottleneck identification [52]	Christina Latsou et al.	The manufacturing systems use automated systems to detect anomalies and find their operational problems. The multi-agent system uses DT technology to create its cyber-physical system.	Anomaly detection, bottleneck identification, multi-agent approach: Improved decision-making, real-time detection.	Manufacturing
2020	DT-enabled Collaborative Data Management for Metal Additive Manufacturing Systems [53]	Chao Liu et al.	The metal additive manufacturing process uses collaborative data management. The framework enables collaborative data management through DT technology.	Cloud-based collaboration, deep learning-enabled defect analysis: Enhanced process understanding, improved quality.	Manufacturing

Table 4. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2021	DTs-based smart manufacturing system design in Industry 4.0: A review [54]	Jiewu Leng et al.	Smart manufacturing system design using DTs, FSBCIP framework for DT-based SMS design.	Unified model development, semi-physical simulations: Reduced time and cost, effective SMS design.	Manufacturing
2020	Digital-twin-driven geometric optimization of the centrifugal impeller with free-form blades [55]	Yu Zhou et al.	The project aims to develop an optimal design for centrifugal impellers, which will be achieved through geometric optimization methods and through the implementation of DT-based optimization techniques.	Tool-path generation, aerodynamic performance analysis, reinforcement learning: Improved machining efficiency, balance of performance.	Manufacturing
2019	Enabling technologies and tools for DT [56]	Qinglin Qi, Fei Tao, Tianliang Hu, Nabil Anwer et al.	DT implementation requires specific technologies and tools that allow its realization. The operation of DT systems depends on particular enabling technologies and associated supporting tools.	5-dimensional DT model, enabling technologies and tools overview: Reference guidance for DT applications.	Cross-domain
2021	Establishing a reliable mechanism model of the DT machining system [57]	Shimin Liu et al.	Reliability evaluation for DT machining systems, Adaptive evaluation network approach.	Reliability evaluation, adaptive decision-making: Enhanced decision-making, reduced errors.	Manufacturing
2022	Four Rs Framework for the development of a DT [58]	John Osho et al.	DT development framework implementation, Four Rs framework.	Representation, replication, reality, relational phases: Improved DT development.	Manufacturing
2020	Framework for manufacturing-tasks semantic modeling and manufacturing-resource recommendation [59]	Xixing Li et al.	On the acquisitions of DT shop floors, this research takes up the topic of a theoretical study of semantic modeling and resource suggestion. Moreover, a framework comprising MT&MR was conceived.	Ontology-based modeling, dynamic resource recommendation: Improved scheduling accuracy, real-time optimization.	Manufacturing
2020	How to model and implement connections between physical and virtual models for DT systems [60]	Qinling Zhang et al.	Connection modeling between physical and virtual models for DTs, literature review.	Connection modeling methods, DT systems: Reference for connection modeling methods.	Cross-domain
2025	Using a DT and smart services to enable automatic generation of context-sensitive instructions [61]	Karl Lossie et al.	DT + real-time data to generate adaptive instructions; prototype and validation.	Smart automated instructions; improved efficiency and accuracy; industrial validation. Add AI, improve scalability, and extend to other applications.	Manufacturing
2022	A consistency evaluation method for DT models [11]	Zhang, He Qi, Qinglin Tao, Fei	Consistency evaluation framework for DT models using AHP before/after model assembly and fusion.	Comprehensive DT model evaluation; integration of geometry, physics, behavior, and rule models; improved model reliability. Enhance evaluation metrics, extend to diverse industrial scenarios, and integrate real-time validation.	Smart Manufacturing

Table 4. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2022	DT modeling [62]	Tao, Fei Xiao et al.	Systematic review and classification of DT modeling based on multiple dimensions and theoretical aspects.	Comprehensive analysis of DT models; classification framework; identification of enabling technologies. Improve modeling methods, enhance universality, and develop advanced tools and standards.	Smart Manufacturing
2021	Automated manufacturing system discovery and DT generation [63]	Lugaresi, Giovanni Matta, Andrea	Data-driven automatic generation of DT models with an optimal level of detail from production logs.	Efficient DT model generation; reduced complexity; improved performance estimation accuracy. Enhance adaptability to dynamic systems, improve data quality handling, and extend to diverse industries.	Manufacturing
2021	A matrix analytic approach for Bayesian network modeling and inference [64]	Ding Zhang et al.	Analytical model of Bayesian network for manufacturing system, Proposed matrix analytic approach.	Improved analytical model for maintenance services; efficient probability network modeling; real-world verification: Application of the matrix analytic approach in diverse manufacturing systems.	Manufacturing
2020	Digital-twin-driven geometric optimization of centrifugal impeller [55]	Yu Zhou et al.	Geometric optimization of centrifugal impeller; DT-based approach, DT-based optimization strategy for balancing machinability and aerodynamic performance.	Integrated design and manufacturing using DT; machining efficiency improvement; aerodynamic performance analysis; real-world experimentation: Further research on DT-driven optimization strategies; exploration of DT applications in other manufacturing processes.	Manufacturing
2022	A multi-dimensional cognitive framework for cognitive manufacturing [65]	Tengyuan Jiang et al.	Cognitive framework for dynamic production system cognition; OAR model, proposal of a multidimensional cognitive framework based on OAR model; dynamic cognition dimensions and capabilities; computation DT model development.	Development of cognitive manufacturing mechanisms; computation DT model construction; cognitive capabilities provision; feasibility demonstration: Application of cognitive framework in diverse production systems; continuous enhancement of cognitive capabilities.	Manufacturing
2023	Towards smart layout design for a reconfigurable manufacturing system [66]	Halldor Arnarson et al.	Smart layout design system for reconfigurable manufacturing systems, integration of Industry 4.0 technologies, simulation, and optimization for smart layout design.	Improved responsiveness and autonomy in layout design; reduction in human intervention; optimization of RMS efficiency: further development and refinement of smart layout design system; application in various manufacturing contexts.	Manufacturing
2020	DT-based assembly data management and process traceability for complex products [67]	Cunbo Zhuang, Jingcheng Gong, Jianhua Liu	Assembly data management and process traceability for complex products, DT-based approach with dynamic evolutionary process analysis.	Framework for DT-based data management; core techniques for workflow, synchronous modeling, hierarchical management: Implementation of DT-APMCS in aerospace industries, future research directions.	Manufacturing
2020	Predictive maintenance integrated decision-making approach supported by DT-driven cooperative awareness [68]	Shanghua Mi et al.	The first system uses predictive maintenance to help decision-making processes. The second system uses a DT-based framework to establish cooperative awareness between different entities that need to connect.	Integrated mathematical model, NSGA-II hybrid algorithm, case study validation: Guidance for implementing predictive maintenance with higher accuracy and reliability.	Cross-domain

Table 4. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2023	The adoption of digital technologies in the manufacturing world: A systematic review [69]	Leonardo Maretto, Maurizio Faccio, Daria Battini	Evaluation of digital technology adoption in manufacturing: A systematic review of 229 real-life case studies.	Categorization of digital technologies, performance measurement, economic benefit analysis: Identification of five new research directions.	Manufacturing
2023	Assessing the impact of automation in pharmaceutical quality control labs using a DT [70]	Tiago Coito et al.	Impact assessment of automation in pharmaceutical quality control labs, simulation model-based approach.	Development of simulation model; comparison between current and future workflows; analysis of throughput, resource occupation, and annual man-hours gained: Projection of increase in analyst and equipment availability based on production data.	Healthcare
2024	Research on DT monitoring systems during milling of large parts [71]	Yao Lu et al.	DT monitoring in milling, Unity 3D-based virtual system, OPC UA, LabVIEW.	Improved machining safety and quality: Develop adaptive DT-based chatter suppression techniques.	Manufacturing
2020	A DT commissioning method for machine tools based on scenario simulation [72]	Yao Lu et al.	DT commissioning for machine tools, Scenario simulation, Unity 3D, MySQL.	Improved safety, reduced errors: Expand DT testing scenarios for broader applications.	Design/Simulation
2024	A review and outlook of airframe DTs for structural health management [73]	Joelle W.Y. Chia et al.	Airframe DT for aviation maintenance, Systematic literature review.	Identified trends in SPHM: Develop advanced environmental condition models.	Healthcare
2024	Simulation-based DT for enhancing human–robot collaboration in assembly systems [74]	Antonio Cimino et al.	DT for human–robot collaboration, FIWARE/FIROS simulation-based DT.	Improved HRC efficiency in assembly lines: Address real-time data exchange challenges.	Manufacturing
2025	An LLM-guided SD-LDM DT Construction Strategy (LSDT) for multi-industrial scenarios: Enhancing adaptability and efficiency [75]	Feixiang Wang et al.	LLM-guided SD-LDM framework for rapid 3D model generation and multi-scale DT construction; validated via case studies.	Fast DT construction method (LSDT); multimodal 3D generation; improved efficiency and usability, enhanced model generalization, integrated more data sources, and extended to broader industrial scenarios.	Manufacturing
2025	Multi-robot collaborative manufacturing driven by DTs: Advancements, challenges, and future directions [76]	Gang Wang et al.	Comprehensive review of DT-driven multi-robot collaborative manufacturing (MRCM): concepts, architecture, and technologies.	Structured analysis of DT-based MRCM; identification of challenges; integration of AI for multi-robot collaboration. Improve modeling, coordination strategies, and scalability; integrate advanced AI for better collaboration.	Manufacturing/Privacy

4.2. Enabling Technologies and Digital Infrastructure

The development of DT systems depends on the integration of multiple enabling technologies rather than on a single technological component. The reviewed corpus identifies IoT/IIoT, simulation, artificial intelligence and machine learning, cloud computing,

edge computing, industrial communication protocols, sensing technologies, and data-management platforms as the principal technological foundations of contemporary DT implementations.

Figure 5 summarizes the frequency of the principal enabling technologies identified across the 230 reviewed studies.

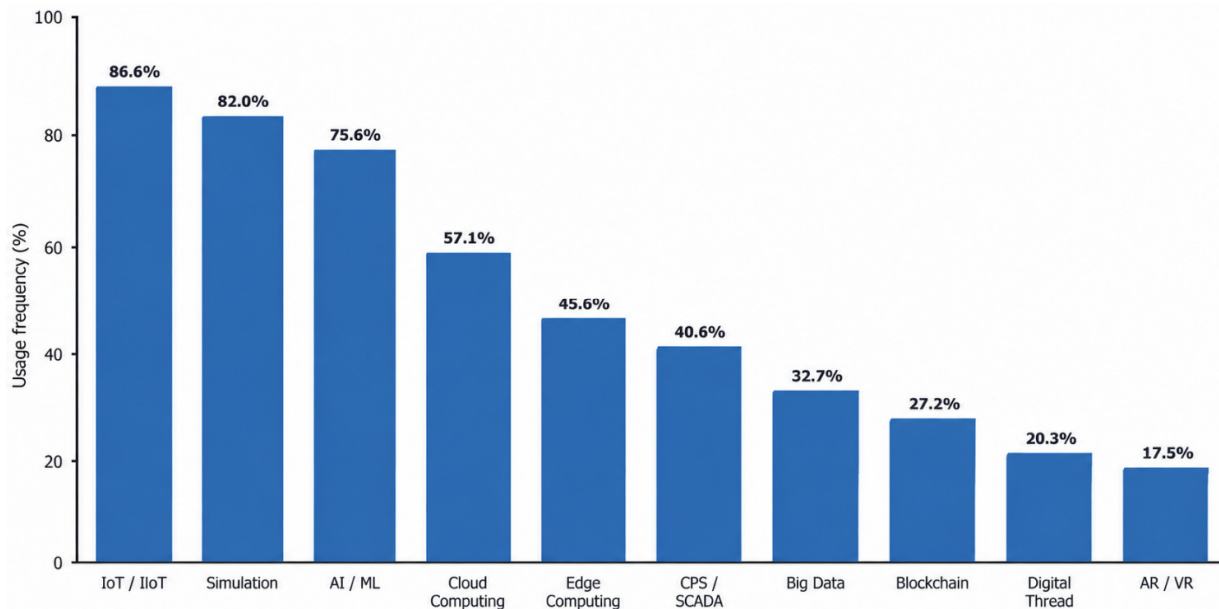


Figure 5. Enabling technologies identified in the DT corpus (2018–2026, n = 230 papers).

IoT/IIoT represents the most frequently reported enabling technology, appearing in 86.6% of the analyzed studies, followed by simulation at 82.0% and AI/machine learning at 75.6%. Cloud computing appears in 57.1% of the studies, while edge computing is reported in 45.6%. These frequencies demonstrate that contemporary DT architectures increasingly depend on the combination of sensing, communication, simulation, and computational intelligence.

The high prevalence of IoT/IIoT confirms the central role of continuous sensing and data acquisition in establishing the connection between physical assets and their digital counterparts. Sensors, actuators, PLCs, industrial controllers, and other data-acquisition devices provide the operational information required to maintain the virtual representation.

Simulation remains another fundamental component. Simulation environments allow DTs to reproduce physical processes, evaluate alternative operating scenarios, predict system behavior, and test control strategies without directly modifying the physical system. Depending on the application, simulation may involve discrete-event simulation, finite-element analysis, computational-fluid-dynamics models, manufacturing simulation, or three-dimensional virtual environments.

AI and machine learning constitute an increasingly important component of DT intelligence. Their applications include prediction, anomaly detection, classification, diagnosis, quality assessment, predictive maintenance, optimization, and decision support. Deep learning architectures such as CNNs, LSTMs, and GNNs are increasingly incorporated into DT workflows, while physics-informed and hybrid approaches attempt to combine physical knowledge with data-driven learning.

Cloud and edge computing provide complementary computational capabilities. Cloud platforms facilitate large-scale storage, centralized analytics, and computationally intensive processing, whereas edge computing supports low-latency processing close to physical

assets. The increasing use of edge computing reflects the need for real-time or near-real-time DT operation, particularly in industrial environments.

Other technologies identified in the corpus include blockchain, digital-thread technologies, semantic models, ontologies, 5G/6G communication, federated learning, generative AI, and physics-informed machine learning. These technologies remain less prevalent than the established DT foundations but indicate the direction of technological development toward more distributed, interoperable, secure, and autonomous DT ecosystems.

Table 5 summarizes the main enabling technologies integrated with digital twins, highlighting their applications, contributions to DT capabilities, and the research gaps that remain to be addressed.

Table 5. Enabling technologies integrated with digital twins: applications, contributions, and research gaps.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2023	A reduced order model on adaptive proper orthogonal decomposition for a DT in the process industry [77]	Xiaoyang Zhu, Yangjian Ji	DT technology in the process industry, reduced-order model with adaptive updating ability.	The high-precision fitting method enables users to achieve extensive time savings when applying the complete order model. The upcoming phase of the project will test through various industrial processes to confirm its validity.	Manufacturing
2023	Construction of a DT for a clamped near-net-shape blade in adaptive manufacturing [78]	Yiming Guo et al.	DT for adaptive manufacturing of near-net-shape blades, innovative modeling method for clamped adaptive manufacturing of near-net-shape blades (CADT)	Consistency between CADT and the adaptive model, and accurate finishing guidance. Future: Application to other large-sized near-net-shape components.	Manufacturing
2022	Design of Gaussian process-based model predictive control for seam tracking in a laser welding DT environment [79]	Zhehao Zhang et al.	Laser welding seam tracking control, Gaussian process-based model predictive control.	Improved seam tracking accuracy and robustness. Future: Integration into industrial laser welding systems.	Design/Simulation
2022	Development of FEM-based DTs for machining difficult-to-cut materials: A roadmap for sustainability [80]	Ribeiro-Carvalho et al.	Machining simulations for sustainable production, Finite Element Method (FEM) simulations for coolant-assisted machining.	Practical tool for selecting cutting configurations and awareness of challenges. Further development of numerical models for sustainable cooling techniques.	Manufacturing
2021	DT modeling for temperature field during friction stir welding [81]	Gaoqiang Chen et al.	DT for friction stir welding, Sensor-based numerical simulation with cyber-physics fusion algorithm.	Real-time calculation of in-process 3D temperature field; synchronization with physical process, validation in diverse FSW scenarios; integration into industrial FSW systems.	Design/Simulation
2021	Neural networks and NARXs to replicate extrusion simulation in DTs for fused filament fabrication [82]	A. Rossi, M. Moretti, N. Senin	DT for fused filament fabrication, Nonlinear autoregressive models with exogenous variables (NARXs).	Replication of complex extrusion simulation with reduced computational time, integration into real FFF machines, and in-process monitoring capabilities.	AI/Machine Learning

Table 5. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2022	Physical modeling for DT of the Continuous Damping Control damper [83]	Tao Li, Zhongyuan Liao, Yi Cai	DT for CDC damper, Hybrid model combining lumped parameter and neural network models.	High accuracy and low computational cost for CDC damper modeling. Application to the monitoring and control of CDC dampers in various systems.	AI/Machine Learning
2023	Smart recoating: A DT framework for optimisation and control of powder spreading in metal additive manufacturing [84]	Arden Phua et al.	DT for powder spreading control in metal AM, Bayesian optimization for real-time control, Discrete Element Method simulations.	Improved layering consistency, mitigation of process variation, integration into metal additive manufacturing systems, and exploration of new process strategies.	Manufacturing
2023	Towards a DT of laser powder bed fusion with a focus on gas flow variables [85]	C.G. Klingaa et al.	DT for laser powder bed fusion, Investigation of gas flow variables on part quality metrics.	Understanding the influence of gas flow on part quality, development of response surface models, implementation in laser powder bed fusion systems, and decision-making under uncertainty.	Manufacturing
2021	Validation of materials-informed DT: Mapping residual strains in HSLA steel weldment using high-energy X-rays [86]	Charles R. Fisher et al.	Materials-informed DT for structural analysis, finite element analysis (FEA), welding simulations, comparison with energy-dispersive diffraction (EDD).	Validation of a computational method for predicting residual strains in weldments. Integration of fabrication data into structural analysis for increased accuracy.	Energy
2024	DT-based anomaly detection for real-time tool condition monitoring in machining [87]	Zepeng Liu et al.	Real-time tool condition monitoring (TCM) in machining using DTs, A DT framework integrating physical machining processes, real-time data-driven modeling, and diagnostic algorithms for anomaly detection.	The project implements new methods for monitoring tools by using Model Frequency Features, which track their operational status. The research will be expanded to study advanced machining components while validating their lifespan forecasting capabilities.	Manufacturing
2024	A DT framework for anomaly detection in industrial robot systems [88]	Shijie Wang et al.	Anomaly detection in industrial robots using DTs, a hybrid convolutional autoencoder (MPI-HCAE) integrating multiple physical variables as digital assets.	Development of a physics-informed hybrid convolutional autoencoder; achieved RMSE below 1.5%, F1-score over 98.23%. Expand the model's applicability to more complex industrial robots; enhance real-time processing.	Cross-domain
2025	Research on the online monitoring method of cutting tool wear based on the mechanism-data fusion concept of DT [89]	Zhou et al.	Mechanism–data fusion DT using DSCNN (PTFT), similarity-based reasoning, and particle filter for tool wear monitoring.	High-accuracy DT model; improved generalization under varying conditions; efficient online tool wear monitoring. Extend to more materials and machining conditions; enhance model robustness; integrate real-time industrial deployment.	Manufacturing/AI
2025	DT for weld pool evolution by data-physics integrated driving [90]	Jiao, Wenhua et al.	Regression model with improved loss function (MLE), transfer learning, and DT for weld pool monitoring and visualization.	Enhanced prediction accuracy; reduced data dependency; DT-based visualization of weld pool evolution. Improve data quality, extend to complex welding scenarios, and integrate advanced AI models.	Manufacturing/AI

The overall evidence suggests that DT development is increasingly characterized by technological convergence. IoT provides data acquisition, communication technologies provide connectivity, simulation provides virtual representation, AI provides intelligence, and cloud/edge infrastructure provides computational resources. The challenge is therefore no longer simply the development of individual technologies, but their reliable and interoperable integration into a coherent DT architecture.

4.3. *Application Domains and Functional Uses*

The reviewed corpus covers several application domains, with manufacturing representing the dominant area of DT research. Healthcare, smart cities, and energy systems constitute additional major application domains and demonstrate the increasing generalization of DT concepts beyond industrial production.

4.3.1. Manufacturing

Manufacturing constitutes the largest application domain in the reviewed corpus. DTs are employed for predictive maintenance, process monitoring, quality control, production transition from using DTs primarily for monitoring toward using them for prediction, optimization, and operational decision-making. In advanced manufacturing environments, DT scheduling, process optimization, condition monitoring, robotics, assembly, machining, additive manufacturing, and cyber–physical production systems.

The literature indicates a progressive transition from using DTs primarily for monitoring toward using them for prediction, optimization, and operational decision-making. In advanced manufacturing environments, DTs increasingly integrate machine learning models, real-time sensor data, simulation, edge computing, and industrial communication technologies.

Several reviewed studies also address high-mix low-volume production, human–robot collaboration, sustainable manufacturing, and intelligent configuration management. These studies indicate that DTs can support manufacturing environments characterized by high product variety, changing production requirements, and complex interactions between humans and machines.

4.3.2. Healthcare

Healthcare represents a distinct application environment in which DTs are applied to patients, medical devices, hospital systems, and healthcare infrastructure. The reviewed literature includes applications involving patient monitoring, medical cyber–physical systems, neonatal monitoring concerning privacy, safety, reliability, data governance, and clinical validation. The use of sensitive patient information also creates additional cybersecurity and ethical considerations. Consequently, healthcare DT validation cannot rely exclusively on conventional engineering performance indicators spatial and organizational scale than most manufacturing applications. The reviewed studies address urban planning, transportation, environmental monitoring, infrastructure management, energy management, and to combine information from sensors, transportation systems, buildings, energy infrastructure, geographic information systems, and public services. Scalability, interoperability, privacy, and real-time synchronization, energy storage, monitoring, predictive maintenance, and energy optimization. The reviewed studies demonstrate the potential of DTs to support both asset, personalized healthcare, and AI-supported medical decision-making.

Unlike manufacturing, healthcare DTs are subject to particularly stringent requirements concerning privacy, safety, reliability, data governance, and clinical validation. The use of sensitive patient information also creates additional cybersecurity and ethical consid-

erations. Consequently, healthcare DT validation cannot rely exclusively on conventional engineering performance indicators and requires domain-specific validation procedures.

4.3.3. Smart Cities and Infrastructure

Smart-city DTs operate at a broader spatial and organizational scale than most manufacturing applications. The reviewed studies address urban planning, transportation, environmental monitoring, infrastructure management, energy management, and green mobility.

The main challenge in this domain is the integration of heterogeneous and geographically distributed data sources. Smart-city DTs may need to combine information from sensors, transportation systems, buildings, energy infrastructure, geographic information systems, and public services. Scalability, interoperability, privacy, and real-time synchronization therefore become particularly important.

4.3.4. Energy Systems

Energy-related DT applications include power generation, renewable-energy systems, smart grids, batteries, energy storage, monitoring, predictive maintenance, and energy optimization. The reviewed studies demonstrate the potential of DTs to support both asset-level monitoring and system-level energy management.

Energy applications impose strict requirements for reliability, availability, prediction accuracy, and real-time operation. Renewable-energy systems additionally introduce uncertainty associated with weather conditions and fluctuating generation, increasing the importance of predictive and adaptive DT models.

Table 6 provides a comparative synthesis of DT applications across manufacturing, healthcare, smart cities, and energy systems, highlighting their main application areas, contributions, and domain-specific challenges.

Table 6. Comparative synthesis of DT applications across manufacturing, healthcare, smart cities, and energy systems.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2020	Efficient container virtualization-based DT simulation of smart industrial systems [91]	Ting Yu Lin et al.	The first system provides on-demand simulation through its DT-based simulation system. The second system uses container virtualization to deliver simulation services through its CVSimaaS methodology.	Lightweight container virtualization, matrix-based management model. Implement CVSimaaS for efficient and resource-conserving DT system deployment.	Cross-domain
2022	A DT-based approach for optimizing operation energy consumption at automated container terminals [92]	Yinping Gao et al.	Optimizing energy consumption in automated container terminals, DT-based approach, Q-learning algorithm.	Virtual container yard, energy consumption minimization model, comparison with GA and PSO algorithms. Use DT to visualize the operational environment and support ASC energy optimization.	Energy
2021	A function-oriented optimizing approach for smart product service systems using DT [93]	Chunlong Wu et al.	Optimizing Smart PSS at the conceptual design stage using DT, hybrid modeling, integrating function modeling, and 5D DT framework.	Function value ranking with TFN-based calculation, systematic ideality improvement. Apply the proposed method to enhance Smart PSS competitiveness and systematic ideality.	Cross-domain

Table 6. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2021	A graph-based Monte Carlo simulation supporting a DT for excavation material flows [94]	Simon Züst et al.	Managing material flows in construction for the circular economy, graph-based Monte Carlo simulation, and DT.	Effective steering inputs for government agencies, material flow quantification. Apply DT to understand and predict material flow impacts and evaluate potential scenarios.	Construction
2019	Big data-driven Hierarchical DT Predictive Remanufacturing paradigm [95]	Yankai Wang et al.	Sustainable multi-life-cycle remanufacturing through DT, big data-driven layered architecture, hierarchical CPS-digital-twin control mechanism.	Feasibility of BDHDTPREMfg, benefits of lifecycle penetration. Focus research on integrating smart enabling technologies in remanufacturing processes.	Manufacturing
2020	Data fusion-based sustainable DT system of intelligent detection robotics [96]	Bin He, Xiaoyang Cao, Yicheng Hua	Enhancing the sustainability of intelligent detection robots, decision-level and data-level fusion, DS evidence theory.	Sustainable design quantitative model, entropy weight method for indicator evaluation. Use data fusion to improve product sustainability and comprehensive performance.	Manufacturing
2023	Developing key performance indicators for monitoring sustainability in the ceramic industry [97]	Giuditta Contini et al.	The ceramic industry needs sustainable monitoring through KPI systems, which require digital process transformation and Industry 4.0 technology implementation.	Methodology for self-monitoring sustainability, sustainability DT concept, invest in digitization and Industry 4.0 technologies for real-time sustainability monitoring.	Manufacturing
2023	Development of a DT for smart farming: Irrigation management system for water saving [98]	Rafael Gomes et al.	Smart irrigation for water saving in agriculture, FIWARE-based IoT platform, discrete event simulation model.	Evaluation of IoT platform and irrigation strategies, real-time system communication. Use DT to improve farm operations, reduce water usage, and evaluate irrigation strategies.	Agriculture
2019	DT aided sustainability-based lifecycle management for railway turnout systems [99]	Sakdirat Kaewunruen, Qiang Lian	Lifecycle management of railway turnouts using DT, 6D BIM integration, Revit-2018, Navisworks-2018 platforms.	Improved information flow, economic and sustainability assessment. Adopt BIM for efficient management across the lifecycle of railway turnouts.	Transportation
2023	DT of end-of-life process chains for a circular economy adapted product design [100]	Jeff Mangers et al.	Circular economy in product design for PET bottles, C-VSM, digital state flow representation, decision-support tool.	Alignment of product design with EOL processes improved circularity. Consider EOL infrastructure in product design to enhance circular resource flows.	Construction
2023	DT-enabled human-robot collaborative teaming towards sustainable built environments [101]	Weisheng Lu et al.	Human–robot collaboration for facility management, DT-enabled framework, dynamic simulation.	Safe and efficient human–robot collaboration, real-time data capture, and leveraging DT to optimize human–robot teamwork in managing built environments.	Healthcare
2021	Digital-twin driven energy-efficient multi-crane scheduling and crane number selection [102]	Ning Zhao et al.	Energy-efficient scheduling in multi-crane systems using DT, DT framework, and simulation-based solution generation.	Accurate energy consumption evaluation and interference avoidance. Use DT for efficient multi-crane scheduling and energy-saving strategies.	Energy
2021	DTs-based remote semi-physical commissioning of flow-type smart manufacturing systems [103]	Jiewu Leng et al.	Remote commissioning of manufacturing systems using DT, Remote semi-physical simulation, open architecture design.	Reduced physical commissioning costs, case study validation, implement DT for sustainable commissioning of smart manufacturing systems.	Manufacturing

Table 6. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2025	Soft-sensors to drive manufacturing toward clean production: LCA based on DT [104]	Piron, Mirco Bovo et al.	Integration of DT (ISO 23247) with LCA (ISO 14040) using soft sensors for real-time environmental impact assessment [105].	Real-time environmental DT model; energy and GWP analysis; improved sustainability via optimization and eco-design. Extend to other processes, enhance sensor accuracy, and integrate broader sustainability metrics.	Manufacturing
2025	Comparative analysis of experimental and modelling of bifacial PV panel: a step towards DT [106]	Halwani et al.	DT modeling of bifacial PV panels using analytical, PVsyst, and Simulink models for performance prediction.	High-accuracy power forecasting; comparison of models; DT for monitoring and predictive maintenance. Extend to large-scale PV systems, improve model integration, enhance real-time optimization.	Smart Energy

4.3.5. Cross-Domain Comparison

Across the four principal application domains, the technological foundations of DTs are broadly similar, but the operational constraints differ. Manufacturing emphasizes real-time control, production optimization, and quality; healthcare emphasizes privacy, safety, and clinical reliability; smart cities emphasize scalability and heterogeneous infrastructure integration; and energy systems emphasize reliability, prediction, and system stability.

The cross-domain analysis demonstrates that DT concepts are transferable at the architectural level but not necessarily at the implementation level. Domain-specific data characteristics, safety requirements, operational constraints, and validation procedures must therefore be considered when adapting DT architectures between application environments.

The reviewed corpus demonstrates that DT applications extend beyond manufacturing to healthcare, smart cities, energy systems, and other infrastructure-oriented domains. Although manufacturing remains dominant, the additional studies published in MDPI journals provide useful evidence of the expansion of DT research toward healthcare, energy, and smart-city applications (see Table 7). These studies also illustrate how DTs are increasingly combined with AI, IoT, cybersecurity, and advanced communication technologies across different application contexts.

Table 7. Synthesis of additional DT studies identified in MDPI journals (2024–2026), including application domains, enabling technologies, contributions, and research gaps.

Ref.	Authors (Year)	Journal	Domain	Key Methodologies	Core Contribution
[106]	Nguyen et al. (2025)	<i>Sensors</i>	Smart Manufacturing	Deep reinforcement learning, CNNs, IoT sensor fusion, multi-twin synchronization	Categorizes AI-DTs across four hierarchical levels (machine, cell, shop floor, enterprise) for predictive maintenance and real-time control
[107]	Omigbodun (2026)	<i>Sustainability</i>	Sustainable Manufacturing	Machine learning, predictive analytics, carbon-aware control, life-cycle impact modeling	Reframes DTs as decision-making tools integrating energy, material, and carbon intensity for circular economy goals
[108]	Konstantinos Eet al. (2026)	<i>Information</i>	Industrial Cybersecurity (OT)	ISO 23247 architecture, attack-detection algorithms, literature synthesis	Defines functional/security requirements and proposes an ISO 23247-compliant DT architecture for incident detection and response

Table 7. Cont.

Ref.	Authors (Year)	Journal	Domain	Key Methodologies	Core Contribution
[109]	Fontana & Zinatlou Ajabshir (2026)	<i>Computation</i>	Healthcare & Personalized Medicine	Medical imaging, patient-specific biomechanical/hemodynamic simulations, bibliometric analysis	Maps methodological progress in human DTs (cardiovascular, musculoskeletal, neurological) for procedural planning
[110]	Tasmurzayev et al. (2025)	<i>Sensors</i>	Proactive Cardiovascular Care	AI multi-agent systems, continuous biomedical IoT sensor streams, physiological modeling	Outlines an end-to-end architecture connecting wearable sensors to AI agents for early cardiac-risk identification
[111]	Mazzetto (2024)	<i>Sustainability</i>	Smart Cities & Urban Planning	GIS integration, IoT spatio-temporal data aggregation, urban system simulations	Evaluates macro-level urban twin implementations for infrastructure optimization and resource management
[112]	Lis & Mađziel (2026)	<i>Applied Sciences</i>	Green Transportation Networks	Real-time traffic-flow optimization, deep-learning traffic prediction, emission modeling	Integrates urban mobility DTs with real-time signal control to reduce congestion and vehicle carbon output
[113]	Ba et al. (2025)	<i>Sustainability</i>	Energy Efficiency Assessment	Systematic literature review, thermodynamic physics models, ML energy benchmarking	Synthesizes DT strategies for industrial and building energy-efficiency optimization and waste reduction
[114]	Abdullah & Khubaib (2026)	<i>Engineering Proceedings</i>	Building Performance Assessment	Integrated structural-energy simulation, BIM-to-DT workflows, gap analysis	Highlights current gaps in combining structural health monitoring with dynamic energy assessments
[115]	Maldonado-Correa et al. (2026)	<i>Energies</i>	Wind Turbine Asset Management	Physics-informed neural networks, Remaining Useful Life (RUL) modeling, vibration analysis	Reviews predictive-maintenance models for offshore and onshore wind turbines to lower O&M expenditures
[116]	Madani et al. (2025)	<i>Batteries</i>	Battery Management Systems (BMS)	Cloud-edge hybrid computing, electro-thermal physics models, SoC/SoH estimation	Proposes cloud-edge AI-DT architectures for Li-ion cell degradation tracking and lifecycle extension
[117]	Łach (2026)	<i>Sustainability</i>	Building Energy Management	Smart-grid integration, uncertainty quantification (UQ), physics-guided ML	Formulates a deployment roadmap for smart-grid-interactive buildings under operational uncertainty
[118]	Kim et al.	<i>Sustainability</i>	Clean Energy Systems	Multi-physics simulations, hybrid data-driven physics modeling, state-of-the-art review	Synthesizes applications across hydrogen, wind, and solar systems to establish dynamic clean-energy twins
[119]	Eltamaly et al. (2026)	<i>Processes</i>	Smart Grid Energy Storage	Online reinforcement learning, adaptive self-learning control loops, real-time grid telemetry	Demonstrates a self-learning DT for real-time optimal charging/discharging of grid-connected batteries
[120]	Rajendran et al. (2025)	<i>Energies</i>	Solar PV Grid Integration	Standards review, grid-code compliance analysis, power-quality modeling	Analyzes technical requirements, standards, and grid-stability challenges for high-penetration PV systems

The MDPI-published studies complement the primary corpus by providing additional evidence from healthcare, energy, and smart-city applications. In healthcare, the reviewed studies address personalized medicine, cardiovascular monitoring, and medical digital twins, whereas energy-oriented studies consider wind, solar, battery, and smart-grid applications. Smart-city contributions include urban planning and green transportation. Across these domains, recurring challenges include real-time synchronization, cybersecurity, computational constraints, interoperability, and uncertainty quantification.

4.4. Communication, Data Integration, Synchronization, and Interoperability

Reliable communication and data integration constitute fundamental requirements for maintaining the relationship between physical and virtual entities. The reviewed literature frequently employs IoT/IIoT infrastructures and industrial communication protocols such as OPC UA and MQTT to transfer information between sensors, controllers, DT platforms, and analytical services.

Data integration remains challenging because DT systems often combine heterogeneous data sources generated by sensors, PLCs, enterprise systems, simulation environments, databases, and external services. Legacy industrial systems further increase this complexity because they may employ proprietary interfaces and data formats.

Real-time synchronization is another persistent challenge. The usefulness of a DT depends partly on how accurately and rapidly changes in the physical system are reflected in its digital counterpart. Delays, missing data, communication failures, and inconsistent sampling rates can reduce the fidelity and reliability of the DT.

Edge computing has emerged as an important mechanism for addressing these limitations. By processing data closer to the physical asset, edge architectures can reduce communication latency and decrease the amount of information transferred to centralized cloud platforms. This is particularly important for applications involving real-time monitoring and control.

Interoperability remains one of the most persistent unresolved issues. The reviewed literature identifies the need for standardized information models, semantic representations, ontologies, and interoperable communication interfaces that allow DTs developed using different platforms to exchange information reliably.

Emerging communication technologies, including 5G and 6G, are increasingly investigated as potential mechanisms for supporting large-scale, low-latency, and distributed DT ecosystems. However, their industrial validation remains comparatively limited compared with established IoT, cloud, and edge technologies (see Table 8).

Table 8. Communication, data integration, synchronization, and interoperability mechanisms in DT systems.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2022	XPlaM: A toolkit for automating the acquisition of BDI agent-based DTs of organizations [106]	Ahmad Alelaimat, Aditya Ghose, Hoa Khanh Dam	DTs for organizations using BDI agents, leveraging externally observable behavior to generate BDI agent programs.	Effective use of abduction for generating DTs of organizations. Further research on improving the hypothesis search space for BDI agents.	Manufacturing
2023	Updating DTs: Methodology for data accuracy quality control using ML techniques [107]	Fabio Rodríguez et al.	Ensuring data quality in DTs, methodology using neuro-fuzzy systems and recurrent neural networks.	High accuracy in detecting and predicting data errors. Application of methodology in other real-time systems.	AI/Machine Learning
2023	Towards situational aware cyber-physical systems: blockchain-based DTs [108]	Sabah Suhail, Saif Ur Rehman Malik et al.	Enhancing security in CPS using blockchain-based DTs, a blockchain framework for data integrity and security.	Proof of concept for automotive CPS, integrity checking mechanisms, and further integration of blockchain for more comprehensive security solutions.	Transportation

Table 8. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2023	Towards live decision-making for service-based production: Integrated with DTs and Deep-Q-Learning [109]	Zai Müller-Zhang, Thomas Kuhn, Pablo Oliveira Antonino	Production operations use decision-making processes that utilize DTs for their real-time decision-making needs. Deep Q-Learning technology enables complete process planning and scheduling through its integrated system.	Efficient learning designs for different production scenarios. Expansion to other production systems and contexts.	Design/Simulation
2023	Towards adaptive DTs architecture [110]	Rotimi Ogunsakin et al.	Real-time optimization and adaptivity in DTs, proposed architecture for Adaptive DTs.	Demonstrated continuous production adaptation in mass personalization. Implementation in other manufacturing environments.	Manufacturing
2022	The OMiLAB Digital Innovation environment: Agile conceptual models for PSS development [111]	Dimitris K et al.	Bridging business and engineering perspectives in PSS development, an agile DT environment using Design Science principles.	Framework for integrated PSS prototyping application in diverse domains for enhanced digital innovation.	Cross-domain
2022	Simplexity testbed: A model-based DT testbed [112]	Texin Wang et al.	Facilitating research in DT technologies, testbed with integrated multiple models for simulations.	Enabled research on context-aware, autonomous capabilities. Expansion to other modeling paradigms and scenarios.	Design/Simulation
2019	Building a DT for additive manufacturing through the exploitation of blockchain: A case analysis of the aircraft industry [113]	Mandolla et al.	Integration of DT with blockchain technology for additive manufacturing in the aircraft industry.	Secure and traceable manufacturing data; DT framework for additive processes; improved supply chain transparency. Enhance scalability, integrate real-time data, and extend to broader industrial applications.	Manufacturing
2022	Requirements for the application of the DT Paradigm to offshore wind turbine structures [114]	Jack Jorgensen et al.	DTs for fatigue analysis in offshore wind turbines, Gaussian process surrogate modeling approach.	Defined requirements for modeling complex assets under uncertainty. Practical guidelines for uncertainty modeling in DT applications.	Energy
2023	Reinforcement learning-based trustworthy recommendation model for DT-driven decision-support [115]	Flávia Pires et al.	Improving decision-support in manufacturing using DTs, trust-based recommendation system with reinforcement learning.	Accurate recommendations in cold-start and data sparsity scenarios. Further integration of recommendation systems in various industrial settings.	Manufacturing
2023	Real-time optimization for a DT of a robotic cell with human operators [116]	Teresa Albini et al.	Optimization in robotic cells with human operators using DTs, real-time simulation and optimization algorithm.	Effective decision-making despite human behavior variability: Extension to other human-assisted robotic systems.	Manufacturing

Table 8. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2023	Realizing zero-waste value chains through DT-driven S&OP: A case of grocery retail [117]	Sourav Sengupta, Heidi Dreyer	The grocery retail case study uses two methods to achieve zero-waste value chains by applying digital technology. The grocery retail case study uses two methods to achieve zero-waste value chains through digital technology implementation.	Extends the zero-defect concept to grocery retail value chains; proposes DT-enabled planning. Implements DT-supported S&OP to reduce food waste and reallocate surplus.	Manufacturing
2023	Petri nets-based DT drives dual-arm cooperative manipulation [118]	Fuwen Hu, Wei Wang, Jinghua Zhou	Enhancing dual-arm cooperative robotic systems using a DT framework, Survey of DT modeling frameworks, and presentation of a Petri net-based DT framework.	Demonstrates a DT environment for dual-arm cooperative operations, integrating operational and IT through the industrial IoT. Future: Utilize Petri net-based DT for complex robotic tasks, combining discrete event simulation and 3D offline programming.	Manufacturing
2020	Peeking into the void: DTs for construction site logistics [119]	Toni Greif, Nikolai Stein, Christoph M. Flath	Improving construction site logistics through DTs, collaboration with a building materials supplier to develop a DT for logistics.	Identifies opportunities for informational, automation, and transformational business value via full-level monitoring. Design decision-support systems for logistics processes to enhance efficiency.	Smart city
2023	OpenTwins: An open-source framework for next-gen compositional DTs [120]	Julia Robles, Cristian Martín, Manuel Díaz	Developing an open-source framework for compositional DTs; framework development integrating 3D visualization, IoT data streams, and real-time ML predictions.	The Petrochemical Industry 4.0 Future shows that the open-source framework can create advanced DTs that industries can use to build their own DTs.	Cross-domain
2023	Online validation of DTs for manufacturing systems [121]	Giovanni Lugaresi et al.	Ensuring the validity of DTs for manufacturing systems during operation. Proposes a methodology for online validation with small datasets and sequence similarity measurement.	Validates the digital model's alignment with the physical system using realistic settings. Implements online validation techniques for DTs in dynamic manufacturing contexts.	Manufacturing
2022	On the alleviation of imminent technical and business challenges of long-lasting functional DTs [122]	Akhtar Zeba et al.	Addressing challenges of long-lasting functional DTs, discussion of risks and strategies for long-term DT operation	Identifies interoperability issues and proposes strategies for updating simulation models with current tools. Develop adaptable DT models to ensure long-term viability and compatibility.	Design/Simulation
2022	Model-based data integration along the product & service life cycle supported by DTning [123]	Robert Woitsch, Anna Sumereder, Damiano Falcioni	Bridging data integration gaps in the product & service life cycle using DTs, model-based approach, and a European project case study (Change2Twin).	Presents a meta-model for data integration and demonstrates a pilot in paint production. Applies model-based DTning to enhance data integration and servitization in manufacturing.	Manufacturing
2023	ENIGMA: An explainable DT security solution for cyber-physical systems [124]	Masoud Mohammadi, Maria Rashidi, Yang Yu, Bijan Samali	Enhancing bridge asset management using BrIM and DSS, a comprehensive methodology integrating TLS-derived BrIM with a DSS.	Demonstrates effective bridge management and decision-making via a case study on Werrington Bridge. Implement BrIM-oriented BMS with DSS for improved bridge maintenance and remedial planning.	Manufacturing

Table 8. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2023	DTs in Condition-Based Maintenance Apps: A Case Study for Train Axle Bearings [125]	Adolfo Crespo Marquez et al.	Design and implementation of DT for CBM of train axle bearings, practical application in maintenance management.	Generic framework for digital maintenance; tested on TALGO high-speed trains; addresses conceptual and functional challenges. Tools and models to facilitate DT implementation in CBM; replicable in other operational contexts.	Manufacturing
2022	DTs: An Analysis Framework and Open Issues [126]	Hugh Boyes, Tim Watson	Analysis framework for DTs, framework proposal to compare different DTs.	Reduces confusion from multiple DT definitions; focuses on functionality. Use the framework to standardize DT comparisons and improve understanding.	Manufacturing
2021	DT-Enabled Smart Modular Integrated Construction System for On-Site Assembly [127]	Yishuo Jiang, Ming et al.	DT for Modular Integrated Construction (MiC) Converts on-site resources into Smart MiC Objects (SMiCOs).	Real-time data collection and integration; cloud-based services for monitoring and control. Implement DTs to enhance quality, productivity, and sustainability in MiC.	Manufacturing
2022	Development and Validation of a DT Framework for SMT Manufacturing [128]	Reinhardt Seidel et al.	DT framework for electronics manufacturing, ML-enabled framework for data acquisition and analysis.	Structured data collection during PCB manufacturing; validates framework with process quality criteria. Integrate data analysis technologies into industrial processes for improved quality and efficiency.	Manufacturing
2022	Cost-Efficient DTs for Design Space Exploration: A Modular Platform Approach [129]	Massimo Panarotto, Ola Isaksson, Vanessa Vial	Cost-efficient DT development for new product design, a modular approach for creating reusable DT modules.	Focus on cost-efficiency and reusability. Applied to the space manufacturing case, adopt a modular approach to DT development to enhance cost-efficiency and validate new designs.	Manufacturing
2023	Context-Aware Representation of DTs' Data: The Ontology Network Role [130]	Mariela Rico et al.	DT data representation in a digital factory, use of contextualized ontologies for data exchange.	Facilitates syntactic, semantic, and semiotic integration; improves decision-making. Employ contextualized ontologies to enhance data integration and decision-making in digital factories.	Manufacturing
2023	Cognitive DTs for Freight Parking Management in Last Mile Delivery [131]	Yu Liu et al.	The Freight Parking Management Problem (FPMP) affects last-mile delivery operations in smart cities. The four-layer architectural framework transforms logistics objects into smart cities through its integrated design.	Semantic-enabled DTs enhance delivery environment understanding; case study with Thing'in platform and AnyLogic simulation. Develop DTs with augmented semantic capabilities for urban logistics and resource optimization.	Smart city
2019	Review of DT applications in manufacturing [132]	Cimino, Chiara Negri, Elisa Fumagalli, Luca	Literature analysis + practical implementation of DT integrated with MES in an assembly line.	Identification of DT gaps; integration with MES; enhancement of DT services (monitoring, control, optimization); improve DT-MES integration, expand service capabilities, enable full closed-loop control.	Manufacturing

Table 8. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2021	Autonomous, Context-Aware, Adaptive DTs—State of the Art and Roadmap [133]	Karl Hribernik et al.	The development path for DTs technology will progress through three stages, which start with basic DT capabilities and then advance towards autonomous operation with context-based decision-making skills and flexible system adjustments.	Establishes a working definition of DTs; identifies research gaps and future potentials. Develop DTs with sensing, processing, and adaptive capabilities for future digital factories.	Manufacturing
2023	Automated DT Generation of Manufacturing Systems with Complex Material Flows [134]	Giovanni Lugaresi, Andrea Matta	The DT framework applies to manufacturing systems that have complex material flow operations. The study examines two different methods, which are process mining and object-centric process mining.	Algorithm for proper digital model generation; successfully applied to real manufacturing systems. Implement automated model generation techniques to handle complex production environments.	Manufacturing
2021	Application of the DT for In-Process Monitoring of the Micro Injection Moulding Process Quality [135]	Gianfranco E. Modoni, Benedetta Stampone, Gianluca Trotta	In-process monitoring of micro injection molding process quality, Methodological approach leveraging DTs for process optimization.	Real-time parameter monitoring; proof of concept validated in a real case study. Adopt DTs for continuous monitoring and quality assurance in micro manufacturing.	Manufacturing
2022	A Wasserstein Generative DT Model in Health Monitoring of Rotating Machines [136]	Wenyang Hu, Tianyang Wang, Fulei Chu	Health monitoring and diagnosis of rotating machines, Wasserstein Generative Adversarial Network (WGAN).	High-fidelity virtual samples; Adaptivity, autonomy, and context-awareness. Use WGAN-based DTs for efficient health monitoring, early fault detection, and degradation tracking.	Healthcare
2023	A Machine Learning DT Approach for Critical Process Parameter Prediction [137]	Matteo Perno, Lars Hvam, Anders Haug	Prediction of critical process parameters in catalyst manufacturing, ML-based DT framework.	Accurate real-time predictions; Improved manufacturing process optimization; implement ML-based DTs for real-time process parameter prediction and optimization.	Manufacturing
2021	A Framework for Data-Driven DTs of Smart Manufacturing Systems [138]	Jonas Friederich et al.	Automated generation of simulation models for DTs in smart manufacturing, a data-driven framework utilizing ML and process mining.	Continuous model improvement and validation; case study illustration: Develop data-driven DT frameworks to handle dynamic manufacturing environments.	Manufacturing
2022	A DT Hierarchy for Metal Additive Manufacturing [139]	A. Phua, C.H.J. Davies, G.W. Delaney	DT framework for metal additive manufacturing, hierarchical approach to DT development.	The developer framework enables the creation of intelligent systems that include both AM and other systems. The first main use of hierarchical DT frameworks enables organizations to oversee their entire product development process.	Manufacturing
2022	A DT Approach for Tunnel Construction Safety Early Warning and Management [140]	Zijian Ye et al.	Safety management in tunnel construction, multi-information intelligent early warning platform.	Real-time dynamic simulation; successful prediction of tunnel collapse. Implement DT-based safety management platforms for real-time monitoring and early warning in construction projects.	Construction

Table 8. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2022	A Design Framework for a System of DTs and Services [141]	C. Human, A.H. Basson, K. Kruger	Designing systems of DTs and services for complex physical systems, a six-step design framework with reference architecture.	Facilitates systematic design decisions; case studies on heliostat field and smart city. Future: Use design frameworks to systematically develop integrated DT systems for complex applications.	Smart city
2022	A Collaborative Network of DTs for Anomaly Detection Applications [142]	Pablo Calvo-B et al.	Anomaly detection in industrial systems using DT ecosystems, Snitch DT (SDT) concept for behavioral anomaly detection.	Quantile regression and behavioral indexes: Case study on power generator cooling system. Develop collaborative DT networks for enhanced anomaly detection and diagnosis in industrial systems.	Healthcare
2024	DT Stakeholder Communication: Characteristics, Challenges, and Best Practices [143]	Christian Kober et al.	Exploratory study using interviews and focus groups; grounded theory and Gioia methodology for analysis.	Identification of DT communication challenges; classification into human and organizational factors; practical mitigation strategies. Improve stakeholder communication, define clear objectives, and adopt gradual implementation strategies.	Smart Manufacturing
2025	Improving interoperability in robot DTning for facility management: An industry foundation class-represented RoboAvatar approach [144]	Chen, Junjie Lu et al.	IFC-based integration of Robot DT (RDT) with BIM; experimental validation using a trash-picking robot.	First methodology enabling RDT–BIM interoperability; improved data exchange and robot control in FM. Extend to complex robots and buildings, enhance interoperability standards, and scale real-world deployment.	Manufacturing

Overall, the literature indicates that future DT ecosystems will require interoperability at multiple levels: communication protocols, data models, semantic representations, simulation models, and application interfaces. Standardization initiatives and frameworks such as ISO 23247 and IEC 62832 therefore represent important directions for future research.

4.5. AI-Enabled DTs and Intelligent Decision-Making

The integration of AI represents one of the most significant developments identified in the reviewed DT literature. AI techniques increasingly transform DTs from systems primarily concerned with representation and monitoring into systems capable of supervised learning and are frequently applied to classification and prediction tasks, while unsupervised approaches support anomaly detection and clustering. Deep learning models, including CNNs, LSTMs, and GNNs, are increasingly employed when DTs must process complex prediction, diagnosis, optimization, decision support, and, in some cases, autonomous control.

Machine learning methods are used for a wide range of applications. Supervised learning is frequently applied to classification and prediction tasks, while unsupervised approaches support anomaly detection and clustering. Deep learning models, including CNNs, LSTMs, and GNNs, are increasingly employed when DTs must process complex visual, temporal, spatial, or multimodal data.

In manufacturing, AI-enabled DTs support quality inspection, predictive maintenance, process optimization, scheduling, fault diagnosis, and production planning. In

healthcare, AI can assist in patient monitoring, diagnosis, and personalized decision support. Energy knowledge-based or physics-based models. Physics-informed machine learning and hybrid DT architectures seek to exploit both physical constraints and data-driven learning. These approaches may improve generalization and reduce the amount of training data required in comparison with combined with FL, optimization algorithms, rule-based systems, or human supervision before a control decision is generated. This approach can applications employ AI for forecasting, anomaly detection, energy optimization, and asset maintenance.

The literature also demonstrates increasing interest in combining AI with conventional knowledge-based or physics-based models. Physics-informed machine learning and hybrid DT architectures seek to exploit both physical constraints and data-driven learning. These approaches may improve generalization and reduce the amount of training data required in comparison with purely data-driven models.

Decision-making is increasingly implemented as a multilayer process rather than as a direct output of an AI model. For example, a machine learning prediction may be combined with fuzzy logic, optimization algorithms, rule-based systems, or human supervision before a control decision is generated. This approach can improve robustness and incorporate operational constraints that are not directly represented by the learning model.

Recent studies also investigate federated learning, generative AI, reinforcement learning, and self-evolving DTs. Federated learning addresses data-sharing and privacy concerns, generative AI introduces new possibilities for natural-language interaction and automated, the increasing autonomy of AI-enabled DTs introduces additional challenges related to explainability, robustness, bias, cybersecurity, model drift, uncertainty, and represents a critical dimension of DT research because a digital representation is useful only if its behavior sufficiently corresponds to the physical system for the intended application. The reviewed literature employs different levels of validation, ranging from purely simulation-based studies to laboratory prototypes, pilot-scale implementations, and industrial AI models under controlled conditions. Simulation is particularly useful during early-stage development because it facilitates different interactions with its virtual counterpart. While these implementations allow researchers to investigate real sensor data, PLC communication, synchronization, and AI inference, fully industrial-scale DT validation remains comparatively less common in the reviewed literature. Industrial deployment introduces additional factors that are difficult to reproduce in laboratory environments, including equipment variability, communication failures, maintenance constraints, cybersecurity threats, operational costs, legacy systems, long-term model precision, recall, F1-score, ROC-AUC, and prediction error, whereas industrial DT studies may additionally evaluate throughput, downtime, maintenance performance, energy consumption, OEE, latency, or economic benefits of DT assistance; reinforcement learning supports adaptive decision-making, and self-evolving architectures seek to update DT models as physical systems change (see Table 9).

Nevertheless, the increasing autonomy of AI-enabled DTs introduces additional challenges related to explainability, robustness, bias, cybersecurity, model drift, uncertainty, and human oversight. These issues become particularly important when AI-generated decisions influence safety-critical or high-value physical systems.

The reviewed evidence therefore suggests a transition from DT + AI for analysis toward DT + AI for adaptive decision-making. However, the industrial maturity of highly autonomous AI-enabled DTs remains less established than that of monitoring and predictive applications.

Table 9. AI-enabled digital twins: machine learning, deep learning, decision support, and emerging intelligent technologies.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Category/Domain
2023	3DGraphSeg: Unified Graph Representation-Based Point Cloud Segmentation for Railway DTs [145]	Yixuan Geng et al.	The study investigates point cloud semantic segmentation PCSS methods, which are used to analyze high-speed railway DTs through UAV-borne LiDAR and local embedding super-point graph and gated integration graph convolutional network GIGCN technology.	Novel structural representation algorithm; adaptive weighted cross-entropy loss function; state-of-the-art on SemanticRail dataset. Further optimization of loss functions and real-time implementation for railway monitoring.	AI and Machine Learning/Transportation
2020	A DT-Based Industrial Automation and Control System Security Architecture [146]	Christian G et al.	Security architecture for industrial automation using DTs State synchronization design, proof-of-concept security framework.	Secure software upgrade, improved data sharing, and control for security-critical processes. Work on refining security models and performance optimization.	DT for Process Optimization/Cross-domain
2022	A Graph Neural Network-Based DT for Network Slicing Management [147]	Haozhe Wang et al.	Network slicing management for Industry 4.0 and 5G networks, Graph neural networks (GNN), and DT for monitoring end-to-end (E2E) metrics.	Accurate prediction of E2E latency; scalable DT for diverse topologies. Extend the model to 6G networks and improve adaptability to dynamic environments.	AI and Machine Learning/AI/ML
2023	A Novel Anomaly Detection Method for DT Data Using Deconvolution [148]	Zheng Li et al.	The research focuses on detecting anomalies in industrial DT data through the application of a multidimensional deconvolutional network, which utilizes an attention mechanism for its operation.	Real-time anomaly detection; improved precision and F1 score. Enhanced the interpretability and efficiency of the anomaly detection framework.	AI and Machine Learning/Cross-domain
2022	Adaptive DT and Multiagent Deep Reinforcement Learning for Vehicular Edge Computing [149]	Ke Zhang, Jiayu Cao, Yan Zhang	Vehicular edge computing using DTs and AI, multi-agent deep reinforcement learning, coordination graph-based task offloading.	Efficient edge service matching, intelligent scheduling, and improved offloading costs. Further validation on large-scale vehicular networks and real-world deployment.	AI and Machine Learning/AI/ML
2021	Adaptive Federated Learning and DT for Industrial IoT [150]	Wen Sun et al.	DT-enhanced federated learning for Industrial IoT, trust-based aggregation, adaptive learning frequency adjustment.	Improved learning accuracy, energy efficiency, asynchronous federated learning framework. Explore blockchain integration for enhanced security and data integrity.	AI and Machine Learning/Energy
2023	BSDP: Blockchain-Based Smart Parking for Digital-Twin Empowered Vehicular Sensing Networks [151]	Can Zhang, Liehuang Zhu, Chang Xu	Smart parking using DTs and blockchain, smart contracts, vehicular sensing networks (VSN).	Secure and efficient parking monitoring, privacy protection for drivers, and VSN participants. Extend to large-scale urban smart parking and explore real-world implementation.	DT for Process Optimization/Smart city
2021	Application-Driven Network-Aware DT Management in Industrial Edge Environments [152]	Paolo Bellavista et al.	DT-based network management for industrial IoT, software-defined networking (SDN), and application-driven middleware.	Improved network resource allocation, enhanced interoperability of industrial IoT, and further exploration of AI-driven automation for DT networking.	DT for Process Optimization/Manufacturing
2023	Chaos Engineering for Resilience Assessment of DTs [153]	Mattia Fogli et al.	Resilience assessment of DTs in Industry 4.0, chaos engineering, fault injection, automated testing.	Identified resilience factors; developed chaos testing methodologies. Applied chaos engineering to different DT domains; enhanced automated resilience testing.	Validation and Simulation-Based DTs/Maintenance
2022	Cloud-Based DTning for Structural Health Monitoring Using Deep Learning [154]	Hung V. Dang et al.	Structural health monitoring using DTs and AI, cloud-based DT, deep learning, IoT-based monitoring.	Real-time structural analysis, high-accuracy damage detection, improve real-world deployment, and integration with 5G/6G networks.	DT for Process Optimization/Healthcare
2023	Cloud-Edge-Device Collaborative Reliable DT for Low-Carbon Electrical Equipment Management [155]	Haijun Liao et al.	DT for electrical equipment management in smart industrial parks, cloud-edge-device collaboration, and AI-driven optimization.	Real-time intelligent management, optimized low-carbon operations, extended to broader industrial applications, and enhanced real-time analytics.	DT for Process Optimization/Energy
2021	Communication-Efficient Federated Learning for DT Edge Networks in Industrial IoT [156]	Yunlong Lu et al.	DT edge networks (DITENs) for IIoT, using federated learning, asynchronous model updates, and deep neural networks.	Improves communication efficiency, reduces transmission energy cost. Optimizes federated learning for real-world deployment in IIoT.	AI and Machine Learning/Energy

Table 9. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Category/Domain
2023	Data Evolution Governance for Ontology-Based DT Product Lifecycle Management [157]	Zijie Ren et al.	Enhancing DT data governance using ontology, four-layered ontology architecture, unified evolution model, ICandyBox simulation.	Improves data reusability, enhances knowledge sharing in DT-based PLM. Extend ontology-based governance to broader manufacturing applications.	AI and Machine Learning/Manufacturing
2023	Computer Vision Enabled Building DT Using Building Information Model [158]	Xiaoping Zhou et al.	Integration of computer vision with BIM for building DTs, 2D object detection, 3D object estimation, and object matching techniques.	Maintains an up-to-date digital model; improves object detection accuracy in BDT. Future: Expand applications to large-scale smart buildings.	DT for Process Optimization/Construction
2022	Data-Model Combined Driven DT of Life-Cycle Rolling Bearing [159]	Yi Qin, Xingguo Wu, Jun Luo	DT for rolling bearing lifecycle management, combines data-driven and dynamic modeling, CycleGAN for mapping virtual-physical spaces.	Enhances degradation analysis and fault detection. Expand the methodology to other rotating machinery.	DT for Process Optimization/Maintenance
2021	Deep Reinforcement Learning for Stochastic Computation Offloading in DT Networks [160]	Yueyue Dai et al.	Optimizing computation offloading in DT-enabled IIoT networks, Lyapunov optimization, asynchronous actor-critic reinforcement learning.	Reduces energy consumption and improves efficiency in the IIoT network. Investigate other AI-based optimization techniques for IIoT.	AI and Machine Learning/Energy
2023	Delay Safety-Aware DT Empowered Industrial Sensing-Actuation Systems [161]	Hansong Xu et al.	Addressing high end-to-end delay in DT industrial systems, transferable and reinforcement learning models for delay minimization.	Reduces end-to-end delays and optimizes the training process. Applies to diverse industrial sectors beyond manufacturing.	DT for Process Optimization/Manufacturing
2022	DT and Data-Driven Quality Prediction of Complex Die-Casting Manufacturing [162]	Dong Liu et al.	Quality prediction in die-casting manufacturing using DT and AI, virtual-real interaction DT, XGBoost for real-time prediction, and deep learning for defect detection.	Improves real-time quality monitoring and high-precision defect detection. Expand AI-based defect detection techniques to other manufacturing processes.	DT in Manufacturing/Manufacturing
2023	DT-Driven End-Face Defect Control Method for Hot-Rolled Coil [163]	Feng Xiang et al.	Defect control in hot-rolled coil manufacturing, cloud-edge collaboration, virtual model for defect tracking.	Enhances defect prediction, enables real-time control. Implements cloud-edge collaboration in other manufacturing applications.	DT in Manufacturing/Manufacturing
2023	DT Empowered Industrial IIoT Based on Credibility-Weighted Swarm Learning [164]	Wei Xiang et al.	DT-based IIoT security and efficiency using swarm learning, Credibility-weighted swarm learning (CSL), and DT-assisted deep reinforcement learning.	Enhances security, reliability, and energy efficiency in IIoT. Future: Explore decentralized learning techniques beyond IIoT.	AI and Machine Learning/Energy
2023	DT for Real-time Li-Ion Battery State of Health Estimation [165]	Yan Qin et al.	Real-time SOH estimation of lithium-ion batteries using DT, DT framework with energy discrepancy-aware cycling synchronization, time-attention SOH estimation.	Accurate real-time SOH estimation with less than 1% error rate using partially discharged data. Model updating with transfer learning and accurate detection of the ‘knee point’ for better estimation accuracy.	AI and Machine Learning/Healthcare
2023	DT of Large-Scale Coaxiality Measuring Instrument With Six Dimensions [166]	Yingjie Mei et al.	DT system with coaxiality prediction, cloud data interaction, and AR-based guidance for rotor assembly.	Integration of measurement and assembly; real-time guidance; improved precision and assembly quality; extend to complex assemblies, enhance AR integration, improve real-time data processing.	DT in Manufacturing/Manufacturing
2022	DT-Assisted Real-Time Traffic Data Prediction Method for 5G-Enabled Internet of Vehicles [167]	Chunhua Hu et al.	Real-time traffic data prediction using DT for IoV and 5G; analysis of traffic flow and velocity data using IoV sensors and 5G; TFVPTIME-LSH prediction method.	Feasibility of smart traffic flow and velocity prediction; validated on a real-world traffic dataset from Nanjing city. Optimization of prediction goals, privacy preservation, and energy cost considerations.	DT in Manufacturing/Manufacturing
2023	DT-Driven Industrialization Development of Underwater Gliders [168]	Ming Yang et al.	The development of underwater gliders through industrialization uses a DT-driven methodology. The DT-driven architecture develops quick personalized design capabilities for rapid individualized design and complete product lifecycle management.	Detailed introduction of DT-driven RID and FLM steps; verification of feasibility through Petrel UG; development of high-fidelity models, self-adaptation control under uncertainties, and cluster networking applications.	DT in Manufacturing/Manufacturing

Table 9. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Category/Domain
2023	DT-Driven Robotic Disassembly Sequence Dynamic Planning Under Uncertain Missing Condition [169]	Jiayi Liu et al.	Robotic disassembly sequence planning under uncertain missing conditions using DT, framework for DT-RDSDP, DT establishment, and deep Q-learning network (DQN).	Dynamic generation of optimal disassembly solutions in real time; improved efficiency using the DQN model. Addressing recognition of missing conditions and handling multiple missing components.	DT in Manufacturing/Manufacturing
2022	DT-based Adaptive Development Environment for Automotive Cyber-Physical Systems [170]	Guoqi Xie et al.	The project develops a DT-based adaptive development environment for testing automotive cyber-physical systems. The project develops an integrated DT cloning system, which includes DT board technology.	Achievement of high adaptability, short development cycle, low complexity, low cost, and high scalability in automotive CPS development. Further improvement of development efficiency and scalability.	DT for Process Optimization/Transportation
2023	DTs for Anomaly Detection in the Industrial IoT: Conceptual Architecture and PoC [171]	De Benedictis et al.	DT + Autonomic Computing (MAPE-K loop) for anomaly detection in IIoT systems.	DT-based anomaly detection architecture; adaptive reconfiguration using a feedback loop; validated in a railway system. Improve scalability, enhance anomaly detection accuracy, and extend to diverse IIoT applications.	AI and Machine Learning/Smart city
2023	Digital-Twin Consistency Checking Based on Observed Timed Events With Unobservable Transitions [172]	Moon Gi Seok et al.	DT consistency checking in smart manufacturing using time-colored Petri net (TCPN), Development of a DT consistency-checking approach using TCPN, SCG, and iterative methods.	Achievement of high fidelity in DT by comparing streaming physical events with virtual estimates. Further improvement of SCG evolution speed and handling of complex manufacturing processes.	DT in Manufacturing/Manufacturing
2019	Digital-Twin-Based Job Shop Scheduling Toward Smart Manufacturing [173]	Yilin Fang et al.	Job shop scheduling in smart manufacturing using DT, development of DT-based job shop scheduling architecture, and dynamic interactive scheduling strategies.	Improved scheduling accuracy; timely response to dynamic events; feasibility verification through a prototype system. Further development of scheduling evolution mechanisms based on perception data from real workshops.	DT in Manufacturing/Manufacturing
2023	Distributed Incentives for Intelligent Offloading and Resource Allocation in DT Driven Smart Industry [174]	Kai Peng et al.	The research study investigates two primary areas of industrial IoT edge networks that operate through driven by distributed time-based systems. The research study established a dual-phase incentive framework that implements a Stackelberg-based ADMM solution for its operational framework.	Optimized resource allocation and privacy investment; improved efficiency in IoT edge computing. Extend the approach to intelligent medical care and intelligent transportation using learning-aided mean-field methods.	DT for Process Optimization/Healthcare
2022	DTPAAL: DTning Pepper and Ambient Assisted Living [175]	Lucia Cascone et al.	DTning for social robotics and ambient-assisted living (AAL) Development of VPepper, a virtual replica of the humanoid robot Pepper, for ML training and simulation.	Enabled AI/ML training in virtual environments; seamless transfer of learned skills; validated with 25 caregivers. Improve physical accuracy of simulation and refine DT-based AI/ML training for real-world applications.	DT in Manufacturing/Manufacturing
2025	Process Mining for DT Development of Industrial Cyber-Physical Systems [176]	Vitale, Francesco Guarino et al.	DT framework combining process mining with data-driven and process-based analysis (offline + online phases)	Improved explainability and anomaly detection; integration of process models with DT. Improve model quality, extend to complex CPS, and enhance real-time monitoring.	Manufacturing
2025	Tokamak O&M Robot Dynamic Control by Using Optimized FABRIK and Spatial Partition Strategies in DT System [177]	Lv, Jian Mao et al.	DT-based robot control using spatial partitioning and perception potential field FABRIK algorithm.	Real-time kinematics, obstacle avoidance, and virtual-real interaction for maintenance robots. Extend to complex environments, improve autonomy, and enhance multi-robot coordination.	Manufacturing

4.6. Validation Approaches and Evidence Levels

Validation represents a critical dimension of DT research because a digital representation is useful only if its behavior sufficiently corresponds to the physical system for the intended application. The reviewed literature employs different levels of validation, ranging from purely simulation-based studies to laboratory prototypes, pilot-scale implementations, and industrial deployments.

Simulation-based validation represents a substantial portion of the reviewed corpus. Such studies allow researchers to evaluate DT architectures, communication mechanisms, control strategies, and AI models under controlled conditions. Simulation is particularly

useful during early-stage development because it allows different operating scenarios to be tested without exposing physical equipment to risk.

Laboratory-scale validation provides a higher level of experimental evidence by integrating physical equipment with its virtual counterpart. These implementations allow researchers to investigate real sensor data, PLC communication, synchronization, AI inference, and human–machine interaction (see Table 10).

Pilot-scale and industrial validation provide stronger evidence concerning scalability, robustness, and operational usefulness. However, fully industrial-scale DT validation remains comparatively less common in the reviewed literature. Industrial deployment introduces additional factors that are difficult to reproduce in laboratory environments, including equipment variability, communication failures, maintenance constraints, cybersecurity threats, operational costs, legacy systems, and long-term model drift.

Table 10. DT validation approaches, evidence levels, evaluation metrics, and reported limitations.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2021	A construction method of DT model for contact characteristics of assembly interface [178]	Chao Zhang et al.	Precise modeling of assembly interfaces and maintaining consistency in DT updates; interface virtual thin-layer element with nonuniform parameters; real-time data assimilation using surrogate model and genetic algorithm.	General DT framework for assembly contact; interface gradient virtual material modeling; real-time model update and verification with the machining center; extended to multi-joint structures for real-time mechanical performance prediction.	Manufacturing
2022	A DT framework for large comprehensive ports and a case study of Qingdao Port [179]	Wenqiang Yang et al.	Intelligent operation and management of large ports through DT, five-layer DT architecture for ports; model fusion, hybrid sensing, and distributed mapping.	Port-specific DT framework; multi-source data fusion; real-time monitoring and optimization. Develop unified DT standards; improve wide-area hybrid data awareness.	Construction
2023	A DT-driven monitoring framework for dual-robot collaborative manipulation [180]	Jianguo Duan et al.	Real-time monitoring of robotic arms using DT for smart manufacturing, equipment twin modeling, data acquisition, virtual–real fusion, and real-time monitoring on UR5/UR10.	Six-dimensional DT architecture; real-time robotic assembly monitoring; verification on collaborative robots. Extend to full assembly scene; address real-time delay in IoT communication.	Manufacturing
2022	A life-cycle digital-twin collaboration framework based on the industrial internet identification and resolution [181]	Yepeng Fan et al.	Full life-cycle DT collaboration in smart manufacturing using Industrial Internet (I3R), I3R system, ontology mapping, and distributed collaboration across industrial chains.	Generic life-cycle DT modeling; ontology-driven sharing and invocation; collaborative prototyping and product anomaly reasoning. Further research on DT-ontology integration; expand anomaly reasoning with natural language.	Manufacturing
2020	DT-based cyber physical production system architectural framework for personalized production [182]	Kyu Tae Park et al.	Overcoming performance hurdles in personalized production, a CPPS architectural framework was proposed based on DTs with five services operating on the P4R model.	Introduced object-oriented P4R model; achieved ~26.87% improvement in makespan; suggested service composition for interoperability; automated extraction of customer requirements; integrated with CPPS for seamless design to production.	Cross-domain

Table 10. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2018	DT-based smart production management and control framework for the complex product assembly shop-floor [183]	Cunbo Zhuang et al.	Smart management of complex product assembly using DTs. Developed a DT-based framework incorporating real-time data acquisition, big data, and predictive analytics.	Proposed predictive manufacturing using DT and big data; developed a smart management and control system; applied to the satellite assembly shop-floor. Optimize IoT network; built and validated DTs for complex assemblies; developed decision-making algorithms.	Manufacturing
2022	DT-driven fault diagnosis for CNC machine tool [184]	Ruijuan Xue et al.	Accurate fault diagnosis with limited data for CNC machine tools; built a DT model library, used the CART algorithm for model selection, and integrated real sensor data for fault diagnosis.	Accurate fault diagnosis with limited data; DT library covers various fault scenarios; CART-based selector improves model effectiveness. Improve high-fidelity DT model development; enable adaptive diagnosis and traceability online.	Healthcare
2022	DT-based sustainable intelligent manufacturing: a review [185]	Bin He, Kai-Jian Bai	Review of DT and intelligent manufacturing with focus on sustainability.	Integration of DT with sustainable manufacturing; analysis of systems, equipment, and services. Enhance sustainability strategies, improve DT integration, and develop future intelligent systems.	Manufacturing
2022	Model construction of material distribution system based on DT [186]	Yunrui Wang et al.	Optimize workshop material distribution with DT and LSTM; LSTM for material demand prediction; route optimization model; case study in async line.	Full-cycle DT-based material distribution mechanism improves virtual workshop fidelity and synchronization.	Manufacturing
2022	DT for thermal characteristics of motorized spindle [187]	Jianying Xiao et al.	Thermal simulation of motorized spindle using DT, ANSYS-based simulation with sensor data and correction models.	>95% prediction accuracy; correction of thermal boundaries. Extend to other thermal systems; improve correction models.	Data Management
2022	Toward digital validation for rapid product development [188]	Sihan Huang et al.	Digital product validation to replace physical trials, framework for DT-based product development and validation.	Framework for ultrahigh-fidelity digital prototype & validation. Develop an integrated software platform; advance DT technologies.	Cross-domain
2024	DT for Aquaponics Factory: Analysis, Opportunities, and Research Challenges [189]	Xu, Ling Yu et al.	Literature review of DT concepts, architecture, and applications in aquaponics.	Clarification of DT concepts; exploration of DT potential in aquaponics; analysis of use cases. Extend DT to agriculture, improve implementation strategies, and develop practical applications.	Industry 4.0
2025	A time-varying contact dynamic modeling method of kinematic pairs based on DT [190]	Chen, Yu Zhang et al.	DT-based framework integrating sensor data for time-varying dynamic modeling of mechanical systems.	Improved accuracy considering uncertainties and dynamic variations; predictive maintenance support. Extend to complex systems, enhance data fusion, and improve real-time analysis.	Manufacturing

The evaluation metrics reported in the literature also vary substantially. AI-oriented studies frequently report accuracy, precision, recall, F1-score, ROC-AUC, or prediction error, whereas industrial DT studies may additionally evaluate throughput, downtime, maintenance performance, energy consumption, OEE, latency, or economic benefits. This variation makes direct comparison between studies difficult.

The reviewed evidence therefore indicates a need for more standardized DT validation frameworks. In particular, future research should establish clearer relationships between

model studies consistently require a mechanism for connecting physical entities to their digital representations through sensing and communication infrastructure. Second, simulation and modeling remain central to representing physical-system behavior. Third, AI and analytics are increasingly integrated to transform DT data into predictions and decisions. Fourth, cloud and edge computing provide complementary computational resources for centralized and distributed DT operation. Finally, application-level interfaces provide users with visualization, monitoring, control, or cross-domain comparison also reveals several common research challenges. These include data heterogeneity, interoperability, synchronization, cybersecurity, model validation, scalability, explainability, and the manufacturing. However, the transferability of a particular DT implementation should not be assumed. Architectural principles may be generalized across domains, whereas data models are strongly concentrated in manufacturing. This concentration is important when interpreting the maturity of DT technologies: high publication frequency in second layer provides the connectivity and data-management infrastructure required to transfer, store, synchronize, and preprocess information. IoT/IIoT networks, OPC UA, MQTT, industrial communication systems, cloud platforms, edge computing, and data-integration mechanisms discrete-event simulation, and three-dimensional virtual environments. AI-based approaches employ methods such as CNNs, LSTMs, GNNs, and other machine learning models. More recent studies increasingly which DT capabilities are translated into operational actions or measurable performance improvements. Increasingly, AI models, optimization algorithms, fuzzy LSEA laboratory implementations presented in Section 5. The physical manufacturing equipment corresponds to Layer 1; PLCs, communication mechanisms, and the Raspberry Pi edge devices contribute to Layer 2; CIROS Studio and Factory I/O provide the simulation and virtual-representation components of Layer 3; VGG16, MobileNet, and FL decision support operate within Layer 4; and Node-RED and Gradio provide the HMI components of Layer 5. The two implementations therefore illustrate two distinct technology stacks that can be mapped onto the that the five-layer architecture has been experimentally validated across healthcare, smart-city, energy, or other application domains. Rather, they provide concrete examples of how convergence between physical systems, distributed data infrastructures, AI-enabled analytics, and human-centered decision-making. Emerging technologies such as generative AI, federated learning, 6G, quantum-enhanced optimization, semantic interoperability, and self-evolving DTs may further extend these capabilities. However, their long-term industrial impact remains uncertain because their validation and adoption are still less mature than those of established DT technologies such as IoT/IIoT, simulation, AI/autonomous systems. At the same time, interoperability, cybersecurity, real-time synchronization, model fidelity, scalable validation, and trustworthy AI remain central barriers to large-scale DT deployment. These findings provide the basis for the detailed discussion of challenges and fidelity, synchronization accuracy, AI performance, system-level operational indicators, and real-world industrial outcomes.

4.7. Cross-Domain Synthesis

The thematic analysis demonstrates that DT research has expanded significantly beyond its original manufacturing-oriented foundations. Nevertheless, several technological patterns recur across manufacturing, healthcare, smart cities, energy systems, and other application areas.

First, the reviewed studies consistently require a mechanism for connecting physical entities to their digital representations through sensing and communication infrastructure. Second, simulation and modeling remain central to representing physical-system behavior. Third, AI and analytics are increasingly integrated to transform DT data into predictions

and decisions. Fourth, cloud and edge computing provide complementary computational resources for centralized and distributed DT operation. Finally, application-level interfaces provide users with visualization, monitoring, control, or decision-support capabilities.

Despite these common foundations, the relative importance of individual components differs by domain. Manufacturing places strong emphasis on real-time control, production optimization, and quality; healthcare emphasizes privacy, safety, and clinical reliability; smart cities emphasize scalability and heterogeneous infrastructure; and energy systems emphasize reliability, forecasting, and system stability.

The cross-domain comparison also reveals several common research challenges. These include data heterogeneity, interoperability, synchronization, cybersecurity, model validation, scalability, explainability, and the reliable integration of AI into operational decision-making. Table 11 presents a cross-domain synthesis of DT structures, enabling technologies, applications, verification requirements, and research gaps.

Table 11. Cross-domain synthesis of DT architectures, enabling technologies, applications, validation requirements, and research gaps.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2023	A DT-based fault diagnostic method for subsea control systems [191]	Haohang Tao et al.	Fault diagnosis for subsea control systems, physics-informed temporal convolutional network (PITCN) integrated with CNN.	Improved diagnostic accuracy from 91.87% to 97.5%; low reliance on labeled data. Extend PITCN to other industrial systems; use for online diagnostics.	Manufacturing/Industrial Systems (Offshore Energy Equipment)
2023	A novel approach to building DT transformers by combining virtual–real sensing [192]	Hao Luo et al.	DTs for transformers focusing on internal parameter estimation, combined with virtual–real sensing (VRS) with temperature, moisture, and DP modeling.	Achieved accurate visualization of DP distribution with <3.5% error rate; foundational model for DT transformers. Account for gravity and mechanical stress in future models.	Energy
2023	Developing a DT model for monitoring building structural health [193]	Jinghai Xu et al.	Structural health monitoring of buildings, fusion of BIM and 3D models with sensor data integration.	Real-time spatial mapping of sensors; model applied to Nanjing Museum Old Hall Future: Investigate dynamic inversion and real-time health status methods.	Healthcare/Buildings
2023	DT-driven fatigue life prediction framework of mechanical structures using a power density theory [194]	Chang-kai Wen et al.	Fatigue life prediction for off-road vehicle axles Real-time DT framework with stress measurement and power density theory.	Accurate prediction (error ~3.95%) of fatigue life and failure location. Expand to internal driveline shaft components; enhance model precision.	Energy/Structural
2021	Error identification of measurement software based on DT of gear measuring center [195]	Chunxia Lu et al.	Error identification in gear measurement software, Development of a DT Gear Measuring Center (DTGMC) with simulated digital workpieces.	Independent evaluation of software errors; elimination of physical artifact dependency; generalizable platform for various measurement software. Extend method to other types of software; promote digital artifacts over physical ones.	Evaluation/Metrology
2023	Freeform DT approach to develop the HP 300 freeform verification standard [196]	J. Sýkora et al.	Calibration of freeform verification standard using a DT, Creation of a FreeForm DT (FFDT) using tactile scanning and mathematical modeling.	A DT with 1 μm geometric accuracy; dual representation (mathematical + CAD); improved verification standard; improved scanning techniques; consider uncertainty modeling for broader application.	Metrology/Standards

Table 11. Cont.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2022	Intelligent decision method for position and attitude self-adjustment of hydraulic supports in mining [197]	Xiubo Jiao et al.	Intelligent self-adjustment of hydraulic supports in mining using DT; virtual decision-making and control system based on reconstructed pose data.	Real-time pose adjustment via virtual simulations; lab prototype testing; compensates for existing tech limitations. Study the full mining cycle; enhance adjustment capacity; adapt to geological conditions.	Smart City/Mining
2022	The replacement of dysfunctional sensors based on the DT method during the cutter suction dredger construction process [198]	Bin Wang et al.	Handling sensor failure during dredging, DT + stacking learning regression model for sensor replacement.	Ensures continuity in CSD operation; $R^2 > 0.9$. Future: Pre-training models required; improve generalization.	Transportation/Dredging
2021	Proposal of DT for testing and measuring of rubber-textile conveyor belts within Industry 4.0 [199]	Gabriel Fedorko et al.	Testing and analysis of rubber-textile conveyor belts, FEM-based DT using Abaqus to model a testing stand.	Reduces testing time and effort; detects conditions using belt drift; Industry 4.0 alignment. Combine with statistical analysis; apply to real belt-drift issues.	Manufacturing
2024	A laser ultrasonic intelligent inspection method for metal surface defects based on a DT model [200]	Zhang, Yunhao Zhou et al.	DT-based defect detection using FEM, GAN, wavelet transform, and deep learning (ResNet).	Solves small data problems; high detection accuracy; strong generalization capability. Improve real-time performance, extend to other defect types, and enhance dataset diversity.	Manufacturing
2025	A time-varying contact dynamic modeling method of kinematic pairs based on DT [190]	Chen, Yu Et al	DT-based framework integrating sensor data for time-varying dynamic modeling of kinematic systems.	Improved modeling accuracy; consideration of uncertainties and dynamic variations. Extend to complex systems, improve data integration, and enhance predictive maintenance.	Manufacturing

The literature therefore supports the interpretation of DTs as a general technological paradigm rather than a technology restricted to manufacturing. However, the transferability of a particular DT implementation should not be assumed. Architectural principles may be generalized across domains, whereas data models, validation criteria, operational constraints, and safety requirements generally remain domain-specific.

The broader evidence also confirms that the reviewed corpus is still strongly concentrated in manufacturing. This concentration is important when interpreting the maturity of DT technologies: high publication frequency in manufacturing should not be interpreted as evidence that the same technological maturity has been achieved in healthcare, smart cities, or energy systems.

4.8. Convergent Five-Layer DT Architecture

The preceding thematic synthesis indicates that DT architectures reported across different application domains frequently contain a common set of functional components, although the terminology, implementation, and degree of integration vary considerably. Based on the synthesis of the reviewed studies, these recurring components can be organized into a five-layer reference architecture comprising:

- Physical Assets;
- Data and Communication;
- DT Modeling and Simulation;
- Services and Analytics;

- Application and Human–Machine Interface (HMI).

This architecture is not proposed as a universal architecture to which all DT systems must conform. Rather, it represents a review-derived analytical framework that enables comparison of heterogeneous DT implementations across different sectors and technological maturity levels.

Layer 1—Physical Assets

The first layer represents the physical entities and sensing infrastructure that generate operational data. It includes machines, equipment, robots, PLCs, sensors, actuators, medical devices, infrastructure assets, energy equipment, and other instrumented physical entities.

Reliable sensing is fundamental to DT operation because the digital representation depends on the quality, accuracy, and timeliness of information acquired from the physical system.

Layer 2—Data and Communication

The second layer provides the connectivity and data-management infrastructure required to transfer, store, synchronize, and preprocess information. IoT/IIoT networks, OPC UA, MQTT, industrial communication systems, cloud platforms, edge computing, and data-integration mechanisms may operate at this layer.

A recurring challenge identified across the reviewed studies is the synchronization of heterogeneous data streams while satisfying the latency requirements of real-time DT applications.

Layer 3—DT Modeling and Simulation

The third layer constitutes the computational core of the DT. It contains physics-based models, data-driven models, simulation environments, and hybrid modeling approaches.

Conventional approaches include finite-element and computational-fluid-dynamics models, discrete-event simulation, and three-dimensional virtual environments. AI-based approaches employ methods such as CNNs, LSTMs, GNNs, and other machine learning models. More recent studies increasingly investigate hybrid and physics-informed approaches, including PINNs, to combine physical knowledge with data-driven learning.

Layer 4—Services and Analytics

The fourth layer converts DT data and models into operational intelligence. The reviewed studies associate this layer with predictive maintenance, anomaly and fault detection, quality assessment, process optimization, scheduling, diagnosis, energy management, forecasting, and decision support.

This layer represents the point at which DT capabilities are translated into operational actions or measurable performance improvements. Increasingly, AI models, optimization algorithms, FL, and other decision-support mechanisms operate at this level.

Layer 5—Application and Human–Machine Interface

The fifth layer provides interaction between the DT and its users or operational environment. Typical implementations include dashboards, visualization platforms, web-based HMIs, augmented and virtual reality interfaces, mobile applications, and decision-support systems.

Increasingly, this layer also incorporates explainable AI and human-centered interaction mechanisms to improve transparency and support human decision-making in AI-enabled DT environments.

The resulting five-layer architecture is presented in Figure 6 as a synthesis of the recurring functional elements identified across the reviewed literature.

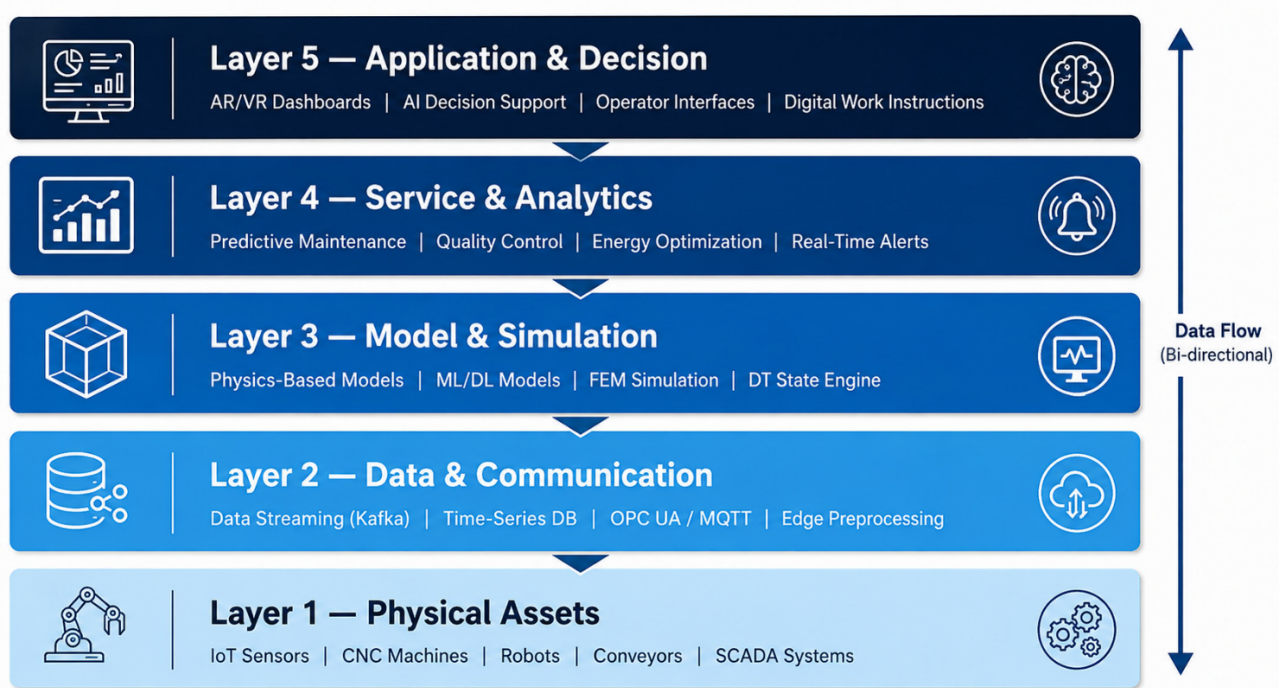


Figure 6. Five-layer DT reference architecture synthesized from the reviewed literature (2018–2026), illustrating the information flow from physical assets and data acquisition through communication, modeling and simulation, analytics and services, to application and human–machine interaction.

Emerging standards and future interoperability. Emerging standards such as ISO 23247 and IEC 62832 are expected to play an important role in improving interoperability in future DT ecosystems. ISO 23247 provides a standardized framework for DTs in manufacturing, helping to structure the relationships between physical entities, digital representations, data, and DT-related services. IEC 62832, through its digital factory framework, supports standardized representation and organization of digital factory elements and their associated information. Together, such standards can reduce dependence on proprietary architectures and facilitate more consistent information exchange across heterogeneous DT platforms, industrial systems, and organizational boundaries. This standardization will become particularly important for autonomous DT ecosystems, in which multiple DTs may need to exchange data, coordinate services, and support AI-driven decisions with limited human intervention. However, standards alone do not guarantee interoperability; their practical effectiveness will also depend on semantic alignment, compatible communication technologies, cybersecurity mechanisms, and consistent implementation across vendors and industrial domains.

The five-layer model also provides a useful framework for positioning the two LSEA laboratory implementations presented in Section 5. The physical manufacturing equipment corresponds to Layer 1; PLCs, communication mechanisms, and the Raspberry Pi edge devices contribute to Layer 2; CIROS Studio and Factory I/O provide the simulation and virtual-representation components of Layer 3; VGG16, MobileNet, and fuzzy-logic decision support operate within Layer 4; and Node-RED and Gradio provide the HMI components of Layer 5. The two implementations therefore illustrate two distinct technology stacks that can be mapped onto the same review-derived functional architecture.

This mapping should nevertheless be interpreted cautiously. The two LSEA implementations constitute laboratory-scale manufacturing demonstrations and do not establish that the five-layer architecture has been experimentally validated across healthcare, smart-city, energy, or other application domains. Rather, they provide concrete examples of how the

functional principles identified through the systematic literature synthesis can be implemented in a manufacturing environment. Table 12 presents the mapping of the formulated five-layer DT architecture to the representative technologies and reviewed applications.

Table 12. Mapping of the synthesized five-layer DT architecture to representative technologies and reviewed applications.

Year	Title [Ref.]	Authors	Methodology (Focus & Approach)	Key Contributions & Recommendations	Domain
2023	A framework and method for equipment DT dynamic evolution based on IExATCN [201]	Wang, Kunyu Zhang et al.	Dynamic evolution of black-box equipment DTs, 3-part framework (data acquisition, evolution triggering, algorithm) with IExATCN model.	Formalized dynamic evolution concept; designed IExATCN; validated via 3D equipment attitude estimation. Integrate real-time sensor data with prior knowledge for more interpretable evolution.	Equipment Monitoring
2019	A six-layer architecture for the DT: A manufacturing case study implementation [202]	A. J. H. Redelinghuys et al.	Multilayer architecture for DT in manufacturing, Six-layer architecture from data acquisition to simulation; case study implementation.	Modular, scalable framework; supports legacy systems; provides real-time and service-based infrastructure. Address latency and cloud connection issues; refine gateway functions.	Manufacturing Systems/CPPS
2019	Design and application of DT system for the blade-rotor test rig [203]	Jian-Guo Duan, Tian-Yu Ma et al.	DT system for real-time monitoring of blade-rotor test rig, Five-layer architecture including communication protocols (RS-485, TCP/IP); VR integration.	Achieves real-time data mapping and visual monitoring; enhances equipment safety and visibility. Expand to virtual control; use big data analysis for smart maintenance.	Monitoring Systems/VR
2021	Real-time machining data application and service based on IMT DT [204]	Xin Tong et al.	IMT-based DT for machining process optimization, Multisensor fusion, MTConnect protocol, digital model for real-time monitoring.	Real-time mapping of machining process; visualization of trajectory and status; optimization modules. Research full product lifecycle; integrate advanced modeling, big data, and 5G networks.	Process Optimization/Smart Manufacturing
2024	DT for product versus project lifecycles' development in manufacturing and construction industries [205]	Abanda, F. H et l	Systematic review comparing DT applications in manufacturing and construction.	Comparative analysis; identification of benefits and barriers; lessons for adoption. Standardization, hardware deployment, lifecycle integration, and data protection.	Manufacturing
2025	Modern trends and industrial use cases of DT technology with 3D behavioral representation [206]	Machacek et al.	Comprehensive review of 3D DT modeling, simulation, and industrial applications across the lifecycle.	Definition of 3D behavior; multiple industrial use cases; integration across lifecycle stages. Improve tools, enhance lifecycle integration, expand industrial adoption.	Manufacturing

Finally, the thematic synthesis reveals that the future evolution of DT technology is likely to involve increasing convergence between physical systems, distributed data infrastructures, AI-enabled analytics, and human-centered decision-making [207,208]. Emerging technologies such as generative AI, federated learning, 6G, quantum-enhanced optimization, semantic interoperability, and self-evolving DTs may further extend these capabilities. However, their long-term industrial impact remains uncertain because their validation and adoption are still less mature than those of established DT technologies such as IoT/IIoT, simulation, AI/ML, cloud computing, and edge computing [207,208].

Overall, the systematic review indicates that DT research has evolved from virtual representation and monitoring toward interconnected, intelligent, adaptive, and increasingly autonomous systems [208]. At the same time, interoperability, cybersecurity, real-time synchronization, model fidelity, scalable validation, and trustworthy AI remain central bar-

riers to large-scale DT deployment [209]. These findings provide the basis for the detailed discussion of challenges and research gaps in Sections 6 and 7 and for the direct answers to the research questions presented in Section 9.

Scalability in geographically distributed industrial environments. The synthesized five-layer architecture can conceptually support geographically distributed industrial environments in which physical assets, production lines, or facilities are located across multiple sites. In such scenarios, edge computing can be deployed locally at each site to perform data acquisition, preprocessing, and time-sensitive analytics, while cloud or centralized services can provide cross-site data aggregation, model coordination, and higher-level decision support. Standardized communication and interoperability mechanisms, such as OPC UA and MQTT, can facilitate data exchange between distributed DT instances, while synchronization mechanisms are required to maintain consistency between local physical assets and their corresponding digital representations. However, geographically distributed deployment introduces additional challenges, including network latency, intermittent connectivity, heterogeneous site configurations, cybersecurity and data-governance requirements, and the coordination of multiple DT instances. The scalability of the synthesized architecture across geographically distributed industrial sites has not been experimentally evaluated in the present study and therefore remains a subject for future multi-site validation.

5. Case Studies: Two LSEA Digital-Twin Implementations for Industrial Quality Control

5.1. Relationship to Previously Published Work and Contribution Boundary

This section presents two independent, peer-reviewed DT implementations developed at the LSEA, University of Medea, Algeria, in collaboration with the LAADI, University of Djelfa. Although both studies share several co-authors (notably Yehya Aniba and Mounir Bouhedda) and address quality control in a manufacturing context using CNN-based visual inspection, they describe two distinct systems, built with different simulation environments, different CNN architectures, different decision layers, and different human-machine interfaces. To avoid conflating them, the two studies are presented separately below and referred to as CS-1 and CS-2 throughout the remainder of this paper.

- CS-1: Aniba, Y., Bouhedda, M., Bachene, M., Rahim, M., Benyezza, H., & Tobbal, A. Digital twin-enabled quality control through deep learning in Industry 4.0: A framework for enhancing manufacturing performance. *Int. J. Model. Simul.* **2024**, 1–21. <https://doi.org/10.1080/02286203.2024.2395899> [210]
- CS-2: Aniba, Y., Bouhedda, M., Bachene, M., Seddiki, M., Tobbal, A., Hamrani, A., & Benyezza, H. Enhanced digital twin development for a conveyor belt system: integrating PLC control, CNN decision-making, Gradio-based HMI, and fuzzy logic. *Braz. J. Technol.* **2024**, 7, e75933. <https://doi.org/10.38152/bjtv7n4-035> [211]

The laboratory prototypes summarized below (CS-1 and CS-2) are not presented as an independent, novel experimental study in this review (Figure 7). They are the authors' own previously published, peer-reviewed work, reused here strictly as an illustrative validation case that maps the architectural and technological principles synthesized from the systematic review (Sections 2–4) onto two physical DT implementations. No previously reported result is presented as a new finding of this review. Table 13 below identifies, for each component or result, its previously published source, what is reused verbatim or near-verbatim here, and what new analysis or extension this review contributes beyond the original publications.

Section 5 Summary — Two LSEA Digital Twin Case Studies for Industrial Quality Control

Author-created summary diagram synthesizing Sections 5.1–5.6 — not reproduced from CS-1 or CS-2

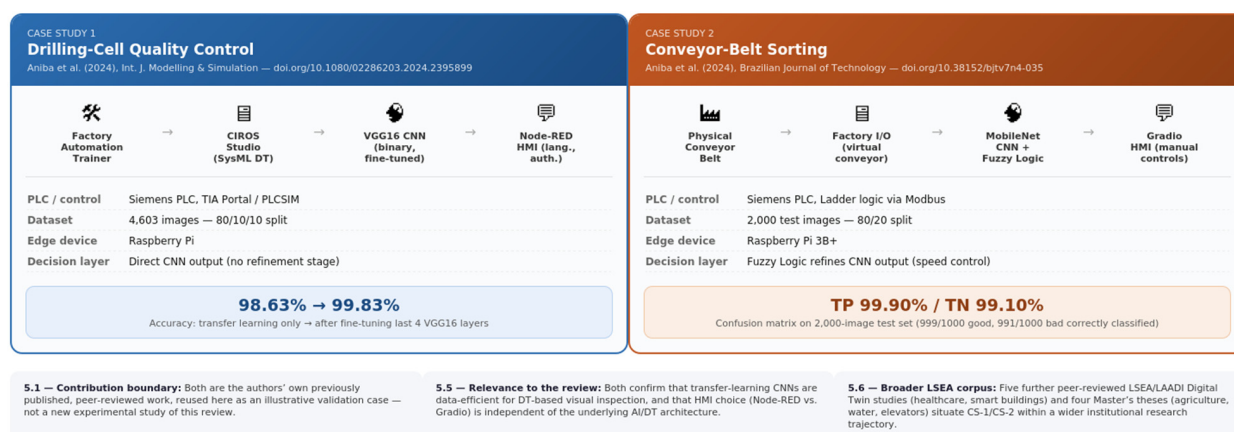


Figure prepared by the review authors to summarize Section 5; all values are traceable to Tables in Sections 5.2–5.4 and to the original CS-1/CS-2 publications.

Figure 7. Visual summary of the two LSEA DT case studies presented in Section 5 (author-created synthesis diagram; not reproduced from CS-1 or CS-2).

Table 13. Mapping of original publications, reused components, and new contributions of the present review.

Component/Result	Previously Published Source	Element Reused Here	New Analysis or Extension in This Review
FAT drilling-cell architecture, SysML/CIROS Studio/Node-RED design, VGG16 training protocol, and all CS-1 numerical results (98.63% → 99.83% accuracy, confusion matrices, ROC curves)	Aniba, Bouhedda, Bachene, Rahim, Benyezze & Tobbal (2024), Int. J. Modelling and Simulation, https://doi.org/10.1080/02286203.2024.2395899	Description of the system and the originally reported metrics, cited and attributed throughout Section 5.2	Explicit mapping of CS-1's five-layer architecture onto the reference DT layer patterns discussed in the review; side-by-side comparison with CS-2 (Section 5.4) that CS-1 alone does not provide
Conveyor-belt DT architecture, Factory I/O/MobileNet/Fuzzy Logic/Gradio design, and all CS-2 numerical results (TP 99.90%, TN 99.10%)	Aniba, Bouhedda, Bachene, Seddiki, Tobbal, Hamrani & Benyezze (2024), Brazilian Journal of Technology, https://doi.org/10.38152/bjtv7n4-035	Description of the system and the originally reported metrics, cited and attributed throughout Section 5.3	Explicit separation from CS-1 (previous manuscript drafts had conflated the two systems); comparative positioning against the review's synthesized DT-AI decision-refinement patterns
Wider LSEA DT research corpus (healthcare, agriculture, water management, smart infrastructure)	DT-01, DT-04, DT-05, MS-01–MS-04, TH-02, EN-01–EN-02 (Section 5.6, each with its own citation)	Bibliographic listing only—titles, authors, year, and DOI/link where available	Positions CS-1/CS-2 within the laboratory's broader trajectory and grounds the domain-generalization limitation discussed in Section 8

5.2. Case Study 1 (CS-1): DT-Enabled Quality Control for a Drilling Operation

5.2.1. Evaluation Protocol and Physical System

Evaluation protocol. The quantitative evaluation of CS-1 was performed at the image-classification level rather than at the production-line KPI level. A total of 4603 images were collected, with 80% used for training, 10% for validation, and 10% retained as a held-out test set (460 images). The same held-out test set was used to compare the transfer-learning-only and fine-tuned VGG16 configurations.

5.2.2. Physical System and Institutional Context

CS-1 was developed at the LSEA and LAADI laboratories with funding from the Directorate General for Scientific Research and Technological Development (DGRSDT) of the Algerian Ministry of Higher Education and Scientific Research. The physical system, called the Factory Automation Trainer (FAT), is a laboratory-scale manufacturing cell that performs a drilling operation on metal parts stored in a warehouse. Pneumatic cylinders and a conveyor belt move the parts through six sequential functions: (1) material-presence detection via an optical fiber sensor, (2) drilling, (3) transfer of the drilled part to the conveyor by a single-action cylinder, (4) camera-based inspection of the drilled hole, (5) extraction of defective parts, and (6) sorting of accepted parts.

Figure 8 illustrates the structural pathway of the two LSEA case studies, extending from the physical micro-factory to the operator's human-machine interface (HMI) (diagram prepared by the author; not adapted from CS-1 or CS-2). The figure provides a consolidated overview of the two LSEA DT case studies, highlighting their distinct industrial applications and technologies while demonstrating their common end-to-end architecture, from the physical system and digital simulation to communication, AI-based decision-making, and human-machine interaction.

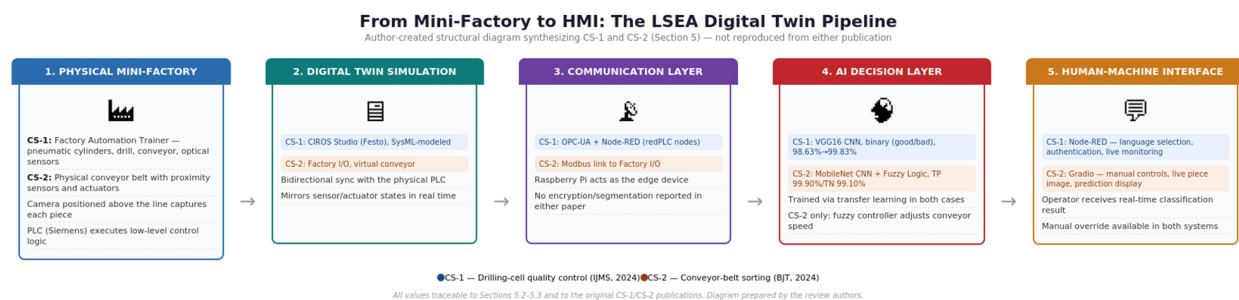


Figure 8. Structural pipeline of the two LSEA case studies, from the physical mini-factory to the operator HMI (author-created diagram; not reproduced from CS-1 or CS-2).

5.2.3. DT Architecture

The DT was modeled in SysML using Cameo Systems Modeler, then implemented as a 3D virtual replica in CIROS Studio (Festo), which also supports PLC programming and simulation. The physical PLC is programmed and validated via TIA Portal/PLCSIM, and communicates with a Node-RED-based HMI using OPC-UA and redPLC nodes. A Raspberry Pi acts as the edge device linking the cloud-hosted AI inference service to the PLC. The authors describe the resulting system as a five-layer architecture: Physical Devices, Local Controllers (OPC-UA), IoT Gateway, Cloud Services (hosting the AI quality-control model), and Virtual Layer (the DT itself).

5.2.4. CNN-Based Quality Control

Quality inspection uses a VGG16 convolutional neural network in a binary classification setting (good part vs. defective part), based on the size, centering, and absence of incisions around the drilled hole. A dataset of 4603 images was collected via OpenCV/MOG2 background subtraction from a camera positioned above the conveyor, resized to $224 \times 224 \times 3$, and split 80%/10%/10% for training/validation/testing. Training proceeded in two phases: (1) 20 epochs at a learning rate of 10^{-4} with the VGG16 backbone frozen, and (2) 10 additional epochs at a learning rate of 10^{-5} with the last four VGG16 layers unfrozen for fine-tuning 30 epochs in total.

5.2.5. Results

To quantitatively assess the contribution of fine-tuning to the performance of the proposed VGG16-based classification model, a comparative evaluation was conducted between the transfer-learning-only configuration and the fine-tuned configuration. The comparison considers several complementary performance indicators, including overall accuracy, true-positive and true-negative rates, false-positive and false-negative rates, ROC AUC, and training time. As summarized in Table 14, the reported results show higher descriptive classification performance after fine-tuning compared with the transfer-learning-only configuration. Accuracy increased from 98.63% to 99.83%, while the reported false-positive and false-negative rates decreased. These values are descriptive performance measures obtained on the held-out test set and are not interpreted here as statistically significant differences, because formal significance testing was not reported in the original study. In particular, the fine-tuned model achieves near-perfect discrimination between good and defective parts, as reflected by the improved ROC AUC and the higher true-positive and true-negative rates. These results indicate that fine-tuning the pretrained VGG16 model provides a measurable performance gain for the proposed drilling-operation quality-control application, although this improvement is accompanied by a moderate increase in training time.

Table 14. Comparative performance of the VGG16-based classification model before and after fine-tuning.

Metric	Transfer Learning Only	Transfer Learning + Fine-Tuning
Accuracy	98.63%	99.83%
True Positive (good part)	99.68%	100.00%
True Negative (bad part)	98.10%	99.74%
False Positive	1.90%	0.26%
False Negative	0.32%	0.00%
ROC AUC	0.9995	0.9999
Training time (Google Colab)	25 min	42 min

Testing was performed on a held-out set of 460 images (10% of the 4603-image dataset).

5.2.6. Human–Machine Interface

The operator interface was built in Node-RED and provides three functions: language selection (Arabic, French, English), user authentication, and real-time outcome monitoring (start/stop control, diagnostics, and live status of the physical and virtual FAT).

5.3. Case Study 2 (CS-2): Enhanced DT for a Conveyor Belt with Fuzzy-Logic Decision Support CS-2

Evaluation protocol. The quantitative evaluation of CS-2 was performed using a held-out test set of 2000 images, comprising 1000 good and 1000 defective pieces. Performance was assessed using true-positive, true-negative, false-positive, and false-negative rates. The evaluation therefore concerns image-classification performance rather than full production-line KPIs such as OEE, downtime, MTTR, energy consumption, or throughput.

5.3.1. System and Objectives

CS-2, published in the Brazilian Journal of Technology, targets a conveyor-belt system rather than a drilling cell. The DT was built in Factory I/O rather than CIROS Studio, modeling a conveyor with proximity sensors and actuators; scenarios such as misplacements, speed changes, and blockages were simulated for testing. A PLC (programmed in ladder logic) synchronizes the virtual and physical conveyor in real time and communicates with Factory I/O over the Modbus protocol; a Raspberry Pi 3B+ acts as the edge device linking the PLC, camera, CNN, and fuzzy logic modules.

5.3.2. CNN and Fuzzy-Logic Decision Layer

Unlike CS-1, quality inspection in CS-2 uses a MobileNet-based CNN with transfer learning. The model was trained using the dataset and evaluated on a held-out test set of 2000 images, comprising 1000 good and 1000 defective pieces. The model classifies the conveyed pieces as accepted or rejected and provides a corresponding confidence score. A fuzzy logic (FL) controller then refines the CNN output by using the CNN confidence score, the computed rejection rate, and the current production speed as inputs. Based on predefined fuzzy rules, the controller dynamically adjusts the conveyor production speed among slow, moderate, and fast operating modes; for example, the production speed can be reduced when the CNN confidence is low and the rejection rate is high.

5.3.3. Results

On a test set of 2000 images (1000 good, 1000 bad pieces), the model correctly identified 999/1000 good pieces (true-positive rate 99.90%) and 991/1000 bad pieces (true-negative rate 99.10%), giving a false-positive rate of 0.10% (1 good part misclassified as bad) and a false-negative rate of 0.90% (9 bad parts misclassified as good). Training and validation accuracy curves both converged toward 1.0, while the corresponding losses converged toward low values. These observations suggest limited evidence of overfitting under the reported experimental conditions; however, no formal statistical test of generalization or significance was reported.

5.3.4. Human–Machine Interface

Unlike CS-1's Node-RED interface, CS-2's HMI is built with Gradio, a Python-native web interface. It displays a start/stop conveyor control, the captured piece image, a production-speed slider, the CNN's Good/Bad prediction, the fuzzy-logic efficiency evaluation, and the conveyor's status and speed. The authors present this Gradio interface, combined with the fuzzy logic layer, as the main improvement over a traditional, non-DT conveyor baseline with a basic control panel and no automated defect detection.

5.4. Comparison Between the Two LSEA Case Studies

Table 15 compares the two LSEA case studies, CS-1 and CS-2, which share a common research context but address different industrial processes, DT architectures, AI models, and experimental results. Therefore, they represent two distinct and complementary contributions that should be discussed and cited separately.

The exact dataset split should be reported consistently with the original CS-2 publication. Both papers share several co-authors and belong to the same LSEA/LAADI research program on DT-enabled quality control, but they describe two distinct architectures, models, and results.

Table 15. Comparative analysis of the two LSEA DT-enabled quality control case studies (CS-1 and CS-2).

Feature	CS-1	CS-2
Evaluation level	Image classification	Image classification
Test set	460 images	2000 images
Main reported metrics	Accuracy, TPR, TNR, FPR, FNR, ROC AUC	TPR, TNR, FPR, FNR
Reported performance	Accuracy: 98.63% → 99.83%	TPR: 99.90%; TNR: 99.10%
Industrial KPIs	Not evaluated	Not evaluated

5.5. Scientific Contributions and Relationship to the Systematic Review

Together, CS-1 and CS-2 provide two independent, laboratory-scale illustrations of the DT architectures synthesized from the systematic review.

- Architecture and AI performance (CS-1): CS-1 instantiates a five-layer DT architecture (Physical Devices, Local Controllers, IoT Gateway, Cloud Services with AI, and a Virtual Layer) using CIROS Studio, TIA Portal, Node-RED, and a cloud-deployed VGG16 model, and reports a substantial accuracy gain (98.63% → 99.83%) from fine-tuning a small number of upper convolutional layers.
- Decision refinement and HMI diversity (CS-2): CS-2 illustrates a complementary decision-support pattern in which CNN outputs (from MobileNet) are not used directly, but refined by a fuzzy logic layer before being acted upon, and demonstrates an alternative, Python-native (Gradio) HMI paradigm distinct from the Node-RED dashboards used in CS-1.
- Scope of the reported results: Neither case study reports the extended industrial KPI sets—such as OEE, MTTR, energy consumption, downtime, and throughput—that are sometimes used to evaluate full-scale industrial DT deployments. Both instead report classification-level performance metrics obtained from held-out image test sets in laboratory-scale prototypes.

Both case studies provide laboratory-scale illustrations that are consistent with two recurring patterns identified in the reviewed literature: that transfer learning from ImageNet-pretrained CNNs (VGG16, MobileNet) is an effective and data-efficient approach for visual quality inspection within a DT loop, and that the choice of HMI technology (Node-RED vs. Gradio) is largely independent of the underlying DT/AI architecture.

However, because both implementations are laboratory-scale manufacturing systems, their experimental results should be interpreted as domain-specific validation rather than evidence of generalizability across healthcare, smart cities, or energy systems.

Clarification of KPI Scope and Statistical Interpretation

The KPI scope of the two case studies should be distinguished from the broader industrial-performance indicators discussed in the systematic review. CS-1 and CS-2 do not experimentally measure OEE, downtime, MTTR, energy consumption, rejection rate used as an input to the fuzzy logic controller at the production-line level, or throughput. Their quantitative evaluation is restricted to image-classification performance obtained under laboratory conditions. Accordingly, the numerical differences reported for accuracy, true-positive rate, true-negative rate, false-positive rate, false-negative rate, and ROC AUC are presented as descriptive experimental results rather than statistically validated causal

effects. Formal statistical significance testing was not reported in the original publications and is therefore not claimed in the present review.

5.6. Broader LSEA Digital Twin Research Corpus

Beyond CS-1 and CS-2, the LSEA, University of Medea, has produced a wider body of DT research spanning healthcare, smart agriculture [212,213], water management, and smart infrastructure [214,215]. This corpus is summarized below to situate CS-1 and CS-2 within the laboratory's broader research trajectory. Entries without a published DOI are internal or in-progress works; a placeholder is left in the Link column for these and can be completed once a public reference becomes available [216–223].

5.6.1. Main Peer-Reviewed DT Studies

Table 16 presents the main peer-reviewed DT studies considered in this review, summarizing their publication details, application domains, and relevance to the discussed DT architectures and case studies.

Table 16. Overview of the main peer-reviewed DT studies reviewed.

ID	Year	Work	Authors	Type	DT Domain	Link
DT-01	2023	DTs for Health Care Monitor: Baby Incubator Temperature and Humidity Monitoring	Saad Abderrahmane, Reda Kara, Mounir Bouhedda	IEEE Conference	Healthcare/neonatal incubator	https://doi.org/10.1109/IC2EM59347.2023.10419837 [224]
DT-02	2024	DT-enabled quality control through deep learning in industry 4.0 (=CS-1, Section 5.2)	Aniba, Bouhedda, Bachene, Rahim, Benyezza, Tobbal	Journal article	Industry 4.0/Manufacturing	https://doi.org/10.1080/02286203.2024.2395899 [210]
DT-03	2024	Enhanced DT development for a conveyor belt system (=CS-2, Section 5.3)	Aniba, Bouhedda, Bachene, Seddiki, Tobbal, Hamrani, Benyezza	Journal article	Industry 4.0/Conveyor system	https://doi.org/10.38152/bjtv7n4-035 [211]
DT-04	2024	A DT-Based Platform for Medical Cyber-Physical Systems	Messaoud Rahim, Wassila Lalouani, Elbahi Toubal, Lloyd Emokpae	IEEE Access	Healthcare/Medical CPS	https://doi.org/10.1109/ACCESS.2024.3502077 [225]
DT-05	2025	Innovative AI strategies for enhancing smart building operations through DTs: A survey	Oulefki, Kheddar, Amira, Kurugollu, Himeur, Bounceur	Review article	Smart Buildings	https://doi.org/10.1016/j.enbuild.2025.115567 [226]

5.6.2. Enabling Publications

- AI-Driven IoT Healthcare System for Real-Time ECG Analysis and Comprehensive Patient Monitoring (Seddiki, Bouhedda, Tobbal, Rebouh, Aniba, 2024) provides the IoT/AI monitoring infrastructure used within the laboratory's healthcare DT research stream. <https://doi.org/10.54327/set2024/v4.i2.149> [227].
- Study and Design of a Low-Power Water Meter (Elmohri, Kara, Bouhedda, Bengherbia, Manseur, Tobbal, 2023) provides the embedded sensing infrastructure relevant to the laboratory's water-management DT research stream. <https://doi.org/10.1109/IC2EM59347.2023.10419545> [228].

5.6.3. Applied Research Project

DT Platform Based on IoT and AI Techniques for the Effective Management of Drinking-Water Distribution Networks is an applied research project led by Mounir Bouhedda (University of Medea/Algérienne des Eaux, ADE), combining IoT, AI, and DT technologies for supervision, leak detection, and predictive maintenance of water networks. As a socio-economic applied project rather than a peer-reviewed publication, it is reported here as institutional context and not counted among the systematically reviewed papers.

6. Key Challenges in DT Implementation

Although the reviewed literature demonstrates substantial progress in DT technologies, their transition from research prototypes to reliable industrial systems remains constrained by a combination of technical, organizational, cybersecurity, validation, and human-centric challenges. The cross-domain analysis presented in the preceding sections indicates that these challenges are interconnected rather than independent. Data interoperability affects synchronization performance; synchronization influences model fidelity and decision-making; and the increasing autonomy of AI-enabled DTs introduces additional cybersecurity, ethical, and regulatory requirements.

The following subsections synthesize the principal challenges identified across the reviewed literature and relate them to the practical experience gained from the LSEA laboratory prototype described in Section 5.

6.1. Data Integration and Data Quality

Data integration remains one of the fundamental barriers to large-scale DT implementation. Industrial DTs typically need to combine heterogeneous information originating from SCADA systems, PLCs, IoT sensors, ERP and MES databases, historical repositories, simulation models, and external information systems. Differences in data formats, semantic structures, sampling frequencies, communication protocols, and data quality can prevent these sources from being integrated into a consistent representation of the physical asset.

This implementation demonstrates that interoperability can be achieved at laboratory scale; however, the development of standardized semantic models capable of integrating heterogeneous industrial data across organizations and platforms remains an important research priority.

6.2. Cybersecurity and Privacy

The increasing connectivity of DTs expands the potential attack surface of industrial systems. A DT may simultaneously expose physical equipment, communication networks, databases, simulation models, AI models, and operator interfaces. Consequently, security threats can extend beyond conventional network attacks to include unauthorized access, data manipulation, man-in-the-middle attacks, denial-of-service attacks, and AI-specific threats such as model poisoning.

The reviewed studies indicate that distributed-ledger and blockchain-based mechanisms can provide additional integrity and traceability capabilities, although they should be regarded as complementary security mechanisms rather than complete cybersecurity solutions. The combination of industrial network security, authentication, encryption, access control, secure data exchange, and AI-model protection is required for comprehensive DT security.

Regulatory developments further increase the importance of trustworthy AI. For AI-enabled DT applications, the requirements of the EU AI Act concerning risk management, transparency, cybersecurity, human oversight, and technical robustness should be considered according to the specific risk classification and deployment context of the system. Therefore, compliance should not be interpreted as a single technical feature but as a lifecycle-oriented governance requirement.

Neither CS-1 nor CS-2 really gives anything like a systematic treatment of cybersecurity, so it is quite unreliable. In CS-1, the Node-RED HMI uses basic operator authentication, with a standard username and password mechanism, as an access-control measure, yet neither publication discusses encryption, certificate management, network segmentation, or even threat modeling for the OPC-UA/Modbus communication layers they depend on. A full industrial deployment would require more than that, like certificate management,

segmentation of the network, secure firmware and software updates, intrusion detection, role-based authorization, and also systematic cybersecurity testing, and in fact none of that is reported in either case study.

6.3. Real-Time Synchronization and Latency

Real-time synchronization represents another major challenge because the value of a DT depends on the extent to which the virtual representation accurately reflects the current state of the physical system. Distributed sensing, communication delays, computational workloads, and cloud-dependent architectures can introduce latency and temporal inconsistencies between physical and virtual states.

The literature reviewed in Table 6 shows increasing interest in edge computing, 5G/6G communication, distributed computing, and communication–computation co-design as approaches for reducing synchronization latency in large-scale industrial DT deployments. Although advanced wireless technologies may provide significant advantages for geographically distributed systems, they are not necessarily required for every DT application.

The two LSEA case studies illustrate this distinction using different technology stacks. CS-1 synchronizes its physical and virtual environments via OPC-UA and Node-RED, while CS-2 synchronizes Factory I/O and the physical PLC via the Modbus protocol. Neither paper reports a directly measured end-to-end synchronization latency in milliseconds; both instead emphasize architectural design choices (edge processing, lightweight industrial protocols) intended to support real-time operation.

Neither CS-1 nor CS-2 reports a measured end-to-end synchronization latency, and that is admittedly a significant gap. The whole architectural angle of using lightweight industrial protocols like OPC-UA and Modbus across both prototypes makes it seem that lab-scale and SME oriented DT systems can work without leaning on advanced 5G/6G infrastructure. But what we have here is more like an architectural inference than anything truly demonstrated, because neither paper actually shows the latency numbers. If we try to scale either setup to something bigger, like large geographically distributed sites, multi-line runs, and multiple plants, there are several very concrete issues that neither paper really addresses: (i) network jitter and packet loss when you get sustained traffic from many devices; (ii) failover and redundancy, especially when an edge device such as the Raspberry Pi (in both cases) or a PLC link drops offline; (iii) security segmentation between the physical side, the edge tier, and the cloud tier, without letting one layer accidentally leak into another; and finally (iv) cross-site governance plus model versioning across multiple DT instances for the same process. That last part is often overlooked until operations become messy. So, future research should look at more adaptive architectures, where processing gets distributed dynamically between edge, fog, and cloud resources based on measured latency, jitter, and reliability needs. And importantly, the measurements should be reported empirically, not just guessed from protocol choices alone.

6.4. Model Fidelity, Uncertainty, and Validation

A persistent challenge in DT development is the trade-off between model fidelity and computational efficiency. Highly detailed physics-based models can accurately represent complex physical processes but may require substantial computational resources, making them unsuitable for real-time applications. Conversely, purely data-driven models can provide fast predictions but may perform poorly when operating conditions differ from those represented in the training data.

The reviewed literature increasingly addresses this problem through hybrid modeling, particularly physics-informed machine learning and PINNs, as identified in Table 8. These

approaches seek to combine the generalization capabilities of data-driven learning with the physical consistency of domain-based models.

A related challenge is the validation of DT models outside controlled laboratory conditions. Model accuracy alone is insufficient to establish the reliability of an industrial DT because uncertainty may arise from sensor errors, model assumptions, changing operating conditions, data drift, and communication failures. The uncertainty-quantification approaches identified in the reviewed literature, including the Bayesian frameworks reported in Table 8, therefore represent an important direction for establishing more rigorous DT validation procedures.

The LSEA case studies contribute to this issue by evaluating their CNN models using images acquired from physical prototypes rather than relying exclusively on synthetic or simulated data. CS-1's fine-tuned VGG16 model achieved 99.83% test accuracy (up from 98.63% with transfer learning alone), and CS-2's MobileNet-based model achieved true-positive and true-negative rates of 99.90% and 99.10%, respectively. Nevertheless, these results should be interpreted as application-specific validation on laboratory prototypes rather than universal model validation. Future research should evaluate model robustness under changing lighting conditions, production rates, equipment states, product variants, sensor degradation, and long-term data drift. Establishing common validation protocols, potentially incorporating accredited measurement and calibration practices such as those associated with ISO/IEC 17025 where applicable, remains an important research need.

6.5. Human Factors, Explainability, and Ethical AI

As DTs increasingly incorporate autonomous AI systems, technical performance alone is insufficient to ensure successful adoption. Human factors, operator trust, explainability, safety, workload, and organizational acceptance are becoming increasingly important dimensions of DT design. This transition is consistent with the Industry 5.0 paradigm, which places greater emphasis on human-centricity, resilience, and sustainability.

The studies identified in Table 7 indicate that human-centric DT interfaces can improve operator interaction while reducing cognitive burden. Effective HMI design should therefore provide operators with understandable information about system status, AI confidence, detected anomalies, and recommended actions rather than presenting opaque automated decisions.

The two LSEA case studies address this requirement with two different HMI paradigms. CS-1 uses a Node-RED-based interface offering language selection (Arabic, French, English), user authentication, and real-time outcome monitoring, which improves accessibility within the Algerian industrial context. CS-2 uses a Gradio-based interface presenting the captured piece image, the CNN's Good/Bad prediction, the fuzzy-logic efficiency evaluation, and manual conveyor controls. Together, they illustrate that human-centric HMI design can be achieved with different underlying web frameworks depending on the target deployment context.

However, explainability should not be equated simply with displaying a confidence score. For safety-critical or high-impact industrial decisions, operators may also need information about why a decision was produced, which data influenced it, how uncertain the prediction is, and when human intervention is required. Future DT research should therefore develop human–AI interaction mechanisms that combine explainability, uncertainty communication, human oversight, and accountability.

6.6. Cross-Cutting Research Priorities

The five challenges identified above are strongly interconnected. Improving one component of a DT without addressing the others may therefore have limited practical

value. For example, increasing model accuracy without improving data quality may not improve system reliability, while reducing communication latency without addressing cybersecurity may increase operational risk.

Based on the systematic review and the LSEA prototype, the major research priorities can be summarized in Table 17 as follows:

Table 17. Key challenges, emerging solutions, and prototype responses in DT implementation.

Challenge	Current Research Direction	Remaining Gap	Implication for the LSEA Prototype
Data integration	Ontologies, knowledge graphs, ISO 23247, IEC 62832	Universal semantic interoperability	Extend OPC UA/MQTT integration toward semantic DT models
Cybersecurity & privacy	Secure communication, blockchain, edge security	End-to-end DT and AI security	Strengthen authentication, segmentation, encryption, and AI-model protection.
Synchronization	Edge computing, 5G/6G, distributed architectures	Scalable low-latency synchronization	Extend sub-100 ms performance toward multi-line and multi-site systems.
Model fidelity & validation	Hybrid models, PINNs, uncertainty quantification	Standardized real-world validation	Test robustness under changing operating and environmental conditions.
Human-centric AI	Explainable AI, adaptive HMI, Industry 5.0	Trustworthy autonomous decision-making	Extend confidence-based explanations toward uncertainty-aware human oversight.

Overall, the evidence suggests that the next phase of DT development will depend less on the creation of isolated DT models and more on the development of interoperable, secure, real-time, validated, and human-centered DT ecosystems. The LSEA case study provides a practical laboratory-scale demonstration of this direction by integrating industrial hardware, standardized communication protocols, edge computing, AI-based quality control, fuzzy decision support, and operator-oriented HMIs within a unified architecture. The remaining challenge is to validate and scale this architecture across different machines, production environments, organizations, and industrial sectors while maintaining reliability, cybersecurity, explainability, and regulatory compliance.

6.7. Domain Classification Criteria

Studies were classified into one of five domain categories using explicit criteria applied consistently across Tables 4–11: Manufacturing/Industrial Systems (production, process control, equipment condition monitoring, industrial robotics, and offshore/subsea industrial equipment); Healthcare/Biomedical (patient care, medical devices, clinical or physiological monitoring); Smart Cities/Built Environment/Urban Infrastructure (urban planning, traffic, buildings, public infrastructure); Energy/Power (generation, storage, transmission, grid systems); and Cross-domain/General Method (studies proposing a DT method, framework, or architecture not tied to a specific application sector).

6.8. Evidence-Level Framework and Critical Synthesis

The synthesis presented in Sections 3, 4 and 6 is primarily descriptive and aggregative (frequency counts, domain distributions, technology-adoption percentages). To move toward a more critical evidence synthesis, we introduce here an evidence-level framework distinguishing five levels of validation maturity: (1) conceptual/framework proposals with no implementation; (2) simulation-only studies; (3) laboratory prototypes (physical

hardware, controlled conditions); (4) pilot or field studies (real operational environment, limited scale or duration); and (5) industrial deployment (sustained production use). A systematic per-study classification of the full 217-paper corpus against these five levels was not performed during the original data-extraction phase and cannot be reconstructed retrospectively from the extracted tables alone; we report this explicitly as a limitation (Section 8) rather than approximate it.

Where the review can speak with confidence, we apply this framework directly. Both case studies presented in Section 5 correspond unambiguously to evidence level 3 (laboratory prototype): CS-1 and CS-2 are each evaluated on a physical benchtop system under controlled conditions, using held-out image test sets rather than a production line, and neither reports pilot-scale nor industrial deployment data. This classification is used throughout Sections 5.5 and 8 to qualify the generalizability of their reported accuracy figures: a 99.83% (CS-1) or 99.90%/99.10% (CS-2) result at evidence level 3 supports a claim about laboratory-scale feasibility, not about industrial-scale reliability, and should not be read as equivalent to a pilot- or deployment-level validation.

At the level of the broader corpus, the review can identify convergence and tension in the reported findings without requiring a full per-study evidence grading. Convergent finding: transfer learning from ImageNet-pretrained CNNs is consistently reported as effective and data-efficient for visual quality inspection across manufacturing, healthcare, and energy applications alike (Sections 4 and 5.5), suggesting this is a comparatively mature, cross-domain technique regardless of validation level. Point of tension: the enabling-technology adoption percentages reported in Figure 5 (e.g., IoT/IIoT at 86.6% versus AR/VR at 17.5%) should not be read as a direct measure of underlying technology maturity, since they aggregate studies across all evidence levels; a technology reported in many conceptual or simulation-only studies could appear more “adopted” than one used in fewer but more rigorously validated laboratory or pilot studies. Distinguishing these two readings would require exactly the per-study evidence-level classification identified above as an open task.

We therefore recommend, as a priority for future work on this corpus, a structured re-extraction pass that tags each of the 230 studies with one of the five evidence levels defined above, enabling the five-layer architecture and enabling-technology frequencies to be re-reported as evidence-weighted syntheses rather than as simple aggregate counts.

7. Future Research Directions for DT Technology (2025–2032)

The systematic synthesis of the 230-paper corpus identified eight priority research directions that are expected to shape the development of DT technology between 2025 and 2032. These directions were derived from the technological trends, implementation challenges, and research gaps identified across the reviewed literature and are therefore directly connected to the challenges discussed in Section 6. The proposed directions encompass advances in AI, communication infrastructure, privacy-preserving architectures, human-centric design, interoperability and standardization, sustainable computing, optimization, and autonomous DT evolution.

Table 18 summarizes these research priorities according to their underlying rationale, expected impact, anticipated research horizon, and supporting references. Together, these directions indicate a transition from conventional DT systems focused primarily on monitoring and simulation toward intelligent, interconnected, sustainable, human-centric, and increasingly autonomous DT ecosystems.

Table 18. Priority research directions and emerging trends in DT technology (2025–2032).

Research Direction	Rationale	Expected Impact	Horizon	Key References
Generative AI-Enhanced DT	LLMs and diffusion models enable natural language DT interaction and synthetic training data generation, addressing data scarcity challenges	High: democratizes DT deployment; reduces expert dependency	2025–2027	Wang et al. (2025) [76]: LLM-guided SD-LDM DT construction strategy for rapid multi-scale DT generation (Table 4)
6G-Enabled DT Networks	Sub-millisecond latency unlocks true real-time DT synchronization for autonomous vehicles, remote surgery, and real-time infrastructure management	Very High: foundational for next-generation DT applications	2026–2030	Wang, H. et al. (2022) [147]: GNN-based DT for network slicing management, proposed as extendable to 6G networks (Table 8); no reviewed study directly implements or evaluates a 6G-DT system
Industry 5.0 Human-Centric DT	DT systems that augment human capabilities and monitor operator cognitive ergonomics, addressing the adoption barrier identified in Section 5.5	High: improves safety and productivity in human–robot collaboration	2025–2028	Cimino et al. (2024) [74]: Simulation-based DT for enhancing human–robot collaboration in assembly systems (Table 4)
Sustainable & Carbon-Aware DT	DT systems must quantify and minimize their own carbon footprint while enabling decarbonization of physical systems critical for Paris Agreement alignment	High: essential for net-zero industrial commitments	2025–2028	Piron et al. (2025) [104]: Soft-sensors and LCA-based DT for clean production and carbon/environmental impact assessment (Table 6)
Autonomous Self-Evolving DT	DT models that autonomously update their structure as physical systems evolve are fundamental for long-term DT maintainability and economic viability	High: eliminates human re-engineering bottleneck	2026–2030	Wang, K. et al. (2023): [201] DT dynamic evolution framework (IExATCN) (Table 11); Hribernik et al. [136]—Autonomous, context-aware, adaptive DTs: state of the art and roadmap (Table 7)

The subsequent table contains all instruments and systems, communication methods, AI frameworks, human–machine interface libraries, and standards that were utilized or mentioned in this study and in our LSEA Laboratory prototype [CS-1, CS-2]. The table presents resource information through official URLs, which show resource functions for the DT system and resource deployment status in our research work. The table exists to enable complete reproduction of results while providing a useful guide to researchers and engineers who want to create an identical DT quality control system for their laboratory or industrial operations.

Table 19 provides a comprehensive inventory of the tools, platforms, communication protocols, AI frameworks, HMI technologies, and standards used in or referenced by this study and the LSEA Laboratory prototype [CS-1, CS-2]. For each resource, the table specifies its role within the DT architecture, its implementation status, access conditions, and official source. This information supports methodological transparency and facilitates the reproducibility of the proposed DT-enabled quality control system for researchers, academic laboratories, and industrial practitioners.

Table 19. DT tools, platforms, communication protocols, AI frameworks, and standards: roles, usage, and access information.

Category	Tool/Platform	Role in DT System	Used in This Work	Official URL	Access
DT Simulation Environment	Factory I/O v2.5.9	3D factory simulation environment for a virtual conveyor belt, connected to a PLC via Modbus. Used as the virtual replica in CS-2 only.	YES, core DT environment in CS-2 only (CS-1 uses CIROS Studio, not Factory I/O)	https://factoryio.com/	Commercial (30-day free trial)
DT Simulation Environment	ANSYS Twin Builder	Physics-based DT modelling—FEM simulation, LSTM/CNN hybrid models, real-time DT state engine. Industry standard for high-fidelity DT validation.	Referenced in the literature	https://ansys.synopsys.com/products/digital-twin (accessed on 10 January 2026)	Commercial

Table 19. Cont.

Category	Tool/Platform	Role in DT System	Used in This Work	Official URL	Access
DT Simulation Environment	NVIDIA Omniverse	Photorealistic, physics-accurate DT simulation platform with OpenUSD and AI integration. Industry 5.0 autonomous factory DTs at scale.	Referenced in the literature	https://www.nvidia.com/en-us/use-cases/industrial-facility-digital-twins/ (accessed on 1 May 2026)	Free (NVIDIA Developers)
Communication Protocols	Eclipse Mosquitto (MQTT Broker)	Open-source MQTT broker for IoT sensor-data streaming. Not named as a communication protocol in either CS-1 or CS-2.	NOT used in CS-1 or CS-2; referenced only in the broader reviewed literature	https://mosquitto.org/	Open-Source (Free)
Communication Protocols	OPC UA (IEC 62541)	Industrial communication standard for PLC-to-DT data exchange. CS-1 describes its Local Controllers Layer as employing OPC-UA protocols; the specific PLC brand/model is not stated in either paper.	YES, described (generically) as part of CS-1's architecture; not mentioned in CS-2	https://opcfoundation.org/	Open Standard
Communication Protocols	Node-RED v3.x	Flow-based tool used to build the operator HMI and to bridge the PLC (via redPLC/S7 nodes) in CS-1. Not used in CS-2, which instead uses Gradio.	YES, HMI and PLC communication layer in CS-1 only	https://nodered.org/	Open-Source (Free)
Data Storage & Analytics	InfluxDB v2.x	Time-series database for sensor data and KPIs. Not mentioned in either CS-1 or CS-2.	NOT used in CS-1 or CS-2; referenced only in the broader reviewed literature	https://www.influxdata.com/	Open-Source (Free tier)
Data Storage & Analytics	Grafana v10.x	Real-time KPI visualization dashboard. Not mentioned in either CS-1 or CS-2.	NOT used in CS-1 or CS-2; referenced only in the broader reviewed literature	https://grafana.com/	Open-Source (Free)
AI/Deep Learning	TensorFlow/Keras (VGG16)	Deep learning framework for the CS-1 CNN quality-control model. VGG16, pre-trained on ImageNet, is used with a two-phase transfer-learning + fine-tuning strategy, reaching 99.83% accuracy after fine-tuning (up from 98.63%).	YES, VGG16 CNN core model in CS-1 (CS-2 uses MobileNet instead)	https://www.tensorflow.org/	Open-Source (Apache 2.0)
AI/Deep Learning	scikit-fuzzy (Fuzzy Logic)	Python fuzzy logic library for post-CNN decision refinement. In CS-2, a fuzzy controller adjusts conveyor speed based on CNN confidence, rejection rate, and current speed. Not used in CS-1.	YES, fuzzy-logic decision layer in CS-2 only	https://pythonhosted.org/scikit-fuzzy/ (accessed on 20 May 2026)	Open-Source (BSD)
HMI Interfaces	Gradio v4.x	Python web framework used for the CS-2 HMI: start/stop control, piece-image display, a production-speed slider, the CNN Good/Bad prediction, and the fuzzy logic evaluation. Not used in CS-1, which uses a Node-RED HMI with language selection and authentication instead.	YES, primary HMI in CS-2 only	https://gradio.app/	Open-Source (Apache 2.0)
HMI Interfaces	Streamlit v1.28	Python dashboard framework. Not mentioned in CS-1 or CS-2—no evidence of use in either source paper.	NOT used in CS-1 or CS-2	https://streamlit.io/	Open-Source (Apache 2.0)
PLC/Automation	Siemens TIA Portal v17	Engineering environment used in CS-1 for PLC programming and for virtual/physical FAT control-program testing (with PLCSIM). CS-2 does not name a specific PLC programming environment.	YES, PLC programming environment in CS-1 only	http://siemens.com/tia-portal (accessed on 25 May 2026)	Commercial
PLC/Automation	Siemens S7-PLCSIM	PLC simulation extension used in CS-1 to test the virtual FAT control program before deployment to the physical PLC.	YES, virtual PLC testing environment in CS-1	https://docs.factoryio.com/ (accessed on 1 May 2026)	Commercial (with TIA Portal)
Cloud DT Platforms	Microsoft Azure DTs	Cloud-native DT platform for graph-based industrial twin modelling and IoT integration. Referenced extensively in the <i>Computers in Industry</i> literature (Table 5).	Referenced in the literature	https://learn.microsoft.com/en-us/azure/digital-twins/ (accessed on 15 January 2026)	Commercial (Azure subscription)
Cloud DT Platforms	Eclipse Ditto v3.x	Open-source IoT DT framework for device shadow management and NGSI-LD. Implements W3C Web of Things and ISO 23247 data models for vendor-neutral DT interoperability.	Referenced in the literature	https://eclipse.dev/ditto/ (accessed on 1 January 2026)	Open-Source (EPL-2.0)

Table 19. Cont.

Category	Tool/Platform	Role in DT System	Used in This Work	Official URL	Access
Standards & Frameworks	ISO 23247 (DT Manufacturing)	International reference architecture standard for DT in manufacturing. Not referenced in CS-1 or CS-2; used here only as a general architectural framework in the review's own synthesis.	NOT referenced in CS-1 or CS-2; used only as a synthesis framework in this review	https://www.iso.org/standard/75066.html (accessed on 1 January 2026)	ISO Standard (paid access)
Standards & Frameworks	RAMI 4.0 (IEC 62890)	Reference Architecture Model for Industry 4.0. Not referenced in CS-1 or CS-2; used here only as a general architectural framework in the review's own synthesis.	NOT referenced in CS-1 or CS-2; used only as a synthesis framework in this review	https://www.plattform-i40.de/IP/Navigation/DE/Home/home.html	Open Access

8. Limitations and Threats to Validity

Despite the systematic methodology adopted in this review, several limitations should be acknowledged. First, the analysis was restricted to a purposive set of journals (eight primary titles plus nine MDPI-published titles) and therefore may not capture the full breadth of DT research published in other journals, conference proceedings, books, and industrial reports. Second, the review covered publications from 2018 to 2026; consequently, emerging developments published after the search period may not be fully represented. Third, the classification of technologies, application domains, architectural layers, and research gaps involved a degree of researcher interpretation, despite the use of predefined analytical categories. Fourth, the reported technology frequencies should be interpreted as indicators of research trends within the selected corpus rather than as measurements of the overall maturity of DT technologies across industry.

Fifth, the experimental validation is limited to two laboratory-scale digital-twin implementations developed for manufacturing and industrial quality-control applications. Although the systematic review covers four major application domains—manufacturing, healthcare, smart cities, and energy systems—the experimental evidence does not provide equivalent validation across these domains. Therefore, the performance results obtained from the LSEA/LAADI prototypes should not be directly generalized to healthcare, smart-city, energy, or other application contexts, where data characteristics, operational constraints, safety requirements, system architectures, and validation conditions may differ substantially. Similarly, the laboratory-scale results should not be interpreted as evidence of performance at large industrial scale without further validation. Cross-domain and large-scale experimental studies are therefore required to assess the transferability, robustness, and scalability of the identified DT-AI architectures.

Sixth, title/abstract screening and exclusion ($n = 1085$) were conducted by the review team without a formally documented dual-reviewer, independent-coding protocol with an inter-rater agreement statistic; this is noted as a methodological limitation relative to the PRISMA 2020 recommended practices. Finally, some emerging technologies, including generative AI, 6G, federated learning, and quantum computing, remain at relatively early stages of industrial DT adoption, making their long-term impact difficult to assess with high confidence.

Future studies should therefore extend the review to additional databases, journals, conference proceedings, and industrial sources; apply multi-reviewer screening and coding procedures; and validate the identified DT architectures and LSEA prototypes across different manufacturing environments, industrial scales, and application domains.

9. Answers to the Research Questions

To maintain focus and explicitly link the synthesized evidence to the objectives of the review, each research question is answered below using findings supported by the reviewed

literature. Where the LSEA case studies are mentioned, they are clearly distinguished from the evidence derived from the systematic review and are treated only as laboratory-scale illustrative validation.

9.1. RQ1: How Has DT Technology Evolved in Terms of Architectures, Modeling Approaches, Data Integration, Communication, Synchronization, and Interoperability?

The reviewed literature indicates a transition from predominantly static, geometry-oriented digital representations toward dynamic, data-driven, and increasingly intelligent cyber–physical systems. DT architectures have progressively incorporated sensing, communication, simulation, analytics, and application layers rather than relying on a single standardized architecture. Based on the reviewed studies, these developments can be synthesized into five functional layers: physical assets, data and communication, modeling and simulation, services and analytics, and application/HMI. IoT/IIoT, OPC UA, MQTT, edge/cloud computing, and AI increasingly support data exchange and real-time interaction. Nevertheless, synchronization, semantic interoperability, heterogeneous data integration, and architectural standardization remain unresolved issues.

9.2. RQ2: What Are the Principal Applications of DT Technology in Manufacturing, Healthcare, Smart Cities, and Energy Systems?

The reviewed corpus shows that DT applications extend across all four target domains, although their emphasis differs. Manufacturing is the most strongly represented domain and includes predictive maintenance, quality inspection, process monitoring, production optimization, and intelligent control. Healthcare applications include patient monitoring, medical cyber–physical systems, clinical decision support, and healthcare infrastructure management, with greater emphasis on privacy, safety, and reliability. Smart-city applications primarily address transportation, infrastructure, environmental monitoring, and energy management at large scale. Energy-system applications include energy generation, transmission, storage, monitoring, optimization, and predictive maintenance. Thus, the four domains share common DT foundations but differ in their operational constraints and validation requirements.

9.3. RQ3: Which Enabling Technologies Are Being Integrated with DTs?

Among the most frequently reported enabling technologies are IoT/IIoT, artificial intelligence and machine learning, simulation, cloud computing, and edge computing. Deep learning approaches, including CNNs and LSTMs, are increasingly used for prediction, classification, anomaly detection, and decision support. Industrial communication technologies such as OPC UA and MQTT support connectivity and data exchange, while blockchain and semantic approaches are increasingly investigated for security, trust, traceability, and interoperability. More emerging technologies, including federated learning, 6G, generative AI, physics-informed machine learning, and quantum-enhanced optimization, appear in the literature but remain less mature in terms of demonstrated industrial deployment.

9.4. RQ4: How Are DTs Being Employed for Real-Time Monitoring, Anomaly Detection, Prediction, Diagnosis, Optimization, Maintenance, Decision Support, and Control?

The reviewed studies show that DTs are used throughout the operational cycle of monitoring, analysis, prediction, and decision-making. Common applications include real-time monitoring, anomaly and fault detection, predictive maintenance, quality assessment, process optimization, scheduling, diagnosis, and decision support. These functions are mainly associated with the services and analytics components of DT architectures, where sensor and operational data are combined with simulation and AI models. The LSEA case studies provide laboratory-scale illustrations of this pattern: CS-1 uses VGG16-based

visual inspection, while CS-2 combines MobileNet-based classification with a fuzzy-logic decision layer for conveyor-speed adjustment. These examples illustrate specific DT-AI integration mechanisms but do not constitute evidence of general performance across industrial sectors.

9.5. RQ5: What Experimental, Simulation-Based, Laboratory, Pilot-Scale, or Industrial Validation Approaches Have Been Reported?

The reviewed literature includes simulation-based studies, laboratory prototypes, pilot-scale implementations, and industrial applications, with the level of empirical validation varying substantially between studies. Fully validated industrial-scale deployments are less frequently documented than simulation and laboratory demonstrations. The two LSEA case studies provide additional laboratory-scale physical validation of DT-enabled quality-control architectures. CS-1 evaluates a VGG16 classifier on a held-out set of 460 images and reports an accuracy increase from 98.63% to 99.83% after fine-tuning. CS-2 evaluates a MobileNet-based system using 2000 test images, comprising 1000 good and 1000 defective pieces, and reports a true-positive rate of 99.90% and a true-negative rate of 99.10%. These results represent application-specific laboratory evidence and should not be interpreted as industrial-scale or cross-domain validation.

9.6. RQ6: What Are the Principal Challenges Associated with DT Implementation?

Five interconnected challenge areas emerge consistently from the reviewed literature: (1) heterogeneous data integration and data quality, (2) cybersecurity and privacy, (3) real-time synchronization and communication latency, (4) model fidelity, uncertainty, and validation, and (5) human factors, explainability, and ethical considerations. These challenges become more pronounced as DT deployments increase in scale, heterogeneity, autonomy, and dependence on AI. In particular, reliable synchronization between physical and virtual entities, interoperability between heterogeneous platforms, secure data exchange, and validation under non-controlled operating conditions remain important barriers to large-scale deployment.

9.7. RQ7: What Research Gaps and Future Research Directions Can Be Identified from the Existing Literature?

The synthesis identifies eight major research directions: generative-AI-enabled DTs, 6G-enabled DT networks, federated and privacy-preserving DT architectures, human-centric DTs aligned with Industry 5.0, standardization and interoperability, quantum-enhanced optimization, sustainable and carbon-aware DTs, and autonomous self-evolving DT systems. These directions reflect a broader transition from DTs primarily used for monitoring and visualization toward systems capable of intelligent prediction, autonomous decision-making, secure information exchange, adaptive learning, and sustainable operation. However, many of these directions remain at an emerging stage and require further experimental, cross-domain, and industrial-scale validation.

Overall, the seven research questions indicate that DT technology has progressed from relatively static digital representations toward integrated, data-driven, AI-enabled, and increasingly autonomous cyber-physical systems. Nevertheless, interoperability, cybersecurity, real-time synchronization, robust validation, scalability, and human-centered design remain important challenges identified across the reviewed literature. The LSEA case studies provide concrete laboratory-scale evidence of selected DT-AI integration patterns in manufacturing quality control, but their manufacturing-specific context limits direct generalization to healthcare, smart cities, energy systems, and other application domains. Consequently, future work should combine broader cross-domain validation with larger-scale industrial deployments to determine whether the architectural and technological

patterns identified in this review remain robust under different operational, safety, data, and regulatory conditions.

10. Conclusions

This study systematically reviewed 230 peer-reviewed articles published between 2018 and 2026 across seventeen distinct scientific journals to provide a comprehensive assessment of the evolution, enabling technologies, applications, challenges, and future directions of DT technology. The findings provide an integrated evidence base for researchers and industrial practitioners seeking to understand and implement DT systems across different application domains.

The review demonstrates that DT technology has evolved from relatively simple virtual representations and geometric simulation models into increasingly sophisticated cyber-physical systems that integrate IoT/IIoT, AI, machine learning, real-time data analytics, and autonomous decision-making. Manufacturing remains the dominant application domain within the reviewed corpus, while healthcare, smart cities, energy, and other emerging domains are experiencing increasing adoption as sensing, connectivity, computing, and AI capabilities continue to mature.

The analysis also confirms that DT performance increasingly depends on the integration of several enabling technologies. Across the reviewed literature, IoT/IIoT, simulation, AI/ML, and cloud computing represent the most established technological foundations, while federated learning, 6G communication, generative AI, and quantum computing represent emerging technologies with the potential to extend DT capabilities beyond current limitations. These developments are expected to support more autonomous, interconnected, privacy-preserving, and intelligent DT ecosystems.

The two experimental case studies presented in Section 5, based on the authors' peer-reviewed research conducted at the LSEA and the Laboratory of Applied Automation and Industrial Diagnostics (LAADI), Algeria, provide practical evidence that DT-enabled quality control can be implemented using accessible industrial hardware and software technologies. CS-1 (drilling-operation quality control) achieved 99.83% classification accuracy after fine-tuning a VGG16 model, using a CIROS Studio DT and a Node-RED HMI. CS-2 (conveyor-belt sorting) achieved true-positive and true-negative rates of 99.90% and 99.10% using a MobileNet-based CNN refined by a FL controller, a Factory I/O DT, and a Gradio HMI. Together, these results demonstrate the feasibility of implementing DT-AI quality-control architectures at laboratory scale using two independent technology stacks, and provide a potentially transferable model for universities and manufacturing SMEs in emerging economies.

Despite this progress, the review identifies persistent barriers to large-scale DT adoption, particularly data integration and interoperability, cybersecurity and privacy, real-time synchronization, model fidelity and validation, and human-centered AI adoption. Addressing these challenges requires closer coordination among academic researchers, technology developers, standards organizations, and industrial stakeholders. In response, eight priority research directions were identified for the 2025–2032 period, including generative AI-enhanced DTs, 6G-enabled DT networks, federated and privacy-preserving DT architectures, Industry 5.0 human-centric DTs, DT standardization and interoperability, quantum-enhanced optimization, sustainable and carbon-aware DTs, and autonomous self-evolving DT systems.

Overall, the findings indicate that the next stage of DT development will be shaped not only by greater computational and AI capabilities, but also by interoperability, sustainability, cybersecurity, explainability, human-centered design, and autonomous adaptation. DTs are therefore increasingly positioned as an important technological foundation for intelligent

and sustainable industrial transformation. The LSEA case study further demonstrates that this transformation is not limited to highly industrialized economies: appropriately designed, standards-aligned, and resource-efficient DT architectures can also support research, education, and technology transfer in Algeria.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/electronics15194576/s1>.

Author Contributions: Conceptualization, Y.A. and H.B.; methodology, Y.A. and H.B.; software, Y.A., M.B. (Mounir Bouhedda) and H.B.; validation, Y.A., A.T. and N.B.; formal analysis, A.S., A.T., M.B. (Mounir Bouhedda), M.B. (Mohamed Boulesnam), M.S. and N.B.; investigation, Y.A. and A.S.; resources, Y.A. and H.B.; data curation, Y.A. and H.B.; writing—original draft preparation, Y.A. and H.B.; writing—review and editing, A.S., A.T., M.B. (Mounir Bouhedda), M.B. (Mohamed Boulesnam), M.S. and N.B.; visualization, A.S., A.T. and N.B.; supervision, M.S. and N.B.; project administration, Y.A. and N.B.; funding acquisition, A.T. All authors have read and agreed to the published version of the manuscript.

Funding: The research was partially supported by the Experimental—Demonstration project PN-IV-P7-7.1-PED-2024-0567 (Improving the Fuel Cell Hybrid Electric Vehicle Drivetrain by Implementing a Novel Optimal Real-Time Power Management Strategy), contract no. 58PED, 2024–2025, and the project “The Effect of Low-Quality Power Supplies and Current Ripples on Water-Electrolysis-Based Hydrogen Production Systems (RippEly)”, funded by the Clean Energy Transition Partnership (CETP-FP-2024-00436) and co-funded by the UEFISCDI, project number COFUND-RippEly-1, No 145/2025.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data supporting this research have been made available in this paper.

Acknowledgments: Additional infrastructure was accessed by the projects 345/2021, SMIS 125119, and 308/2020, SMIS 127318, funded from the European Regional Development Fund within the Competitiveness Operational Program.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

5G/6G	Fifth-/Sixth-Generation Mobile Network
AI	Artificial Intelligence
AR	Augmented Reality
AUC	Area Under the ROC Curve
BDI	Belief–Desire–Intention (agent model)
BIM	Building Information Modeling
CNN	Convolutional Neural Network
CPPS	Cyber–Physical Production System
CPS	Cyber–Physical System
CS-1/CS-2	Case Study 1/Case Study 2
DL	Deep Learning
DSS	Decision-Support System
DT	Digital Twin
FABRIK	Forward And Backward Reaching Inverse Kinematics
FEM	Finite Element Method
GAN/WGAN	Generative Adversarial Network/Wasserstein GAN

GDPR	General Data Protection Regulation
HMI	Human–Machine Interface
HMLV	High-Mix, Low-Volume (manufacturing)
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
IEEE TII	<i>IEEE Transactions on Industrial Informatics</i>
IIoT	Industrial Internet of Things
IoT	Internet of Things
ISO	International Organization for Standardization
JMS	<i>Journal of Manufacturing Systems</i>
KPI	Key Performance Indicator
LAADI	Laboratory of Applied Automation and Industrial Diagnostics, University of Djelfa, Algeria
LCA	Life Cycle Assessment
LSEA	Laboratory of Advanced Electronic Systems, Yahia Fares University of Me-dea, Algeria
LSTM	Long Short-Term Memory (recurrent neural network)
MBSE	Model-Based Systems Engineering
MES	Manufacturing Execution System
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
MTTR	Mean Time To Repair
NUC	Next Unit of Computing (Intel compact edge-computing platform)
OEE	Overall Equipment Effectiveness
OPC UA	Open Platform Communications Unified Architecture
PLC	Programmable Logic Controller
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSS	Product-Service System
RAMI	Reference Architecture Model Industrie 4.0
RL	Reinforcement Learning
ROC	Receiver Operating Characteristic (curve)
SME	Small and Medium-sized Enterprise
SOH	State of Health
TCPN	Timed Colored Petri Net
TIA Portal	Totally Integrated Automation Portal (Siemens engineering software)
VGG16	Visual Geometry Group 16-layer Convolutional Neural Network
VR	Virtual Reality

References

- Schluse, M.; Rossmann, J. From simulation to experimentable digital twins: Simulation-based development and operation of complex technical systems. In Proceedings of the 2016 IEEE International Symposium on Systems Engineering (ISSE), Edinburgh, UK, 3–5 October 2016; pp. 1–6. [\[CrossRef\]](#)
- Hasan, A.; Nguyen, D.T. Integrating agentic AI and digital twins for intelligent decision-making systems. *Array* **2026**, *29*, 100721. [\[CrossRef\]](#)
- Biswas, P.; Kim, T.M.; Kim, W.S. Integration of digital twins and physical AI in cyber-physical systems. *Intell. Syst. Appl.* **2026**, *30*, 200649. [\[CrossRef\]](#)
- Shafro, M.; Conroy, M.; Doyle, R.; Glaessgen, E.; Kemp, C.; LeMoigne, J.; Wang, L. DRAFT Modelling, Simulation, Information Technology & Processing Roadmap—Technology Area 11. NASA 2010, November, 27. Available online: https://www.researchgate.net/publication/280310295_Modeling_Simulation_Information_Technology_and_Processing_Roadmap (accessed on 1 January 2026).
- Nujoom, R.; Mohammed, A.; Wang, Q. A sustainable manufacturing system design: A fuzzy multi-objective optimization model. *Environ. Sci. Pollut. Res.* **2018**, *25*, 24535–24547. [\[CrossRef\]](#)
- Lo, C.K.; Chen, C.H.; Zhong, R.Y. A review of digital twin in product design and development. *Adv. Eng. Inform.* **2021**, *48*, 101297. [\[CrossRef\]](#)

7. Sharma, A.; Kosasih, E.; Zhang, J.; Brintrup, A.; Calinescu, A. Digital twins: State of the art theory and practice, challenges, and open research questions. *J. Ind. Inf. Integr.* **2022**, *30*, 100383. [\[CrossRef\]](#)
8. Hariri-Ardebili, M.A.; Mahdavi, G.; Nuss, L.K.; Lall, U. The role of artificial intelligence and digital technologies in dam engineering: Narrative review and outlook. *Eng. Appl. Artif. Intell.* **2023**, *126*, 106813. [\[CrossRef\]](#)
9. Zhang, M.; Tao, F.; Nee, A.Y.C. Digital twin enhanced dynamic job-shop scheduling. *J. Manuf. Syst.* **2021**, *58*, 146–156. [\[CrossRef\]](#)
10. Ante, L.; Fischer, C.; Strehle, E. A bibliometric review of research on digital identity: Research streams, influential works and future research paths. *J. Manuf. Syst.* **2022**, *62*, 523–538. [\[CrossRef\]](#)
11. Zhang, H.; Qi, Q.; Tao, F. A consistency evaluation method for digital twin models. *J. Manuf. Syst.* **2022**, *65*, 158–168. [\[CrossRef\]](#)
12. Yu, J.; Song, Y.; Tang, D.; Dai, J. A digital twin approach based on nonparametric Bayesian network for complex system health monitoring. *J. Manuf. Syst.* **2021**, *58*, 293–304. [\[CrossRef\]](#)
13. Kumbhar, M.; Ng, A.H.C.; Bandaru, S. A digital twin based framework for detection, diagnosis, and improvement of throughput bottlenecks. *J. Manuf. Syst.* **2023**, *66*, 92–106. [\[CrossRef\]](#)
14. Zhang, D.; Gao, X. A digital twin dosing system for iron reverse flotation. *J. Manuf. Syst.* **2022**, *63*, 238–249. [\[CrossRef\]](#)
15. Jin, J.; Hu, J.; Li, C.; Shi, Z.; Lei, P.; Tian, W. A digital twin system of reconfigurable tooling for monitoring and evaluating in aerospace assembly. *J. Manuf. Syst.* **2023**, *68*, 56–71. [\[CrossRef\]](#)
16. Xia, K.; Sacco, C.; Kirkpatrick, M.; Saidy, C.; Nguyen, L.; Kircaliali, A.; Harik, R. A digital twin to train deep reinforcement learning agent for smart manufacturing plants: Environment, interfaces and intelligence. *J. Manuf. Syst.* **2021**, *58*, 210–230. [\[CrossRef\]](#)
17. Grégorio, J.L.; Lartigue, C.; Thiébaud, F.; Lebrun, R. A digital twin-based approach for the management of geometrical deviations during assembly processes. *J. Manuf. Syst.* **2021**, *58*, 108–117. [\[CrossRef\]](#)
18. Wang, P.; Luo, M. A digital twin-based big data virtual and real fusion learning reference framework supported by industrial internet towards smart manufacturing. *J. Manuf. Syst.* **2021**, *58*, 16–32. [\[CrossRef\]](#)
19. Guo, H.; Chen, M.; Mohamed, K.; Qu, T.; Wang, S.; Li, J. A digital twin-based flexible cellular manufacturing for optimization of air conditioner line. *J. Manuf. Syst.* **2021**, *58*, 65–78. [\[CrossRef\]](#)
20. Li, J.; Zhao, G.; Zhang, P.; Xu, M.; Cheng, H.; Pengfei, H. A digital twin-based on-site quality assessment method for aero-engine assembly. *J. Manuf. Syst.* **2023**, *71*, 565–580. [\[CrossRef\]](#)
21. Lim, K.Y.H.; Zheng, P.; Chen, C.H.; Huang, L. A digital twin-enhanced system for engineering product family design and optimization. *J. Manuf. Syst.* **2020**, *57*, 82–93. [\[CrossRef\]](#)
22. Fan, Y.; Yang, J.; Chen, J.; Hu, P.; Wang, X.; Xu, J.; Zhou, B. A digital-twin visualized architecture for flexible manufacturing system. *J. Manuf. Syst.* **2021**, *60*, 176–201. [\[CrossRef\]](#)
23. Ladj, A.; Wang, Z.; Meski, O.; Belkadi, F.; Ritou, M.; Da Cunha, C. A knowledge-based digital shadow for machining industry in a digital twin perspective. *J. Manuf. Syst.* **2021**, *58*, 168–179. [\[CrossRef\]](#)
24. Hu, W.; Fang, J.; Zhang, T.; Liu, Z.; Tan, J. A new quantitative digital twin maturity model for high-end equipment. *J. Manuf. Syst.* **2023**, *66*, 248–259. [\[CrossRef\]](#)
25. Zhang, J.; Deng, T.; Jiang, H.; Chen, H.; Qin, S.; Ding, G. Bi-level dynamic scheduling architecture based on service unit digital twin agents. *J. Manuf. Syst.* **2021**, *60*, 59–79. [\[CrossRef\]](#)
26. Huang, S.; Wang, G.; Yan, Y.; Fang, X. Blockchain-based data management for digital twin of product. *J. Manuf. Syst.* **2020**, *54*, 361–371. [\[CrossRef\]](#)
27. Zhang, L.; Zhou, L.; Horn, B.K.P. Building a right digital twin with model engineering. *J. Manuf. Syst.* **2021**, *59*, 151–164. [\[CrossRef\]](#)
28. Su, S.; Nassehi, A.; Hicks, B.; Ross, J. Characterisation and evaluation of identity for digital twins for the manufacturing domain. *J. Manuf. Syst.* **2023**, *71*, 224–237. [\[CrossRef\]](#)
29. Wu, C.; Zhou, Y.; Pereira Pessôa, M.V.; Peng, Q.; Tan, R. Conceptual digital twin modeling based on an integrated five-dimensional framework and TRIZ function model. *J. Manuf. Syst.* **2021**, *58*, 79–93. [\[CrossRef\]](#)
30. Wei, Y.; Hu, T.; Zhou, T.; Ye, Y.; Luo, W. Consistency retention method for CNC machine tool digital twin model. *J. Manuf. Syst.* **2021**, *58*, 313–322. [\[CrossRef\]](#)
31. Liu, J.; Liu, J.; Zhuang, C.; Liu, Z.; Miao, T. Construction method of shop-floor digital twin based on MBSE. *J. Manuf. Syst.* **2021**, *60*, 93–118. [\[CrossRef\]](#)
32. Kong, T.; Hu, T.; Zhou, T.; Ye, Y. Data construction method for the applications of workshop digital twin system. *J. Manuf. Syst.* **2021**, *58*, 323–328. [\[CrossRef\]](#)
33. Steed, C.A.; Kim, N. Deep active-learning based model-synchronization of digital manufacturing stations using human-in-the-loop simulation. *J. Manuf. Syst.* **2023**, *70*, 436–450. [\[CrossRef\]](#)
34. Wang, Q.; Jiao, W.; Zhang, Y.M. Deep learning-empowered digital twin for visualized weld joint growth monitoring and penetration control. *J. Manuf. Syst.* **2020**, *57*, 429–439. [\[CrossRef\]](#)

35. Zhang, Q.; Zheng, S.; Yu, C.; Wang, Q.; Ke, Y. Digital thread-based modeling of digital twin framework for the aircraft assembly system. *J. Manuf. Syst.* **2022**, *65*, 406–420. [\[CrossRef\]](#)
36. Tao, F.; Zhang, Y.; Cheng, Y.; Ren, J.; Wang, D.; Qi, Q.; Li, P. Digital twin and blockchain enhanced smart manufacturing service collaboration and management. *J. Manuf. Syst.* **2022**, *62*, 903–914. [\[CrossRef\]](#)
37. Wang, Y.; Xu, R.; Zhou, C.; Kang, X.; Chen, Z. Digital twin and cloud-side-end collaboration for intelligent battery management system. *J. Manuf. Syst.* **2022**, *62*, 124–134. [\[CrossRef\]](#)
38. Pan, Y.H.; Qu, T.; Wu, N.Q.; Khalgui, M.; Huang, G.Q. Digital twin based real-time production logistics synchronization system in a multi-level computing architecture. *J. Manuf. Syst.* **2021**, *58*, 246–260. [\[CrossRef\]](#)
39. Wang, Y.; Tao, F.; Zhang, M.; Wang, L.; Zuo, Y. Digital twin enhanced fault prediction for the autoclave with insufficient data. *J. Manuf. Syst.* **2021**, *60*, 350–359. [\[CrossRef\]](#)
40. Li, X.; Liu, G.; Sun, S.; Yi, W.; Li, B. Digital twin model-based smart assembly strategy design and precision evaluation for PCB kit-box build. *J. Manuf. Syst.* **2023**, *71*, 206–223. [\[CrossRef\]](#)
41. Ji, T.; Huang, H.; Xu, X. Digital twin technology—A bibliometric study of top research articles based on local citation score. *J. Manuf. Syst.* **2022**, *64*, 390–408. [\[CrossRef\]](#)
42. Liu, Q.; Leng, J.; Yan, D.; Zhang, D.; Wei, L.; Yu, A.; Zhao, R.; Zhang, H.; Chen, X. Digital twin-based designing of the configuration, motion, control, and optimization model of a flow-type smart manufacturing system. *J. Manuf. Syst.* **2021**, *58*, 52–64. [\[CrossRef\]](#)
43. Xu, W.; Cui, J.; Li, L.; Yao, B.; Tian, S.; Zhou, Z. Digital twin-based industrial cloud robotics: Framework, control approach and implementation. *J. Manuf. Syst.* **2021**, *58*, 196–209. [\[CrossRef\]](#)
44. Yi, Y.; Yan, Y.; Liu, X.; Ni, Z.; Feng, J.; Liu, J. Digital twin-based smart assembly process design and application framework for complex products and its case study. *J. Manuf. Syst.* **2021**, *58*, 94–107. [\[CrossRef\]](#)
45. Lai, X.; Yang, L.; He, X.; Pang, Y.; Song, X.; Sun, W. Digital twin-based structural health monitoring by combining measurement and computational data: An aircraft wing example. *J. Manuf. Syst.* **2023**, *69*, 76–90. [\[CrossRef\]](#)
46. Liu, S.; Bao, J.; Lu, Y.; Li, J.; Lu, S.; Sun, X. Digital twin modeling method based on biomimicry for machining aerospace components. *J. Manuf. Syst.* **2021**, *58*, 180–195. [\[CrossRef\]](#)
47. Shiu, S.C.; Tang, K.E.; Liu, C.W. Digital twin-driven centering process optimization for high-precision glass lens. *J. Manuf. Syst.* **2023**, *67*, 122–131. [\[CrossRef\]](#)
48. Zhu, Z.; Xi, X.; Xu, X.; Cai, Y. Digital twin-driven machining process for thin-walled part manufacturing. *J. Manuf. Syst.* **2021**, *59*, 453–466. [\[CrossRef\]](#)
49. Huang, H.; Yang, L.; Wang, Y.; Xu, X.; Lu, Y. Digital twin-driven online anomaly detection for an automation system based on edge intelligence. *J. Manuf. Syst.* **2021**, *59*, 138–150. [\[CrossRef\]](#)
50. Xie, Y.; Lian, K.; Liu, Q.; Zhang, C.; Liu, H. Digital twin for cutting tool: Modeling, application and service strategy. *J. Manuf. Syst.* **2021**, *58*, 305–312. [\[CrossRef\]](#)
51. Xu, Z.; Ji, F.; Ding, S.; Zhao, Y.; Zhou, Y.; Zhang, Q.; Du, F. Digital twin-driven optimization of gas exchange system of 2-stroke heavy fuel aircraft engine. *J. Manuf. Syst.* **2021**, *58*, 132–145. [\[CrossRef\]](#)
52. Latsou, C.; Farsi, M.; Erkoyuncu, J.A. Digital twin-enabled automated anomaly detection and bottleneck identification in complex manufacturing systems using a multi-agent approach. *J. Manuf. Syst.* **2023**, *67*, 242–264. Corrigendum in *J. Manuf. Syst.* **2023**, *68*, 303. [\[CrossRef\]](#)
53. Liu, C.; Le Roux, L.; Körner, C.; Tabaste, O.; Lacan, F.; Bigot, S. Digital twin-enabled collaborative data management for metal additive manufacturing systems. *J. Manuf. Syst.* **2022**, *62*, 857–874. [\[CrossRef\]](#)
54. Leng, J.; Wang, D.; Shen, W.; Li, X.; Liu, Q.; Chen, X. Digital twins-based smart manufacturing system design in Industry 4.0: A review. *J. Manuf. Syst.* **2021**, *60*, 119–137. Corrigendum in *J. Manuf. Syst.* **2021**, *61*, 866. [\[CrossRef\]](#)
55. Zhou, Y.; Xing, T.; Song, Y.; Li, Y.; Zhu, X.; Li, G.; Ding, S. Digital-twin-driven geometric optimization of centrifugal impeller with free-form blades for five-axis flank milling. *J. Manuf. Syst.* **2021**, *58*, 22–35. [\[CrossRef\]](#)
56. Qi, Q.; Tao, F.; Hu, T.; Anwer, N.; Liu, A.; Wei, Y.; Wang, L.; Nee, A. Enabling technologies and tools for digital twin. *J. Manuf. Syst.* **2021**, *58*, 3–21. [\[CrossRef\]](#)
57. Liu, S.; Sun, Y.; Zheng, P.; Lu, Y.; Bao, J. Establishing a reliable mechanism model of the digital twin machining system: An adaptive evaluation network approach. *J. Manuf. Syst.* **2022**, *62*, 390–401. [\[CrossRef\]](#)
58. Osho, J.; Hyre, A.; Pantelidakis, M.; Ledford, A.; Harris, G.; Liu, J.; Mykoniatis, K. Four Rs framework for the development of a digital twin: The implementation of representation with a FDM manufacturing machine. *J. Manuf. Syst.* **2022**, *63*, 370–380. [\[CrossRef\]](#)
59. Li, X.; Wang, L.; Zhu, C.; Liu, Z. Framework for manufacturing-tasks semantic modelling and manufacturing-resource recommendation for digital twin shop-floor. *J. Manuf. Syst.* **2021**, *58*, 281–292. [\[CrossRef\]](#)
60. Jiang, H.; Qin, S.; Fu, J.; Zhang, J.; Ding, G. How to model and implement connections between physical and virtual models for digital twin application. *J. Manuf. Syst.* **2021**, *58*, 36–51. [\[CrossRef\]](#)

61. Lossie, K.; Hellmich, J.H.; Liang, J.; Baum, J.; Göppert, A.; Grunert, D.; Schmitt, R.H. Using a digital twin and smart services to enable automatic generation of context-sensitive instructions. *J. Manuf. Syst.* **2025**, *83*, 652–674. [\[CrossRef\]](#)
62. Tao, F.; Xiao, B.; Qi, Q.; Cheng, J.; Ji, P. Digital twin modeling. *J. Manuf. Syst.* **2022**, *64*, 372–389. [\[CrossRef\]](#)
63. Lugaresi, G.; Matta, A. Automated manufacturing system discovery and digital twin generation. *J. Manuf. Syst.* **2021**, *59*, 51–66. [\[CrossRef\]](#)
64. Zhang, D.; Liu, Q.; Yan, H.; Xie, M. A matrix analytic approach for Bayesian network modeling and inference of a manufacturing system. *J. Manuf. Syst.* **2021**, *60*, 202–213. [\[CrossRef\]](#)
65. Jiang, T.; Zhou, J.; Zhao, J.; Wang, M.; Zhang, S. A multi-dimensional cognitive framework for cognitive manufacturing based on OAR model. *J. Manuf. Syst.* **2022**, *65*, 469–485. [\[CrossRef\]](#)
66. Arnarson, H.; Yu, H.; Olavsbråten, M.M.; Bremdal, B.A.; Solvang, B. Towards smart layout design for a reconfigurable manufacturing system. *J. Manuf. Syst.* **2023**, *68*, 354–367. [\[CrossRef\]](#)
67. Zhuang, C.; Gong, J.; Liu, J. Digital twin-based assembly data management and process traceability for complex products. *J. Manuf. Syst.* **2021**, *58*, 118–131. [\[CrossRef\]](#)
68. Mi, S.; Feng, Y.; Zheng, H.; Wang, Y.; Gao, Y.; Tan, J. Prediction maintenance integrated decision-making approach supported by digital twin-driven cooperative awareness and interconnection framework. *J. Manuf. Syst.* **2021**, *58*, 329–345. [\[CrossRef\]](#)
69. Maretto, L.; Faccio, M.; Battini, D. The adoption of digital technologies in the manufacturing world and their evaluation: A systematic review of real-life case studies and future research agenda. *J. Manuf. Syst.* **2023**, *68*, 576–600. [\[CrossRef\]](#)
70. Coito, T.; Martins, M.S.E.; Firme, B.; Figueiredo, J.; Vieira, S.M.; Sousa, J.M.C. Assessing the impact of automation in pharmaceutical quality control labs using a digital twin. *J. Manuf. Syst.* **2022**, *62*, 270–285. [\[CrossRef\]](#)
71. Lu, Y.; Yue, C.; Liu, X.; Wang, L.; Liang, S.Y.; Xia, W.; Dou, X. Research on digital twin monitoring system during milling of large parts. *J. Manuf. Syst.* **2024**, *77*, 834–847. [\[CrossRef\]](#)
72. Sun, X.; Zhang, F.; Niu, X.; Wang, J. A digital twin commissioning method for machine tools based on scenario simulation. *J. Manuf. Syst.* **2024**, *77*, 697–707. [\[CrossRef\]](#)
73. Chia, J.W.Y.; Verhagen, W.J.C.; Silva, J.M.; Cole, I.S. A review and outlook of airframe digital twins for structural prognostics and health management in the aviation industry. *J. Manuf. Syst.* **2024**, *77*, 398–417. [\[CrossRef\]](#)
74. Cimino, A.; Longo, F.; Nicoletti, L.; Solina, V. Simulation-based digital twin for enhancing human-robot collaboration in assembly systems. *J. Manuf. Syst.* **2024**, *77*, 903–918. [\[CrossRef\]](#)
75. Wang, F.; Liu, X.; Lv, F.; Wang, C.; Shi, J.; Zheng, X.; Li, C. An LLM-guided SD-LDM digital twin construction strategy (LSDT) for multi-industrial scenarios: Enhancing adaptability and efficiency. *J. Manuf. Syst.* **2025**, *80*, 995–1012. [\[CrossRef\]](#)
76. Wang, G.; Zhang, C.; Liu, S.; Zhao, Y.; Zhang, Y.; Wang, L. Multi-robot collaborative manufacturing driven by digital twins: Advancements, challenges, and future directions. *J. Manuf. Syst.* **2025**, *82*, 333–361. [\[CrossRef\]](#)
77. Zhu, X.; Ji, Y. A reduced order model based on adaptive proper orthogonal decomposition incorporated with modal coefficient learning for digital twin in process industry. *J. Manuf. Process.* **2023**, *102*, 780–794. [\[CrossRef\]](#)
78. Guo, Y.; Ren, J.; Liang, Y.; Ding, Y. Construction of digital twin for clamped near-net-shape blade in adaptive manufacturing. *J. Manuf. Process.* **2023**, *108*, 12–25. [\[CrossRef\]](#)
79. Zhang, Z.; Malashkhia, L.; Zhang, Y.; Shevtshenko, E.; Wang, Y. Design of Gaussian process based model predictive control for seam tracking in a laser welding digital twin environment. *J. Manuf. Process.* **2022**, *80*, 816–828. [\[CrossRef\]](#)
80. Sílvia, R.C.; Lauro, C.H.; Ana, H.; Davim, J.P. Development of FEM-based digital twins for machining difficult-to-cut materials: A roadmap for sustainability. *J. Manuf. Process.* **2022**, *75*, 739–766. [\[CrossRef\]](#)
81. Chen, G.; Zhu, J.; Zhao, Y.; Hao, Y.; Yang, C.; Shi, Q. Digital twin modeling for temperature field during friction stir welding. *J. Manuf. Process.* **2021**, *64*, 898–906. [\[CrossRef\]](#)
82. Rossi, A.; Moretti, M.; Senin, N. Neural networks and NARXs to replicate extrusion simulation in digital twins for fused filament fabrication. *J. Manuf. Process.* **2022**, *84*, 64–76. [\[CrossRef\]](#)
83. Li, T.; Liao, Z.; Cai, Y. Physical modeling for digital twin of continuous damping control damper. *J. Manuf. Process.* **2023**, *99*, 96–104. [\[CrossRef\]](#)
84. Phua, A.; Cook, P.S.; Davies, C.H.J.; Delaney, G.W. Smart recoating: A digital twin framework for optimisation and control of powder spreading in metal additive manufacturing. *J. Manuf. Process.* **2023**, *99*, 382–391. [\[CrossRef\]](#)
85. Klingaa, C.G.; Mohanty, S.; Funch, C.V.; Hjermtitslev, A.B.; Haahr-Lillevang, L.; Hattel, J.H. Towards a digital twin of laser powder bed fusion with a focus on gas flow variables. *J. Manuf. Process.* **2021**, *65*, 312–327. [\[CrossRef\]](#)
86. Fisher, C.R.; Nygren, K.E.; Beaudoin, A.J. Validation of materials-informed digital twin: Mapping residual strains in HSLA steel weldment using high energy X-rays. *J. Manuf. Process.* **2022**, *74*, 75–87. [\[CrossRef\]](#)
87. Liu, Z.; Lang, Z.Q.; Gui, Y.; Zhu, Y.P.; Laalej, H. Digital twin-based anomaly detection for real-time tool condition monitoring in machining. *J. Manuf. Syst.* **2024**, *75*, 163–173. [\[CrossRef\]](#)
88. Wang, S.; Tao, J.; Jiang, Q.; Chen, W.; Qin, C.; Liu, C. A digital twin framework for anomaly detection in industrial robot system based on multiple physics-informed hybrid convolutional autoencoder. *J. Manuf. Syst.* **2024**, *77*, 798–809. [\[CrossRef\]](#)

89. Zhou, T.; Zhang, M.; Hu, T.; Meng, L.; Yi, M.; Zhang, J.; Xu, C. Research on the online monitoring method of cutting tool wear based on the mechanism-data fusion concept of digital twin. *J. Manuf. Process.* **2025**, *148*, 386–407. [[CrossRef](#)]
90. Jiao, W.; Zhao, D.; Mei, X.; Yang, S.; Zhang, X.; Li, L.; Xiong, J. Digital twin for weld pool evolution by data-physics integrated driving. *J. Manuf. Process.* **2024**, *131*, 947–957. [[CrossRef](#)]
91. Lin, T.Y.; Shi, G.; Yang, C.; Zhang, Y.; Wang, J.; Jia, Z.; Guo, L.; Xiao, Y.; Wei, Z.; Lan, S. Efficient container virtualization-based digital twin simulation of smart industrial systems. *J. Clean. Prod.* **2021**, *281*, 124443. [[CrossRef](#)]
92. Gao, Y.; Chang, D.; Chen, C.H. A digital twin-based approach for optimizing operation energy consumption at automated container terminals. *J. Clean. Prod.* **2023**, *385*, 135782. [[CrossRef](#)]
93. Wu, C.; Chen, T.; Li, Z.; Liu, W. A function-oriented optimising approach for smart product service systems at the conceptual design stage: A perspective from the digital twin framework. *J. Clean. Prod.* **2021**, *297*, 126597. [[CrossRef](#)]
94. Züst, S.; Züst, R.; Züst, V.; West, S.; Stoll, O.; Minonne, C. A graph based Monte Carlo simulation supporting a digital twin for the curatorial management of excavation and demolition material flows. *J. Clean. Prod.* **2021**, *310*, 127453. [[CrossRef](#)]
95. Wang, Y.; Wang, S.; Yang, B.; Zhu, L.; Liu, F. Big data driven hierarchical digital twin predictive remanufacturing paradigm: Architecture, control mechanism, application scenario and benefits. *J. Clean. Prod.* **2020**, *248*, 119299. [[CrossRef](#)]
96. He, B.; Cao, X.; Hua, Y. Data fusion-based sustainable digital twin system of intelligent detection robotics. *J. Clean. Prod.* **2021**, *280*, 124181. [[CrossRef](#)]
97. Contini, G.; Peruzzini, M.; Bulgarelli, S.; Bosi, G. Developing key performance indicators for monitoring sustainability in the ceramic industry: The role of digitalization and Industry 4.0 technologies. *J. Clean. Prod.* **2023**, *414*, 137664. [[CrossRef](#)]
98. Alves, R.G.; Maia, R.F.; Lima, F. Development of a digital twin for smart farming: Irrigation management system for water saving. *J. Clean. Prod.* **2023**, *388*, 135920. [[CrossRef](#)]
99. Kaewunruen, S.; Lian, Q. Digital twin aided sustainability-based lifecycle management for railway turnout systems. *J. Clean. Prod.* **2019**, *228*, 1537–1551. [[CrossRef](#)]
100. Mangers, J.; Amne Elahi, M.; Plapper, P. Digital twin of end-of-life process-chains for a circular economy adapted product design—A case study on PET bottles. *J. Clean. Prod.* **2023**, *382*, 135287. [[CrossRef](#)]
101. Lu, W.; Chen, J.; Fu, Y.; Pan, Y.; Ghansah, F.A. Digital twin-enabled human-robot collaborative teaming towards sustainable and healthy built environments. *J. Clean. Prod.* **2023**, *412*, 137412. [[CrossRef](#)]
102. Zhao, N.; Fu, Z.; Sun, Y.; Pu, X.; Luo, L. Digital-twin driven energy-efficient multi-crane scheduling and crane number selection in workshops. *J. Clean. Prod.* **2022**, *336*, 130175. [[CrossRef](#)]
103. Leng, J.; Zhou, M.; Xiao, Y.; Zhang, H.; Liu, Q.; Shen, W.; Su, Q.; Li, L. Digital twins-based remote semi-physical commissioning of flow-type smart manufacturing systems. *J. Clean. Prod.* **2021**, *306*, 127278. Corrigendum in *J. Clean. Prod.* **2021**, *320*, 128836. [[CrossRef](#)]
104. Piron, M.; Bovo, E.; Lucchetta, G.; Manzardo, A. Soft-sensors to drive manufacturing toward clean production: LCA based on digital twin. *J. Clean. Prod.* **2025**, *498*, 145192. [[CrossRef](#)]
105. Alelaimat, A.; Ghose, A.; Dam, H.K. XPLaM: A toolkit for automating the acquisition of BDI agent-based digital twins of organizations. *Comput. Ind.* **2023**, *145*, 103805. [[CrossRef](#)]
106. Halwani, S.; Hamid, A.-K.; Ahmad, F.F.; Hussein, M. Comparative analysis of experimental and modelling of bifacial PV panel: A step towards digital twin. *Int. J. Thermofluids* **2025**, *29*, 101377. [[CrossRef](#)]
107. Rodríguez, F.; Chicaiza, W.D.; Sánchez, A.; Escaño, J.M. Updating digital twins: Methodology for data accuracy quality control using machine learning techniques. *Comput. Ind.* **2023**, *151*, 103958. [[CrossRef](#)]
108. Suhail, S.; Malik, S.U.R.; Jurdak, R.; Hussain, R.; Matulevičius, R.; Svetinovic, D. Towards situational aware cyber-physical systems: A security-enhancing use case of blockchain-based digital twins. *Comput. Ind.* **2022**, *141*, 103699. [[CrossRef](#)]
109. Müller-Zhang, Z.; Kuhn, T.; Antonino, P.O. Towards live decision-making for service-based production: Integrated process planning and scheduling with digital twins and Deep-Q-Learning. *Comput. Ind.* **2023**, *149*, 103933. [[CrossRef](#)]
110. Ogunsakin, R.; Mehandjiev, N.; Marin, C.A. Towards adaptive digital twins architecture. *Comput. Ind.* **2023**, *149*, 103920. [[CrossRef](#)]
111. Karagiannis, D.; Buchmann, R.A.; Utz, W. The OMiLAB Digital Innovation environment: Agile conceptual models to bridge business value with digital and physical twins for Product-Service Systems development. *Comput. Ind.* **2022**, *138*, 103631. [[CrossRef](#)]
112. Wang, T.; Tan, C.; Huang, L.; Shi, Y.; Yue, T.; Huang, Z. Simplexity testbed: A model-based digital twin testbed. *Comput. Ind.* **2023**, *145*, 103804. [[CrossRef](#)]
113. Mandolla, C.; Petruzzelli, A.M.; Percoco, G.; Urbanati, A. Building a digital twin for additive manufacturing through the exploitation of blockchain: A case analysis of the aircraft industry. *Comput. Ind.* **2019**, *109*, 134–152. [[CrossRef](#)]
114. Jorgensen, J.; Hodkiewicz, M.; Cripps, E.; Hassan, G.M. Requirements for the application of the digital twin paradigm to offshore wind turbine structures for uncertain fatigue analysis. *Comput. Ind.* **2023**, *145*, 103806. [[CrossRef](#)]

115. Pires, F.; Leitão, P.; Moreira, A.P.; Ahmad, B. Reinforcement learning based trustworthy recommendation model for digital twin-driven decision-support in manufacturing systems. *Comput. Ind.* **2023**, *148*, 103884. [\[CrossRef\]](#)
116. Albini, T.; Brocchi, A.; Murgia, G.; Pranzo, M. Real-time optimization for a digital twin of a robotic cell with human operators. *Comput. Ind.* **2023**, *146*, 103858. [\[CrossRef\]](#)
117. Sengupta, S.; Dreyer, H. Realizing zero-waste value chains through digital twin-driven S&OP: A case of grocery retail. *Comput. Ind.* **2023**, *148*, 103890. [\[CrossRef\]](#)
118. Hu, F.; Wang, W.; Zhou, J. Petri nets-based digital twin drives dual-arm cooperative manipulation. *Comput. Ind.* **2023**, *147*, 103880. [\[CrossRef\]](#)
119. Greif, T.; Stein, N.; Flath, C.M. Peeking into the void: Digital twins for construction site logistics. *Comput. Ind.* **2020**, *121*, 103264. [\[CrossRef\]](#)
120. Robles, J.; Martín, C.; Díaz, M. OpenTwins: An open-source framework for the development of next-gen compositional digital twins. *Comput. Ind.* **2023**, *152*, 104007. [\[CrossRef\]](#)
121. Lugaresi, G.; Gangemi, S.; Gazzoni, G.; Matta, A. Online validation of digital twins for manufacturing systems. *Comput. Ind.* **2023**, *150*, 103942. [\[CrossRef\]](#)
122. Zeb, A.; Kortelainen, J.; Rantala, T.; Saunila, M.; Ukko, J. On the alleviation of imminent technical and business challenges of long-lasting functional digital twins. *Comput. Ind.* **2022**, *141*, 103701. [\[CrossRef\]](#)
123. Woitsch, R.; Sumeder, A.; Falcioni, D. Model-based data integration along the product & service life cycle supported by digital twinning. *Comput. Ind.* **2022**, *140*, 103648. [\[CrossRef\]](#)
124. Suhail, S.; Iqbal, M.; Hussain, R.; Jurdak, R. ENIGMA: An explainable digital twin security solution for cyber-physical systems. *Comput. Ind.* **2023**, *151*, 103961. [\[CrossRef\]](#)
125. Crespo Marquez, A.; Marcos Alberca, J.A.; Guillén López, A.J.; De La Fuente Carmona, A. Digital twins in condition-based maintenance apps: A case study for train axle bearings. *Comput. Ind.* **2023**, *151*, 103980. [\[CrossRef\]](#)
126. Boyes, H.; Watson, T. Digital twins: An analysis framework and open issues. *Comput. Ind.* **2022**, *143*, 103763. [\[CrossRef\]](#)
127. Jiang, Y.; Li, M.; Guo, D.; Wu, W.; Zhong, R.Y.; Huang, G.Q. Digital twin-enabled smart modular integrated construction system for on-site assembly. *Comput. Ind.* **2022**, *136*, 103594. [\[CrossRef\]](#)
128. Seidel, R.; Rachinger, B.; Thielen, N.; Schmidt, K.; Meier, S.; Franke, J. Development and validation of a digital twin framework for SMT manufacturing. *Comput. Ind.* **2023**, *145*, 103831. [\[CrossRef\]](#)
129. Panarotto, M.; Isaksson, O.; Vial, V. Cost-efficient digital twins for design space exploration: A modular platform approach. *Comput. Ind.* **2023**, *145*, 103813. [\[CrossRef\]](#)
130. Rico, M.; Taverna, M.L.; Galli, M.R.; Caliusco, M.L. Context-aware representation of digital twins' data: The ontology network role. *Comput. Ind.* **2023**, *146*, 103856. [\[CrossRef\]](#)
131. Liu, Y.; Pan, S.; Folz, P.; Ramparany, F.; Bolle, S.; Ballot, E.; Coupaye, T. Cognitive digital twins for freight parking management in last mile delivery under smart cities paradigm. *Comput. Ind.* **2023**, *153*, 104022. [\[CrossRef\]](#)
132. Cimino, C.; Negri, E.; Fumagalli, L. Review of digital twin applications in manufacturing. *Comput. Ind.* **2019**, *113*, 103130. [\[CrossRef\]](#)
133. Hribernik, K.; Cabri, G.; Mandreoli, F.; Mentzas, G. Autonomous, context-aware, adaptive Digital Twins—State of the art and roadmap. *Comput. Ind.* **2021**, *133*, 103508. [\[CrossRef\]](#)
134. Lugaresi, G.; Matta, A. Automated digital twin generation of manufacturing systems with complex material flows: Graph model completion. *Comput. Ind.* **2023**, *151*, 103977. [\[CrossRef\]](#)
135. Modoni, G.E.; Stampone, B.; Trotta, G. Application of the Digital Twin for in process monitoring of the micro injection moulding process quality. *Comput. Ind.* **2022**, *135*, 103568. [\[CrossRef\]](#)
136. Hu, W.; Wang, T.; Chu, F. A Wasserstein generative digital twin model in health monitoring of rotating machines. *Comput. Ind.* **2023**, *145*, 103807. [\[CrossRef\]](#)
137. Perno, M.; Hvam, L.; Haug, A. A machine learning digital twin approach for critical process parameter prediction in a catalyst manufacturing line. *Comput. Ind.* **2023**, *151*, 103987. [\[CrossRef\]](#)
138. Friederich, J.; Francis, D.P.; Lazarova-Molnar, S.; Mohamed, N. A framework for data-driven digital twins for smart manufacturing. *Comput. Ind.* **2022**, *136*, 103586. [\[CrossRef\]](#)
139. Phua, A.; Davies, C.H.J.; Delaney, G.W. A digital twin hierarchy for metal additive manufacturing. *Comput. Ind.* **2022**, *140*, 103667. [\[CrossRef\]](#)
140. Ye, Z.; Ye, Y.; Zhang, C.; Zhang, Z.; Li, W.; Wang, X.; Wang, L.; Wang, L. A digital twin approach for tunnel construction safety early warning and management. *Comput. Ind.* **2023**, *144*, 103783. [\[CrossRef\]](#)
141. Human, C.; Basson, A.H.; Kruger, K. A design framework for a system of digital twins and services. *Comput. Ind.* **2023**, *144*, 103796. [\[CrossRef\]](#)
142. Calvo-Bascones, P.; Voisin, A.; Do, P.; Sanz-Bobi, M.A. A collaborative network of digital twins for anomaly detection applications of complex systems. *Snitch Digit. Twin concept. Comput. Ind.* **2023**, *144*, 103767. [\[CrossRef\]](#)

143. Kober, C.; Medina, F.G.; Benfer, M.; Wulfsberg, J.P.; Martinez, V.; Lanza, G. Digital Twin Stakeholder Communication: Characteristics, Challenges, and Best Practices. *Comput. Ind.* **2024**, *161*, 104135. [\[CrossRef\]](#)
144. Chen, J.; Lu, W.; Ji, X.; Fu, Y. Improving interoperability in robot digital twinning for facility management: An industry foundation class-represented RoboAvatar approach. *Comput. Ind.* **2025**, *173*, 104384. [\[CrossRef\]](#)
145. Geng, Y.; Wang, Z.; Jia, L.; Qin, Y.; Chai, Y.; Liu, K.; Tong, L. 3DGraphSeg: A Unified Graph Representation-Based Point Cloud Segmentation Framework for Full-Range High-Speed Railway Environments. *IEEE Trans. Ind. Inform.* **2023**, *19*, 11430–11443. [\[CrossRef\]](#)
146. Gehrmann, C.; Gunnarsson, M. A digital twin based industrial automation and control system security architecture. *IEEE Trans. Ind. Inform.* **2020**, *16*, 669–680. [\[CrossRef\]](#)
147. Wang, H.; Wu, Y.; Min, G.; Miao, W. A Graph Neural Network-Based Digital Twin for Network Slicing Management. *IEEE Trans. Ind. Inform.* **2022**, *18*, 1367–1376. [\[CrossRef\]](#)
148. Li, Z.; Duan, M.; Xiao, B.; Yang, S. A Novel Anomaly Detection Method for Digital Twin Data Using Deconvolution Operation With Attention Mechanism. *IEEE Trans. Ind. Inform.* **2023**, *19*, 7278–7286. [\[CrossRef\]](#)
149. Zhang, K.; Cao, J.; Zhang, Y. Adaptive Digital Twin and Multiagent Deep Reinforcement Learning for Vehicular Edge Computing and Networks. *IEEE Trans. Ind. Inform.* **2022**, *18*, 1405–1413. [\[CrossRef\]](#)
150. Sun, W.; Lei, S.; Wang, L.; Liu, Z.; Zhang, Y. Adaptive Federated Learning and Digital Twin for Industrial Internet of Things. *IEEE Trans. Ind. Inform.* **2021**, *17*, 5605–5614. [\[CrossRef\]](#)
151. Zhang, C.; Zhu, L.; Xu, C. BSDP: Blockchain-Based Smart Parking for Digital-Twin Empowered Vehicular Sensing Networks With Privacy Protection. *IEEE Trans. Ind. Inform.* **2023**, *19*, 7237–7246. [\[CrossRef\]](#)
152. Bellavista, P.; Giannelli, C.; Mamei, M.; Mendula, M.; Picone, M. Application-Driven Network-Aware Digital Twin Management in Industrial Edge Environments. *IEEE Trans. Ind. Inform.* **2021**, *17*, 7791–7801. [\[CrossRef\]](#)
153. Fogli, M.; Giannelli, C.; Poltronieri, F.; Stefanelli, C.; Tortonesi, M. Chaos Engineering for Resilience Assessment of Digital Twins. *IEEE Trans. Ind. Inform.* **2024**, *20*, 1134–1143. [\[CrossRef\]](#)
154. Dang, H.; Tatipamula, M.; Nguyen, H.X. Cloud-Based Digital Twinning for Structural Health Monitoring Using Deep Learning. *IEEE Trans. Ind. Inform.* **2022**, *18*, 3820–3830. [\[CrossRef\]](#)
155. Liao, H.; Zhou, Z.; Liu, N.; Zhang, Y.; Xu, G.; Wang, Z.; Mumtaz, S. Cloud-Edge-Device Collaborative Reliable and Communication-Efficient Digital Twin for Low-Carbon Electrical Equipment Management. *IEEE Trans. Ind. Inform.* **2023**, *19*, 1715–1724. [\[CrossRef\]](#)
156. Lu, Y.; Huang, X.; Zhang, K.; Maharjan, S.; Zhang, Y. Communication-Efficient Federated Learning for Digital Twin Edge Networks in Industrial IoT. *IEEE Trans. Ind. Inform.* **2021**, *17*, 5709–5718. [\[CrossRef\]](#)
157. Ren, Z.; Shi, J.; Imran, M. Data Evolution Governance for Ontology-Based Digital Twin Product Lifecycle Management. *IEEE Trans. Ind. Inform.* **2023**, *19*, 1791–1802. [\[CrossRef\]](#)
158. Zhou, X.; Sun, K.; Wang, J.; Zhao, J.; Feng, C.; Yang, Y.; Zhou, W. Computer Vision Enabled Building Digital Twin Using Building Information Model. *IEEE Trans. Ind. Inform.* **2023**, *19*, 2684–2692. [\[CrossRef\]](#)
159. Qin, Y.; Wu, X.; Luo, J. Data-Model Combined Driven Digital Twin of Life-Cycle Rolling Bearing. *IEEE Trans. Ind. Inform.* **2022**, *18*, 1530–1540. [\[CrossRef\]](#)
160. Dai, Y.; Zhang, K.; Maharjan, S.; Zhang, Y. Deep Reinforcement Learning for Stochastic Computation Offloading in Digital Twin Networks. *IEEE Trans. Ind. Inform.* **2021**, *17*, 4968–4977. [\[CrossRef\]](#)
161. Xu, H.; Wu, J.; Pan, H.; Gu, J.; Guan, X. Delay Safety-Aware Digital Twin Empowered Industrial Sensing-Actuation Systems Using Transferable and Reinforced Learning. *IEEE Trans. Ind. Inform.* **2023**, *19*, 10811–10820. [\[CrossRef\]](#)
162. Liu, D.; Du, Y.; Chai, W.; Lu, C.Q.; Cong, M. Digital Twin and Data-Driven Quality Prediction of Complex Die-Casting Manufacturing. *IEEE Trans. Ind. Inform.* **2022**, *18*, 8119–8128. [\[CrossRef\]](#)
163. Xiang, F.; Zhou, S.; Zuo, Y.; Tao, F. Digital Twin Driven End-Face Defect Control Method for Hot-Rolled Coil With Cloud-Edge Collaboration. *IEEE Trans. Ind. Inform.* **2023**, *19*, 1674–1682. [\[CrossRef\]](#)
164. Xiang, W.; Li, J.; Zhou, Y.; Cheng, P.; Jin, J.; Yu, K. Digital Twin Empowered Industrial IoT Based on Credibility-Weighted Swarm Learning. *IEEE Trans. Ind. Inform.* **2024**, *20*, 775–784. [\[CrossRef\]](#)
165. Qin, Y.; Arunan, A.; Yuen, C. Digital Twin for Real-time Li-Ion Battery State of Health Estimation With Partially Discharged Cycling Data. *IEEE Trans. Ind. Inform.* **2023**, *19*, 7247–7257. [\[CrossRef\]](#)
166. Mei, Y.W.; Liu, Y.; Li, J.; Wu, H.; Sun, C.; Wang, D. Digital Twin of Large-Scale Coaxiality Measuring Instrument With Six Dimensions Realizing the Unification of Aeroengine Rotors Measurement and Assembly. *IEEE Trans. Ind. Inform.* **2023**, *20*, 4504–4516. [\[CrossRef\]](#)
167. Hu, C.; Fan, W.; Zeng, E.; Hang, Z.; Wang, F.; Qi, L.; Bhuiyan, M.Z.A. Digital Twin-Assisted Real-Time Traffic Data Prediction Method for 5G-Enabled Internet of Vehicles. *IEEE Trans. Ind. Inform.* **2022**, *18*, 2811–2819. [\[CrossRef\]](#)
168. Yang, M.; Wang, Y.; Wang, C.; Liang, Y.; Yang, S.; Wang, L.; Wang, S. Digital Twin-Driven Industrialization Development of Underwater Gliders. *IEEE Trans. Ind. Inform.* **2023**, *19*, 9680–9690. [\[CrossRef\]](#)

169. Liu, J.; Xu, Z.; Xiong, H.; Lin, Q.; Xu, W.; Zhou, Z. Digital Twin-Driven Robotic Disassembly Sequence Dynamic Planning under Uncertain Missing Condition. *IEEE Trans. Ind. Inform.* **2023**, *19*, 11846–11855. [\[CrossRef\]](#)
170. Xie, G.; Yang, K.; Xu, C.; Li, R.; Hu, S. Digital Twinning Based Adaptive Development Environment for Automotive Cyber-Physical Systems. *IEEE Trans. Ind. Inform.* **2022**, *18*, 1387–1396. [\[CrossRef\]](#)
171. De Benedictis, A.; Flammini, F.; Mazzocca, N.; Somma, A.; Vitale, F. Digital Twins for Anomaly Detection in the Industrial Internet of Things: Conceptual Architecture and Proof-of-Concept. *IEEE Trans. Ind. Inform.* **2023**, *19*, 11553–11563. [\[CrossRef\]](#)
172. Seok, M.G.; Tan, W.J.; Cai, W.; Park, D. Digital-Twin Consistency Checking Based on Observed Timed Events With Unobservable Transitions in Smart Manufacturing. *IEEE Trans. Ind. Inform.* **2023**, *19*, 6208–6219. [\[CrossRef\]](#)
173. Fang, Y.; Peng, C.; Lou, P.; Zhou, Z.; Hu, J.; Yan, J. Digital-Twin-Based Job Shop Scheduling Toward Smart Manufacturing. *IEEE Trans. Ind. Inform.* **2019**, *15*, 6425–6435. [\[CrossRef\]](#)
174. Peng, K.; Huang, H.; Bilal, M.; Xu, X. Distributed Incentives for Intelligent Offloading and Resource Allocation in Digital Twin Driven Smart Industry. *IEEE Trans. Ind. Inform.* **2023**, *19*, 3133–3143. [\[CrossRef\]](#)
175. Cascone, L.; Nappi, M.; Narducci, F.; Passero, I. DTPAAL: Digital Twinning Pepper and Ambient Assisted Living. *IEEE Trans. Ind. Inform.* **2022**, *18*, 1397–1404. [\[CrossRef\]](#)
176. Vitale, F.; Guarino, S.; Flammini, F.; Faramondi, L.; Mazzocca, N.; Setola, R. Process Mining for Digital Twin Development of Industrial Cyber-Physical Systems. *IEEE Trans. Ind. Inform.* **2025**, *21*, 866–875. [\[CrossRef\]](#)
177. Lv, J.; Mao, S.; Qiang, L.; Hou, Y.; Song, D.A. Tokamak O&M Robot Dynamic Control by Using Optimized FABRIK and Spatial Partition Strategies in Digital Twin System. *IEEE Trans. Ind. Inform.* **2025**, *21*, 1595–1604. [\[CrossRef\]](#)
178. Zhang, C.; Sun, Q.; Sun, W.; Mu, X.; Wang, Y. A construction method of digital twin model for contact characteristics of assembly interface. *Int. J. Adv. Manuf. Technol.* **2021**, *113*, 2685–2699. [\[CrossRef\]](#)
179. Yang, W.; Bao, X.; Zheng, Y.; Zhang, L.; Zhang, Z.; Zhang, Z.; Li, L. A digital twin framework for large comprehensive ports and a case study of Qingdao Port. *Int. J. Adv. Manuf. Technol.* **2024**, *131*, 5571–5588. [\[CrossRef\]](#)
180. Duan, J.; Gong, X.; Zhang, Q.; Qin, J. A digital twin-driven monitoring framework for dual-robot collaborative manipulation. *Int. J. Adv. Manuf. Technol.* **2023**, *125*, 4579–4599. [\[CrossRef\]](#)
181. Fan, Y.; Dai, C.; Huang, S.; Hu, P.; Wang, X.; Yan, M. A life-cycle digital-twin collaboration framework based on the industrial internet identification and resolution. *Int. J. Adv. Manuf. Technol.* **2022**, *123*, 2883–2911. [\[CrossRef\]](#)
182. Park, K.T.; Lee, J.; Kim, H.J.; Noh, S.D. Digital twin-based cyber physical production system architectural framework for personalized production. *Int. J. Adv. Manuf. Technol.* **2020**, *106*, 1787–1810. [\[CrossRef\]](#)
183. Zhuang, C.; Liu, J.; Xiong, H. Digital twin-based smart production management and control framework for the complex product assembly shop-floor. *Int. J. Adv. Manuf. Technol.* **2018**, *96*, 1149–1163. [\[CrossRef\]](#)
184. Xue, R.; Zhang, P.; Huang, Z.; Wang, J. Digital twin-driven fault diagnosis for CNC machine tool. *Int. J. Adv. Manuf. Technol.* **2024**, *131*, 5457–5470. [\[CrossRef\]](#)
185. He, B.; Bai, K.J. Digital twin-based sustainable intelligent manufacturing: A review. *Adv. Manuf.* **2021**, *9*, 1–21. [\[CrossRef\]](#)
186. Wang, Y.; Jiang, Z.; Wu, Y. Model construction of material distribution system based on digital twin. *Int. J. Adv. Manuf. Technol.* **2022**, *121*, 4485–4501. [\[CrossRef\]](#)
187. Xiao, J.; Fan, K. Research on the digital twin for thermal characteristics of motorized spindle. *Int. J. Adv. Manuf. Technol.* **2022**, *119*, 5107–5118. [\[CrossRef\]](#)
188. Huang, S.; Wang, G.; Lei, D.; Yan, Y. Toward digital validation for rapid product development based on digital twin: A framework. *Int. J. Adv. Manuf. Technol.* **2022**, *119*, 2509–2523. [\[CrossRef\]](#)
189. Xu, L.; Yu, H.; Qin, H.; Chai, Y.; Yan, N.; Li, D.; Chen, Y. Digital Twin for Aquaponics Factory: Analysis, Opportunities, and Research Challenges. *IEEE Trans. Ind. Inform.* **2024**, *20*, 5060–5073. [\[CrossRef\]](#)
190. Chen, Y.; Zhang, F.; Yang, G. A time-varying contact dynamic modeling method of kinematic pairs based on digital twin. *Measurement* **2025**, *256*, 118219. [\[CrossRef\]](#)
191. Tao, H.; Jia, P.; Wang, X.; Chen, X.; Wang, L. A digital twin-based fault diagnostic method for subsea control systems. *Meas. J. Int. Meas. Confed.* **2023**, *221*, 113461. [\[CrossRef\]](#)
192. Luo, H.; Cheng, L.; Yang, L.; Zhao, X.; Liao, R.; Zhang, Y. A novel approach to building digital twin transformers by combining virtual-real sensing: An example of degree of polymerization distribution. *Meas. J. Int. Meas. Confed.* **2023**, *222*, 113714. [\[CrossRef\]](#)
193. Xu, J.; Shu, X.; Qiao, P.; Li, S.; Xu, J. Developing a digital twin model for monitoring building structural health by combining a building information model and a real-scene 3D model. *Meas. J. Int. Meas. Confed.* **2023**, *217*, 112955. [\[CrossRef\]](#)
194. Wen, C.K.; Liu, Z.-Y.; Wu, G.-W.; Zhao, C.-J.; Chen, L.-P.; Yin, Y.-X.; Meng, Z.-J. Digital twin-driven fatigue life prediction framework of mechanical structures using a power density theory: Application to off-road vehicle front axle housing. *Meas. J. Int. Meas. Confed.* **2023**, *220*, 113352. [\[CrossRef\]](#)
195. Lu, C.; Wang, J.; Yin, P.; Wang, L. Error identification of measurement software based on digital twin of gear measuring center. *Meas. J. Int. Meas. Confed.* **2021**, *173*, 108666. [\[CrossRef\]](#)

196. Sýkora, J.; Linkeová, I.; Skalník, P. Freeform digital twin approach to develop the HP 300 freeform verification standard. *Meas. J. Int. Meas. Confed.* **2023**, *218*, 113227. [\[CrossRef\]](#)
197. Jiao, X.; Xie, J.; Wang, X.; Yan, Z.; Hao, Z.; Wang, X. Intelligent decision method for the position and attitude self-adjustment of hydraulic support groups driven by a digital twin system. *Meas. J. Int. Meas. Confed.* **2022**, *202*, 111722. [\[CrossRef\]](#)
198. Wang, B.; Fan, S.; Chen, Y.; Zheng, L.; Zhu, H.; Fang, Z.; Zhang, M. The replacement of dysfunctional sensors based on the digital twin method during the cutter suction dredger construction process. *Meas. J. Int. Meas. Confed.* **2022**, *189*, 110523. [\[CrossRef\]](#)
199. Fedorko, G.; Molnár, V.; Vasil', M.; Salai, R. Proposal of digital twin for testing and measuring of transport belts for pipe conveyors within the concept Industry 4.0. *Measurement* **2021**, *174*, 108978. [\[CrossRef\]](#)
200. Zhang, Y.; Zhou, H.; Yao, R.; Wu, M. A laser ultrasonic intelligent inspection method for metal surface defects based on digital twin model. *Measurement* **2024**, *237*, 115219. [\[CrossRef\]](#)
201. Wang, K.; Zhang, L.; Jia, Z.; Cheng, H.; Lu, H.; Cui, J. A framework and method for equipment digital twin dynamic evolution based on IExATCN. *J. Intell. Manuf.* **2024**, *35*, 1571–1583. [\[CrossRef\]](#)
202. Redelinghuys, A.J.H.; Basson, A.H.; Kruger, K. A six-layer architecture for the digital twin: A manufacturing case study implementation. *J. Intell. Manuf.* **2020**, *31*, 1383–1402. [\[CrossRef\]](#)
203. Duan, J.G.; Ma, T.Y.; Zhang, Q.L.; Liu, Z.; Qin, J.Y. Design and application of digital twin system for the blade-rotor test rig. *J. Intell. Manuf.* **2023**, *34*, 753–769. [\[CrossRef\]](#)
204. Tong, X.; Liu, Q.; Pi, S.; Xiao, Y. Real-time machining data application and service based on IMT digital twin. *J. Intell. Manuf.* **2020**, *31*, 1113–1132. [\[CrossRef\]](#)
205. Abanda, F.H.; Jian, N.; Adukpó, S.; Tuhaise, V.V.; Manjia, M.B. Digital twin for product versus project lifecycles' development in manufacturing and construction industries. *J. Intell. Manuf.* **2025**, *36*, 801–831. [\[CrossRef\]](#)
206. Machacek, Z.; Hercik, R.; Vaclavik, A.; Zemanek, J.; Hameed, I.A.; Koziorek, J. Modern trends and industrial use cases of digital twin technology with 3D behavioral representation. *J. Intell. Manuf.* **2025**, *37*, 1–34. [\[CrossRef\]](#)
207. Nguyen, P.; Kim, M.; Nichols, E.; Yoon, H. AI-Driven Digital Twins for Manufacturing: A Review Across Hierarchical Manufacturing System Levels. *Sensors* **2026**, *26*, 124. [\[CrossRef\]](#)
208. Omigbodun, F.T. AI-Driven Digital Twins in Sustainable Manufacturing: A Critical Review. *Sustainability* **2026**, *18*, 5785. [\[CrossRef\]](#)
209. Kampaourakis, K.E.; Gkioulos, V. Cybersecurity Digital Twins for Industrial Systems: From Literature Synthesis to Framework Design. *Information* **2026**, *17*, 286. [\[CrossRef\]](#)
210. Fontana, C. Human Digital Twins in Personalized Medicine: A Systematic Review and Bibliometric—Thematic Synthesis of Methodological Advances and Clinical Applications. *Computation* **2026**, *14*, 143. [\[CrossRef\]](#)
211. Tasmurzayev, N.; Amangeldy, B.; Imanbek, B.; Baigarayeva, Z. Digital Cardiovascular Twins, AI Agents, and Sensor Data: A Narrative Review from System Architecture to Proactive Heart Health. *Sensors* **2025**, *25*, 5272. [\[CrossRef\]](#)
212. Mazzetto, S. A Review of Urban Digital Twins Integration, Challenges, and Future Directions in Smart City Development. *Sustainability* **2024**, *16*, 8337. [\[CrossRef\]](#)
213. Lis, M.; Maksymilian, M. Green Transportation Planning for Smart Cities: Digital Twins and Real-Time Traffic Optimization in Urban Mobility Networks. *Appl. Sci.* **2026**, *16*, 678. [\[CrossRef\]](#)
214. Ba, L.; Tangour, F.; El Abbassi, I.; Absi, R. Analysis of Digital Twin Applications in Energy Efficiency: A Systematic Review. *Sustainability* **2025**, *17*, 3560. [\[CrossRef\]](#)
215. Abdullah, H.; Khubaib, M. Digital Twins for Integrated Energy and Structural Performance Assessment of Buildings: A Systematic Review and Research Gap Analysis. *Eng. Proc.* **2026**, *147*, 12. [\[CrossRef\]](#)
216. Maldonado-correa, J.; Cuenca-Granda, J.; Torres-Cabrera, J.; Mejía, G.C.; Barragan, W.D.B.; Guapulema, R.; Paccha-Herrera, E.; Solano, J.C.; Tapia-Peralta, D.; Benavides, J.; et al. Digital Twin Technology in Wind Turbine Condition Monitoring, Predictive Maintenance, and RUL Estimation: A Systematic Literature Review. *Energies* **2026**, *19*, 1477. [\[CrossRef\]](#)
217. Madani, S.S.; Shabeer, Y.; Fowler, M.; Panchal, S.; Chaoui, H.; Mekhilef, S.; Dou, S.X.; See, K. Artificial Intelligence and Digital Twin Technologies for Intelligent Lithium-Ion Battery Management Systems: A Comprehensive Review of State Estimation, Lifecycle Optimization, and Cloud-Edge Integration. *Batteries* **2025**, *11*, 298. [\[CrossRef\]](#)
218. Łach, Ł. AI-Powered Digital Twins for Building Energy Management: Modeling Frameworks, Validation and Uncertainty Quantification, Smart Grid Integration, and Deployment Roadmap. *Sustainability* **2026**, *18*, 6908. [\[CrossRef\]](#)
219. Kim, M.; Ghobadi, F.; Saman, A.; Charmchi, T.; Lee, M.; Lee, J. Digital Twins for Clean Energy Systems: A State-of-the-Art Review of Applications, Integrated Technologies, and Key Challenges. *Sustainability* **2026**, *18*, 43. [\[CrossRef\]](#)
220. Eltamaly, A.M.; Almutairi, Z.; Al-senaidi, S.H. Real-Time Self-Learning Digital Twin for Lithium-Ion Battery Energy Storage Systems in Smart Grids. *Processes* **2026**, *14*, 1864. [\[CrossRef\]](#)
221. Rajendran, G.; Raute, R.; Caruana, C. A Comprehensive Review of Solar PV Integration with Smart-Grids: Challenges, Standards, and Grid Codes. *Energies* **2025**, *18*, 2221. [\[CrossRef\]](#)

222. Saad Abderrahmane, M.B.; Kara, R. Digital Twins for Health Care Monitor: Baby Incubator Temperature and Humidity Monitoring. In Proceedings of the 2023 2nd International Conference on Electronics, Energy and Measurement (IC2EM), Medea, Algeria, 28–29 November 2023. [[CrossRef](#)]
223. Aniba, Y.; Bouhedda, M.; Bachene, M.; Rahim, M.; Benyezza, H.; Tobbal, A. Digital twin-enabled quality control through deep learning in industry 4.0: A framework for enhancing manufacturing performance. *Int. J. Model. Simul.* **2024**, 1–21. [[CrossRef](#)]
224. Aniba, Y.; Bouhedda, M.; Bachene, M.; Seddiki, M.; Tobbal, A. Enhanced digital twin development for a conveyor belt system: Integrating PLC control, CNN decision-making, Gradio-based HMI, and fuzzy logic. *Braz. J. Technol.* **2024**, 7, e75933. [[CrossRef](#)]
225. Rahim, M.; Lalouani, W.; Toubal, E.; Emokpae, L. A Digital Twin-Based Platform for Medical Cyber-Physical Systems. *IEEE Access* **2024**, 12, 174591–174607. [[CrossRef](#)]
226. Oulefki, A.; Kheddar, H.; Amira, A.; Kurugollu, F.; Himeur, Y.; Bounceur, A. Innovative AI strategies for enhancing smart building operations through digital twins: A survey. *Energy Build.* **2025**, 335, 115567. [[CrossRef](#)]
227. Seddiki, M.; Bouhedda, M.; Tobbal, A.; Rebouh, S.; Aniba, Y. AI-Driven IoT Healthcare System for Real-Time ECG Analysis and Comprehensive Patient Monitoring. *Sci. Eng. Technol.* **2024**, 4, 61–81. [[CrossRef](#)]
228. Elmohri, M.; Kara, R.; Bouhedda, M.; Bengherbia, H.; Manseur, S.; Tobbal, A. Study and Design a Low-Power Water Meter. In Proceedings of the 2023 2nd International Conference on Electronics, Energy and Measurement (IC2EM), Medea, Algeria, 28–29 November 2023. [[CrossRef](#)]

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