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Digital Twin for Smart Manufacturing: Synthesis of Results, Methodology, and Research Gaps - Implementation

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Abstract

This study maps the development and research directions of Digital Twin (DT) in manufacturing by reviewing 25 recent publications that examine frameworks, methodologies, and the implementation of data-driven technologies, artificial intelligence, big data, and machine learning. The findings indicate that DT can enhance productivity, efficiency, and predictive accuracy, while also supporting human–robot collaboration and predictive maintenance through simulation, sensor integration, and synthetic data generation. The dominant methods applied include data-driven approaches, finite element modeling, generative models, knowledge graphs, Markov decision processes, as well as integration with large language models and augmented reality. On the other hand, several limitations remain prominent, such as dependence on data quality, high computational demands, limited validation in real industrial environments, and the lack of methodological standards that can be adopted across sectors. This review highlights that although DT has strong potential to become the backbone of smart manufacturing, the gap between academic research and industrial practice remains wide. Therefore, future research should focus on standardization, interoperability, and validation of DT implementation in real-world industrial settings.

1. Introduction

In the vortex of Industry 4.0, Digital Twin (DT) is often positioned as a bridge between the physical and virtual worlds, capable of predicting system behavior, minimizing production defects, and maintaining harmonious human-machine interactions. Although touted as the key to the future of manufacturing, the reality of DT still leaves a dilemma: to what extent can it truly be implemented in the field, and when does it stop being merely an academic experiment? Emerging research offers a variety of approaches—from artificial intelligence, data-driven modeling, to modular knowledge frameworks—that demonstrate DT's immense potential for efficiency and optimization. However, all of this promise is not free from serious challenges: fragile data quality, high computational requirements, and limited validation that often only takes place in the laboratory. Ironically, the more literature describing "digital intelligence" becomes, the more the gap between theory and industrial practice becomes apparent. It is precisely at this point that DT research becomes interesting, because it is not just about technology, but also about the courage to bridge futuristic visions with the pragmatic realities of manufacturing.

Based on the research objectives and secondary data analysis of 25 articles related to Digital Twin, the research questions posed are: How will Digital Twin trends, methodologies, and applications evolve in the manufacturing context from 2020 to 2026, and to what extent will they contribute to productivity, efficiency, and human-robot collaboration? In addition, what are the key challenges identified in the literature, particularly regarding data quality, computational requirements, and limitations of industrial validation, and how can a research agenda be designed to bridge the gap between academic findings and industrial practice?

2. Research methodology

2.1. Design

This study employed a mixed-methods design with exploratory bibliometric and qualitative approaches. Bibliometric analysis was conducted on 25 articles related to Digital Twin (2020–2026) using RStudio bibliometrix to map trends, dominant keywords, co-authorship, and co-citation.

2.2. Observations and Interviews

Observations were conducted by identifying patterns of Digital Twin implementation reported in case studies and experiments in each article, such as process efficiency, cost reduction, accuracy improvement, and implementation limitations. Indirect interviews were conducted through analysis of quotes, discussions, and conclusions from the original authors of the articles, who served as expert voices to capture both industry and academic perspectives. This approach allowed researchers to gain insights from documented practical experiences and theoretical perspectives without direct interaction with participants.

2.3. Research Tools

The research tools used in this study include RStudio with the bibliometrix package for bibliometric analysis, including data cleaning, descriptive analysis, science mapping, and network visualization. To support methodology documentation, Mermaid diagrams were used to generate flowcharts of research procedures and sequence diagrams of data-to-decision flows in Digital Twin. Literature analysis was managed using Mendeley for reference management and metadata export, while Microsoft Excel was utilized for processing supporting data such as keyword frequencies. With this combination of tools, the study produced a comprehensive knowledge map, a narrative research agenda, and a visual model that strengthens the interpretation of the findings.

2.4. Research Procedure

This research procedure began with the collection of 25 Digital Twin articles (2020–2026) from Scopus/Web of Science, then the data was converted to bibliometrix format in

RStudio, cleaned from duplications and standardized for keywords. Descriptive analysis was conducted to calculate publication trends per year, citations, authors, journals, and dominant keywords, followed by science mapping through co-occurrence, co-authorship, co-citation, thematic maps, and trend topics to map research connections. Next, performance analysis was carried out using the h-index, g-index, and article citations, followed by interpretation of the results that resulted in a research agenda: DT validation in complex scenarios, AI/LLM integration for decision support, Human Digital Twin (HDT) development for manufacturing ergonomics, and IIoT interoperability on legacy machines, all of which were visualized through bibliometrix such as publication trend graphs, thematic maps, and keyword connection maps.

2.5. Framework of thinking

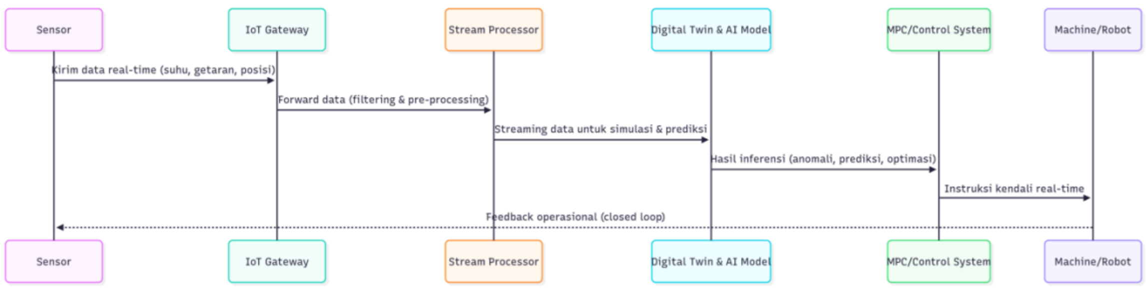

Figure 1. Research Flowchart

3. Results and Discussion

3.1. Result

3.1.1. Literature Review

Literature reviews of digital twins demonstrate significant contributions to improving manufacturing productivity, efficiency, flexibility, and sustainability through the integration of AI, ML, big data, and knowledge graphs. However, successful implementation still depends heavily on data quality, integration complexity, high computational requirements, and limited validation in real-world industrial environments (Table 1).

Table 1. Literature Review

No	Author, Year / Title	Results	Method	Weakness
1	(Friederich et al., 2022)A framework for data-driven digital twins for smart manufacturing	Increased productivity, reduced costs & energy savings in smart factories.	Data-driven framework based on ML & process mining for automated simulation.	Difficult to handle rapidly changing demands, requires high-quality data, still relies on expert expertise.
2	(Urgo & Terkaj, 2025)Integrating digital factory twin and AI for monitoring manufacturing systems through synthetic data generation and vision transformers	Improve the accuracy of anomaly detection & factory asset monitoring with AI integration.	DT generates synthetic data to train Vision Transformers in object detection & segmentation.	The quality of synthetic data does not always match real conditions, requiring high computation & diverse data.
3	(Mo et al., 2023)A framework for manufacturing system reconfiguration and optimization utilizing digital twins and modular artificial intelligence	Increased flexibility & efficiency (10% time efficiency) with automatic reconfiguration of manufacturing systems.	Knowledge graph & modular AI for system configuration optimization, tested on robotic cells.	Depends on data quality, AI integration complexity, computational challenges & system compatibility.
4	(Aznar Lapuente et al., 2026)Methodologies in digital twin for manufacturing industry: A systematic literature review	The trend of DT methodology research in industry is increasing, DT is understood as a complex system.	Systematic literature review (SLR) of 3 major databases.	There is minimal comparative analysis between methodologies; many studies are still theoretical/narrow case studies.

5	(Psarommatis, 2021)A generic methodology and a digital twin for zero defect manufacturing (ZDM) performance mapping towards design for ZDM	Helping manufacturers choose a Zero Defect Manufacturing (ZDM) strategy & generating ZDM performance maps.	Simulation with Taguchi design of experiments to create DT; testing various ZDM parameters.	Depends on model accuracy & simulation data quality; requires validation in complex industrial scenarios.
6	(De Giacomo et al., 2023)Digital twins composition in smart manufacturing via Markov decision processes	Generates an optimal policy for assigning devices to manufacturing tasks.	Markov Decision Processes (MDPs) to develop adaptive assignment policies.	High complexity & requires large computations for industrial scale; effectiveness depends on model & data accuracy.
7	(Risling et al., 2024)Analyzing The Purpose And Technologies Of Digital Twins In Distributed Manufacturing: A Systematic Literature Review	Improving connectivity & added value in distributed manufacturing.	Systematic review to map DT technologies & objectives in distributed manufacturing.	There are no methodological standards, many conceptual studies, limited real-world evidence on a global scale.
8	(Jin et al., 2024)Big data, machine learning, and digital twin assisted additive manufacturing: A review	The integration of big data, ML, & DT improves the efficiency, accuracy, & sustainability of Additive Manufacturing (AM).	Review paper that examines ML & DT research in the context of AM.	There are minimal studies that explicitly link the three, integrative implementation is still conceptual.
9	(Hinchy et al., 2020)Using finite element analysis to develop a digital twin of a manufacturing bending operation	High bending angle prediction accuracy (0.5°-3° error) in bending operations.	Finite Element Modeling (FEM) to predict product stress & bending angle, validated by physical testing.	Testing is limited to simple scenarios, requiring highly accurate material data.
10	(Mu et al., 2024)Online distortion simulation using generative machine learning models: A step toward digital twin of metallic additive manufacturing	The adaptive online simulation model predicts distortion in WAAM (RMSE < 0.9 mm).	Diffusion model (VQVAE-GAN) & Recurrent Neural Network (RNN) were trained offline with FEM data.	Limited to simple structures, requires large computations, requires validation for complex geometries.
11	(Perno et al., 2023)A machine learning digital twin approach for critical process parameter prediction in a catalyst manufacturing line	More accurate process parameter prediction with ML-based DT framework.	ML-based DT framework for data collection & processing, predictive model building, & visualization.	Data integration challenges & modeling complexity, lack of literature in process industries, limited scalability.
12	(S. Chen, Thompson, et al., 2025)A comparison between robust design and digital twin approaches for Non-Crimp fabric (NCF) forming	Reduces wrinkling & increases process resistance in NCF formation.	Simulation-based optimization with Gaussian Process & active learning; comparing robust vs. DT strategies.	The cost & complexity of DT is high, the advantages of DT over robust strategies are not yet clear.
13	(Baratta et al., 2024)Digital twin for human-robot collaboration enhancement in manufacturing systems: Literature review and direction for future developments	DT improves productivity & safety in Human-Robot Collaboration (HRC).	Literature review & analysis of commercial simulation software.	High costs & complexity, skills & regulation gaps, no platform standards yet.
14	(Abed et al., 2023)Swift feedback and immediate error control using a lightweight simulation approach – A case study of the digital-twin-in-the-loop for machining thin-wall structures	Improved machining accuracy of thin-wall structures, reduced error by 78.96%.	Digital-Twin-in-the-Loop with mass-spring-lattice model for real-time error control.	Testing is limited to specific cases; requires high computation for complex scenarios.
15	(Moussa et al., 2025)Industry 4.0 in Automotive Manufacturing: A Digital Twin Approach	Improve prediction efficiency & accuracy with ANN & OPC UA connectivity.	The DT framework integrates sensors, FlexSim simulation, & ML algorithms (ANN).	Testing is limited to specific cases, ANN models are prone to overfitting if the data is less diverse.
16	(Lang et al., 2025)Sensor placement utilizing a digital twin for thermal error compensation of machine tools	Reduced the number of sensors (from 22 to 7) & reduced thermal error (75-85%).	DT framework for determining sensor positions; SVD & LASSO regression for sensor selection.	Validation is needed on other manufacturing scenarios with varying materials & environmental conditions.
17	(YP Chen et al., 2025)Real-time decision-making for Digital Twin in additive manufacturing with Model Predictive Control using time-series deep neural networks	Precision control of melt pool temperature & reducing porosity in AM with DT-based MPC.	The DT-MPC framework uses TiDE (Time-Series Deep Neural Network) as a surrogate model.	Effectiveness depends on the accuracy of the TiDE model, requiring high computing resources for real-time.
18	(Liu et al., 2024)Digital twin-based anomaly detection for real-time tool condition monitoring in machining	Real-time anomaly detection & tool wear diagnosis (tool condition monitoring).	DT framework with integrated data-driven model & model frequency feature (MFF).	Depending on sensor quality & model accuracy, it requires advanced real-time data infrastructure.
19	(Gautam et al., 2025)IIoT-enabled digital twin for legacy and smart factory machines with LLM integration	LLM (Large Language Model) serves as a virtual expert for machine data diagnosis & visualization.	LLM multi-agent framework integrates data from legacy & modern machines via IIoT protocols.	The limitations of LLM interpretation of complex data require stable & secure IIoT infrastructure.
20	(Chand et al., 2024)A vision-enabled fatigue-sensitive human digital twin towards human-centric human-robot collaboration	Assessing operator physical & cognitive condition (fatigue) in HRC with Human Digital Twin (HDT).	A non-invasive video-based approach to activity detection & fatigue assessment.	Limited to simple assembly scenarios, accuracy is affected by lighting & individual variations.
21	(S. Chen, Turanoglu Bekar, et al., 2025)AI-enhanced digital twins in maintenance: Systematic review, industrial	AI & DT have the potential to optimize predictive maintenance.	SLR & in-depth interviews to identify gaps between academic research & industry practice.	Complexity of data integration, difficult to implement on a large scale, lack of HR readiness.

	challenges, and bridging research–practice gaps			
22	(Yang et al., 2025)A digital twin-driven industrial context-aware system: A case study of overhead crane operation	Adaptive context-aware system for crane operations.	The DT framework integrates data sources, ontologies, & Augmented Reality (AR) visualizations.	Still being tested on a lab scale, validation in a more complex real industrial environment is needed.
23	(Su et al., 2023)Characterization and evaluation of identicality for digital twins for the manufacturing domain	The "identicality" characteristic is used to evaluate the ability of a DT to represent a physical system.	Ontology-based information model & evaluation of 4 "identicality" attributes (completeness, trueness, precision, latency).	Testing is limited to single cases, depending on the quality of the ontology & human expertise.
24	(Chia et al., 2024)A review and outlook of airframe digital twins for structural prognostics and health management in the aviation industry	Enhanced fidelity airframe DT (ADT) for Structural Prognostics & Health Management (SPHM).	SLR on the evolution of the ADT framework in the aviation industry.	The challenges of modeling complex conditions, regulating civil industry, many studies focus on the military context.
25	(Cimino et al., 2024)Simulation-based Digital Twin for enhancing human-robot collaboration in assembly systems	Simulation-based DT improves HRC in assembly systems (car doors).	DT based on simulation & FIWARE/FIROS platform for real-time data exchange.	Limited to a single assembly line; large-scale implementation relies on IoT & FIWARE infrastructure.

3.1.2. Bibliometrix Visualization

A sharp increase in the number of publications over time. Starting with just one publication in 2017 and 2018, this number experienced moderate growth until 2022. In 2023, the number of publications increased to 17, marking a stronger trend. The peak occurred in 2024 with 39 publications, indicating a significant surge in interest or research activity that year. Although the number decreased slightly in 2025 and is projected to decline sharply in 2026, the overall trend indicates that research in this area has been very active in recent years (Table 2).

Table 2. Number of Publications

Year	Number of Publications
2017	1
2018	1
2019	3
2020	10
2021	8
2022	10
2023	17
2024	39
2025	24
2026	5

A literature search on digital twins shows a significant year-on-year increase in publications. Starting with one publication in 2017 and 2018, the number jumped dramatically to 39 in 2024 and 24 in 2025. This increase indicates that the topic of digital twins is becoming increasingly relevant and attracting the attention of researchers, particularly in the manufacturing sector. This growth aligns with the development of related technologies such as Industry 4.0 and artificial intelligence, which form the basis for digital twin implementation.

Most publications are concentrated in highly reputable journals and proceedings. PROCEDIA CIRP is the most dominant source of publications with 36 articles, followed by Journal of Manufacturing Systems (17 articles), Manufacturing Letters (10 articles), and

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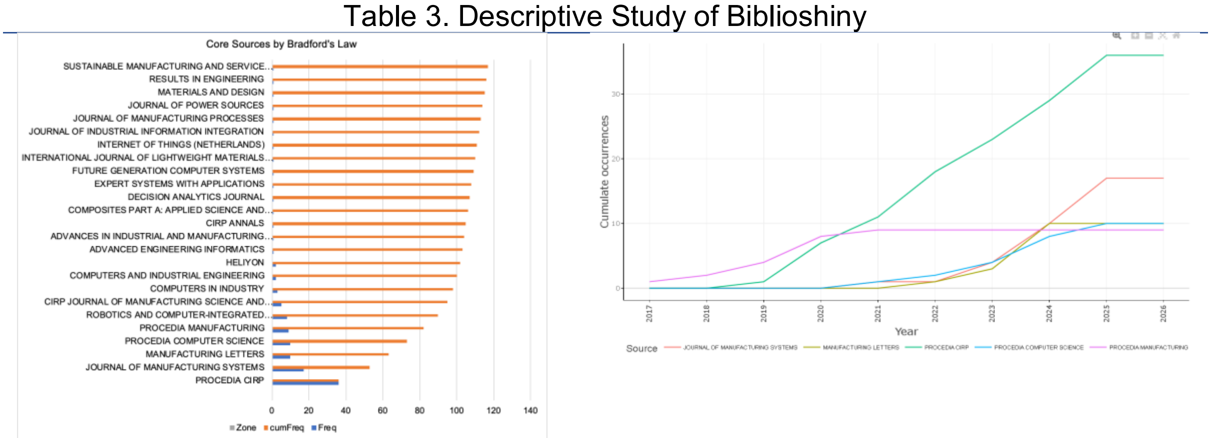
Procedia Computer Science (10 articles). These journals fall into Zones 1 and 2, indicating high quality and visibility. This concentration underscores the importance of specific scientific platforms for disseminating research results and also demonstrates that the digital twin research community is highly active in leading journals.

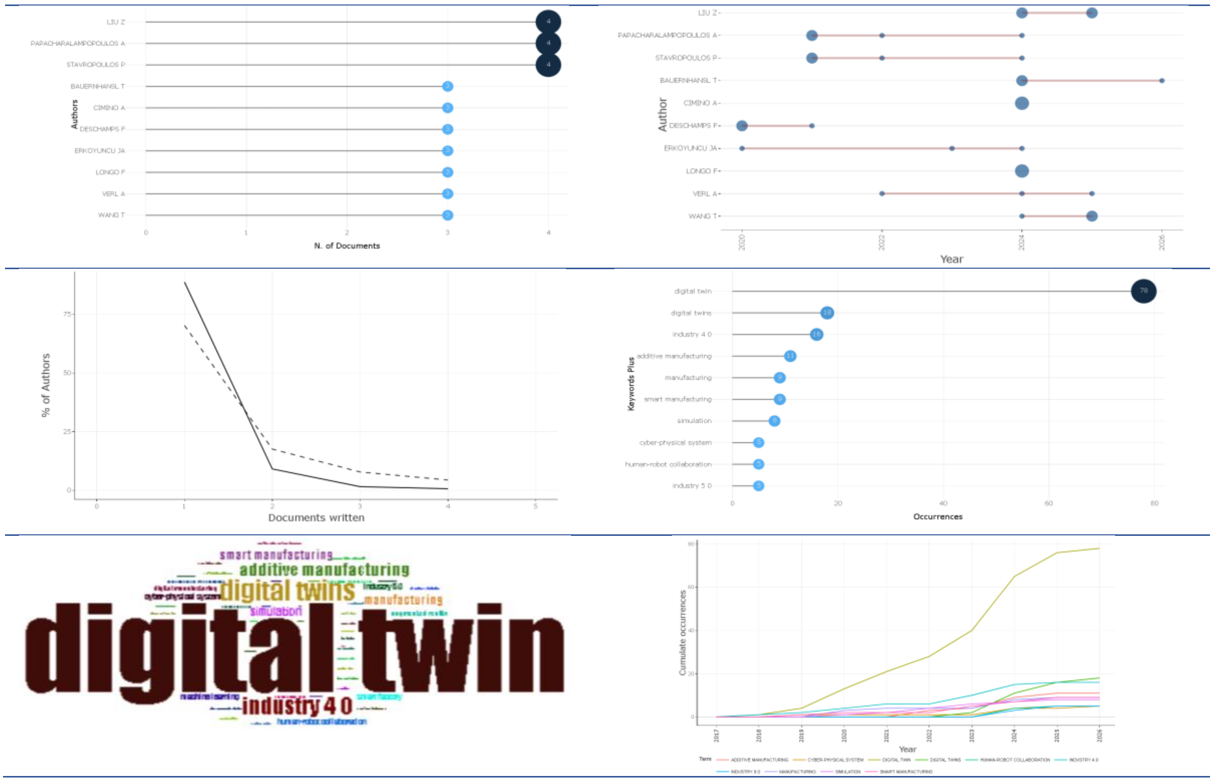
Author analysis reveals several names that consistently contribute to this literature. LIU Z, PAPACHARALAMPOPOULOS A, and STAVROPOULOS P are the most prolific authors, each with four articles. Other authors such as BAUERNHANSL T, CIMINO A, and DESCHAMPS F also have significant contributions. This pattern suggests collaboration and specialization in the digital twin field. Some recent research by these authors, such as that by LIU Z, focuses on human-centric digital twins and multi-robot systems, reflecting a shift in research focus toward more complex applications oriented toward human-machine interaction.

Key themes emerging from this literature are dominated by the digital twin concept itself, with 78 occurrences. Other related concepts such as Industry 4.0 (16), additive manufacturing (11), intelligent manufacturing (9), and simulation (8) are also frequently discussed. This demonstrates that digital twins do not stand alone, but are instead an integral part of a broader manufacturing technology ecosystem. Specific applications, such as human-robot collaboration and predictive maintenance, are frequently explored, demonstrating a focus on practical implementation and solutions to industry challenges.

Digital twins are experiencing rapid and mature development, supported by high-quality publications in leading journals. The research focus is shifting from basic concepts to more sophisticated and integrated applications, such as digital twins for human-centric manufacturing and cognitive digital twins. This development reflects the evolution of manufacturing technology, where digitalization and automation are no longer mere trends but fundamental elements for achieving efficiency, resilience, and sustainable innovation (Table 3).

Table 3. Descriptive Study of Biblioshiny

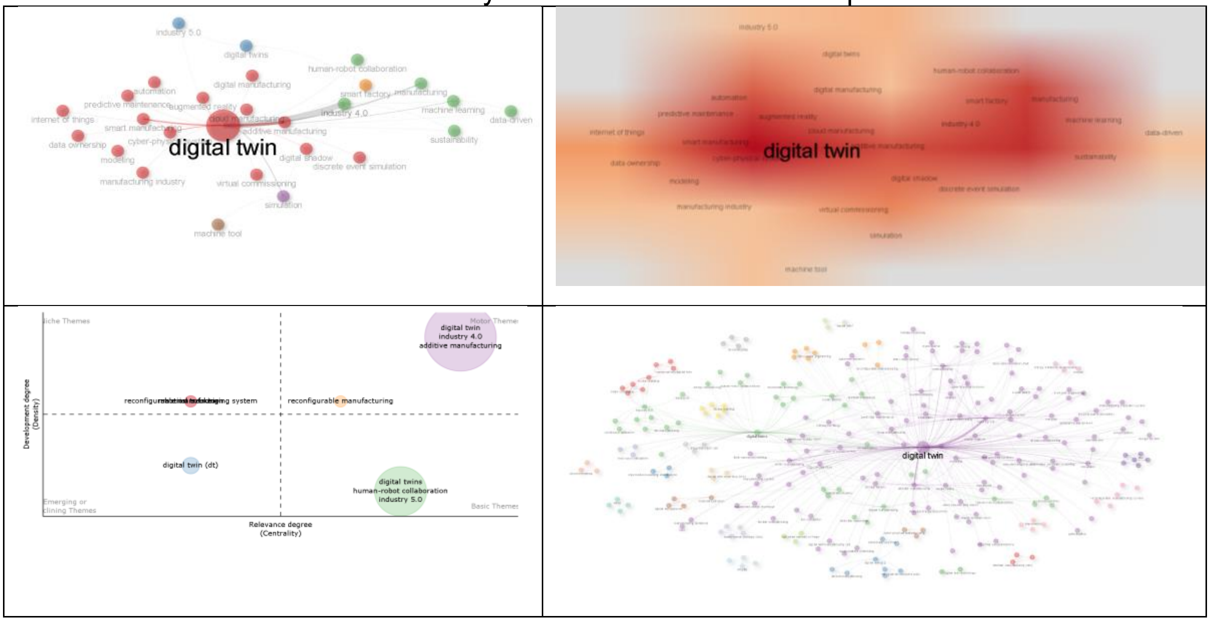




3.1.3. Keyword Network Modeling

The dataset reveals a comprehensive landscape of digital twin research, highlighting key nodes, clusters, and citation metrics. The most prominent node is "digital twin" itself, with a Betweenness centrality of 17,221,749 and a PageRank of 0.127, indicating its central role within the network. Other significant nodes include "digital twins," "industry 4.0," "industry 5.0," and "smart factory," reflecting their importance in the evolving manufacturing landscape. Clusters are categorized based on thematic similarities, with Cluster 4 ("digital twin") having the highest frequency (179 occurrences) and a substantial Betweenness centrality (17,221,749). This indicates a dense focus on digital twin applications in manufacturing and industry 4.0 contexts. Similarly, Cluster 3 ("digital twins") shows high centrality, emphasizing its relevance across various research themes such as AI integration, predictive maintenance, and virtual commissioning. The citation data from various articles further underscores the prominence of digital twins in current research. Notably, recent publications (2024-2026) reflect ongoing interest, covering topics such as AI-enhanced digital twins, Industry 5.0 integration, smart manufacturing, and real-time monitoring. Overall, the analysis indicates a vibrant research community centered around digital twin technologies, with a strong emphasis on Industry 4.0 and the emerging Industry 5.0 paradigms. The convergence of IoT, AI, and simulation techniques continues to shape innovative manufacturing solutions, driving both theoretical advances and practical implementations in digital twin development (Table 4).

Table 4. Key Network and Thematic Maps



3.2. Discussion

This research focuses on developing an adaptive and scalable Digital Twin (DT) for distributed manufacturing, combining data-driven ML, synthetic-data augmentation, and real-time control (MPC/closed-loop). The main gaps are: (a) high dependence on real-world data quality, (b) lack of validation of complex and distributed scenarios, (c) expensive real-time computing, and (d) limited interoperability across platforms. The present study aims to design a modular DT architecture that is (i) resilient to variable data quality (using synthetic data + uncertainty-aware models), (ii) capable of real-time decision making via surrogate models/MPC, and (iii) scalable in hybrid environments (legacy + smart machines) (Figure 2).

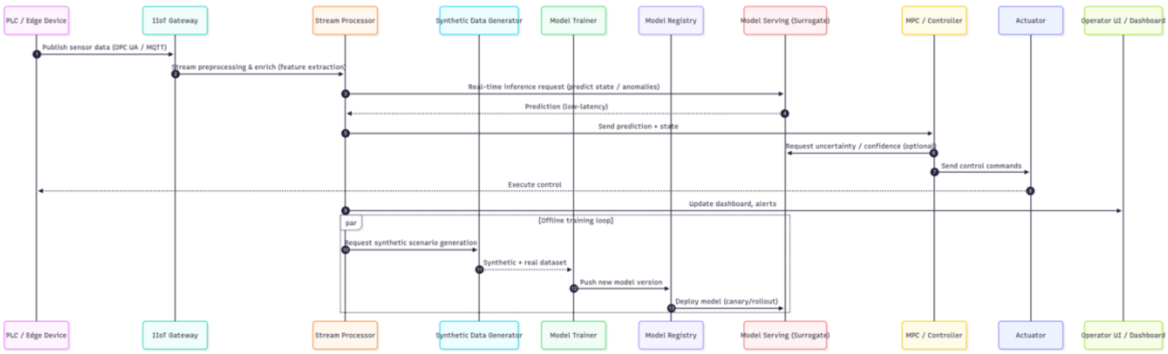


Figure 2. Digital Twin Data-to-Decision Sequence

The digital twin research agenda focuses on developing adaptive and scalable architectures for distributed manufacturing through the integration of AI, ML, big data, and real-time model surrogates, with the data flow from sensor–gateway–stream processor–model serving–controller–actuator depicted in a sequence diagram; this research includes the utilization of synthetic data to improve generalization, the application of lightweight predictive models to overcome control latency, and IIoT interoperability pipelines that enable gradual adoption on legacy machines, while the main contribution is directed at improving the accuracy, efficiency, and sustainability of modern manufacturing systems while still considering the limitations of data, computing, and industrial-scale validation.

4. Conclusions and Recommendations

A review of the Digital Twin literature in manufacturing shows that this technology has developed into a key foundation for supporting smart manufacturing, contributing to increased productivity, efficiency, flexibility, sustainability, and human-robot collaboration. Proposed methodologies include data-driven approaches, AI/ML integration, knowledge graphs, and predictive simulation, all of which strengthen DT's role as a bridge between the physical and virtual worlds. However, significant challenges remain, including varying data quality, high computational requirements, limited validation in real-world settings, and the lack of established methodological standards. For academics, this study emphasizes the need for an interdisciplinary approach to developing DT, integrating data science, systems engineering, artificial intelligence, and human engineering. For industry, the application of DT can provide a competitive advantage in the form of more adaptive, predictive, and sustainable production processes, although this requires adequate investment in digital infrastructure and human resource readiness. For policymakers, the gap between academic research and industrial implementation indicates the need for more concrete standards, regulations, and practical guidance. Future research should focus on three main areas: first, strengthening data quality and integration through multimodal approaches, IoT, and data security; Second, the development of lighter, scalable, real-time DT models without sacrificing accuracy; and third, industry-scale validation through cross-sector trials to establish methodological standards that can be widely adopted. Furthermore, other important agenda items include examining aspects of human-robot collaboration, AI ethics in DT, and exploring integration with other emerging technologies such as industrial metaverses and LLM for natural language-based decision-making.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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CRediT authorship contribution statement

Wawan Setyo Budi, Anang Siswanto, Saiful Rowi: Conceptualization, Methodology, Data Curation, Writing – Original Draft Preparation. Wawan Setyo Budi, Anang Siswanto: Validation, Formal Analysis, Writing – Review & Editing. Wawan Setyo Budi, Anang Siswanto: Investigation, Visualization, Project Administration. Muhammad Ainul Fahmi: Resources, Software, Data Analysis. Anang Siswanto: Supervision, Writing – Review & Editing.

Data Availability Statement

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