Sensors & Transducers, Vol. 270, Issue 3, September 2025, pp. 1-10

Sensors & Transducers
Published by IFSA Publishing, S. L., 2025
http://www.sensorsportal.com

Artificial Intelligence and Digital Twins for Sustainable Production Systems

[1, *] Asmae ABADI, [2] Chaimae ABADI and [3] Mohammed ABADI
[1] Euromed University of Fes, UEMF, Morocco
[2] ENSAM, Moulay Ismail University, Meknes, Morocco
[3] Team Optimization of Production Systems and Energy, Laboratory of Advanced Research in Industrial and Logistic Engineering (LARILE), Hassan II University of Casablanca, Morocco
[*] E-mail: asmae.abadi@gmail.com

Received: 15 July 2025 / Revised:20 August / Accepted: 25 August 2025 / Published: 15 September 2025

Abstract: Artificial Intelligence (AI) and Digital Twin (DT) technologies are increasingly converging to support the transition toward sustainable and resilient manufacturing. This study conducts a comprehensive analysis of 118 high-impact indexed publications (2013–2025) using bibliometric, thematic clustering, and content analysis methods to map the evolution, applications, and gaps at the intersection of AI-DT and sustainable manufacturing. The results identify five core thematic clusters reflecting a shift from process-level optimization to system-wide sustainability: i) Environmental Intelligence and Energy Efficiency, ii) Industrial Cyber-Physical Infrastructure, iii) Intelligent Human–Machine Collaboration, iv) Smart Sustainable Manufacturing, and v) Automation and Predictive Maintenance. The analysis reveals that research primarily targets energy/resource efficiency, smart decision-making, and Industry 5.0 human-centric systems, with Machine Learning (29.2%), Cyber-Physical Systems (17.7%), and IoT (14.4%) as dominant associated enabling technologies. Despite notable progress, critical gaps persist in cybersecurity (3.1%), explainable AI, and the integration of lifecycle and circular economy principles. This study highlights the urgent need for interoperable, secure, and human-aware AI-DT architectures and proposes a capability framework to guide future developments. The insights provide a strategic roadmap for researchers and practitioners aiming to unlock the full potential of AI and digital twins in driving sustainable industrial transformation.

Keywords: Sustainable development, Industry, Innovation and infrastructure, Sustainable production, Artificial intelligence, Digital twins, Responsible consumption and production.

1. Introduction

In today's global landscape, marked by pressing environmental challenges and increasing regulatory demands, sustainability and environmental performance have become essential criteria in the development of industrial products. Modern industries, driven by technological advancements from Industry 4.0 and evolving toward Industry 5.0 paradigms, strive to harmonize innovation, efficiency, and ecological responsibility [1,2] This entails integrating sustainable development principles and promoting responsible consumption and production throughout the product lifecycle.

Among the transformative technologies enabling this shift, Artificial Intelligence (AI) and Digital Twins stand out as pivotal tools [3]. They provide unprecedented capabilities for real-time monitoring, simulation, and optimization of manufacturing processes, directly impacting energy efficiency, resource utilization, and emission [4, 5]. Furthermore, their integration within cyber-physical systems supports the design of smart, adaptive manufacturing environments aligned with affordable and clean energy objectives.

This paper systematically clusters and synthesizes the rapidly expanding body of research at the intersection of Artificial Intelligence, Digital Twins, and sustainable manufacturing, with a particular focus on environmental performance optimization. Unlike prior studies that often address these technologies separately [6, 7] or focus on isolated applications [8, 9], this work integrates technological and ecological perspectives to provide a holistic understanding of how AI and Digital Twins jointly enable real-time, adaptive, and multi-objective optimization in industrial product development.

By identifying thematic clusters, current challenges, and emerging trends, the study offers a structured roadmap for researchers and practitioners aiming to overcome existing barriers such as data heterogeneity, scalability, and the lack of standardized evaluation frameworks. Ultimately, this study advances the academic discourse and supports practical implementation strategies for fostering resilient, eco-efficient, and sustainable manufacturing ecosystems aligned with global sustainability goals.

The paper is structured as follows: Section 2 provides background and definitions related to AI, Digital Twins, and sustainability in manufacturing. Section 3 presents the methodology then Section 4 and 5 presents the results of the bibliometric, cluster-based, thematic and content analyses. Section 6 outlines future research directions and emerging trends, including the shift towards Industry 5.0. Finally, Section 6 concludes with a summary of the study's contributions and implications for sustainable industrial product development.

2. Background

The convergence of Artificial Intelligence (AI) and Digital Twin (DT) technologies has emerged as a pivotal enabler of Smart Manufacturing (SM), driving transformative improvements in efficiency, flexibility, and sustainability. Digital Twins provide real-time virtual replicas of physical assets and processes [9], enabling continuous monitoring, simulation, and predictive analysis [10]. When augmented with AI capabilities, such as machine learning, deep learning, and advanced analytics, DTs evolve into intelligent systems capable of autonomous decision-making, anomaly detection, and proactive optimization.

This synergistic integration unlocks unprecedented potential for enhancing manufacturing operations, including improved quality control [11], predictive maintenance [12], energy efficiency [13], and supply chain resilience [14]. The reviewed literature highlights several core benefits: enhanced system visibility, faster and more accurate decision support, and adaptive responses to dynamic manufacturing environments.

However, despite the rapid growth of individual research streams on AI, DT, and SM, no prior work has comprehensively gathered and analyzed the intersection of all three in a unified, systemic framework. This study fills that gap by systematically mapping current AI-driven DT applications across key smart manufacturing domains, identifying the most prevalent AI techniques, enabling technologies, and sustainability-oriented outcomes.

By uncovering prevailing trends, open challenges, and critical research gaps, the review provides a foundational understanding and a forward-looking agenda to guide future innovations in the systemic engineering of AI-powered Digital Twins for smart, sustainable manufacturing.

3. Methodology

This study adopts a structured literature review methodology comprising a rigorous four-step process, guided by established theoretical frameworks as proposed by Tranfield et al., Aria et al. and Seuring et al. [45]. The methodology ensures systematic identification, screening, analysis, and synthesis of relevant research, thereby enhancing the reliability and reproducibility of the review.

The data source used for this work is Scopus database, chosen for its comprehensive coverage of high-quality peer-reviewed literature. A comprehensive keyword search targeting Artificial Intelligence, Digital Twins, sustainable manufacturing, and environmental performance yielded an initial set of 276 documents spanning the period from 2013 to 2025. The advanced search string constructed was: (TITLE-ABS-KEY ("artificial intelligence" OR "machine learning" OR "deep learning") AND TITLE-ABS-KEY ("digital twin") AND TITLE-ABS-KEY ("green" OR "sustainability" OR "sustainable") AND TITLE-ABS-KEY ("manufacturing" OR "industry" OR "industrial" OR "robotic")).

Following initial retrieval, a thorough screening process was undertaken to remove duplicates, non-peer-reviewed publications, conference proceedings, book chapters, and articles not directly relevant to the study's thematic focus or not written in English. This refinement resulted in a final sample of 118 documents suitable for in-depth analysis (Fig. 1).

The 118 selected documents were published across 95 sources including journals. The corpus demonstrates a robust annual growth rate of 80.86%, with an average citation rate of 9.37 per document, reflecting strong research interest and impact in AI-DT for Sustainable Manufacturing systems.

The dataset includes contributions from 506 authors, averaging 4.54 co-authors per publication, and international collaborations account for 41.53% of co-authorships, underscoring the global nature of research efforts as presented in Table 1.

Content analysis techniques were applied to the corpus to extract meaningful patterns and themes. Bibliometric indicators including publication trends, authorship statistics, and collaboration networks were analyzed to characterize the intellectual structure of the field. Specifically, keyword co-occurrence, thematic clustering and content analysis were employed to identify major research clusters and emerging research trends and challenges within the domain.

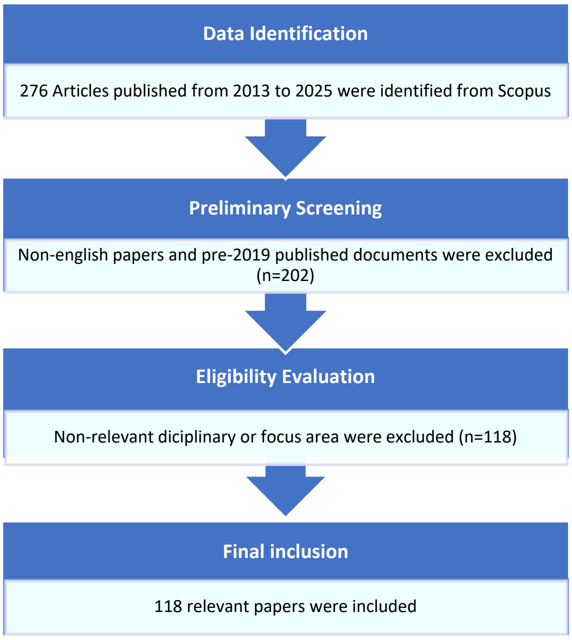


Fig. 1. The structured methodology of the study.

Table 1. Main information on the bibliometric Data.

Parameter name	Results
Time span	2013:2025
Sources (Journals, Books, etc.)	95
Documents	118
Annual Growth Rate %	80.86
Average citations per document	9.373
Authors	506
Co-Authors per Document	4.54
International co-authorships %	41.53

4. Results of Bibliometric Analysis

4.1. Annual Scientific Production

To explain the choice of the time span 2019:2025 and exclusion of works published before 2019, the annual distribution of the initial 276 publication annual evolution was analyzed in Fig. 2. In fact, the annual production demonstrates a sharp upward trajectory in scholarly interest in the integration of Artificial Intelligence (AI) and Digital Twins (DT) for sustainable manufacturing over the past decade. From modest beginnings in the early 2010s, with just isolated studies between 2013 and 2017, the field has experienced exponential growth beginning in 2020. This trend reflects a broader industrial and academic shift toward digital transformation and sustainability-driven innovation.

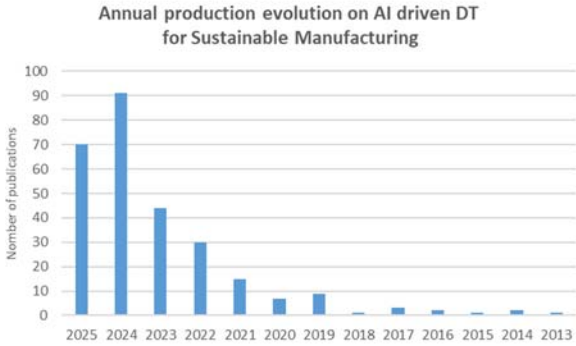


Fig. 2. Annual production evolution on AI driven DT for Sustainable Manufacturing.

A noticeable inflection point occurs in 2021, where the number of publications doubled from 15 in 2021 to 30 in 2022, and then surged to 44 in 2023. This escalation coincides with the global emphasis on Industry 4.0 technologies, the acceleration of green transition policies, and the increasing adoption of AI-based tools for environmental optimization in manufacturing contexts.

The peak of publication activity appears in 2024 (91 publications) and 2025 (70 publications, ongoing), suggesting that research in this area has reached critical momentum. These figures reflect the maturity and multidisciplinary nature of the domain, intersecting machine intelligence, cyber-physical systems, environmental science, and industrial engineering.

The growth rate, particularly between 2020 and 2025, indicates not only an expanding research community but also growing recognition of AI-DT integration as a strategic lever for real-time environmental performance optimization, resource efficiency, and decarbonized industrial systems. This bibliometric signal highlights a research field in rapid development, with increasing contributions from academia, applied research institutions, and cross-sector industrial partnerships.

4.2. Source Distribution

The distribution of articles across journals reveals a diverse and interdisciplinary research landscape, reflecting the broad applicability of AI and Digital Twins in sustainable manufacturing (Fig. 3). While no single journal dominates, Journal of Intelligent Manufacturing leads with 3 articles, followed by a group of well-regarded journals: Applied Sciences, IEEE Access, Sensors, Sustainability, and Robotics and Computer-Integrated Manufacturing, each contributing 2 articles. The presence of sources from fields such as engineering, energy and process industries underscores the cross-sectoral relevance of the topic. This dispersion highlights the fragmented yet growing scholarly interest in converging intelligent systems and environmental performance within manufacturing ecosystems.

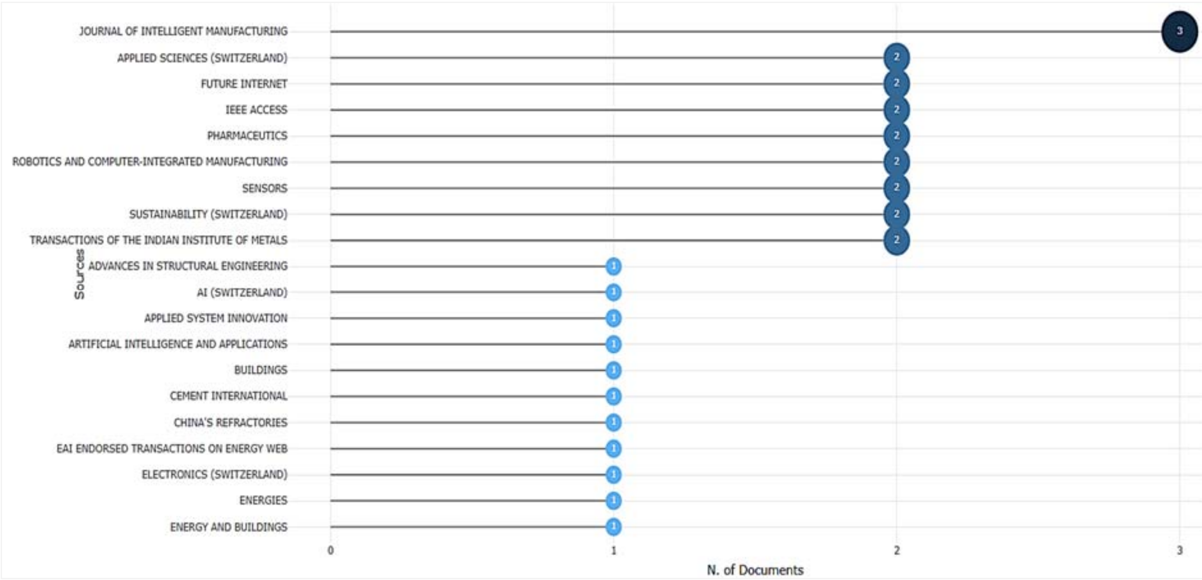


Fig. 3. Top 20 journals publishing on AI driven DT for Sustainable Manufacturing

4.3. Most Cited Contributions of AI-DT Integration to Sustainable Manufacturing

The review of the most cited research reveals that AI-enhanced digital twin (DT) technologies have been instrumental in advancing sustainable manufacturing across various domains (Table 2). Among the most impactful contributions, Arsiwala et al. in [15] achieved high visibility with a DT framework integrating AI, BIM, and IoT for real-time monitoring and predictive control of CO_2 emissions in buildings, significantly supporting net-zero initiatives and sustainable retrofitting (106 citations, TC/year: 35.33). [16] advanced the field by proposing a socio-cyber-physical system (SCPS) that integrates AI, blockchain, cobots, and digital twins to facilitate the transition toward Industry 5.0, emphasizing human-centric and resource-efficient manufacturing (95 citations, TC/year: 47.5).

In the energy and mobility sector, Rimal et al. developed in [17] a smart EV charging system that employs DT and Internet of Vehicles (IoV) concepts to manage peak demand and grid stability, thereby enhancing sustainable energy distribution (62 citations, TC/year: 15.5). Huang et al. introduced a hybrid learning-based DT architecture to enhance real-time process control and quality monitoring on the shop floor, addressing adaptability and resource efficiency in dynamic manufacturing environments (57 citations, TC/year: 19.0). In robotics, Hu et al. demonstrated in [19] the deployment of a CNN-integrated DT for intelligent robotic grasping, improving precision and reducing operational waste (25 citations, TC/year: 6.25). Lastly, Costa et al. developed in [20] an adaptive DT for pressure swing adsorption (PSA) systems, incorporating online learning and uncertainty tracking to improve performance and sustainability in complex, cyclic chemical processes (15 citations, TC/year: 7.5).

These highly cited works collectively illustrate the breadth of AI-DT applications and their substantial contributions to optimizing energy use, reducing emissions, enhancing product quality, and enabling adaptive, data-driven manufacturing processes aligned with sustainability goals. While the most cited works illustrate the growing potential of AI-integrated digital twins to advance sustainable manufacturing, a critical examination reveals important nuances and limitations.

These studies successfully demonstrate proof-of-concept implementations across sectors such as energy, mobility, construction, and advanced manufacturing, showcasing benefits like emissions reduction, process adaptability, and resource efficiency. However, many contributions remain at the prototype or pilot stage, with limited evidence of large-scale deployment or long-term environmental impact. Moreover, several approaches are heavily context-dependent, requiring high-quality data streams, robust connectivity, and domain-specific expertise factors that can limit scalability and generalization. The integration of advanced AI models, such as hybrid learning and uncertainty-aware systems, while promising, introduces challenges in transparency, interpretability, and computational cost.

Table 2. Most Cited Contributions of AI-Digital Twin Integration to Sustainable manufacturing.

Ref.	Journal	TC/Year	Norm. TC	AI-DT Technologies	Application Focus	Contribution to Sustainable Manufacturing
[15]	Energy and Buildings	35.3	5.24	DT + IoT + BIM + ML + Dashboard	Smart Building Operations & Retrofitting	Predictive CO_2 monitoring and data-driven retrofitting for net-zero goals.
[16]	Journal of Intelligent Manufacturing	47.5	12.63	DT + AI + Blockchain + Edge + SIoT + Cobots	Industry 5.0 / Smart Value Chains	Human-centric meta manufacturing for resilient and sustainable systems.
[17]	Energies	15.5	4.37	DT-IoV + AI + Blockchain + Cloud + Smart Charging	Smart Energy / Mobility	Optimized EV charging and energy management for sustainable infrastructure.
[18]	Robotics and Computer-Integrated Manufacturing	19.0	2.82	Hybrid AI-DT + Digital Thread + Metadata	Shopfloor & Real-Time Process Control	Improves real-time process reliability and reduces waste.
[21]	Transactions of the Indian Institute of Metals	7.86	1.00	DT + IoT + AI + ML	Aluminium Smelting	Predictive control enhances energy efficiency and reduces emissions.
[22]	Journal of Vacuum Science & Technology B	20.0	5.32	AI-DT for Plasma Etching + Hybrid Modeling	Semiconductor Manufacturing	Energy-efficient, precise plasma etching addressing microelectronics sustainability.
[19]	Robotics and Computer-Integrated Manufacturing	6.25	1.76	DT for Robotic Grasping	Smart Robotics	Enhances robotic precision and reduces human error in automation.
[20]	Engineering Applications of Artificial Intelligence	7.5	1.99	Adaptive DT + Online AI + Uncertainty Management	Process Eng. / Gas Separation	Real-time optimization improves PSA system efficiency and reduces waste.

Crucially, while AI-DT systems are positioned as enablers of net-zero goals and Industry 5.0 ideals, few studies provide quantifiable metrics or life-cycle assessments to substantiate their sustainability claims. Thus, future research must move beyond technological validation toward system-wide integration, policy alignment, and cross-sectoral impact measurement. A more critical and evidence-driven approach is needed to truly position digital twins with AI not just as technological tools, but as transformative levers for industrial sustainability.

5. Results of the Thematic Cluster Analysis

5.1. Cluster-based Analysis of the Technological and Ecological Integration

To obtain a comprehensive understanding of the current research landscape surrounding AI-driven Digital Twin (DT) applications in sustainable manufacturing, a thematic clustering of high-frequency keywords and co-occurrences was conducted (Fig. 4 and Fig. 5). The analysis revealed five major thematic clusters, each representing a critical research strand (Table 3). This section presents a critical examination of the thematic focus, interdependencies, and research gaps identified across these clusters, with emphasis on their contribution to smart and sustainable manufacturing paradigms.

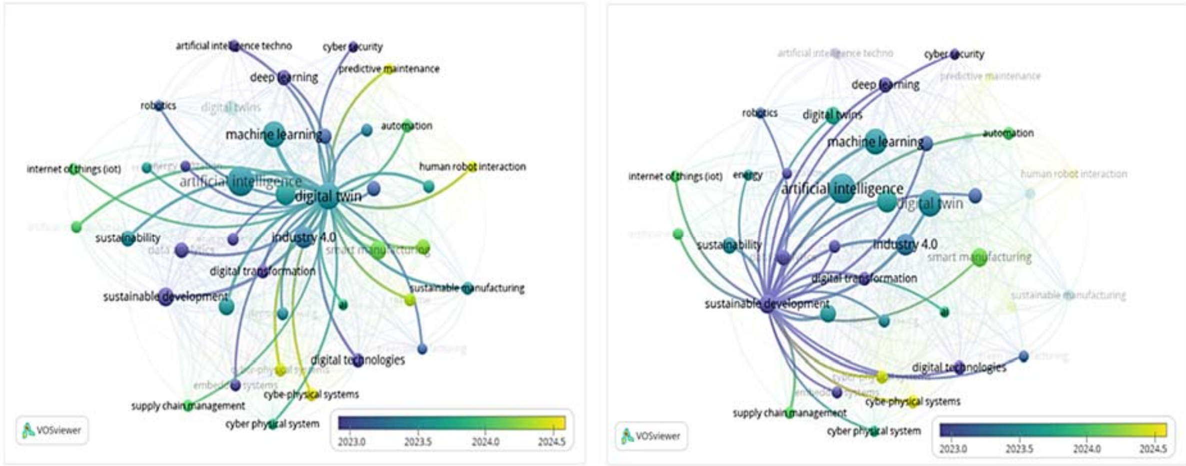
5.1.1. Cluster 1: Technological Foundations for Sustainability - Aware Digital Infrastructure

Cluster 1, composed of high-frequency terms such as AI, Internet of Things, DT, energy consumption, efficiency, and sustainable development, represents the core digital and sustainability-enabling infrastructure of modern manufacturing.

These technologies collectively form the data-driven backbone required to enable real-time sensing, simulation, and optimization of industrial processes. From a sustainability perspective, this cluster provides the essential capabilities to monitor and reduce resource consumption, greenhouse gas emissions, and operational inefficiencies. However, many studies remain technology-centric, lacking robust integration with formal environmental performance frameworks such as ISO 14001, GHG Protocols, or Life Cycle Assessment (LCA) standards.

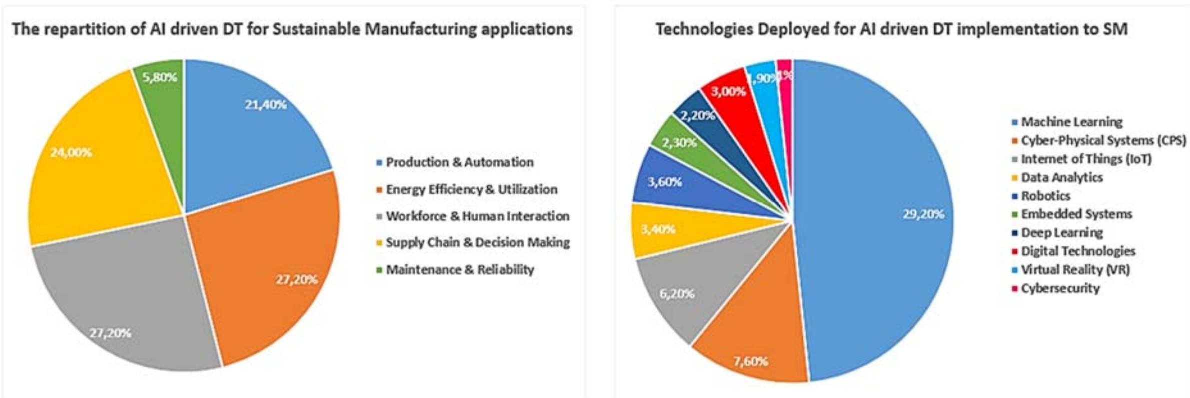
This cluster also addresses the practical implications for sensors integration. In fact, the integration of sensors within AI-DT ecosystems plays a pivotal role in enabling real-time data acquisition, monitoring, and adaptive decision-making in sustainable manufacturing. By deploying interconnected sensor networks, manufacturers can capture key operational, environmental, and energy-related parameters, which feed into digital twins for predictive analytics and optimization.

This facilitates proactive maintenance, resource efficiency, and human-centered process management, while ensuring that AI-driven insights are actionable and aligned with sustainability goals. Moreover, careful consideration of sensor placement, interoperability, and cybersecurity is essential to fully leverage AI-DT.



a) b)

Fig. 4. AI-driven DT (a) and Sustainable Development connected key clusters (b)



a) b)

Fig. 5. AI driven DT for sustainable Manufacturing application domains (a) and integrated industry 4.0 technologies (b).

5.1.2. Cluster 2: Intelligent Infrastructure for Environmentally-Informed Decision-Making

Cluster 2 encompasses cyber-physical systems, data analytics, decision making, embedded systems, and Industry 4.0. These elements define the intelligent decision infrastructure enabling data-driven and adaptive manufacturing environments. The integration of AI and CPS (Cyber-Physical System) allows for the continuous collection, processing, and interpretation of data across physical and digital layers. By embedding environmental data into predictive and prescriptive analytics models, manufacturers can make eco-informed decisions, such as adjusting machine operations to reduce energy during peak loads. Despite these potentials, a key limitation lies in the underutilization of environmental metrics in decision-support systems, with most studies prioritizing productivity and cost efficiency over environmental efficiency.

5.1.3. Cluster 3: Advanced AI and Human-Machine Collaboration for Sustainability Goals

Cluster 3 focuses on deep learning, intelligent robots, virtual reality, engineering education, and learning systems. This cluster reflects the emergence of cognitive DT capable of not only reacting to but learning from operational data.

5.1.4. Cluster 4: Industry 5.0 and the Strategic Shift toward Sustainable Value Creation

Cluster 4 comprises smart manufacturing, industry 5.0, green manufacturing, sustainable manufacturing, and machine learning. It marks the shift from a purely technological orientation to one that integrates human values, sustainability, and long-term strategic transformation. Industry 5.0 emphasizes not only efficiency and automation but also personalization, resilience, and environmental stewardship. Within a systemic sustainability framework, this cluster serves as a strategic enabler for aligning DT and AI implementations with circular economy goals and low-carbon strategies. It supports the reconfiguration of production lines for eco-design, closed-loop supply chains, and real-time environmental feedback integration. Nonetheless, many contributions remain conceptual, with limited real-world deployment or measurable sustainability impact. Furthermore, there is a lack of policy-aligned digital transition roadmaps that incorporate climate targets and green certifications.

Table 3. Integration of AI and Digital Twin potentialities for Sustainability in Manufacturing.

Sustainability Requirement	AI Capabilities	Digital Twin Capabilities	Synergistic Impact / Contribution	References
1. Resource Efficiency	Predictive models (XGBoost, LSTM), reinforcement learning for scrap reduction	Virtual modeling of resource flows, process-material simulations	AI anticipates waste; DT simulates scenarios enabling adaptive resource use	[23, 24, 25]
2. Energy Optimization	Load forecasting (LSTM, ARIMA), evolutionary algorithms for scheduling	Real-time energy profiling, sensor integration	Predictive load balancing and virtual control loops enhance energy efficiency	[26, 27] [16]
3. Emissions Prediction & Control	Anomaly detection (autoencoders), emission classification (SVM, RF)	Real-time emissions monitoring, feedback loops	Early warnings via AI with DT virtual validation of emission control strategies	[28,29]
4. Lifecycle & Circularity	Clustering for reuse/remanufacturing, EoL decision systems	Full lifecycle modeling, degradation & circular flow tracking	DT models lifecycle; AI optimizes circular recovery and reuse strategies	[30, 31]
5. Sustainable Process Optimization	Reinforcement learning (DDPG, PPO), hybrid rule-ML systems	Real-time process simulation, environmental impact scenarios	AI dynamically tunes parameters; DT validates against ecological constraints	[32, 47]
6. Supply Chain Sustainability	Multi-objective optimization (NSGA-II), graph neural networks	Digital supply chain models, green logistics simulation	Joint optimization of emissions, delays, and green sourcing strategies	[33, 34, 35]
7. Predictive Maintenance	Deep learning for Remaining Useful Life, Bayesian diagnostics	Virtual sensor integration, asset behavior modeling	Proactive maintenance reduces downtime and energy waste	[36, 37, 38]
8. Real-Time Eco-Decisions	Fuzzy logic, multi-agent systems for adaptive decisions	Real-time visualization, KPI dashboards	Improved responsiveness and alignment with eco-objectives through joint AI-DT decision-making	[39, 40, 41]
9. Worker Safety & Ergonomics	Computer vision (YOLO, ResNet), activity & posture prediction	Human-in-the-loop ergonomic DTs, risk scenario testing	Safer, sustainable human-machine interactions via AI-informed DT	[42, 43]
10. Sustainability Audit	NLP for report automation (BERT), ESG analytics	Data aggregation, dashboards	Automated traceability and intelligent reporting ensure compliance	[44, 46]

5.1.5. Cluster 5: Operational Resilience and Cybersecurity in Sustainable Smart Factories

Cluster 5 includes automation, cybersecurity, predictive maintenance, and overlaps with machine learning. It is centered on the sustainability of operations, specifically in terms of system reliability, autonomous maintenance, and secure data infrastructure. Predictive maintenance, powered by AI-integrated DTs, enables companies to prevent breakdowns, extend equipment lifespans, and reduce unnecessary energy use. The role of this cluster in environmental performance is particularly significant in reducing downtime-associated waste, energy leaks, and resource overuse. Yet, this cluster rarely addresses green cybersecurity or energy-aware automation, and environmental metrics are still not systematically embedded into predictive models.

5.2. Application sectors of AI-driven Digital Twins in Sustainable Manufacturing

The content analysis of the reviewed literature highlights five primary application sectors where AI-driven Digital Twins (DTs) contribute to Sustainable Manufacturing (SM), excluding core conceptual terms such as AI, DT, and general sustainability themes (Fig. 5a). Energy efficiency and utilization (27.2%) and workforce and human interaction (27.2%) emerge as the most addressed domains. Production and automation (21.4%) concentrate on synchronizing real-time operations and enabling adaptive manufacturing systems. Maintenance and reliability, despite its industrial maturity, receives limited attention (5.8%), potentially indicating research saturation or a redirection toward broader systemic challenges. Overall, the literature distribution reveals a growing integration of socio-technical elements and anticipatory intelligence in SM, underscoring the evolving role of AI-DT technologies beyond technical optimization.

5.3. Enabling Technologies Supporting AI-DT Integration in SM

From a technological standpoint, the reviewed papers deploy a broad range of digital and cyber-physical technologies that support the operationalization of AI-driven Digital Twins in Sustainable Manufacturing. Machine Learning (29.2%) emerges as the most frequently used technology, confirming its central role in prediction, optimization, and system intelligence (Fig. 5b). However, most studies do not clearly distinguish between basic and advanced ML methods, highlighting a need for greater methodological rigor and transparency. Alarmingly, cybersecurity (1.0%) is the least addressed, despite the growing vulnerability of interconnected industrial systems. This critical gap calls for a stronger emphasis on security-by-design strategies in future AI-DT ecosystems. In sum, while the technological foundation for AI-DT integration in SM is evident, a more holistic and interdisciplinary approach—combining performance, interoperability, human factors, and cybersecurity—is essential to fully unlock the transformative potential of digital twins in sustainable industry.

6. Future Trends and Research Agenda in AI Driven DT Development for Sustainable Manufacturing

The convergence of Artificial Intelligence (AI) and Digital Twins (DTs) is driving a new era of intelligent, adaptive, and sustainable manufacturing systems. Key future trends shaping this evolution are presented in Table 3. To overcome these limitations, future research should prioritize:

- Systemic Engineering Frameworks that unite AI lifecycle management and DT modeling in a unified, modular approach.
- Advanced Data Management Techniques for real-time, secure, and semantically enriched data fusion across heterogeneous sources.
- Interpretable and Trustworthy AI tailored for DTs, incorporating uncertainty quantification and user-centered feedback.
- Multidisciplinary Co-Design Platforms that foster collaboration among engineers, AI specialists, and sustainability experts.
- Robust and Adaptive Learning Algorithms capable of online adaptation, anomaly detection, and continual learning under evolving manufacturing scenarios.
- Lifecycle and Sustainability Integration by embedding environmental KPIs, material flow data, and circular economy metrics into DT models.

7. Conclusion and Perspectives

This study integrates bibliometric, thematic cluster, and content analyses of 118 high-impact indexed papers to comprehensively map the landscape of AI-driven digital twins in sustainable manufacturing. The findings highlight that most applications concentrate on energy and resource efficiency, smart decision-making, and human-centric Industry 5.0 systems. Key enabling technologies include Artificial Intelligence, Cyber-Physical Systems, and Machine Learning. The research identifies five core thematic clusters reflecting a progression from technical process optimization toward system-wide sustainability and resilience. Content analysis further reveals a strong focus on energy efficiency and human–machine collaboration, followed by supply chain and decision-making and automation. Machine Learning leads technologically (29.2%), with Cyber-Physical Systems (17.7%) and IoT (14.4%) enabling real-time interaction and integration. Despite these advances, critical gaps persist in cybersecurity (3.1%), explainable AI, and comprehensive lifecycle assessment, underscoring urgent research needs.

Looking forward, advancing AI-DT for sustainable manufacturing demands interoperable, secure, and human-aware architectures that deeply integrate environmental KPIs and circular economy principles. Real-world validated implementations, particularly in energy-intensive and resource-constrained sectors, are essential to unlock the full transformative potential of AI-driven digital twins for resilient and responsible industrial ecosystem.

References

[1]. O. Mata, P. Ponce, C. Perez, M. Ramirez, B. Anthony, B. Russel, *et al.*, Digital twin designs with generative AI: crafting a comprehensive framework for manufacturing systems, *Journal of Intelligent Manufacturing*, 2025, 24 p.

[2]. V. Karkaria, Y. K. Tsai, Y. P. Chen, W. Chen, An optimization-centric review on integrating artificial intelligence and digital twin technologies in manufacturing, *Engineering Optimization*, Vol. 57, No. 1, 2025, pp. 161–207.

[3]. A. Abadi, C. Abadi, M. Abadi, Intelligent decision making and knowledge management system for Industry 4.0 maturity assessment, *Statistics, Optimization & Information Computing*, Vol. 14, Issue 1, 2025, pp. 207–228.

[4]. L. Shittu, A. D. Samuel, C. J. Ozurumba, Employing digital twins and AI to advance sustainable outcomes, *Journal of Artificial Intelligence, Machine Learning & Data Science*, Vol. 3, No. 1, 2025, 5 p.

[5]. I. Honcharenko, M. Oskina, S. Chumachenko, O. Lunova, O. Targonskyi, Odour emissions from agricultural industries—implications for environmental safety and local sustainability, *Ecological Engineering & Environmental Technology*, Vol. 26, No. 1, 2025, pp. 111–123.

[6]. G. Singh, R. Rajesh, S. C. Misra, S. Singh, Analyzing the role of digital twins in developing a resilient sustainable manufacturing supply chain: A grey influence analysis (GINA) approach, *Technological Forecasting and Social Change*, Vol. 209, 2024, Article 123763.

[7]. K. Agrawal, P. Goktas, M. Holtkemper, C. Beecks, N. Kumar, AI-driven transformation in food manufacturing: a pathway to sustainable efficiency and quality assurance, *Frontiers in Nutrition*, Vol. 12, 2025, Article 1553942.

[8]. N. Ouahabi, A. Chebak, O. Kamach, M. Zegrari, Leveraging digital twin into dynamic production scheduling: A review, *Robotics and Computer-Integrated Manufacturing*, Vol. 89, 2024, Article 102778.

[9]. M. Resman, N. Herakovič, M. Debevec, Integrating digital twin technology to achieve higher operational efficiency and sustainability in manufacturing systems, *Systems*, Vol. 13, No. 3, 2025, Article 180.

[10]. A. Abadi, C. Abadi, M. Abadi, Bridging the gap between Industry 4.0 readiness and maturity assessment models: an ontology-based approach, *International Journal of Advanced Computer Science & Applications*, Vol. 16, Issue 2, 2025.

[11]. Y. Aniba, M. Bouhedda, M. Bachene, M. Rahim, H. Benyezza, A. Tobbal, DT-enabled quality control through deep learning in industry 4.0, *International Journal of Modelling and Simulation*, 2024, pp. 1–21.

[12]. D. D'Urso, F. Chiacchio, S. Cavalieri, S. Gambadoro, S. M. Khodayee, Predictive maintenance of standalone steel industrial components powered by a dynamic reliability digital twin model with artificial intelligence, *Reliability Engineering & System Safety*, Vol. 243, 2024, Article 109859.

[13]. L. V. Cakir, K. Duran, C. Thomson, M. Broadbent, B. Canberk, AI in energy digital twining: A reinforcement learning-based adaptive digital twin model for green cities, in *Proceedings of the IEEE International Conference on Communications (ICC 2024)*, 2024, pp. 4767–4772.

[14]. D. Ivanov, Intelligent digital twin (iDT) for supply chain stress-testing, resilience, and viability, *International Journal of Production Economics*, Vol. 263, 2023, Article 108938.

[15]. A. Arsiwala, F. Elghaish, M. Zoher, Digital twin with machine learning for predictive monitoring of CO_2 equivalent from existing buildings, *Energy and Buildings*, Vol. 284, 2023, Article 112851.

[16]. X. Yao, N. Ma, J. Zhang, K. Wang, E. Yang, M. Faccio, Enhancing wisdom manufacturing as industrial metaverse for industry and society 5.0, *Journal of Intelligent Manufacturing*, Vol. 35, No. 1, 2024, pp. 235–255.

[17]. B. P. Rimal, C. Kong, B. Poudel, Y. Wang, P. Shahi, Smart electric vehicle charging in the era of internet of vehicles, emerging trends, and open issues, *Energies*, Vol. 15, No. 5, 2022, Article 1908.

[18]. Z. Huang, M. Fey, C. Liu, E. Beysel, X. Xu, C. Brecher, Hybrid learning-based digital twin for manufacturing process: Modeling framework and implementation, *Robotics and Computer-Integrated Manufacturing*, Vol. 82, 2023, Article 102545.

[19]. Z. Hu, L. Hua, X. Qin, M. Ni, Z. Liu, C. Liang, Region-based path planning method with all horizontal welding position for robotic curved layer wire and arc additive manufacturing, *Robotics and Computer-Integrated Manufacturing*, Vol. 74, 2022, Article 102286.

[20]. E. A. Costa, C. M. Rebello, L. Schnitman, J. M. Loureiro, A. M. Ribeiro, I. B. Nogueira, Adaptive digital twin for pressure swing adsorption systems, *Engineering Applications of Artificial Intelligence*, Vol. 127, 2024, Article 107364.

[21]. A. K. Gupta, B. Basu, Sustainable primary aluminium production: Technology status and future opportunities, *Transactions of the Indian Institute of Metals*, Vol. 72, Issue 8, 2019, pp. 2135–2150.

[22]. G. S. Oehrlein, S. M. Brandstadter, R. L. Bruce, J. P. Chang, P. L. Ventzek, Future of plasma etching for microelectronics, *Journal of Vacuum Science & Technology B*, Vol. 42, No. 4, 2024, Article 040802.

[23]. P. Campana, R. Censi, A. M. Tarola, R. Ruggieri, Artificial intelligence and digital twins for sustainable waste management: Review, *Applied Sciences*, Vol. 15, No. 11, 2025, Article 6337.

[24]. S. R. Seyyedi, E. Kowsari, M. Gheibi, A. Chinnappan, S. Ramakrishna, A comprehensive review integration of digitalization and circular economy in waste management by adopting AI approaches, *Journal of Cleaner Production*, Vol. 453, 2024, Article 142584.

[25]. D. B. Olawade, O. Fapohunda, O. Z. Wada, S. O. Usman, O. Ajisafe, B. I. Oladapo, Smart waste management: A paradigm shift enabled by artificial intelligence, *Waste Management Bulletin*, Vol. 5, Issue 1, 2024, pp. 1–7.

[26]. L. Ba, F. Tangour, I. El Abbassi, R. Absi, Analysis of digital twin applications in energy efficiency, *Sustainability*, Vol. 17, No. 8, 2025, Article 3560.

[27]. A. K. Sleiti, J. S. Kapat, L. Vesely, Digital twin in energy industry: Proposed robust digital twin for power plant and other complex capital-intensive large engineering systems, *Energy Reports*, Vol. 8, 2022, pp. 3704–3726.

[28]. J. Yun, S. Kim, J. Kim, Digital twin technology in the gas industry: A comparative simulation study, *Sustainability*, Vol. 16, No. 14, 2024, Article 5864.

[29]. M. O. Agho, N. L. Eyo-Udo, E. C. Onukwulu, A. K. Sule, C. Azubuike, Digital twin technology for real-time monitoring of energy supply chains, *International Journal of Research and Innovation in Applied Science*, Vol. 9, Issue 12, 2024, pp. 564–592.

[30]. P. Bhambri, S. Rani, A. Khang, AI-driven digital twin and resource optimization in Industry 4.0 ecosystem, in *Intelligent Techniques for Predictive Data Analytics*, Springer, 2024, pp. 47–69.

[31]. Z. A. Ali, M. Zain, R. Hasan, H. Al Salman, B. F. Alkhamees, Circular economy advances with artificial intelligence and digital twin: multiple-case study of Chinese industries in agriculture, *Journal of the Knowledge Economy*, 2024, 37 p.

[32]. Q. Min, Y. Lu, Z. Liu, C. Su, Machine learning based digital twin framework for production optimization in petrochemical industry, *International Journal of Information Management*, Vol. 49, 2019, pp. 502–519.

[33]. J. O. Enyejo, O. P. Fajana, I. S. Jok, C. J. Ihejirika, B. O. Awotiwon, T. M. Olola, Digital twin technology, predictive analytics, and sustainable project management in global supply chains for risk mitigation, optimization, and carbon footprint reduction through green initiatives, *International Journal of Innovative Science and Research Technology*, Vol. 9, No. 11, 2024.

[34]. Z. Zhang, T. Qu, K. Zhao, K. Zhang, Y. Zhang, L. Liu, G. Q. Huang, Optimization model and strategy for dynamic material distribution scheduling based on digital twin: A step towards sustainable manufacturing, *Sustainability*, Vol. 15, No. 23, 2023, Article 16539.

[35]. S. S. Kamble, A. Gunasekaran, H. Parekh, V. Mani, A. Belhadi, R. Sharma, Digital twin for sustainable manufacturing supply chains: Current trends, future perspectives, and an implementation framework, *Technological Forecasting and Social Change*, Vol. 176, 2022, Article 121448.

[36]. E. Mikołajewska, D. Mikołajewski, T. Paczkowski, Generative AI in AI-based digital twins for fault diagnosis for predictive maintenance, *Applied Sciences*, Vol. 15, No. 6, 2025, Article 3166.

[37]. J. Henderson, M. Sanders, AI driven predictive maintenance: Reducing downtime and enhancing productivity, Preprint, *Manufacturing Environments*, 2025.

[38]. S. S. Akter, M. M. H. Munna, K. I. H. Turjo, M. A. S. Emon, K. Redwan, M. Ahmed, M. F. A. Al Sohan, IoT-enabled digital twin ecosystem for optimizing maintenance and minimizing downtime in smart manufacturing, in *Proceedings of the 7th International Conference on Industrial Engineering and Operations Management (IEOM Bangladesh)*, Dec. 2024.

[39]. M. Pantelidakis, K. Mykoniatis, Extending the digital twin ecosystem: A real-time digital twin of a LinuxCNC-controlled subtractive manufacturing machine, *Journal of Manufacturing Systems*, Vol. 74, 2024, pp. 1057–1066.

[40]. Z. Liu, Z. Q. Lang, Y. Gui, Y. P. Zhu, H. Laalej, Digital twin-based anomaly detection for real-time tool condition monitoring in machining, *Journal of Manufacturing Systems*, Vol. 75, 2024, pp. 163–173.

[41]. L. Zhang, J. Guo, X. Fu, R. L. K. Tiong, P. Zhang, Digital twin enabled real-time advanced control of TBM operation using deep learning, *Automation in Construction*, Vol. 158, 2024, Article 105240.

[42]. Z. Song, Z. Zhang, J. Wu, Z. Liu, Digital twin technology and ergonomics for comprehensive improvement of safety in the petrochemical industry, *Process Safety Progress*, Vol. 43, Issue 5, 2024, pp. 507–522.

[43]. Q. He, L. Li, D. Li, T. Peng, X. Zhang, Y. Cai, R. Tang, From digital human modeling to human digital twin: Framework and perspectives in human factors, *Chinese Journal of Mechanical Engineering*, Vol. 37, 2024, Article 9.

[44]. I. A. Awodele, E. C. Eze, A. M. G. Municio, M. S. Ramabodu, N. A. Olatunde, Advancing circular economy transition in the Nigeria construction industry through digital twin technology adoption, *Green Technologies and Sustainability*, Vol. 3, 2025, Article 15.

[45]. M. Aria, C. Cuccurullo, bibliometrix: An R-tool for comprehensive science mapping analysis, *Journal of Informetrics*, Vol. 11, Issue 4, 2017, pp. 959–975.

[46]. A. Garg, S. Vemaraju, Enhancing environmental stability through green logistics management: Current trends and future prospects in sustainable logistics performance, *Ecological Engineering & Environmental Technology*, Vol. 26, No. 7, 2024, pp. 68–78.

[47]. J. Mügge, A. Seegrün, T. K. Hoyer, T. Riedelsheimer, K. Lindow, Digital twins within the circular economy: Literature review and concept presentation, *Sustainability*, Vol. 16, No. 7, 2024, Article 2748.