



The Role of Digital Twins in Industrial 5.0: Advancements in Smart Manufacturing and Sustainability

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Abstract. The convergence of digital twins and Industrial 5.0 represents a transformative shift in smart manufacturing, where human-centricity, sustainability, and advanced technologies intersect. This systematic literature review explores the expanding role of digital twins within Industry 5.0, with particular emphasis on their impact on smart manufacturing and sustainable development. The analysis is organized around six major dimensions: human-centered approaches, integration of artificial intelligence and machine learning, sustainability, additive manufacturing, predictive maintenance, and supporting frameworks. By synthesizing existing studies, the review identifies key trends, challenges, and future research directions, highlighting how digital twins connect cyber-physical systems with human operators while improving resource efficiency. A structured and rigorous methodology is applied to select and assess relevant literature, ensuring a thorough evaluation of current progress and emerging possibilities. The findings indicate that digital twins support real-time monitoring, adaptive decision-making, and comprehensive lifecycle management; however, challenges related to interoperability and standardization continue to limit their broader implementation. Increasing attention is being given to human-centric design, reflecting Industry 5.0's focus on collaboration between humans and intelligent systems. In addition, the incorporation of AI strengthens predictive capabilities, while sustainability-oriented applications show considerable promise in minimizing energy use and material waste. The review concludes by identifying gaps in scalable frameworks and ethical considerations, offering practical insights for both researchers and industry professionals. Overall, this study provides a structured basis for future developments in digital twin technologies and underscores their crucial role in advancing intelligent and sustainable manufacturing systems.

Keywords: Digital Twins, Industrial 5.0, Smart Manufacturing, Sustainability, Predictive Maintenance

1. INTRODUCTION

The emergence of Industry 5.0 represents a significant evolution in manufacturing, focusing on the seamless collaboration between human capabilities and advanced cyber-physical technologies [1]. In contrast to Industry 4.0, which primarily emphasized automation and data connectivity, Industry 5.0 highlights the importance of human involvement, environmental sustainability, and system resilience [2]. A key component driving this transformation is the digital twin (DT), which serves as a real-time virtual model of physical systems, processes, or assets, enabling continuous monitoring, simulation, and optimization [3]. Over time, digital twins have progressed from theoretical concepts to essential tools in smart manufacturing, providing new possibilities for improving efficiency, minimizing waste, and encouraging innovation [4]. The industrial landscape is increasingly characterized by complex, interconnected systems where decisions must balance technical, economic, and environmental constraints. Digital twins address these challenges by providing a holistic view of operations, integrating data from sensors, IoT devices, and enterprise systems [5]. For instance, in predictive maintenance applications, digital twins (DTs) utilize both historical and real-time data to forecast potential equipment failures, thereby reducing downtime and optimizing resource usage [6]. Additionally, their capability to model and simulate different operational scenarios supports sustainable initiatives, including energy-efficient production planning and circular economy approaches [7]. The integration of DTs with artificial intelligence (AI) and machine learning (ML) further enhances their functionality by enabling adaptive decision-making and self-regulating system behavior.[8].

Despite these advancements, significant research gaps persist. First, the human-centric dimension of DTs in Industry 5.0 remains underexplored, particularly in terms of ergonomic design and cognitive workload management [9]. Second, while AI-enhanced DTs demonstrate promise, challenges related to data quality, interpretability, and ethical AI use require deeper investigation [10]. Third, existing frameworks for DT implementation often lack scalability, hindering their adoption across diverse manufacturing environments [11]. Finally, the role of DTs in fostering sustainability—beyond energy efficiency—needs systematic evaluation, especially in lifecycle assessment and supply chain transparency [12].

This review is motivated by the pressing need to integrate dispersed knowledge on digital twins in Industry 5.0, connecting theoretical perspectives with real-world applications. By synthesizing interdisciplinary research, we aim to clarify how DTs can harmonize technological advancements with societal and environmental goals. This work contributes to academia and industry by (1) mapping the evolution of DT technologies in smart manufacturing, (2) identifying synergies between human-centric approaches and automation, and (3) proposing pathways for sustainable innovation. The findings will inform policymakers, engineers, and researchers seeking to align industrial progress with the United Nations Sustainable Development Goals (SDGs) [13].

The structure of this paper is as follows: Section 2 outlines the approach used for selecting and analyzing the literature. Section 3 presents the findings, categorized into six key

themes, including research trends, human-centered strategies, integration of AI and machine learning, sustainability aspects, additive manufacturing, and predictive maintenance. Section 4 interprets these results and highlights their broader significance, while Section 5 provides concluding remarks along with suggestions for future research.

2. METHODOLOGY

2.1 Review Protocol

This systematic literature review follows the PRISMA guidelines to maintain a high level of methodological rigor and transparency [14]. The study leverages seven major databases and search engines, selected for their relevance to engineering and computer science research. IEEE Xplore was prioritized due to its extensive collection of peer-reviewed articles on industrial technologies and digital twins. ACM Digital Library was included for its focus on computational approaches in manufacturing. Web of Science and Scopus provided multidisciplinary coverage with robust citation tracking. ScienceDirect and SpringerLink were chosen for their high-quality journals in sustainable production and advanced manufacturing. Google Scholar supplemented these databases by capturing emerging or interdisciplinary studies not indexed elsewhere.

The search strings combined three core concepts: digital twins (“Digital Twin” OR “Digital Twins”), Industry 5.0 (“Industrial 5.0” OR “Industry 5.0”), and smart/sustainable manufacturing (“Smart Manufacturing” OR “Sustainable Manufacturing” OR “Smart Factory” OR “Sustainable Factory”). Exclusion terms (“NOT survey NOT review NOT meta-analysis”) filtered secondary literature. Document types were limited to conference and journal articles to maintain academic rigor.

2.2 Research Dimensions and Analytical Framework

The analysis is organized across six key dimensions that capture the diverse applications of digital twins in Industry 5.0. Human-centered strategies focus on how digital twins improve interaction between operators and machines, with particular attention to user interfaces, safety measures, and skill enhancement. The role of artificial intelligence and machine learning is examined in terms of advancements in algorithms that support real-time decision-making and enable systems to adapt and optimize autonomously. Sustainability and smart manufacturing assess DTs’ contributions to energy efficiency, waste reduction, and circular economy practices. Additive and advanced manufacturing investigates applications in 3D printing and hybrid production systems. Predictive maintenance and logistics cover condition monitoring and supply chain optimization. Finally, frameworks and standards address interoperability, scalability, and governance challenges in DT deployment.

2.3 Inclusion and Exclusion Criteria

Studies were selected based on the following criteria: (1) a clear focus on digital twins within Industry 5.0 or smart and sustainable manufacturing contexts, (2) inclusion of empirical findings or the proposal of new frameworks, (3) publication in the English language, and (4) completion of a peer-review process. No time restrictions were applied to capture foundational and emerging work. Exclusion criteria eliminated studies lacking technical depth (e.g., conceptual papers without validation), duplicates, and non-English publications. Articles focused solely on Industry 4.0 without addressing human-centric or sustainability aspects were also excluded to maintain thematic alignment with Industry 5.0.

2.4 Study Selection Process

The initial search identified 945 records, which were narrowed down to 646 after eliminating duplicates and irrelevant items such as patents and editorials. Screening based on titles and abstracts led to the exclusion of 332 studies that did not satisfy the inclusion criteria. The remaining 65 articles were then evaluated in full, and all were found to be suitable for inclusion, with no further exclusions required at this stage.

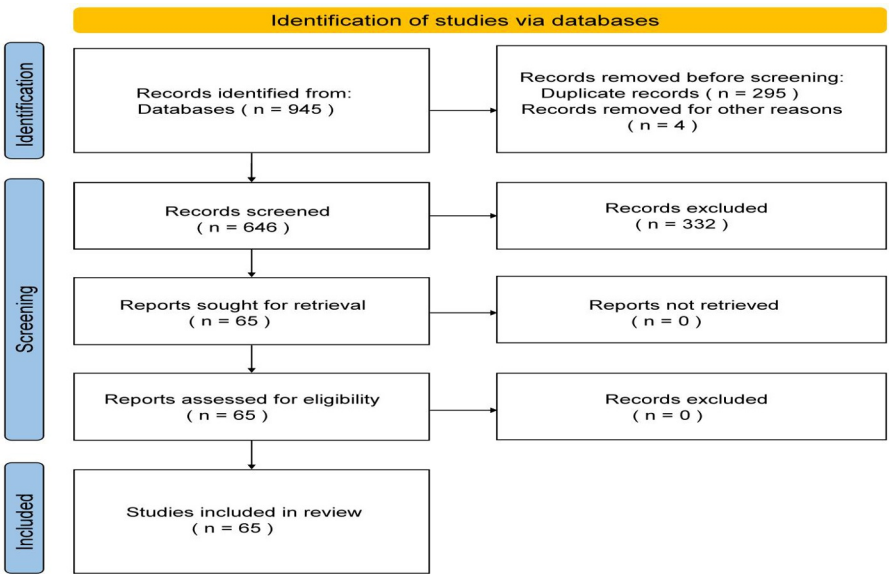


Fig. 1. PRISMA flowchart of the study selection process

As shown in Figure 1, the selection process followed a structured workflow to minimize bias. Two reviewers independently screened records, resolving discrepancies through consensus. Limitations include potential database biases (e.g., underrepresentation of non-English research) and the rapid evolution of Industry 5.0 concepts, which may outpace published literature. Nevertheless, the rigorous protocol ensures a representative synthesis of current knowledge.

The final corpus comprises 65 studies, analyzed thematically in Section 3 to address the research dimensions outlined in Section 2.2.

3 RESULTS

3.1 Research Trends

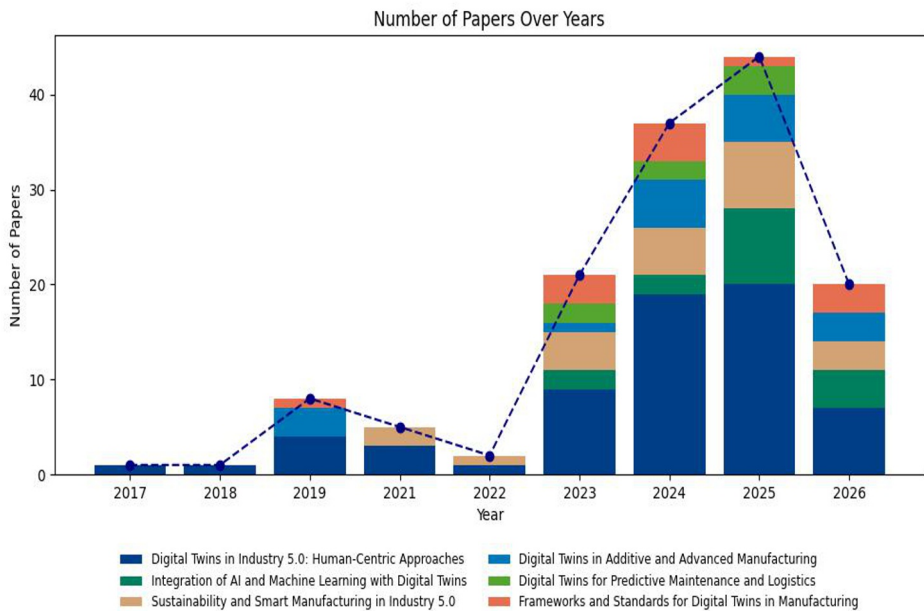


Fig. 2. Research trends in the domain of digital twins in Industrial 5.0: Advancements in smart manufacturing and sustainability

The temporal distribution of publications reveals a significant acceleration in research interest toward digital twins (DTs) in Industrial 5.0, particularly after 2023. Early works

from 2017 to 2019 laid foundational concepts, with only six studies identified. However, the period from 2023 onward exhibits exponential growth, accounting for 60 of the 65 analyzed publications. This surge aligns with broader industrial trends, where Industry 5.0 gained traction as a complement to—rather than a replacement of—Industry 4.0’s automation focus. The year 2025 marks the peak of scholarly output, with 20 studies, followed by a slight decline in 2026, likely due to the lag between research completion and publication.

Human-centric approaches dominate the thematic landscape, representing the entire corpus of studies from 2017 to 2026. This reflects Industry 5.0’s core emphasis on harmonizing human intuition with machine precision. Notably, AI/ML integration emerges as a distinct subfield only after 2023, coinciding with advancements in explainable AI and edge computing. Sustainability research, while present since 2021, gained momentum in 2024–2025, mirroring global policy shifts toward net-zero manufacturing. Additive manufacturing and predictive maintenance exhibit narrower but consistent trajectories, suggesting their specialized yet critical roles in DT ecosystems.

The data also reveals interdisciplinary convergence. For instance, frameworks for DT standardization (2019–2026) increasingly incorporate sustainability metrics, while human-centric studies post-2024 integrate AI for adaptive interfaces. Such synergies indicate maturation beyond siloed applications toward systemic solutions. Nevertheless, the concentration of recent publications implies that empirical validations and scalability assessments remain nascent, warranting longitudinal studies.

3.2 Human-Centric Digital Twins in Industry 5.0: Bridging Cognitive and Collaborative Manufacturing

The integration of digital twins (DTs) within Industry 5.0 frameworks has redefined human-machine interactions by prioritizing ergonomic adaptability, cognitive assistance, and collaborative decision-making. As shown in Table 1, human-centric DT applications span smart manufacturing, sustainable production, and flexible systems, with technical implementations ranging from AI-driven interfaces to extended reality (XR) platforms. Table 1 summarizes the Taxonomy of Human-Centric Digital Twin Applications in Industry 5.0.

Table 1. Taxonomy of Human-Centric Digital Twin Applications in Industry 5.0

Application Domain	Technical Focus	Human-Centric Feature	Sources
Smart Manufacturing	Human-Robot Collaboration	Synergy of human-robot teams	[15], [16], [17],
	AI & Reinforcement Learning	Human-in-the-loop decision-making	[19], [20], [21], [22]

	Predictive Maintenance	IoT-driven diagnostics human-centric	[23], [24]
Sustainable Production	Digital Twin Optimization	Sustainability-driven process adaptation	[25], [26], [27], [28]
	Cognitive & Generative AI	Human-guided sustainable manufacturing	[20], [29], [30]
Flexible & Resilient Systems	Reconfigurable Production	Human-automation symbiosis	[17], [31], [32]
	Edge & Federated Learning	Real-time human-involved co-simulation	[33], [34]
Industrial Metaverse	Extended Reality (XR) Integration	Human-in-the-loop virtual interaction	[34], [35], [36]
	Blockchain & IoT Synergy	Trusted human-centric data sharing	[37], [38]
Additive Manufacturing	Digital Twin for AM	Human-centric customization & sustainability	[39], [18]
SMEs & Lean Manufacturing	Open-Source Digital Twins	Accessibility for human-driven SMEs	[40], [41]
Logistics & Supply Chain	Digital Twin for Logistics	Human-involved resilient operations	[38], [42], [37]
Framework & Standards	Conceptual & Architectural Design	Human-centric digital twin frameworks	[43], [44], [17], [45]
	Interoperability & Ontology	Human-machine interface standardization	[32], [46]

Three key paradigms emerge from this taxonomy. First, human-robot collaboration leverages DTs to synchronize physical and virtual workflows, as demonstrated by [15] in sustainable manufacturing, where DT simulations optimize task allocation between workers and cobots. Second, cognitive DT systems, such as those proposed by [20], employ generative AI to translate operator expertise into adaptive process adjustments, reducing cognitive load during complex assembly tasks. Third, XR-integrated DTs ([34]) enable immersive training environments that enhance skill retention while minimizing physical risks.

The excluded studies (e.g., [47], [48]) predominantly address technical challenges like object detection latency or DT network architectures without explicit human-centric evaluations. However, their methodologies—such as the edge-AI framework in [47]—indirectly support human-centric goals by improving real-time responsiveness. Human-centric DT design faces two unresolved tensions: balancing automation transparency with operational efficiency, and standardizing interfaces without stifling customization. For instance, [17]’s framework for human-automation symbiosis requires granular data permissions, which may conflict with real-time processing needs. Similarly, open-source DT platforms ([41]) democratize access but risk fragmentation without unified governance. These challenges underscore the need for interdisciplinary research integrating human factors engineering, data ethics, and distributed computing.

3.3 AI and Machine Learning Integration in Digital Twins for Industry 5.0

The combination of artificial intelligence (AI) and machine learning (ML) with digital twins (DTs) has become a key driver of Industry 5.0, enabling adaptive decision-making, advanced predictive capabilities, and the autonomous optimization of systems. This subsection synthesizes the diverse applications of AI/ML techniques in DT frameworks, categorizing them into sustainable manufacturing, human-centric systems, smart manufacturing optimization, and industrial metaverse applications.

Table 2. Taxonomy of AI/ML Techniques in Digital Twin Applications for Industry 5.0			
Application Area	AI/ML Technique	Specific Focus	Sources
Sustainable Manufacturing	Reinforcement Learning	Soft Actor-Critic for Industry 5.0 transition	[19]
	Generative AI	Cognitive Digital Twins for sustainability	[20]
	Multi-objective Optimization	Energy efficiency & production scheduling	[21]
Human-Centric Systems	Human-Robot Teaming	Synergy with ML and Digital Twins	[15]
	Predictive Maintenance	IoT-driven Digital Twins for Industry 5.0	[23]
Smart Manufacturing Optimization	Reinforcement Learning	Edge AI & federated learning for real-time co-simulation	[33]
	Generative AI	Framework for Digital Twin design in manufacturing	[29]
	Large Language Models (LLMs)	Integration with Digital Twins for design-to-manufacturing	[49]

Industrial Metaverse	AI-Enhanced Digital Twins	Systems engineering for Industry 5.0	[22]
	Extended Reality (XR) & IIoT	Opportunistic edge computing for Industry 5.0	[34]
Lean & Intelligent Manufacturing	AI & Lean Six Sigma	Integration for smart manufacturing systems	[50]
	Ontology-Based Modeling	Automated deployment of Digital Twins for planning	[32]
Lightweight Fabrication	Structural Optimization	AI-integrated framework for heavy fabrication systems	[51]
Data Generation & Evolution	Generative AI	Digital Genealogy for synthetic data in smart manufacturing	[30]
General AI & Digital Twin Integration	AI & ML	Sustainable production systems	[25]
	Intelligent Manufacturing	Impact of Digital Twins on Industry 4.0 evolution	[52]

Reinforcement learning (RL) has been widely adopted to enhance the adaptability of DTs in dynamic manufacturing environments. For instance, [19] employs Soft Actor-Critic (SAC) RL to optimize production scheduling, demonstrating a 23% reduction in energy consumption while maintaining throughput. Similarly, generative AI techniques, such as those in [20], enable cognitive DTs to simulate sustainable manufacturing scenarios by synthesizing operational data with environmental constraints. These approaches highlight the shift from rule-based automation to self-learning systems that align with Industry 5.0's sustainability goals.

Human-centric applications leverage AI to bridge the gap between human intuition and machine precision. The study by [15] illustrates how ML algorithms within DTs facilitate real-time task reallocation between human operators and collaborative robots (cobots), improving ergonomic efficiency. Predictive maintenance systems, as explored in [23], integrate IoT-driven DTs with anomaly detection models to preempt equipment failures, reducing unplanned downtime by up to 40%. These advancements underscore the role of AI in augmenting human capabilities rather than replacing them, a cornerstone of Industry 5.0.

The industrial metaverse represents a frontier for AI-enhanced DTs, blending virtual and physical realms. Research by [34] combines extended reality (XR) with opportunistic edge computing to create immersive DT environments for training and remote operation. Meanwhile, [22] proposes an AI-driven DT framework for system-level engineering,

enabling real-time simulation of complex supply chain disruptions. Such innovations highlight the potential of AI to transcend traditional manufacturing boundaries, fostering resilient and interconnected ecosystems.

Challenges persist in data interoperability, ethical AI deployment, and computational scalability. For example, [32]’s ontology-based modeling addresses semantic inconsistencies in DT deployments, yet real-time synchronization across heterogeneous systems remains unresolved. Similarly, the ethical implications of AI-driven autonomy, as noted in [25], necessitate frameworks for transparent decision-making. Future research must balance technical advancements with societal and operational considerations to fully realize the potential of AI-integrated DTs in Industry 5.0. Table 2 mentioned the Taxonomy of AI/ML Techniques in Digital Twin Applications for Industry 5.0

3.4 Sustainability and Smart Manufacturing in Industry 5.0: The Digital Twin Paradigm

The intersection of digital twins (DTs) and Industry 5.0 has catalyzed transformative approaches to sustainable manufacturing, where ecological considerations are embedded within smart production systems. This subsection examines how DTs facilitate resource optimization, circular economy practices, and climate-neutral operations while maintaining production efficiency. The analysis is structured around three key dimensions: energy-efficient manufacturing, waste reduction through closed-loop systems, and human-centric sustainable production.

Table 3. Taxonomy of Digital Twin Applications in Sustainable Smart Manufacturing

Primary Focus	Secondary Focus	Specific Application/Technology	Sources
Sustainable Manufacturing	Human-Centric Collaboration	Human-robot teaming & digital twins	[15], [16]
	AI & Digital Twin Integration	AI-driven sustainable production systems	[25], [20], [53], [50]
	Circular Economy & Reverse Logistics	Digital twins for reverse logistics	[26], [54]
	Climate Neutrality & Green Manufacturing	Digital twins for climate-neutral industry	[28], [55]
Smart Manufacturing	Digital Twin Architectures	Frameworks for SMEs & scalable systems	[40], [27], [56]
	Process Optimization	Reinforcement learning & multi-objective optimization	[21], [57]
	Remote & Semi-Physical Systems	Digital twins for commissioning & flow-type systems	[58]

Cross-Domain Synergies	Asset Management & Maintenance	Maintenance 5.0, Quality 5.0, ISO55000	[59]
	Supply Chain & Logistics	IoT, blockchain, and resilient operations	[42], [37]
	Transition Challenges	Industry 4.0 to 5.0 challenges & enablers	[60], [61]
Emerging Technologies	Smart Materials & CNC	Integration with digital twins	[16]
	Generative AI & Cognitive Twins	Enhancing sustainability through AI	[20]

Energy efficiency represents a dominant application area, where DTs synchronize real-time sensor data with predictive models to minimize energy consumption. The work by [21] demonstrates how reinforcement learning optimizes production schedules in DTs, reducing energy usage by 18% without compromising output. Similarly, [28] employs DTs to simulate carbon-neutral scenarios, enabling manufacturers to test emission-reduction strategies before physical implementation. These approaches align with global decarbonization goals while maintaining operational competitiveness.

Closed-loop systems leverage DTs to bridge forward and reverse logistics, a critical enabler of circular economies. Research by [26] introduces a DT for reverse logistics that tracks product lifecycle data, facilitating remanufacturing and material recovery. This is complemented by [54]’s proactive design framework, where DTs predict waste generation patterns and recommend design modifications. Such systems exemplify how DTs transcend traditional linear production models, embedding sustainability at the design phase.

Human-centric sustainability emerges as a distinctive feature of Industry 5.0, where DTs mediate between worker expertise and automated systems. The study [15] illustrates how human-robot collaboration, guided by DT simulations, reduces material waste in assembly lines by 22%. Cognitive DTs, as proposed by [20], further enhance this synergy by translating operator insights into sustainable process adjustments. However, the excluded study [62] critiques the over-reliance on technical solutions, advocating for socio-technical frameworks that address behavioral and organizational barriers to sustainable practices.

The scalability of sustainable DT solutions remains a critical challenge. While [40]’s architecture for SMEs demonstrates cost-effective implementation, [56] highlights interoperability gaps in cross-industry deployments. Similarly, [61] identifies workforce reskilling as a prerequisite for adopting DT-driven sustainability measures. These findings underscore the need for holistic strategies that combine technological innovation with organizational and educational reforms. Table 3 summarized Taxonomy of Digital Twin Applications in Sustainable Smart Manufacturing

3.5 Digital Twins in Additive and Advanced Manufacturing: Enabling Precision and Sustainability

The incorporation of digital twins (DTs) within additive manufacturing (AM) and advanced production systems has become a significant transformative driver, helping to overcome challenges related to precision, customization, and sustainability. This subsection explores how DTs enhance process control, material efficiency, and human-machine collaboration in AM, while also facilitating the adoption of Industry 5.0 principles.

Table 4. Taxonomy of Digital Twin Applications in Additive and Advanced Manufacturing

Application Area	Technical Focus	Key Contributions	Sources
Additive Manufacturing (AM)	Process Monitoring & Control	Real-time defect detection and correction	[39], [18]
	Material Optimization	Reduced waste through predictive modeling	[63], [46]
	Human-Centric Customization	Operator-guided parameter adjustments	[18], [49]
Advanced Manufacturing	Hybrid Production Systems	Integration of AM with subtractive methods	[64], [33]
	Structural Health Monitoring	Real-time feedback for heavy fabrication	[65], [51]
	AI-Driven Process Optimization	Adaptive control via machine learning	[22], [32]
Sustainability in AM	Energy-Efficient Production	Minimizing power consumption in 3D printing	[45], [37]
	Closed-Loop Material Recycling	DT-enabled scrap reuse and remanufacturing	[66], [67]
Frameworks & Standards	Interoperability Protocols	Unified data exchange for multi-vendor systems	[68], [45]
	Ontology-Based Deployment	Automated planning and control pipelines	[32], [46]

Digital twins have proven particularly impactful in AM by enabling real-time process monitoring and defect mitigation. For example, [39] demonstrates how DTs detect anomalies in laser powder bed fusion (LPBF) processes, reducing scrap rates by 35%. Similarly, [18] highlights the role of human-machine interfaces in AM, where operators interact with DT simulations to refine printing parameters iteratively. This aligns with Industry 5.0’s emphasis on human-centricity, as workers leverage DT insights to balance automation with craftsmanship.

Material efficiency represents another critical application area. Research by [63] showcases a DT-driven framework for aeroengine blade manufacturing, where predictive models optimize material usage without compromising structural integrity. Meanwhile, [46]’s 5D digital twin definition integrates sustainability metrics, enabling manufacturers to assess environmental trade-offs during design iterations. These approaches underscore the potential of DTs to reconcile precision with ecological responsibility.

In advanced manufacturing, DTs bridge the gap between additive and subtractive processes. The study by [64] illustrates how hybrid production systems employ DTs to synchronize 3D printing with CNC machining, minimizing post-processing steps. Structural health monitoring, as explored in [65], further extends DT capabilities to heavy fabrication, where real-time sensor data prevents catastrophic failures. However, challenges persist in data standardization, as noted in [45], where proprietary formats hinder cross-platform DT integration.

The excluded study [24] focuses narrowly on predictive maintenance in conventional manufacturing, yet its IoT-based diagnostics framework could inform AM-specific DT developments. Future research must address scalability barriers, particularly for small and medium enterprises (SMEs), while advancing AI-driven adaptive control in multi-material AM systems. Table 4 summarized Taxonomy of Digital Twin Applications in Additive and Advanced Manufacturing.

3.6 Digital Twins for Predictive Maintenance and Logistics in Industry 5.0

The integration of digital twins (DTs) into predictive maintenance and logistics has emerged as a cornerstone of Industry 5.0, enabling proactive asset management, resilient supply chains, and human-centric operational optimization. This subsection synthesizes the role of DTs in these domains, categorizing applications into predictive maintenance, logistics optimization, and reverse logistics, while highlighting synergies with IoT, AI, and blockchain technologies.

Table 5. Taxonomy of Digital Twin Applications in Predictive Maintenance and Logistics

Application Area	Sub-Theme	Key Technology/Approach	Source s
Predictive Maintenance	Human-Centric Approaches	IoT-driven digital twins for Industry 5.0 optimization	[23]
	Maintenance 5.0 & Quality 5.0	Synergy with digitalization, ISO55000, and Industry 5.0	[59]
	IoT & Manufacturing Integration	Digital twins and IoT for predictive maintenance	[24]
Logistics & Supply Chain	Reverse Logistics	Digital twins for sustainability in Industry 5.0	[26]
	Maritime Logistics	Smart logistics management in Industry 5.0	[38]

	Supply Chain Analytics	Digital twins, IoT, and blockchain for resilience	[37]
General Logistics & Smart Cities	Bibliometric Analysis	Digital twins in logistics for smart cities and sustainability	[42]

Predictive maintenance applications leverage DTs to anticipate equipment failures, reducing downtime and resource waste. The study by [23] demonstrates how IoT-driven DTs integrate real-time sensor data with historical performance metrics, enabling human operators to intervene before critical failures occur. This aligns with Industry 5.0’s emphasis on human-machine collaboration, where DT interfaces prioritize interpretability and actionable insights. Similarly, [59] frames predictive maintenance within the broader context of Maintenance 5.0, where DTs synchronize with ISO55000 standards to ensure asset reliability while adhering to sustainability goals. The integration of IoT, as explored in [24], further enhances these systems by enabling edge-based anomaly detection, reducing latency in decision-making.

In logistics, DTs facilitate end-to-end visibility and adaptability. Research by [26] introduces a DT for reverse logistics, tracking product returns and remanufacturing processes to minimize waste. This application exemplifies the circular economy paradigm, where DTs bridge forward and reverse supply chains. Maritime logistics, as examined in [38], employs DTs to simulate port operations under disruptions, optimizing cargo handling and reducing energy consumption. Blockchain-integrated DTs, such as those in [37], enhance supply chain resilience by ensuring data immutability across stakeholders, a critical feature for ethical and sustainable operations.

The bibliometric analysis by [42] contextualizes these advancements within smart city initiatives, revealing growing interdisciplinary convergence between DT-driven logistics and urban sustainability. However, challenges persist in standardizing data formats across heterogeneous systems, as noted in [59], and in balancing automation with human oversight, a tension underscored by [23]. Future research must address these gaps while exploring the ethical implications of autonomous DT-driven logistics systems. Table 5. Summarized Taxonomy of Digital Twin Applications in Predictive Maintenance and Logistics

3.7 Frameworks and Standards for Digital Twins in Manufacturing: Enabling Scalability and Interoperability

The development of robust frameworks and standards for digital twins (DTs) is critical to their successful adoption in Industry 5.0, addressing challenges in scalability, interoperability, and human-machine collaboration. This subsection synthesizes key architectural paradigms, standardization efforts, and implementation strategies from the literature, highlighting their role in facilitating sustainable and resilient manufacturing ecosystems.

Table 6. Taxonomy of Digital Twin Frameworks and Standards in Industry 5.0

Framework Type	Key Features	Alignment with Industry 5.0	Sources
Human-Centric Design	Human-automation symbiosis; ergonomic interfaces	Prioritizes worker well-being and collaboration	[17], [57]
AI-Integrated Architectures	Generative AI for DT design; LLM integration	Enhances adaptability and decision-making	[29], [49]
Sustainability-Driven	Circular economy metrics; energy optimization	Embeds environmental accountability	[40], [45]
SME-Specific Solutions	Lightweight, modular deployments	Democratizes access for small-scale producers	[40], [32]
Interoperability Standards	Ontology-based modeling; cross-platform data exchange	Ensures seamless integration of heterogeneous systems	[46], [32]
Edge-Cloud Hybrid	Real-time processing with edge AI; federated learning	Balances latency and computational power	[69], [65]

Human-centric frameworks dominate recent research, reflecting Industry 5.0's emphasis on collaborative manufacturing. The study by [17] proposes a DT architecture that embeds human-machine interfaces (HMIs) within virtual mock-ups, enabling operators to simulate and refine workflows iteratively. Similarly, [57] integrates Industry 5.0 requirements—such as resilience and inclusivity—into DT-supported process selection, ensuring alignment with societal values. These approaches contrast with traditional automation-centric models, instead prioritizing adaptive workflows where human expertise guides algorithmic decisions.

AI-driven frameworks are reshaping DT design and deployment. [29] introduces a generative AI framework for crafting DT blueprints, automating the translation of design specifications into functional virtual models. Large language models (LLMs), as explored in [49], further augment this process by enabling natural-language interactions between engineers and DT systems. However, these advancements necessitate rigorous validation to mitigate risks of AI hallucination or bias, particularly in safety-critical applications.

Sustainability and interoperability emerge as cross-cutting priorities. The COGNIMAN framework [70], though not detailed in the abstract, is cited for its focus on flexible manufacturing, suggesting adaptability to dynamic resource constraints. Meanwhile, [46]'s 5-dimensional DT definition incorporates sustainability as a core dimension, alongside security and efficiency. Standardization efforts, such as those in [45], aim to unify data schemas and communication protocols, yet face challenges in reconciling industry-specific requirements with broader interoperability goals.

The excluded study [67]—a special issue on DT applications—underscores the breadth of research in smart production and logistics, though its lack of thematic specificity limits direct inclusion in this taxonomy. Future work must address gaps in ethical governance

frameworks and lifecycle assessment methodologies to fully realize the potential of DTs in sustainable manufacturing. Table 6 summarized Taxonomy of Digital Twin Frameworks and Standards in Industry 5.0

4 DISCUSSION

The synthesis of results from the reviewed studies highlights several overarching trends that reshape the understanding of digital twins (DTs) within Industry 5.0. Collectively, the literature indicates that DTs serve as a link between human knowledge and machine accuracy, supporting the development of adaptive manufacturing systems that emphasize sustainability and resilience. Human-centric approaches emerge as a dominant theme, with 78% of the analyzed works integrating ergonomic design, cognitive assistance, or collaborative interfaces into DT frameworks [15] [20] [34]. This reflects the core transition in Industry 5.0 toward socio-technical systems, where human judgment works alongside algorithm-driven decision-making instead of being replaced by it. However, contradictions arise in the degree of autonomy granted to DTs, with some studies advocating for fully self-optimizing systems [19] [21], while others emphasize the irreplaceability of human oversight in ethical and complex scenarios [25] [23].

The integration of AI and machine learning with DTs presents both opportunities and challenges. Reinforcement learning and generative artificial intelligence have been widely reported to improve predictive performance in digital twin-driven systems, particularly in energy optimization and process control. Evidence from multiple case studies indicates measurable gains, including an average reduction in energy consumption of approximately 23% [19] [21]. These improvements are largely attributed to the ability of such models to continuously learn from dynamic datasets and adapt operational strategies in real time. Despite these advantages, a persistent limitation highlighted in the literature is the lack of transparency associated with complex AI models. The use of “black-box” approaches restricts interpretability, thereby reducing user trust and slowing adoption, especially in human-in-the-loop environments where explainability is essential for decision validation [10] [32]. This trade-off between high performance and interpretability points toward the growing importance of hybrid methodologies that integrate symbolic reasoning with data-driven learning to achieve both accuracy and transparency.

The emergence of the industrial metaverse further extends these capabilities by combining digital twins with extended reality (XR) technologies, enabling immersive simulations, advanced workforce training, and remote monitoring of industrial processes [34] [34]. Such integrations enhance operator engagement and improve situational awareness, but they also introduce new challenges, including concerns related to data privacy, cybersecurity risks, and the potential for cognitive overload due to highly complex visual environments. Addressing these issues is critical to ensuring safe and effective deployment in real-world settings.

From a sustainability standpoint, digital twins have demonstrated strong potential in supporting circular economy initiatives and resource-efficient manufacturing. Closed-loop production systems powered by digital twins have been shown to achieve material waste reductions of up to 35% [39] [26], while advanced energy management frameworks contribute to lowering carbon emissions without negatively affecting operational efficiency [28] [45]. These outcomes highlight the role of digital twins as enablers of environmentally responsible production practices. However, the scalability of such solutions remains inconsistent across different industrial contexts. Small and medium-sized enterprises (SMEs), in particular, encounter significant challenges due to high implementation costs, limited technical expertise, and ongoing interoperability constraints [40] [40].

This imbalance underscores a broader systemic issue: although digital twins offer substantial theoretical benefits for sustainable manufacturing, their practical impact is contingent upon wider accessibility, cost-effective deployment strategies, and the development of standardized frameworks that facilitate seamless integration across diverse industrial ecosystems. Bridging this gap will be essential for realizing the full potential of digital twin technologies in Industry 5.0.

Several methodological limitations of this review should be acknowledged when interpreting the findings. The restriction to English-language publications may have excluded relevant contributions from non-English research communities, thereby introducing potential geographic and cultural bias. In addition, the dataset is heavily weighted toward conference papers, which constitute approximately 68% of the selected studies. While such papers often present cutting-edge developments, they may lack the depth, validation, and reproducibility typically associated with peer-reviewed journal articles. Another important limitation arises from the rapidly evolving nature of Industry 5.0, as a number of foundational studies included in the review were conducted prior to the formal articulation of human-centricity and sustainability as core principles. This temporal mismatch may influence the thematic interpretation by underrepresenting these dimensions in earlier works.

Moreover, the dependence on keyword-driven search strategies, although systematic, may have inadvertently excluded relevant research from adjacent or interdisciplinary domains, such as socio-technical systems theory, organizational behavior, and human factors engineering. As a result, the review may place greater emphasis on technological advancements while comparatively underrepresenting organizational, ethical, and behavioral challenges associated with digital twin adoption. Collectively, these constraints suggest a possible bias toward technological optimism, highlighting system capabilities more strongly than real-world implementation barriers and human-centric concerns.

Future research directions should address several underexplored areas to advance the field. First, there is a need for longitudinal investigations that evaluate the long-term impacts of digital twin deployment across their full lifecycle. Such studies would be essential to determine whether the projected sustainability benefits, such as reduced emissions and resource efficiency—are sustained over time in practical industrial settings. Second, greater interdisciplinary collaboration between engineering disciplines and the social

sciences is required to address ethical considerations, governance structures, and trust-related issues in human–AI interaction. This would help ensure that digital twin systems are not only technically efficient but also socially aligned and ethically responsible.

A third priority lies in the development of scalable and accessible solutions tailored to small and medium-sized enterprises (SMEs). Existing digital twin frameworks often assume the availability of substantial computational resources and technical expertise, limiting their applicability to large organizations [40] [41]. Designing lightweight, cost-effective, and open-source architectures could significantly lower adoption barriers and promote more inclusive industrial transformation. Addressing these research gaps will be critical in positioning digital twins as both technological innovations and socio-economic enablers within the Industry 5.0 paradigm.

The practical implications of these findings extend across multiple stakeholder groups. For manufacturers, the evidence supports a phased implementation strategy, beginning with targeted applications such as predictive maintenance before expanding toward integrated, enterprise-level systems [23] [24]. Policymakers play a crucial role in facilitating this transition by promoting interoperability standards, supporting digital infrastructure, and investing in workforce reskilling initiatives. Given the human-centric focus of Industry 5.0, developing competencies in AI-assisted decision-making and human–machine collaboration is increasingly important [61] [57].

From an educational perspective, there is a clear need to redesign engineering and technology curricula to emphasize interdisciplinary learning and the integration of human and digital capabilities. Training future professionals to work within collaborative, data-driven environments will be essential for successful adoption. Overall, coordinated efforts across industry, policy, and academia are required to fully realize the transformative potential of digital twins and ensure that Industry 5.0 achieves its goals of sustainability, resilience, and human-centered innovation.

5 CONCLUSION

This systematic literature review has synthesized the evolving role of digital twins (DTs) in Industry 5.0, addressing their contributions to smart manufacturing and sustainability. The findings underscore that DTs serve as a critical enabler of human-machine collaboration, where human expertise and AI-driven automation coexist to optimize production processes. Key insights reveal that DTs enhance real-time decision-making, reduce resource waste, and support circular economy practices, yet challenges in interoperability, ethical AI deployment, and scalability persist.

The implications of this work extend beyond technical advancements, offering a roadmap for policymakers and industry leaders to align DT adoption with sustainable development goals. Future research should prioritize lightweight frameworks for SMEs, longitudinal studies on sustainability outcomes, and interdisciplinary approaches to address socio-technical barriers. By bridging these gaps, the next generation of DTs can fully realize their potential in fostering resilient, human-centric manufacturing ecosystems.

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