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AI-Enabled Digital Twins for Sustainable Manufacturing: A Systematic Review of Technological Functions, Sustainability Outcomes, and Managerial Implications

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ABSTRACT

Sustainable manufacturing increasingly depends on data-driven technologies to improve productivity, cost efficiency, quality, and sustainability performance. This study reviews literature on AI-enabled digital twins in sustainable manufacturing, focusing on research trends, technological functions, sustainability outcomes, managerial implications, barriers, and future directions. Using a PRISMA-based systematic literature review of Web of Science and Scopus records, the study synthesizes 88 publications: 66 full-text studies for critical synthesis and 22 abstract-based records for descriptive mapping. Analysis combined descriptive, thematic, and integrative synthesis with framework-based coding. The findings indicate that real-time monitoring, simulation, prediction/prognostics, and optimization are the most established functions, whereas control, decision support, and autonomous adjustment remain emerging. Reported outcomes concentrate on energy and resource efficiency, waste and emission reduction, quality, downtime, and operational efficiency. The study highlights governance as a core implementation condition and calls for stronger empirical validation, standardized metrics, and robust data-model governance.

Keywords: AI-enabled digital twins; sustainable manufacturing; technological functions; sustainability outcomes; managerial implications; systematic literature review.

INTRODUCTION

Manufacturing firms face increasing pressure to improve productivity, quality, flexibility, cost efficiency, and sustainability performance. Sustainable manufacturing no longer treats production systems only as mechanisms for generating output, but also as operational systems that must reduce energy consumption, resource use, waste, emissions, and adverse social impacts. This agenda is increasingly linked with Industry 4.0 and Industry 5.0 technologies, circular economy practices, cyber-physical manufacturing, green supply chains, industrial Internet of Things, and smart sustainable manufacturing (Akhai, 2023; Andronie et al., 2021; Bongomin et al., 2025; Ching et al., 2022; Kamble et al., 2022; Khan et al., 2025; Setyadi et al., 2025; Warke et al., 2021).

Digital transformation makes sustainable manufacturing more dependent on real-time data, system connectivity, predictive analytics, and data-driven decision-making. A digital twin (DT) represents an asset, process, production line, or supply chain in virtual form and connects it with the physical system through operational data. In manufacturing, DTs support monitoring, simulation, prediction, optimization, control, and decision support. Artificial intelligence (AI) extends DTs from representation and simulation tools into predictive, prescriptive, and adaptive systems that can detect anomalies, predict failures, optimize process parameters, and support decisions across machine, process, shop-floor, production system and enterprise levels (Alfaro-Viquez et al., 2025; Z. Chen & Huang, 2021; Karkaria et al., 2025; Li et al., 2026; Nguyen et al., 2026)

The integration of AI and DTs is important for green operations because it connects operational visibility, prediction, and optimization with sustainability targets. Current studies associate AI-enabled DTs with energy prediction, energy-efficient manufacturing, adaptive planning, predictive maintenance, quality optimization, additive manufacturing, food and beverage manufacturing, chemical industry efficiency, and digital factory monitoring (Abbruzzese et al., 2025; Abdulhussain et al., 2026; Aivaliotis et al., 2019; Bermeo-Ayerbe et al., 2022; Keramati Feyz Abadi et al., 2025; Li et al., 2026; Lwele et al., 2025; Ma et al., 2022; Nozari et al., 2025; Urgo et al., 2024; Waqar et al., 2026). At the operational level, these technologies are mainly linked with energy efficiency, reliability improvement, downtime reduction, resource optimization, defect control, and process-variation reduction.

Prior reviews have discussed AI-driven DTs, DTs for smart manufacturing, sustainable manufacturing supply chains, computer vision-enabled DTs, circular manufacturing, manufacturing reconfiguration, and energy-efficient manufacturing. However, these reviews remain dispersed across technical, operational, and sustainability domains and have not sufficiently integrated technological functions, sustainability outcomes, and managerial implications within a green operations framework (Faqeer & Khajavi, 2025; Karkaria et al., 2025; Keramati Feyz Abadi et al., 2025; Nguyen et al., 2026; Sajadieh & Noh, 2025; Soori et al., 2023). Table 1 positions this review in relation to selected prior review studies.

Table 1. Positioning of Prior Review Studies

Author(s)	Review focus	Remaining gap addressed in this study
Kamble et al. (2022)	Digital twins for sustainable manufacturing supply chains	AI is not the primary analytical focus
Soori et al. (2023)	Digital twins for smart manufacturing	Sustainability outcomes are not systematically classified

Faqeer & Khajavi (2025)	Digital twin and computer vision in operations management	Focuses on DT-CV integration, not broader AI-enabled DTs for sustainable manufacturing
Nguyen et al. (2026)	AI-driven DT across manufacturing system levels	Managerial implications and sustainability outcomes require further synthesis

Sustainability outcomes in this literature are often associated with energy efficiency, resource efficiency, waste reduction, emissions, quality, reliability, and productivity. Circularity, lifecycle assessment, resilience, and human-centric sustainability have also emerged, but they remain less developed than environmental-operational indicators. Implementation evidence is still limited because many studies are reviews, conceptual frameworks, simulations, proof-of-concept studies, testbeds, or single-case studies. Industrial deployment, longitudinal evaluation, benchmarking, and direct sustainability measurement remain limited, while interoperability, latency, cybersecurity, data quality, and adaptable architectures remain major barriers (Acharya et al., 2024; Faqeer & Khajavi, 2025).

A systematic literature review is therefore needed to clarify how AI-enabled DTs contribute to sustainable manufacturing. PRISMA is used to support transparency in identification, screening, eligibility assessment, and inclusion (Page et al., 2021). Based on this rationale, this study addresses the research questions presented in Table 2. This study aims to synthesize literature on AI-enabled DTs in sustainable manufacturing by examining research development, technological functions, sustainability outcomes, managerial implications, implementation barriers, research gaps, and future research directions. The main contribution lies in integrating three synthesis axes, namely technological functions, sustainability outcomes, and managerial implications, while distinguishing direct sustainability outcomes from indirect sustainability contributions.

Table 2. Research Questions of the Review

Code	Research Question
RQ1	How has the literature on AI-enabled digital twins for sustainable manufacturing developed in terms of publication trends, research contexts, and methodological characteristics?
RQ2	What technological functions of AI-enabled digital twins are identified in sustainable manufacturing studies?
RQ3	What sustainability outcomes are associated with AI-enabled digital twins in sustainable manufacturing, and how can these outcomes be distinguished as direct sustainability outcomes or indirect sustainability contributions?
RQ4	What managerial implications of AI-enabled digital twins are discussed or implied in sustainable manufacturing studies across operational, human resource, financial, and market-oriented dimensions?
RQ5	What implementation barriers, research gaps, and future research directions are identified in the literature on AI-enabled digital twins for sustainable manufacturing?

LITERATURE REVIEW

Digital Twins and Artificial Intelligence in Manufacturing

In manufacturing, a DT refers to a virtual representation of an asset, process, production line, or manufacturing system synchronized with the physical system through operational data. DTs support condition monitoring, anomaly detection, predictive maintenance, production-parameter simulation, quality control, scheduling, energy management, and decision support at machine, process, shop-floor, factory, and supply chain levels (Aivaliotis et al., 2019; Bermeo-Ayerbe et al., 2022; Friederich et al., 2022; Ma et al., 2022; Soori et al., 2023; Urgo et al., 2024). In this sense, DTs should be understood not merely as visualization tools, but also as data-driven decision-making architectures that connect physical components, virtual models, data, processes, people, and supporting technologies (Kamble et al., 2022).

AI strengthens DTs by enabling learning, prediction, classification, optimization, and adaptive decision support. In AI-enabled DT systems, machine learning, deep learning, reinforcement learning, computer vision, surrogate modeling, generative AI, explainable AI, transfer learning, model predictive control, and optimization methods are used for anomaly detection, fault prediction, parameter optimization, digital factory monitoring, predictive maintenance, autonomous control, and manufacturing decision support (Abbruzzese et al., 2025; Achouch et al., 2022; Alfaro-Viquez et al., 2025; Karkaria et al., 2025; Kolate et al., 2026; Li et al., 2026; Nguyen et al., 2026; Urgo et al., 2024; Wahab et al., 2024). However, AI-DT integration still faces challenges related to data quality, explainability, cybersecurity, interoperability, legacy system integration, and technical competence (Acharya et al., 2024; Calixto et al., 2026; Faqeer & Khajavi, 2025).

Sustainable Manufacturing and AI-Enabled Digital Twins

Sustainable manufacturing emphasizes efficient production processes that reduce environmental impacts, conserve resources, support economic-operational performance, and consider worker safety and social impacts. In the literature analyzed, sustainable manufacturing is mainly associated with energy efficiency, resource efficiency, emission reduction, waste reduction, circular economy, productivity, quality improvement, worker safety, and human-centric manufacturing (Andronie et al., 2021; Ching et al., 2022; Khan et al., 2025; Setyadi et al., 2025; Yanytska, 2025).

AI-enabled DTs for sustainable manufacturing refer to the integration of DTs and AI to support efficient, adaptive, energy-efficient, low-waste, and data-driven manufacturing processes. DTs provide virtual representation and data connectivity, while AI provides prediction, diagnosis, optimization, adaptive planning, and decision-support capabilities. This integration appears in sustainable production systems, energy-intensive industries, predictive maintenance, adaptive planning, circular manufacturing, manufacturing supply chains, closed-loop manufacturing, chemical manufacturing, food manufacturing, smart factories, process DTs, textile emissions control, and recycling-oriented decision support (Balasubramanian, 2025; Besigomwe, 2025; Di Orio et al., 2025; Kamble et al., 2022; Keramati Feyz Abadi et al., 2025; Li et al., 2026; Lwele et al., 2025; Ma et al., 2022; Nozari et al., 2025; Sajadieh & Noh, 2025; Waqar et al., 2026). This review is limited to studies that link AI, DTs, and sustainable manufacturing in manufacturing, industrial operations, and manufacturing supply chain contexts.

RESEARCH METHOD

This study employed a systematic literature review (SLR) with qualitative synthesis to identify, classify, and synthesize literature on AI-enabled DTs in sustainable manufacturing. SLR is appropriate for interdisciplinary and rapidly developing fields that require systematic mapping of knowledge development, patterns of findings, study limitations, and future research agendas (Snyder, 2019). The review procedure comprised planning, conducting, and reporting stages. Planning included defining the focus, keywords, inclusion-exclusion criteria, and review protocol. The conducting stage included searching, duplicate removal, screening, retrieval, full-text assessment, data extraction, and quality appraisal. Reporting included descriptive synthesis, thematic synthesis, gap identification, and framework development.

The review was not registered in a systematic review registry. However, the search strategy, inclusion-exclusion criteria, screening decisions, extraction categories, quality appraisal criteria, and synthesis procedures were documented as an internal review protocol and audit trail. The article selection process was reported using PRISMA 2020 principles to explain identification, screening, retrieval, eligibility assessment, and inclusion transparently (Page et al., 2021). SLR protocol principles were also used to ensure that the search, selection, and synthesis processes were explicit and traceable.

The main search sources were Web of Science and Scopus because both databases provide broad coverage of operations management, industrial engineering, smart manufacturing, digital transformation, and sustainability literature. Publisher platforms such as ScienceDirect, SpringerLink, Wiley Online Library, IEEE Xplore, ACM Digital Library, Emerald, Taylor & Francis Online, SAGE Journals, and MDPI were used only as full-text access channels after records had been identified through the main databases. Limited snowballing was conducted from reference lists of studies that passed screening. The search was conducted on 9 May 2026 and targeted titles, abstracts, and keywords using combinations of four concepts: DTs, AI, manufacturing, and sustainability. The search string was adjusted to each database syntax. No strict publication-year restriction was imposed because qualitative synthesis required sufficient conceptual coverage.

Inclusion and exclusion criteria were established before screening and are summarized in Table 3. Eligible studies had to discuss DTs as a main concept or important component, include a connection between DTs and AI or intelligent technologies, focus on manufacturing or manufacturing supply chains, and contain extractable sustainability outcomes or operational relationships relevant to sustainable manufacturing. Non-manufacturing studies, purely conceptual mentions of DTs or AI, publications without adequate metadata, and non-academic or promotional documents were excluded.

Table 3. Inclusion and Exclusion Criteria

Aspect	Inclusion criteria	Exclusion criteria
Technological focus	The article discusses digital twins as a main concept or important component in a manufacturing system.	The article only mentions digital twins in passing without a clear analytical role.
AI integration	The article shows the relationship between digital twins and artificial intelligence, machine learning, deep learning, predictive analytics, computer vision, optimization, generative AI, or other intelligent technologies.	The article discusses AI without digital twins, or digital twins without a connection to AI/intelligent technologies.
Study context	The article is situated in the context of manufacturing, smart manufacturing, sustainable manufacturing, green manufacturing, industrial operations, or manufacturing supply chains.	The article is outside the manufacturing context, such as healthcare, education, smart cities, construction, transportation, or agriculture, unless it has a strong conceptual contribution to sustainable manufacturing.

Sustainability	The article contains or enables the extraction of sustainability outcomes, such as energy efficiency, emission reduction, waste reduction, resource efficiency, circularity, lifecycle impact, environmental performance, or operational sustainability.	The article uses the term sustainability only in a general sense without traceable indicators, outcomes, or operational relationships.
Publication type	Journal articles, review articles, academic conference papers, or other scholarly publications with adequate metadata and abstracts.	Editorials, popular opinions, non-academic white papers, industry reports without peer review, promotional documents, theses, dissertations, or popular books.
Language	Publications in English.	Publications in other languages that cannot be analyzed accurately.
Information availability	The article has at least a title, abstract, keywords, and bibliographic metadata. Full text is prioritized for the main synthesis.	Articles without abstracts, with incomplete metadata, or with insufficient information for assessment.
Duplication	Unique articles based on title, DOI, authors, and publication source.	Articles with the same DOI, title, or metadata were removed as duplicates.

The initial search produced 793 records, consisting of 272 records from Web of Science and 521 records from Scopus. After removing 103 duplicates, 690 records entered title, abstract, and keyword screening. At this stage, 325 records were excluded because they did not fit the combined focus on AI, DTs, manufacturing, and sustainability. A total of 365 reports were sought for retrieval, but 243 reports could not be retrieved or were not available in full text. Subsequently, 122 reports were assessed for eligibility, and 34 reports were excluded for substantive reasons. The final dataset consisted of 88 records: 66 full-text studies and 22 abstract-based supporting records.

Full-text studies were used as the main basis for complete extraction, quality appraisal, thematic synthesis, gap identification, and framework development. Abstract-based supporting records were used only for descriptive mapping and expansion of literature coverage because abstracts do not provide enough information to assess methodological validity, strength of evidence, detailed sustainability outcomes, and managerial implications. Data extraction used a matrix aligned with the research questions. Extracted information included article identity, research objective, DT interpretation, AI role, AI technology, DT level, technological function, manufacturing context, sustainability indicators, research method, main findings, managerial implications, limitations, and future research directions.

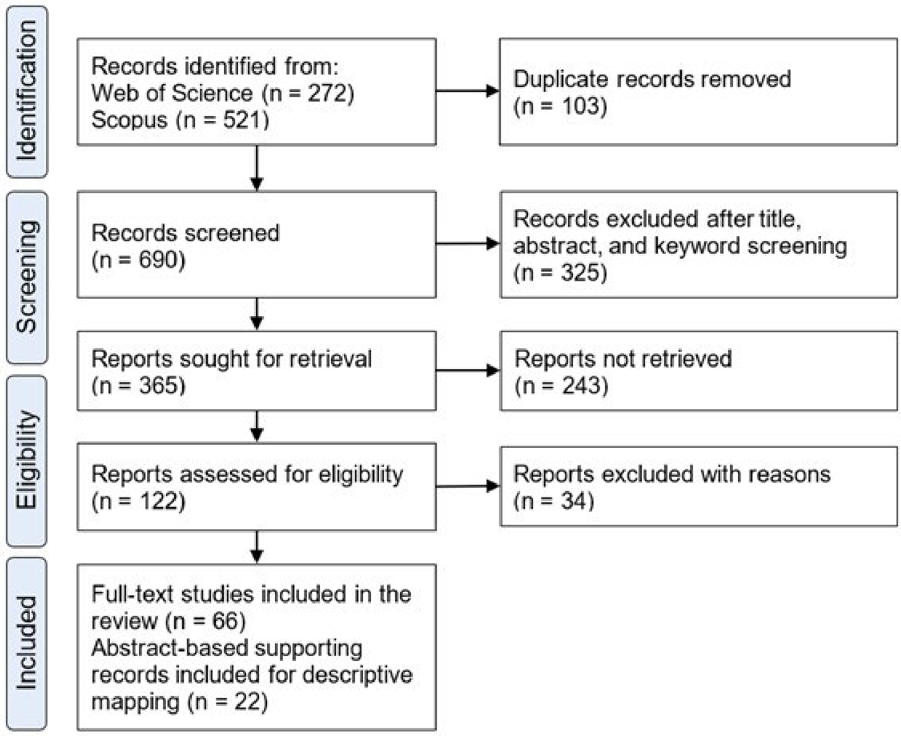
Quality appraisal assessed substantive relevance, strength of evidence, and suitability for synthesis. The appraisal was used to assign evidentiary weight, not to exclude studies automatically. Articles were classified as high relevance for critical synthesis, moderate relevance for thematic support, or limited relevance for descriptive mapping. Full-text studies were prioritized for critical claims, whereas abstract-based records were restricted to descriptive mapping. The analysis used descriptive, thematic, and integrative synthesis supported by framework-based coding (Snyder, 2019). Descriptive synthesis mapped publication patterns, research methods, AI technologies, DT levels, manufacturing contexts, and sustainability indicators. Thematic synthesis grouped findings into technological functions, sustainability outcomes, managerial implications, barriers, and research gaps. Integrative synthesis connected AI capabilities, DT functions, operational mechanisms, sustainability outcomes, and managerial implications. Reliability was maintained through an audit trail covering search strings, databases, record numbers, duplicate removal, screening results, exclusion reasons, extraction categories, appraisal results, and classification decisions.

RESULTS

PRISMA-Based Literature Selection and General Characteristics

The literature selection resulted in 88 records, consisting of 66 full-text studies and 22 abstract-based supporting records. Full-text studies became the main basis for complete extraction, thematic synthesis, quality appraisal, gap identification, and framework development. Abstract-based records were used only for descriptive mapping and were not assigned the same evidentiary weight as full-text studies. Figure 1 presents the PRISMA flow diagram.

Figure 1. PRISMA flow diagram



The analyzed literature is concentrated in 2024-2026, with 70 of the 88 records published since 2024. This concentration indicates that AI-enabled DTs for sustainable manufacturing are still developing through reviews, conceptual frameworks, simulations, prototypes, experiments, and case-based studies. The main contexts include smart manufacturing, sustainable manufacturing, additive manufacturing, CNC machining, textile manufacturing, food and drink manufacturing, battery manufacturing, chemical engineering, circular manufacturing, robotics, recycling, and manufacturing supply chains. These contexts cover machine, process, shop-floor, production-system, supply-chain, circular value-chain, and product lifecycle levels (Abbruzzese et al., 2025;

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Abdulhussain et al., 2026; Balasubramanian, 2025; Guldurek, 2026; Lwele et al., 2025; Mondal et al., 2026; Vadisetty & Polamarasetti, 2024; Waqar et al., 2026; Yu et al., 2025).

Table 4. General Characteristics of the Analyzed Literature

Aspect	Mapping results
Dominant period	2024-2026
Dominant publication types	Review, systematic review, scoping review, conceptual framework, simulation, prototype, and experimental study
Main contexts	Smart manufacturing, sustainable manufacturing, additive manufacturing, CNC machining, circular manufacturing, robotics, manufacturing supply chains
Dominant AI technologies	Machine learning, predictive analytics, deep learning, optimization algorithms, computer vision
Emerging AI technologies	Generative AI, explainable AI, federated learning, edge AI, reinforcement learning, hybrid and physics-informed models
Digital twin application levels	Machine level, process level, shop-floor level, production system level, supply chain level, lifecycle level

The AI technologies most frequently identified include machine learning, predictive analytics, deep learning, optimization algorithms, computer vision, surrogate modeling, reinforcement learning, generative AI, explainable AI, federated learning, edge AI, and hybrid or physics-informed models. These technologies are mainly associated with predictive maintenance, energy prediction, process optimization, quality control, adaptive planning, synthetic-data training, human-cyber-physical systems, and decision support (Assad et al., 2024; Bajestani et al., 2026; Bermeo-Ayerbe et al., 2022; Karkaria et al., 2025; Li et al., 2026; Nguyen et al., 2026; Urgo et al., 2024). However, the role of AI is not explained with equal depth across studies. Some articles specify algorithms, data inputs, outputs, and decision mechanisms, while others mention AI only as a system component.

Technological Functions of AI-Enabled Digital Twins

The synthesis identifies seven technological functions: monitoring, simulation, prediction, optimization, control, decision support, and autonomous adjustment. Monitoring, simulation, prediction, and optimization are dominant. Control, decision support, and autonomous adjustment appear as more advanced but less mature functions. Table 5 presents the technological-function taxonomy.

Table 5. Technological Functions of AI-Enabled Digital Twins

Technological function	Core description	Application form	Status in the literature
Monitoring	Real-time monitoring of machine, process, energy, quality, or production-system conditions	Condition monitoring, energy monitoring, production visibility	Dominant
Simulation	Virtual testing of production scenarios before implementation in the physical system	What-if analysis, process simulation, virtual commissioning	Dominant
Prediction	Prediction of failures, quality, energy consumption, emissions, downtime, or performance	Predictive maintenance, quality prediction, anomaly detection	Dominant

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Optimization	Optimization of schedules, energy, processes, resources, costs, or quality	Adaptive planning, resource optimization, parameter optimization	Dominant
Control	Data-driven control of processes or production systems	Model predictive control, closed-loop process control	Emerging
Decision support	Support for operational and managerial decision-making	Shop-floor decision support, maintenance planning, sustainability decision support	Emerging
Autonomous adjustment	Automatic or adaptive system adjustment	Self-adjusting process parameters, autonomous adaptation, semi-autonomous DT	Limited

Monitoring supports real-time visibility of machine, process, energy, quality, and production-system conditions. Simulation enables virtual testing, scenario analysis, and virtual commissioning. Prediction supports failure prediction, quality prediction, anomaly detection, energy prediction, downtime prediction, and performance forecasting. Optimization supports scheduling, parameter optimization, resource allocation, cost reduction, energy management, and quality improvement. Control and autonomous adjustment indicate a shift toward model predictive control, closed-loop systems, and semi-autonomous DTs, but these functions require stronger validation in real industrial environments characterized by data variability, operational risks, and interoperability constraints (Aivaliotis et al., 2019; Cardoso, 2023; Karkaria et al., 2025; Keramati Feyz Abadi et al., 2025; Li et al., 2026; Ma et al., 2022; Santos et al., 2025; Urgo et al., 2024).

Sustainability Outcomes

Sustainability outcomes were classified by claim status and outcome type. Claim status distinguishes direct sustainability outcomes, indirect sustainability contributions, operational performance only, and unavailable sustainability basis. Outcome types include environmental, economic-operational, social/human, circularity, lifecycle, and operational proxy outcomes. Tables 6 and 7 summarize these classifications.

Table 6. Direct and Indirect Sustainability Outcomes

Sustainability status	Criteria	Example indicators
Direct sustainability outcome	The article explicitly measures or discusses energy efficiency, emission reduction, waste reduction, resource efficiency, circularity, lifecycle impact, or environmental performance	Energy efficiency, carbon reduction, waste reduction, lifecycle impact
Indirect sustainability contribution	The article discusses operational improvements that may support sustainability, but does not directly measure sustainability indicators	Downtime reduction, quality improvement, predictive maintenance, process stability
Operational performance only	The article discusses operational efficiency only, without an explicit or implicit relationship with sustainability	Throughput, cycle time, scheduling efficiency
Not available	There is no basis for linking the result to sustainability	Not available

Table 7. Sustainability Outcomes of AI-Enabled Digital Twins

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Outcome category	Indicators identified	Occurrence status
Environmental outcomes	Energy efficiency, emission reduction, waste reduction, resource efficiency, carbon footprint reduction	Strong
Economic-operational outcomes	Cost reduction, productivity improvement, downtime reduction, maintenance cost reduction, operational efficiency	Strong
Social and human outcomes	Worker safety, ergonomics, human-machine collaboration, operator support, digital skill requirements	Limited and emerging
Circularity outcomes	Reuse, recycling, remanufacturing, reverse logistics, closed-loop manufacturing, circular economy	Moderate
Lifecycle outcomes	Lifecycle optimization, product lifecycle management, lifecycle assessment, sustainability assessment	Emerging, but not yet dominant
Operational proxy outcomes	Defect reduction, scrap reduction, quality improvement, process stability, reliability	Strong as an indirect contribution

Environmental outcomes are the most explicit because they can be linked to sensor data, energy consumption, process-parameter optimization, emissions control, carbon footprint accounting, and environmental functions in DT systems. Frequently identified indicators include energy efficiency, resource efficiency, emission reduction, waste reduction, carbon footprint reduction, and environmental performance (A. Abadi et al., 2025; Bermeo-Ayerbe et al., 2022; Guldurek, 2026; Keramati Feyz Abadi et al., 2025; Ma et al., 2022; Nozari et al., 2025; Popescu et al., 2022). Economic-operational outcomes appear through cost reduction, productivity improvement, downtime reduction, maintenance cost reduction, quality improvement, and operational efficiency. These outcomes should not automatically be treated as direct sustainability outcomes unless explicitly connected to environmental, circularity, lifecycle, or social indicators.

Social and human outcomes remain limited. Worker safety, ergonomics, operator support, digital competence, human-machine collaboration, human oversight, and human-centric manufacturing appear in Industry 5.0 and smart sustainable production studies, but they are not yet dominant in AI-enabled DT research (Bajestani et al., 2026; Bakator et al., 2025; Calixto et al., 2026; Kaur et al., 2026; Massi & Beckman, 2026; Yanytska, 2025). Circularity and lifecycle outcomes appear through reuse, repair, recycling, remanufacturing, reverse logistics, closed-loop manufacturing, product lifecycle management, lifecycle assessment, end-of-life decision support, and circular value creation, but these themes remain less developed than energy, resource, and operational efficiency outcomes (Besigomwe, 2025; Di Orio et al., 2025; Mboli, 2025; Polimetla et al., 2025; Sajadieh & Noh, 2025; Vadisetty & Polamarasetti, 2024).

Managerial Implications, Barriers, and Gaps

Managerial implications are strongest in the operational dimension. AI-enabled DTs support process visibility, predictive maintenance, quality control, scheduling, energy management, downtime reduction, and resource optimization. In the human resource dimension, implementation requires digital competence, operator support, reskilling, worker safety awareness, and human-machine collaboration. In the financial dimension, AI-enabled DTs may support maintenance cost savings, energy cost savings, asset utilization, emissions-aware cost control, and operational efficiency, but evidence on investment cost, payback period, and return on investment remains limited. In the market-oriented dimension, implications relate to responsiveness, customization, green

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value proposition, sustainable product value, customer-oriented design, resilient supply chains, circular value creation, and smart supply chain management. Table 8 summarizes these implications.

Table 8. Managerial Implications of AI-Enabled Digital Twins

Dimensions	Main issues	Evidence status
Operational	Process efficiency, predictive maintenance, quality control, scheduling, energy management, downtime reduction	Strong
Human resource	Digital competence, operator support, worker safety, ergonomics, human-machine collaboration, reskilling	Limited but emerging
Financial	Cost reduction, maintenance cost saving, energy cost saving, investment cost, uncertain return on investment (ROI)	Moderate
Market-oriented	Responsiveness, customization, green value proposition, sustainable product value, customer-oriented design	Limited

The synthesis identifies several barriers: data quality, interoperability, legacy system integration, model fidelity, latency, scalability, cybersecurity, privacy, investment cost, organizational readiness, human resource competence, explainability, and limited empirical validation. These barriers show that AI-enabled DT implementation is not only a technological issue, but also an issue of data architecture, model governance, organizational readiness, and industrial feasibility (Acharya et al., 2024; Calixto et al., 2026; Dossou & Nshokano, 2024; Elrawashdeh et al., 2026; Faqeer & Khajavi, 2025; Kolate et al., 2026). Table 9 summarizes the implementation barriers and research gaps, while Table 10 presents the main thematic synthesis.

Table 9. Implementation Barriers and Research Gaps

Type of gap/barrier	Synthesis results	Suggested research direction
Conceptual/ integrative gap	The relationship among AI, digital twins, sustainability outcomes, and managerial implications remains fragmented	Development of an integrative framework
Technological function gap	AI-DT functions have not been consistently classified across studies	A more stable taxonomy of technological functions
AI capability gap	The role of AI is often mentioned generally without explaining algorithms, inputs-output relationships, and decision mechanisms	Classification of AI as an analytical, predictive, optimization, and decision-support engine
Interoperability and architecture gap	Legacy systems, standardization, synchronization, data integration, and scalability remain major constraints	Studies on interoperable and scalable architectures
Empirical validation gap	Many studies remain reviews, frameworks, simulations, prototypes, or testbeds	Validation in real industrial environments
Sustainability measurement gap	Sustainability is often reduced to energy efficiency or resource optimization	A taxonomy of environmental, economic,

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		social, circularity, and lifecycle outcomes
Circularity and lifecycle gap	The relationship between AI-DT and circular manufacturing has not been explained end-to-end	Integration of circularity and lifecycle assessment
Contextual generalization gap	Manufacturing contexts, firm size, data types, and digital maturity vary	Synthesis based on industrial context and application level
Managerial implementation gap	Managerial implications are often mentioned generally and are weakly connected to organizational decisions	Mapping operational, human resource, financial, and market implications, and identifying governance as an implementation prerequisite
Human-centered gap	Workforce, trust, explainability, reskilling, and human oversight have not been widely tested	Strengthening the human-centered manufacturing dimension
Data and model governance gap	Data quality, model fidelity, uncertainty, privacy, and cybersecurity have not been sufficiently integrated	Integration of data/model governance into the implementation framework

Table 10. Main Thematic Synthesis

Code	Synthesis theme	Core focus	RQ alignment
T1	Transformation of digital twins into intelligent cyber-physical systems	AI extends DT from virtual representation toward predictive, adaptive, cognitive, and semi-autonomous systems	RQ2
T2	Dominant technological functions	Monitoring, simulation, prediction, optimization, control, and decision support	RQ2
T3	Predictive maintenance and reliability	Anomaly detection, fault prediction, condition monitoring, downtime reduction, and reliability improvement	RQ2, RQ3
T4	Energy, carbon, and resource efficiency	Energy efficiency, emission reduction, resource optimization, and energy cost reduction	RQ3
T5	Circular manufacturing and waste reduction	Traceability, recycling, remanufacturing, closed-loop manufacturing, and reverse logistics	RQ3
T6	Process optimization, quality control, and adaptive planning	Adaptive scheduling, quality assurance, defect detection, additive manufacturing, and shop-floor decision support	RQ2, RQ4
T7	Lifecycle, PLM, LCA, and sustainability assessment	Lifecycle management, PLM 5.0, lifecycle assessment, and sustainability metrics	RQ3, RQ5
T8	Multidimensional managerial implications	Operational, human resource, financial, and market-oriented implications	RQ4
T9	Implementation barriers and research gaps	Data quality, interoperability, empirical validation, scalability, cybersecurity, governance, explainability, cost, and sustainability metrics	RQ5

The main gaps lie in the unstable use of the term AI-enabled DT, inconsistent classification of technological functions, weak sustainability measurement, limited industrial validation, and underdeveloped managerial implementation analysis. Energy efficiency and resource efficiency dominate the literature, while social sustainability, lifecycle assessment, circularity, water use, and economic-environmental trade-offs are less developed. Many studies discuss technical benefits but provide limited detail on organizational readiness, investment, human resource competence, data governance, risk management, and managerial decision processes.

DISCUSSION

General Interpretation of the Development

The synthesis shows that AI-enabled DT research in sustainable manufacturing is growing rapidly but remains uneven in maturity. The concentration of publications in 2024-2026 suggests that the field is still dominated by concept formation, application classification, architecture development, and sustainability-indicator mapping. This pattern is consistent with studies on AI-driven DTs, cognitive DTs, generative AI-enabled DTs, metaverse-enabled manufacturing, sustainable production systems, and AI-driven smart manufacturing (A. Abadi et al., 2025; Alfaro-Viquez et al., 2025; Assad et al., 2024; C. Chen et al., 2025; Nguyen et al., 2026; Santos et al., 2025)

The findings confirm that DTs are increasingly understood not only as digital replicas, but also as cyber-physical systems that enable monitoring, simulation, prediction, optimization, and decision support. AI functions as an intelligence layer that extends DTs toward predictive, adaptive, and semi-autonomous systems. However, the dominance of reviews, frameworks, simulations, proof-of-concept studies, and testbeds shows that claims about sustainability impacts should be interpreted cautiously. The current literature provides stronger evidence on technological mechanisms than on verified, large-scale industrial sustainability outcomes. Therefore, the findings should be interpreted as a synthesis of potential mechanisms and reported outcomes rather than as causal evidence of implementation impact. This condition is consistent with Faqeer & Khajavi (2025), who show that DT-computer vision research in operations management remains young and that industrial case studies are still rare.

Technological Functions and Sustainability Outcomes

The technological functions of AI-enabled DTs form a maturity spectrum. Monitoring and simulation strengthen process visibility and scenario testing. Prediction and optimization enable failure prediction, quality prediction, energy prediction, downtime prediction, parameter optimization, scheduling, and resource allocation. These functions dominate because they are directly related to predictive maintenance, energy management, quality control, and process optimization. Control, decision support, and autonomous adjustment indicate a more advanced development direction, but their application is still limited and requires stronger validation in industrial environments.

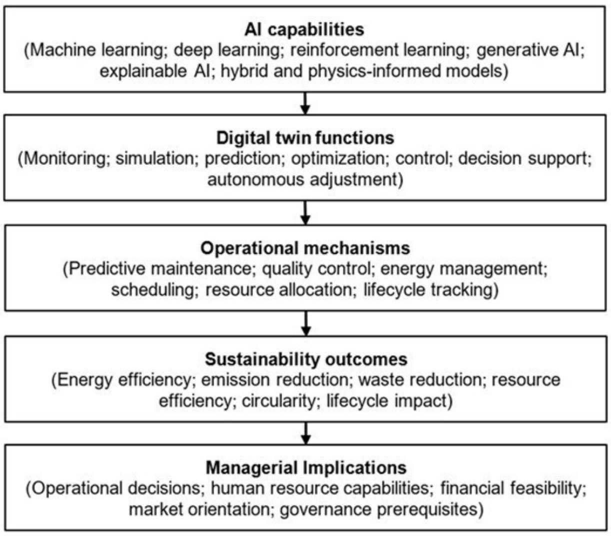
The sustainability contribution of AI-enabled DTs is strongest in energy efficiency, resource efficiency, waste reduction, emission reduction, quality improvement, reliability, downtime reduction, and operational efficiency. Nevertheless, this review distinguishes direct sustainability outcomes from indirect sustainability contributions. Direct outcomes refer to energy, emissions, waste, resources, circularity, lifecycle impact, or environmental performance. Indirect contributions refer to operational improvements such as reliability, productivity, downtime reduction, quality improvement, and process stability when these are not explicitly linked to sustainability indicators. This distinction is necessary to avoid overstating the sustainability value of AI-enabled DTs.

Managerial Implications and Implementation Requirements
The strongest managerial implication lies in operations. AI-enabled DTs can support data-driven decisions in process efficiency, predictive maintenance, quality control, scheduling, energy management, downtime reduction, and resource optimization. In this context, AI-enabled DTs should be understood as decision-making infrastructure rather than merely automation technology. Managers need to define the sustainability problems to be solved, the indicators to be measured, the data to be collected, the AI models to be used, and the mechanisms for evaluating operational and environmental impacts.

Human resource, financial, and market-oriented implications are less explicit but still relevant. Human resource implications include reskilling, digital competence, human oversight, trust, and operator support. Financial implications include investment cost, energy cost savings, maintenance savings, asset utilization, and uncertain return on investment. Market-oriented implications include responsiveness, customization, green value proposition, sustainable product value, and circular value creation. Governance is a cross-cutting prerequisite because data governance, model governance, cybersecurity, privacy, standardization, and interoperability determine the reliability of AI-enabled DTs in operational decisions.

Conceptual Contribution and Future Research
The conceptual contribution of this study lies in an integrative framework linking AI capabilities, DT functions, operational mechanisms, sustainability outcomes, and managerial implications. AI capabilities include machine learning, deep learning, reinforcement learning, generative AI, explainable AI, surrogate modelling, hybrid or physics-informed models, edge AI, and federated learning. DT functions include monitoring, simulation, prediction, optimization, control, decision support, and autonomous adjustment. Operational mechanisms include predictive maintenance, process optimization, quality control, energy management, adaptive scheduling, resource allocation, lifecycle tracking, and circular process support. Sustainability outcomes include environmental, economic-operational, social/human, circularity, and lifecycle outcomes. Managerial implications include operational decisions, human resource capabilities, financial feasibility, governance prerequisites, and market orientation.

Figure 2. Integrative Framework of AI-Enabled Digital Twins for Sustainable Manufacturing



This framework positions AI-enabled DTs as a capability system rather than a single technology because their sustainability value depends on the alignment among data infrastructure, AI models, DT functions, operational decisions, and measurable sustainability indicators. Future research should prioritize industrial deployment, longitudinal evaluation, benchmarking against conventional systems, standardized sustainability metrics, circularity and lifecycle integration, semantic interoperability, small and medium-sized enterprise contexts, developing-country contexts, human-centered manufacturing, governance, cost-benefit analysis, and SDG-aligned circular value creation. These research agendas respond to the current limitations of the evidence base, especially the dominance of conceptual, simulation-based, testbed-based, and single-case studies.

Table 12. Future Research Agenda

Future research agenda	Specific focus
Industrial deployment studies	Longitudinal and real-world evaluation of AI-enabled DT implementation
Standardized sustainability metrics	Energy, carbon, waste, resource efficiency, lifecycle impact, and circularity
Circular and lifecycle integration	Reuse, repair, remanufacturing, recycling, reverse logistics, and end-of-life decision support
SMEs and developing-country contexts	Modular, affordable, interoperable, and scalable AI-DT architectures
Human-centered and governance issues	Reskilling, trust, explainability, privacy, cybersecurity, data ownership, and human oversight
Cost-benefit and return-on-investment analysis	Investment cost, payback period, maintenance savings, and energy cost reduction

CONCLUSION

This systematic literature review synthesized 88 records on AI-enabled DTs in sustainable manufacturing, consisting of 66 full-text studies and 22 abstract-based supporting records. The findings show that the literature is organized around seven technological functions: monitoring, simulation, prediction, optimization, control, decision support, and autonomous adjustment. Monitoring, simulation, prediction, and optimization are dominant because they are closely related to predictive maintenance, quality control, energy management, and process optimization. Sustainability outcomes are concentrated on energy efficiency, resource efficiency, waste reduction, emission reduction, quality improvement, downtime reduction, and operational efficiency, but not all operational improvements should be interpreted as direct sustainability outcomes.

This study contributes an integrative synthesis connecting AI capabilities, DT functions, operational mechanisms, sustainability outcomes, and managerial implications. Managerial implications are most evident in the operational dimension, while human resource, financial, and market-oriented implications remain less explicit. Governance issues, including data governance, model governance, cybersecurity, privacy, and standardization, emerge as implementation prerequisites. Future research should strengthen industrial validation, longitudinal evaluation, standardized sustainability metrics, cost-benefit analysis, human-centered perspectives, circularity, lifecycle assessment, and governance mechanisms for AI-enabled DT implementation.

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DECLARATION OF CONFLICTING INTERESTS

The authors declare no potential conflicts of interest concerning the study, authorship, and/or publication of this article.

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