Advancing Sustainable Manufacturing through AI, IIoT, and Digital Twins: A Systematic Review of Emerging Technologies

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Abstract: *This systematic literature review investigates the possibilities of artificial intelligence, the Industrial Internet of Things, and digital twins for promoting sustainable manufacturing by utilizing the interrelated digital capabilities, operational mechanisms, and socio-technical conditions. Based on the 59 studies included in the predefined review window, and using the PRISMA approach, this review identifies, screens, appraises, codes, and synthesizes the studies. The results show that the IIoT provides the functions of constant sensing and connectivity, and that artificial intelligence transforms industrial data into the realm of the predictable and optimal. Finally, digital twins aid in the modeling, contextualization, simulation, and reasoning of a system's lifecycle. The collaborative usage of these technologies improves the dimensions of sustainable manufacturing such as predictive maintenance, process optimization, quality control, and the efficient use of resources with an emphasis on waste and circularity. The gain of these improvements is conditional on a plethora of factors. Most notably, data governance, interoperability, and cybersecurity, as well as the validity of models and the capability of the workforce. The literature predominantly focuses on operational gains. Therefore, this review synthesizes an integrated taxonomy of capabilities, mechanisms, outcomes, and enabling conditions and suggests longitudinal, multi-site, lifecycle-focused studies with sustainability indicators along with sustainable technology configurations in diverse manufacturing contexts. It also identifies gaps in the existing literature by clarifying the state of existing evidence.*

Keywords: artificial intelligence; circular economy; digital twins; emerging technologies; Industrial Internet of Things; Industry 4.0; sustainable manufacturing; systematic literature review.

1. Introduction

Manufacturing industries must provide services while continuing to reduce energy, materials, waste, emissions, and harm to workers. Sustainable manufacturing provides a solution by incorporating economic, environmental, and social factors. The lifecycles of products must be considered. The combination of artificial intelligence (AI), the Industrial Internet of Things (IIoT), and digital twins helps this cause by linking operations to the physical world, industrial data, analytics, and decisions. With the IIoT, operations gain visibility through a network of connected sensors. In addition, AI processes operational data to create predictions and improvements, while digital twins are the representation of physical systems within a virtual environment. However, the intent of digitalization determines its sustainability. The reliability of data, the bounds of measurement, the objectives of optimization, and the ability of the organization to transform data into responsible action all play a role (Beier et al., 2020). These technologies can function as distinct solutions, and can also act together as a system. When systems are connected, it is much easier to identify energy spikes, equipment breakdowns, loss of materials, and quality control issues that can be missed in regular reports. AI is capable of making these observations to identify and classify failures, improve the scheduling of tasks, and assist in the decision making process. It can also provide a simulation of what the potential outcomes of an operation would be prior to the completion of such an operation. This can lead to a cyclic retention of value. However, companies are different in factors such as technical maturity, system integration, readiness of workforce, cybersecurity, and measurement practices. Thus, the impact sustainability can have can be very different. Some studies have looked into the environmental impacts directly, and some have taken a more indirect approach to sustainability. These indirect approaches have considered operational proxies such as lower downtime, higher yield, and less cycle time (Agrawal et al., 2023).

Evidence spans multiple disciplines, but often focuses on fragmented technologies. Some of the advanced reviews cover industrial AI, predictive maintenance, IIoT, digital twins, circular economy, and Industry 4.0 sustainability, but analysis is often dominated by the technologies themselves. As a result, resources, mechanisms, outcomes, and the contexts of sustainability of value capture may be seen as equivalent, even though they are not. This leads to ambiguities on whether a paper analyzes what a company has, how this capability impacts the operational flow, what is measured, or under what context it can be applied sustainably. It may also lead the frequency of publications to be interpreted as the quality of the evidence, regardless of the considerable variability pertaining to the quality of the design, measurement, replication, and context (Bressanelli et al., 2022). With this in mind, this literature review aims to identify, classify, and synthesize the evidence on how AI, IIoT, and digital twins contribute to sustainable manufacturing. It analyzes the gaps in knowledge in the literature with respect to the resources, mechanisms of change, outcomes of sustainability, and the contexts which are considered. The review presents a 59-study matrix and a four-domain model of the resources of a digital economy, mechanisms of operation, outcomes of sustainability, and enabling socio-technical contexts. It differentiates coverage from consequences and examines the extent to which sustainability claims are directly measured, operate as proxies, or are derived through thinking within the bounds of a lifecycle approach. The review integrates literature to provide a framework for evaluating innovative technology and measuring secure, human-centered, lifecycle-based operations in a sustained and comparative manner.Selection for Inclusion distinguished between the initial and updated searches and exhibited the mathematical relationship for identification, screening, eligibility determination, exclusion, and final inclusion.

The data extraction form collected bibliographic information, year, geography and sector, type of unit, type of research, design, theory, sustainability, expressions of determination and outcome, and limitations. The expressions of determination were coded inductively and compared by definition and function. Standardization was performed when the meanings were sufficiently overlapping. Sixteen determinants were retained, and the remaining expressions were grouped under these determinants. The remaining, higher order expressions were grouped using an inductive-deductive approach to form nine categories. The presence of a determinant was recorded across the studies using a binary matrix. One count for each determinant was recorded for each study. The matrix was interpreted as an evidence map. Therefore, the supportive, contradictory, and null determinations as well as the conditional findings were synthesized narratively and with caution.

2. Methodology

Digital sustainability within manufacturing straddles multiple disciplines. Therefore, a systematic literature review was appropriate. Because of this, and the absence of research on this topic, the review was conducted with consideration to the PRISMA statement (Page et al., 2021) in relation to the selection, screening, assessment and reporting of results. The review was planned with consideration to the publication trend within the Industry 4.0 period (and the coming years). Therefore, the review was planned to be conducted and completed in the near future. The following databases were searched: Scopus, Web of Science Core Collection, IEEE Xplore, ScienceDirect, and SpringerLink. Google Scholar was used to facilitate backward and forward citation searches. The searches were facilitated with combinations of the following terms: manufacturing, artificial intelligence, machine learning, IIoT, industrial connectivity, digital twins, sustainability, energy/resource/efficiency, waste, circular economy, environmental performance, optimization, quality, and predictive maintenance. The combinations of the searches were meant to be complementary and supply the literature of engineering, management, and sustainability research.

Eligible publications considered systems of production or manufacturing, discussed at least one of the focal technologies, related it to an operational or sustainability concern, and provided enough description to allow for extraction. Publications that were considered included English-language, peer-reviewed journal articles and conference papers, as well as high-quality review articles. Publications that were excluded were those that described non-manufacturing contexts, only referred to sustainability in a rhetorical way, described purely technical work with no apparent link to sustainability, were duplicate publications, were not available in full text, and those that were published outside the study timeframe. The primary search resulted in a collection of 607 publications. 168 duplicates were removed, leaving 439 publications to be screened. 337 were removed in the preliminary screenings, and 102 were assessed in the full-text reviews. 57 publications were found to be ineligible, resulting in 45 publications. An iterative search of 14 recent articles was performed, with the articles being evaluated on the same criteria. This resulted in a final total of 59 studies. Results of the iterative search are represented in Figure 1.

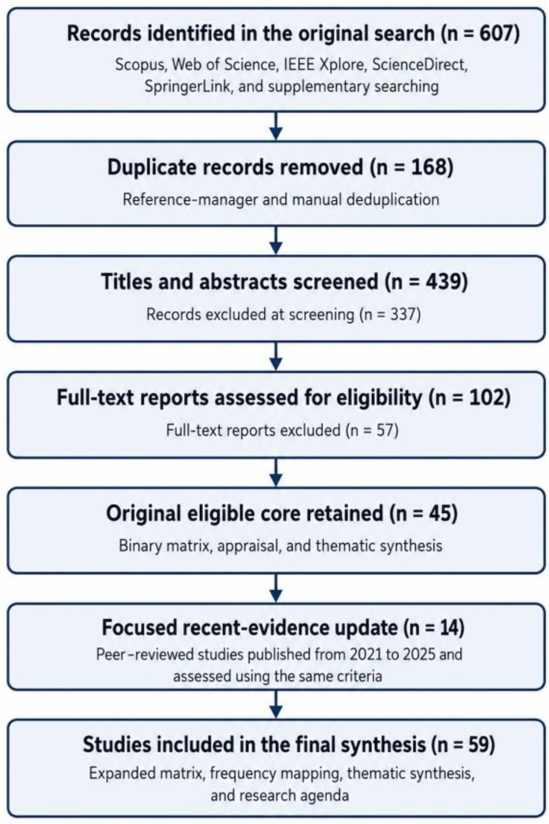

Figure 1: The Systematic Review Process

Figure 1 shows the pathway from initial identification through to final inclusion, and differentiates between core search and recent-evidence update. In the data extraction process, information of publication date, focus of study, context of study, framing of design, link to sustainability, enabling conditions and limitations, and treatment of fourteen recurrent factors was recorded. The quality of study was assessed based on the clarity of aim, description of methodology, relevance to manufacturing, adequacy of analysis, validity of the technology and outcomes link, and the fit of evidence with the conclusions drawn. The coding process followed a mixed deductive/inductive approach that placed a limited number of standardized terms under the headings of digital capabilities, operational mechanisms, sustainability outcomes, and socio-technical enabling conditions, while all the other terms were left unchanged. Binary matrix coding was used to indicate comprehensive coverage of the area and was used to indicate the absence of evidence regarding the effect of relate to the evidence drawn (including statistical significance) and the quality of evidence. Other methods of analysis were also used to indicate the lack of evidence regarding the quality of research (including meta-analysis). These included focus on study design, measurement, context, and evaluation of trade-offs and gaps.

3. Integrated Socio-Technical Innovation Framework and Evidence Mapping

The major insight reported by the surveyed literature is the integration, not the singular application, of AI, IIoT, and digital twins (and a closed information-and-decision architecture). This integrated application is offered as a novel contribution. IIoT networks disseminate time-stamped data across machines, products, and production environments. AI can analyze the data and perform prediction, classification, outlier detection, and even make decisions. Digital twins can hold and maintain data context for the analysis and can run and re-run simulated scenarios iteratively. This complimentary architecture can help to identify problems more readily, and assist with scheduling flexibility and reduce process variability. It can also assist with continued visibility and traceability throughout a product's lifecycle. (He & Bai, 2021; Huang et al., 2021; Qi et al., 2023; Resman et al., 2025). The innovative aspect of this system is the integration of the steps of sense, interpret, simulate, and act, as opposed to the integration of disparate digital systems. The integration of this system should be seen as sustainable only when it meaningfully creates an improvement in verified economic, environmental, circular, or social benefits, as opposed to simply increasing the volume of data, the computational complexity, or the technologies employed.

A second example is the use of configuration-centered assessments in place of the traditional technology-oriented assessments. These assessments take into consideration the quality of data, data interoperability, the skills of workers, the authority of decisions, cybersecurity, and the objective function of the digital optimization process. Digital twins can improve equipment-level maintenance, and AI has the capability of predicting defects and reducing scrap. In both examples, the overall value of the technology is dependent upon the fidelity of the model, the semantic consistency and temporal linkages, and the resistance from the lifecycle data. Because of this, the review conceptualizes innovation as a flexible socio-technical configuration in which the diverse capabilities are mediated by mechanisms and framed by innovative socio-technical systems and flexible boundaries. This also considers the trade-offs, rebound effects, and the impact of the governance structure on the overall organizational preparedness for the transformation.

The review also adds fresh insights by acknowledging a heterogeneous evidence base and sorting it into four categories. These include digital capabilities, operational mechanisms, sustainability outcomes, and socio-technical enabling conditions. Digital capabilities include AI analytics, IIoT connectivity, and twin modeling; operational mechanisms include predictive maintenance, process optimization, and quality control; sustainability outcomes include energy efficiency, resource efficiency, waste, and circularity; and socio-technical enabling conditions include human integration, data governance, interoperability, and cybersecurity. This framework describes what are the elements available to organizations, the ways by which digital capabilities affect the operations of organizations, the sustainability outcomes that organizations wish to achieve, the enabling conditions that sustain the reliable outcome of digital capabilities (Agrawal et al., 2023; Ching et al., 2022; Jamwal et al., 2021). Table 1 speaks to the results of 59 studies and systematically reports on some of the phenomena that are the most recurrent in the studies. A check mark means that a factor was substantially considered, but is constant across studies, and is not to be understood as expressing anything positive about outcomes, causal contribution, the significance of a factor, or the methodology of the studies. This framework provides mechanisms to differentiate and compare technical capabilities, avenues to implementation, sustainability outcomes, and enabling conditions of a given study.

Table 1: Literature Review Matrix

No	Author(s) and Year	AI Analytics	IIoT Connectivity	Twin Modeling	Predictive Maintenance	Energy Efficiency	Resource Efficiency	Waste Reduction	Process Optimization	Quality Control	Circularity	Human Integration	Data Governance	Interoperability	Cybersecurity
1	Lee et al. (2015)		✓						✓				✓	✓	✓
2	Stock and Seliger (2016)		✓			✓	✓	✓	✓		✓	✓		✓	
3	Wuest et al. (2016)	✓			✓				✓	✓		✓	✓		
4	Wan et al. (2016)		✓						✓				✓	✓	✓
5	Lu (2017)	✓	✓	✓					✓			✓	✓	✓	✓
6	Kiel et al. (2017)		✓			✓	✓	✓	✓		✓	✓			
7	Negri et al. (2017)		✓	✓	✓				✓	✓			✓	✓	
8	Tao and Zhang (2017)	✓	✓	✓	✓	✓	✓		✓	✓			✓	✓	
9	Kusiak (2018)	✓	✓		✓				✓	✓		✓	✓		
10	Wang et al. (2018)	✓			✓				✓	✓			✓		
11	Lee et al. (2018)	✓	✓		✓				✓	✓			✓	✓	
12	Sharp et al. (2018)	✓							✓	✓		✓	✓		
13	Tao, Qi, et al. (2018)	✓	✓		✓				✓	✓			✓	✓	
14	Boyes et al. (2018)		✓									✓	✓	✓	✓
15	Sisinni et al. (2018)		✓										✓	✓	✓
16	Kritzinger et al. (2018)		✓	✓	✓				✓	✓			✓	✓	
17	Qi and Tao (2018)	✓	✓	✓	✓				✓	✓			✓	✓	
18	Tao, Cheng, et al. (2018)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	
19	Kamble et al. (2018)	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
20	de Sousa Jabbour et al. (2018)	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓	
21	Müller et al. (2018)		✓			✓	✓	✓	✓			✓	✓		✓
22	Bonilla et al. (2018)	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓		✓

No	Author(s) and Year	AI Analytics	IIoT Connectivity	Twin Modeling	Predictive Maintenance	Energy Efficiency	Resource Efficiency	Waste Reduction	Process Optimization	Quality Control	Circularity	Human Integration	Data Governance	Interoperability	Cybersecurity
23	Barricelli et al. (2019)		✓	✓								✓	✓	✓	✓
24	Tao et al. (2019)	✓	✓	✓	✓				✓	✓			✓	✓	
25	Carvalho et al. (2019)	✓	✓		✓	✓	✓		✓	✓			✓		
26	Ghobakhloo (2020)	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
27	Bai et al. (2020)	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
28	Beier et al. (2020)	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓	✓
29	Peres et al. (2020)	✓	✓		✓				✓	✓		✓	✓	✓	✓
30	Çınar et al. (2020)	✓	✓		✓	✓	✓		✓	✓			✓		
31	Fuller et al. (2020)	✓	✓	✓	✓	✓			✓			✓	✓	✓	✓
32	Jones et al. (2020)		✓	✓	✓				✓	✓			✓	✓	
33	Lu et al. (2020)	✓	✓	✓	✓	✓	✓		✓	✓			✓	✓	
34	Rasheed et al. (2020)	✓	✓	✓	✓	✓			✓			✓	✓	✓	✓
35	Errandonea et al. (2020)	✓	✓	✓	✓	✓	✓		✓				✓	✓	
36	Rosa et al. (2020)	✓	✓	✓		✓	✓	✓	✓		✓		✓	✓	
37	Beltrami et al. (2021)	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
38	Dantas et al. (2021)	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓	
39	Escobar et al. (2021)	✓	✓						✓	✓		✓	✓	✓	✓
40	He and Bai (2021)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
41	Huang et al. (2021)	✓	✓	✓	✓				✓	✓		✓	✓	✓	✓
42	Semeraro et al. (2021)	✓	✓	✓	✓				✓	✓			✓	✓	✓
43	Agrawal et al. (2023)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
44	Ördek et al. (2024)	✓			✓				✓	✓		✓	✓		
45	Homaei et al. (2024)	✓	✓	✓								✓	✓	✓	✓
46	Jamwal et al. (2021)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
47	Ghobakhloo et al. (2021)	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓	✓
48	Chiarini (2021)	✓	✓	✓		✓	✓	✓	✓	✓			✓	✓	
49	Laskurain-Iturbe et al. (2021)	✓	✓	✓			✓	✓	✓		✓	✓	✓	✓	
50	Bag et al. (2021)	✓	✓	✓			✓	✓	✓	✓	✓	✓	✓	✓	
51	Ante (2021)	✓	✓	✓	✓				✓	✓			✓	✓	✓
52	Ching et al. (2022)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
53	Gebhardt et al. (2022)	✓	✓	✓			✓	✓	✓		✓	✓	✓	✓	✓
54	Bai et al. (2022)	✓	✓	✓			✓	✓	✓		✓	✓	✓	✓	
55	Bressanelli et al. (2022)	✓	✓				✓	✓	✓		✓	✓	✓	✓	
56	Qi et al. (2023)	✓	✓						✓				✓	✓	✓
57	Ünal et al. (2023)		✓	✓		✓	✓		✓			✓	✓	✓	
58	Trienens et al. (2024)	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	
59	Resman et al. (2025)		✓	✓		✓	✓	✓	✓	✓		✓	✓	✓	

The matrix shows that scholarship favors Incremental Improvement in Operations through Data as opposed to Improvement in Sustainability Outcomes. IIoT connectivity, data governance, process optimization, and interoperability dominate the literature because they facilitate sensing, data exchange, orchestration, and execution of decisions across diverse applications. AI analytics and twin modeling are also described extensively; however, their combined presence does not support the claim that integrated implementation enhances environmental and social outcomes. Scholars also do not address the concepts of waste reduction and circularity, showing that research still focuses on factory operations, as opposed to reverse logistics, remanufacturing, product passports, and closed-loop systems. Human integration and cybersecurity assume a middle position: both are discussed, but are often viewed as barriers to implementation and not social or resilience outcomes. The evidence, therefore, suggests a layered interpretation. It assumes that digital capabilities support operational mechanisms and that socio-technical conditions define reliability and adoption, while sustainability claims will always assume the provision of independent outcome measurement. While frequency illustrates scholarly interest, confidence will always be determined by the quality of the design, replication, direct measurement, a variety of contexts, and clarity in reporting.

4. Discussion: Thematic Synthesis of Emerging Technologies

This synthesis suggests that for AI, making sustainable manufacturing decisions becomes more important than achieving sustainable manufacturing results. Rather, with mature applications in predictive maintenance and anomaly detection, quality classification, scheduling, and optimization of processes with multiple objectives, AI reduces manufacturing stoppages, identifies defects sooner, normalizes production, and improves the productive use of manufacturing assets. Thus, AI has the potential to reduce manufacturing resource waste and extend the useful life of manufacturing assets (Agrawal et al., 2023; Çınar et al., 2020; Ördek et al., 2024; Peres et al., 2020) (see Section 5 for details about the potential for AI to achieve other specific sustainable manufacturing goals). However, just because something is technically accurate does not mean it is truly better for sustainability. For example, a model that achieves faster production may actually result in greater total production, greater total energy consumption and computation, increased dependence on greater amounts of sensors and increased hardware that must be replaced and upgraded more frequently. AI has the potential to support sustainability most when optimization focuses on balancing sustainability with other factors and when the burden of maintaining the AI solution is low. AI is also most sustainable when there is little added burden to maintain the solution. When studies cite improvements in prediction accuracy, losses due to downtime or yield, these are important data, but do not substantiate claims around energy, emissions, waste and improved outcomes for workers. Improved operational efficiency does not guarantee a positive sustainability outcome; therefore, AI for decision-making should be aimed at understanding the sustainability impact of automation before pursuing use of AI for automation of decisions. IIoT Builds a Visibility Infrastructure for Sustainable Continuous Improvement and Adaptive Control.

The interconnection of sensors, machines, and edge-cloud services provides a way of capturing the peaks and losses that occur in the process, environment, and of the equipment, which periodic snapshots of the process neglect the monitoring of. The maintenance and quality of traceability of data and the quality of control and schedule responsiveness is greatly improved with the enhanced visibility and the data provided to the artificial intelligence and digital twins. Therefore, connectivity is more of an enabling characteristic, rather than a sufficient characteristic. The value of sustainability is determined by the precision and reliability of the sensors, the networks and their latency and scalability, the semantic consistency, and whether the data enable the operational actions if they are brought to a trigger point. Increased connectivity also comes with increased device inventories, network inventories (traffic), storage inventories, energy inventories, and increased exposure to cyber vulnerability. Recent studies, therefore, have stressed the importance of the governance of analytics, the implementation of analytics, and the challenges that are posed by analytics on the technologies that support them (Qi et al., 2023). For a credible assessment, it is necessary to measure the costs of digital infrastructures versus the savings it provides, and the differentiation of local versus system efficiencies. The total responsiveness of the system may not decrease, and the total energy of the system may increase, when the burdens of the system are transferred to data centers, suppliers, and downstream operations. For these reasons, the strongest case is made for IIoT as a foundational technology for measurement and coordination, with consideration of governance, security, and the design of decisions for its contribution to sustainability.

Digital twins advance the existing frameworks by merging contextual models with real-time data on equipment, processes, products, and production systems. A distinguishing aspect of digital twins is their ability to assess multiple options and predict various scenarios to make decisions without the need to alter the real-world system. Multiple systematic reviews showed that monitoring, maintenance, operational planning, quality assurance, and lifecycle management are application domains. Systematic reviews have also referred to the inadequate definitions and maturity of the digital twin concept (Semeraro et al., 2021). Most of these systems lack the dynamism of a twin and, at best, remain digital models or one-way shadows. Sustainability claims are especially sensitive to the dynamic nature of a system. The complexity and scope of the real systems and the uncertainty and complexity of the models determine the credibility of claiming simulated savings. Projects focused on the integrated systems (Resman et al., 2025; Trienens et al., 2024) aim to extend the boundaries of the operational focus to the entire system's lifecycle. Even within the integrated systems perspective, evidence on the circular economy, total system impact, and transboundary data is absent. Digital twins, within the boundaries of the sponsoring organization, provide the ability to sustain the models, serve as dynamic decision-making environments validated by models, and integrate real-world scenarios. Among the three technologies, predictive maintenance, process optimization, and quality control serve as links between digital capacity and sustainability outcomes. In the case of predictive maintenance, alternate crises can be minimized and energy consumption can be reduced by a predictive model to be used during maintenance.

Predictive process optimization can help control and streamline both process and resource scheduling and allocation. Predictive quality control can stop defects from cascades that result in rework, scrapping, returning, or replacing an item. Direct waste reduction and circularity within the matrix are largely overshadowed by focus on process optimization, meaning preference for operational proxies. Of Industry 4.0 technologies, most are easily measurable as factory proxies, while lifecycle emissions and material recovery, as well as social costs, are not easily measurable. However, the fact that most operational proxies are easily measurable creates a gap for the evidence. Technologies within Industry 4.0 do not offer the same level of environmental improvements, as results are based on the kinds of technologies used, how they are integrated and the context they are measured or implemented in. Evaluations ought to concentrate on operational and sustainability indicators. These evaluations should present both absolute and relative metrics, as well as establish baselines and deal with boundaries and rebound effects. Circularity, in this instance, should be considered much more than what is contained in production. Circularity also encompasses design, traceability, disassembly, reuse, remanufacturing, reverse logistics, and recovery beyond firms.

Operational improvements present pathways for firms toward sustainability. While the facilitating conditions illustrate that sustainable digital manufacturing systems are socio-technical, they also demonstrate that data governance frameworks are essential. Within socio-technical systems containing AI, IIoT, and digital twins, data governance frameworks are critical because the data must be accurate, accessible, traceable, and semantically secure and accountable. Interoperability determines the ability of meaning to flow across devices, platforms, functions, providers, and lifecycle phases. Cybersecurity preserves the integrity of connected functions and the availability of automated processes, while the integration of personnel preserves the confidence of employees regarding automated processes and the interpretation, contestation, and acceptance of automated workflows. Lastly, the enabling conditions are INTERDEPENDENT and SOCIAL. This arrangement of enabling conditions illustrates social sustainability. Among the enabling conditions, circular collaboration is best illustrated in social sustainability. Most of the studies on enabling conditions emphasize social sustainability and circular collaboration, and they have also characterized these studies as poorly developed (Gebhardt et al., 2022). Regarding enabling conditions, social sustainability and circular collaboration are the most evident.

The other enabling conditions are largely invisible. In the presence of the other enabling conditions, circular collaboration is clearly evident to social sustainability. If enabling conditions show social sustainability and circular collaboration, then circular collaboration is evident in social sustainability and is largely invisible. A configuration approach is warranted, particularly for small manufacturers, where complementary technology, governance, operational mechanisms, human capability, and direct performance metrics are aligned in a specific context. Frequent citation is not a measure of evidence; more substantial conclusions will follow replicated, longitudinal, multi-site studies with life cycle assessment. This approach further elucidates why multiple, similar configurations yield divergent results across different sectors, contexts, country settings, plants of varying sizes, and differing regulatory frameworks: sustainability performance extends beyond the capability and performance of the technology.

5. Research Gaps and Future Research Directions

The survey identifies gaps and discontinuities in concepts, methods, measurements, and context. Most studies conflate technologies, operational mechanisms, sustainability impacts, and enabling conditions, which blurs the resulting comparison and leads to adoption being equated with performance. More frequently seen are prototypes, simulations, reviews, and single-site studies, rather than longitudinal, multi-site, or quasi-experimental studies. Sustainability claims are made based on inferred downtime, cycle time, yield, or equipment utilization, with little to no actual energy, material, emissions, or waste flow measurements. Circularity is lacking because most studies are limited to factory operations and do not follow products through the design, use, recovery, and remanufacturing cycles, as well as reverse logistics. Measuring social sustainability is even more inadequate, with trust and safety defined in most studies as implementation, rather than as outcomes. For most small scale manufacturers, developing countries, and process industries, and in resource-constrained environments, evidence is inadequate. Although acknowledged, Cybersecurity, Interoperability, Model Uncertainty, Data Quality, Rebound, and the burden of Digital-Infrastructure are often studied in isolation.

Future studies must focus on the arrangements of various technologies rather than studying each technology individually. Long-term, cross-regional research must consider IIoT-only pathways, pathways integrated with AI and digital twins, and integrated pathways with the same initial conditions and system delimitations, as well as sustainability indicators concerning the system and sustainability expressed in absolutes and per-unit terms. Research on digital twins must include issues of fidelity, synchronization, and uncertainty, as well as the scope of their verification and validation. In the case of AI, studies must include explainability and the dimensions of the AI system's verification, as well as the system's retraining cost, computing demand, and the consideration of human overrides. In IIoT, studies must measure reliability, latency, and interoperability, as well as security and the system's supporting infrastructure energy. Research on circularity must link floor shop data with product passports and disassembly, as well as reuse, remanufacturing, and interfirm recovery. Research from a human-centered approach must involve the workers and focus on the design of the system, as well as the measurement of job quality, safety, participation, skills, and the authority to make decisions. To capture contextual contingencies, studies of diverse countries, sectors, firm sizes, and regulatory settings must be conducted. In the pursuit of creating net sustainable value, shared definitions, open datasets, testbeds, negative

6. Conclusion

This systematic literature review analyzed 59 studies to assess the role of Artificial Intelligence, the Industrial Internet of Things, and Digital Twins in conjunction as elements of the framework describing the pathways and mechanisms of the advances in sustainable manufacturing. What the combined studies have shown is that the Industrial Internet of Things generates visibility in the manufacturing process, while Artificial Intelligence is capable of generating predictions along with optimal decisions. Digital Twins provide the context for the physical world, and for both simulation and reasoning throughout the lifecycle. This trifecta influences the design and implementation of systems for predictive maintenance, process improvement, and quality assurance and control. Moreover, data governance and the integration of IoT, Cybersecurity, and Human Factors determine system design, implementation, and operational reliability. The reviewed literature has a stronger focus on improvements in the operational processes that are data-enabled, and a weaker focus on circularity, decreasing the level of waste, social sustainability, and improvements in the environment. Thus, the review provides a framework that describes and separates digital capabilities from pathways, sustainability outcomes, and conditions. The matrices that accompany the review illustrate the gaps in the research.

The results show that not all new technologies develop sustainable manufacturing. Stakeholders must establish common interests and boundaries for their systems and lifecycles. These include reliable and trusted data, metrics, models, interoperable and secure infrastructures, skilled personnel, and direct observations for value to be realized. The synthesis creates possibilities for researchers to conduct configurational, long-term, comparative, and multi-sited studies and for practitioners to assess benefits against costs when making investment decisions. The synthesis specifies the calls for standardized measurements, enhanced circular and social measurements, broader geographical and sector-based measurements, and more thorough and clear documentation of negative outcomes. The review analyzes the demand for social governance, the considerable promise of AI, IIoT and digital twins, and the documented persistent outcomes when the technologies are integrated and intentionally managed as a socio-technical system.

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