

Review

Synergizing Sustainable Materials and Advanced Manufacturing for Sustainability Performance: A Literature Review

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Abstract

The integration of sustainable materials and Industry 4.0 technologies as the overarching paradigm offers significant potential to advance manufacturing sustainability. However, existing research remains fragmented, often focusing on isolated topics such as recycled plastics in additive manufacturing or the use of machine learning and material informatics in material processing. As a result, limited attention has been given to the combined effects of these approaches across the economic, environmental, social, and technological dimensions of sustainability. To address this gap, this study presents a systematic literature review of 156 peer-reviewed articles published between 2015 and 2025 and develops the concept of Sustainable Circular Manufacturing (SCM) as the sweet spot between sustainable materials and Industry 4.0. The review shows that SCM-related studies primarily enhance data acquisition, process transparency, intelligent decision-making, process optimization, automation, and human–technology interaction. The findings also indicate that the literature is strongly weighted toward environmental indicators such as carbon footprint, energy efficiency, and circularity, whereas social sustainability and economic viability remain comparatively underexplored. Building on these insights, the study proposes SCM as an integrative conceptual framework that clarifies the causal pathways linking sustainable material strategies and Industry 4.0 enablers to multidimensional sustainability performance. Finally, the review identifies key implementation barriers and outlines a future research agenda to support digitally enabled circular material strategies.

Keywords: sustainable materials; advanced manufacturing; sustainability; artificial intelligence (AI); machine learning; Industry 4.0; additive manufacturing; life cycle assessment (LCA); circular economy; material selection; sustainable production systems; literature review

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1. Introduction

Sustainable manufacturing (SM) has emerged as a paradigm that integrates economic, environmental, and social considerations into production systems, aiming to reduce resource consumption, minimize waste, and promote circularity [1–3]. The concept draws inspiration from industrial ecology and the circular economy, which advocate for closed-loop material flows and the decoupling of economic growth from environmental

degradation [4–6]. Initial endeavors to enhance manufacturing efficiency originate from lean production concepts established by Toyota, including Just In Time (JIT), value-stream mapping (VSM), and Kaizen, that emphasize waste minimization and ongoing improvement [7–9]. Over time, these principles have been extended to address environmental impacts, leading to the development of eco-design, life cycle assessment (LCA), and design for recycling [10–12]. In this review, Industry 4.0 is used as the broad conceptual paradigm, while additive manufacturing, artificial intelligence, machine learning, IoT, digital twins, simulation, and LCA are treated as distinct enabling technologies within that paradigm. Accordingly, Industry 4.0 emerges as a key enabler of sustainable manufacturing by providing the data, connectivity, and automation needed to translate sustainability objectives into operational improvements.

The shift from Industry 3.0 to Industry 4.0 has done more than upgrade factory hardware; it has embedded digital tools like the Internet of Things (IoT), artificial intelligence, big data analytics, automation, and additive manufacturing directly into production workflows [13–15]. Instead of relying on fixed, sequential processes, modern facilities now use these systems to monitor operations in real time, anticipate equipment failures, and adjust parameters on the fly [16–18]. IoT sensors, for instance, continuously track material movement and energy draw, while machine learning fine-tunes production settings to cut scrap and raise quality standards [19–21]. When this digital capability is aligned with sustainability targets, it creates what researchers now refer to as “smart sustainable manufacturing” — a framework where technology drives environmental, economic, and social outcomes in tandem [22–24].

At the core of this framework is material selection. How we source, process, and deploy inputs ultimately determines whether a digitally advanced factory is also a sustainable one. That is why engineers are increasingly specifying bio-based polymers, natural fibers, recycled content, and low-carbon alternatives [25–27]. Figure 1 traces how this transition has unfolded. Before the 1990s, sustainable material use remained largely experimental, centered on basic natural fibers, early recycled inputs, and foundational eco-design concepts. Between 1990 and 2010, the field matured with biodegradable polymers, plant-derived composites, and initial work on algae and mycelium. The 2010–2020 decade accelerated adoption, bringing advanced bioplastics, large-scale waste upcycling, 3D-printed feedstocks, and the formal integration of circular economy principles into engineering practice. Today, these materials are reaching the commercial scale, with carbon-neutral textiles, next-generation sustainable packaging, and low-impact building materials becoming standard rather than niche.

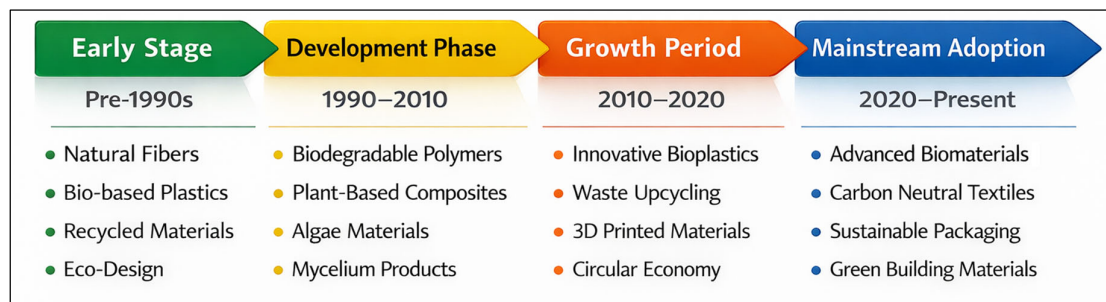


Figure 1. Sustainable materials in an engineering context.

These alternatives offer clear environmental advantages, including lower embodied carbon, renewability, and often inherent biodegradability. They also come with practical trade-offs. Mechanical properties can vary batch to batch, processing windows are nar-

rower, and supply chains for novel biomaterials are still stabilizing [28–30]. That is precisely why pairing sustainable materials with digital and advanced manufacturing methods is not optional; it is the only way to scale them reliably. Smart manufacturing tools can compensate for material inconsistencies, but only if engineers actively address these performance and supply-chain gaps.

To bridge that divide, production teams are turning to targeted advanced techniques. Additive manufacturing enables precise material deposition with minimal waste, while automated sorting and simulation-driven process tuning help normalize inconsistent feedstocks [31–33]. On the evaluation side, life cycle assessment (LCA) has moved from a retrospective academic exercise to a forward-looking design tool, giving manufacturers a clear baseline for the environmental trade-offs across different materials and production routes [34–36]. What is proving most effective is the growing practice of coupling LCA with machine learning and parametric modeling. Rather than relying on static environmental datasets, these integrated approaches dynamically optimize eco-design, making it far easier to balance performance, cost, and sustainability from the earliest stages of product development [37–39].

This convergence of sustainable inputs and Industry 4.0 capabilities is already reshaping several industries, from automotive and aerospace to construction, packaging, and energy [40–42]. In concrete production, for example, digital twins and process simulation have been used to fine-tune recycled aggregate blends, simultaneously lowering costs and embodied carbon [43–45]. AI-driven predictive models are doing similar work for natural fiber composites, mapping out mechanical behavior so these materials can confidently move into structural roles [46–48]. Additive manufacturing has also gained traction because it handles bio-based and recycled filaments efficiently, enabling localized, on-demand production that bypasses traditional supply-chain inefficiencies [49–51]. Yet for all these advances, the research landscape remains highly compartmentalized. Few studies offer a unified framework that ties material selection directly to digital manufacturing workflows while accounting for the full spectrum of sustainability outcomes—environmental, social, and economic [52–54].

This study is contextualized within the current literature on sustainable materials and advanced manufacturing, as stated in Table 1, which covers the primary literature reviews in this topic. This table illustrates that previous assessments emphasize results associated with LCA application, additive manufacturing for the circular economy, and the influence of Industry 4.0 on material selection. Nevertheless, minimal analysis has focused on the interrelated interaction of sustainable materials, advanced manufacturing, and sustainability performance (environmental, social, and economic) within a unified empirical conceptual framework.

Several literature reviews considered the nexus of circular economy, Industry 4.0 and sustainable materials [55–57]. While previous studies mainly highlighted the role of additive manufacturing for circularity [58,59] and the application of machine learning in materials informatics [60,61], social sustainability aspects such as workers's safety, ergonomics and community acceptance remain underaddressed [62,63]. Previous empirical studies often focus on environmental metrics (e.g., carbon footprint, energy efficiency) [64–66], whereas economic performance and long-term durability receive relatively less attention. Multi-level studies that simultaneously account for organization, technology and people aspects are also absent [67,68]. So, with due respect to previous work, this study identifies these issues and creates its conceptual foundation from a broader and more interdisciplinary literature. Major contributions come from literature in life cycle assessment (LCA) [69–71], circular-oriented additive manufacturing [72–74] and application of machine learning in materials science [75–77], complemented by works on industrial symbiosis [78,79], sustainable supply chains [80,81], social LCA [82,83], construction materials

[84,85], biopolymers and biodegradability [86–88], process simulation [89,90], eco-design [91,92], renewable energy integration [93,94], waste management [95,96], building information modeling [97,98], circular business models [99,100] and policy-oriented analysis [101,102]. Literature about methods including system dynamics [103], multi-criteria decision-making (MCDM) [104], blockchain [105], digital product passports [106] and human–technology interaction [107,108] further support this study. All together, these studies highlight the interdisciplinary nature of the field and demonstrate the need for integrated analysis spanning materials design, digital manufacturing and sustainability assessments.

Table 1. Summary of previous literature reviews on sustainable materials, advanced manufacturing, and circular economy.

Researcher(s)	Title	Research Articles Reexamined	Highlights and Results
Tavares et al. (2023) [17]	“The benefits and barriers of additive manufacturing for circular economy: A framework proposal”	73 articles	Benefits and barriers of AM for CE; need for economic viability.
Khan et al. (2021) [66]	“Industry 4.0 and sustainable development: A systematic mapping of triple bottom line, Circular Economy and Sustainable Business Models perspectives”	81 articles	IoT dominant; CE and business models as emerging themes.
Dantas et al. (2021) [77]	“How the combination of Circular Economy and Industry 4.0 can contribute towards achieving the Sustainable Development Goals”	50 articles	CE-I4.0 nexus directly benefits multiple SDGs.
Saha et al. (2025) [75]	“A review of circular economy disruption research: insights into Industry 4.0-enabled circular economy framework for sustainability during turbulent times”	74 articles	Leadership, digital infrastructure, resilience as key for CE-I4.0.
Our study	“Synergizing sustainable materials and advanced manufacturing for sustainability performance: A literature review”	156 articles	Three integration mechanisms; triple-bottom-line sustainability framework.

Sustainable Circular Manufacturing (SCM) is proposed here not as a replacement for existing concepts such as sustainable manufacturing, smart sustainable manufacturing, or circular manufacturing, but as an integrative framework that clarifies how sustainable materials and Industry 4.0 enablers jointly shape circular material flows and multidimensional sustainability performance. While sustainable manufacturing provides the broad sustainability orientation, smart sustainable manufacturing emphasizes digitalization and data-driven control, and circular manufacturing focuses on closing material loops through reuse, repair, remanufacturing, and recycling, SCM explicitly links these strands with material selection, process design, and digital capabilities within a single analytical logic. Its added value lies in explaining how data acquisition, intelligent decision-making, automation, and human–technology interaction translate sustainable material strategies into environmental, social, economic, and technological outcomes. In this sense, SCM frames the causal pathways that connect digital capabilities to circularity and sustainability performance, which are often treated separately in the existing literature. Accordingly, this review not only identifies the technologies most frequently associated with sustainable material integration, but also examines the mechanisms through which these technologies influence sustainability performance and synthesizes the main barriers and sequencing patterns discussed in the literature in order to derive a phased implementation roadmap for SCM.

To strengthen the theoretical foundation of this review, the proposed SCM framework is positioned within the dynamic capabilities perspective, complemented by a socio-technical systems lens. In this context, sensing refers to the ability to identify sustainability-related opportunities and threats across both internal operations and external supply networks, including material inefficiencies, resource constraints, regulatory pressures, and circularity opportunities; seizing refers to the capacity to evaluate and adopt suitable sustainable materials, digital tools, and process configurations that can address these opportunities; and reconfiguring refers to the organizational ability to redesign workflows, resource flows, roles, and production systems so that sustainable materials and Industry 4.0 enablers can be integrated into resilient and circular manufacturing practices. From this viewpoint, data acquisition and process transparency strengthen sensing by improving visibility over material flows, intelligent decision-making supports seizing through adaptive material selection and trade-off management, and automation, together with human–technology interaction, supports reconfiguring by translating digital insights into operational redesign and circular production practices. This interpretation clarifies how the microfoundations of dynamic capabilities manifest specifically in sustainable material integration and shows that these mechanisms are capability-building processes rather than merely standard Industry 4.0 functions.

This research therefore addresses the identified knowledge gap by performing a systematic literature review of 156 peer-reviewed articles analyzing the nexus of sustainable materials, advanced manufacturing and sustainability performances. The SLR is guided by the following research questions:

- RQ1: In what way may modern manufacturing technologies (e.g., additive manufacturing, AI, simulation, IoT) promote the selection, processing, and circularity of sustainable materials, and what contribution do they make to environmental, social, and economic sustainability?
- RQ2: What are the main technological, organizational, and human-related barriers to the integration of sustainable materials with Industry 4.0, and what implementation roadmap can be derived from the literature?

Answering these questions requires a holistic approach that combines digital transformation, sustainable material engineering, and circular economy principles. The remainder of this paper is structured as follows: Section 2 describes the materials and methods; Section 3 presents the descriptive results; Section 4 discusses the integration mechanisms and sustainability implications; and Section 5 concludes with future research directions.

2. Methods and Materials

This literature review adopts a descriptive approach to examine existing research on the incorporation of sustainable materials within contemporary engineering contexts, with a focus on advancing economic, social, technological, and environmental sustainability. The methodological framework consists of a structured search protocol, a systematic descriptive analysis framework to maintain coherence, and well-defined inclusion and exclusion criteria.

2.1. Research Methodology

2.1.1. Phase 1: Selection of Appropriate Research

The analysis focusses on academic works that address the exploitation of sustainable materials in engineering disciplines to support sustainability transitions across sectors. Only peer-reviewed journal publications published in English were considered. Given that research on sustainable materials in engineering has developed notably during the past decade, the temporal scope was defined from 2015 to 2025 to capture recent advances.

2.1.2. Phase 2: Literature Compilation

A keyword-based approach moving from broad to specific terms was employed, aligned with the research objectives. The search strategy unfolded in three stages. Initially, broad terms related to sustainable materials and their engineering applications were used. Subsequently, keywords covering advanced manufacturing, material processing, and digital technologies were incorporated. Finally, sustainability-related terminology was utilized to encompass technological, environmental, social, and economic performance elements. Each of the three theme groups were joined using Boolean operators (“OR” and “AND”) to locate overlapping areas, resulting in the following categories:

Category A: (“Sustainable Materials”, “Green Materials”, “Eco friendly Materials”, “Bio based Materials”, “Biocomposites”, “Natural Fibers”, “Recycled Materials”, “Circular Economy”, “Material Selection”, “Low Carbon Materials”, “Renewable Resources”, “Biodegradable Polymers”, “Green Composites”, “Sustainable Engineering”, “Eco design”);

Category B: (“Advanced Manufacturing”, “Additive Manufacturing”, “3D Printing”, “Material Processing”, “Life Cycle Assessment”, “LCA”, “Material Characterization”, “Digital Manufacturing”, “Industry 4.0”, “AI in Materials”, “Machine Learning”, “Material Informatics”, “Process Optimization”, “Smart Manufacturing”, “Automation”, “Simulation”, “Modeling”);

Category C: (“Sustainability”, “Environmental Performance”, “Carbon Footprint”, “Embodied Energy”, “Life Cycle Analysis”, “Circularity”, “Social Sustainability”, “Economic Viability”, “Resource Efficiency”, “Waste Reduction”, “Durability”, “Recyclability”, “Biodegradability”, “Technological Performance”, “Sustainable Development Goals”, “SDGs”).

2.1.3. Phase 3: Search Strategy and Study Selection

To improve methodological transparency and reproducibility, the literature search was conducted using predefined search strings tailored to each database. The search strategy combined three thematic blocks: (i) sustainable materials, (ii) advanced manufacturing and digital technologies, and (iii) sustainability performance. Within each block, synonyms were connected using OR, while the three blocks were combined using AND to retrieve studies located at the intersection of the target concepts. The exact database-specific search strings and query combinations are reported in the Appendix/Supplementary Material. The selection of Scopus, Web of Science, and IEEE Xplore was motivated by their broad coverage of peer-reviewed literature in materials science, engineering, digital manufacturing, and sustainability research.

We employed a multi-stage filtering process to clean up the records we discovered and ensure that the methods were correct. First, papers unrelated to engineering or materials science were deleted, as were non-journal publications such as conference proceedings, book chapters, and editorials. Duplicate entries were also eliminated. This initial screening yielded 521 peer-reviewed journal articles. Next, title and keyword screening

was performed to exclude studies whose focus diverged from sustainable materials or the core aims of this review, reducing the pool by 365 articles.

The inclusion and exclusion criteria were defined a priori to ensure consistency with the objectives of the review. Studies were included if they: (i) were peer-reviewed journal articles published in English between 2015 and 2025; (ii) addressed sustainable materials, advanced manufacturing, or Industry 4.0-enabled technologies; and (iii) reported at least one sustainability dimension, including environmental, social, economic, or technological performance. Studies were excluded if they were non-journal publications, such as conference proceedings, book chapters, and editorials; if they were unrelated to engineering or materials science; if they focused on sectors outside the scope of this review; or if they included only peripheral references to the target themes without substantive analytical contribution. These criteria were selected to maintain conceptual coherence, ensure comparability across studies, and retain only publications directly relevant to the research questions.

A formal quality assessment was conducted during the eligibility stage of screening. Each full-text article was evaluated using predefined criteria covering the clarity of the research objectives, appropriateness of the study design, transparency of methods and data reporting, relevance to the review questions, and robustness of the findings. Studies were retained only if they met the minimum quality threshold and were considered methodologically reliable for inclusion in the final corpus. This quality appraisal was applied to the retained studies to reduce the risk of incorporating weak or insufficiently documented evidence into the synthesis and was integrated into the PRISMA-based selection process to enhance transparency, consistency, and reproducibility.

Potential selection bias was minimized through several safeguards. Duplicate records were removed before screening, and the selection process followed a multi-stage procedure involving title screening, abstract screening, and full-text verification. All records were assessed against the same predefined eligibility criteria to reduce subjective judgment and improve consistency. Ambiguous cases were revisited during screening to ensure that inclusion and exclusion decisions were applied uniformly. The overall process is reported in a PRISMA-style flow diagram to provide a transparent account of record identification, screening, eligibility assessment, and final inclusion.

Following this process, 156 articles were retained for analysis, including review papers, empirical studies, and conceptual contributions. This final corpus provided a sufficiently broad yet focused evidence base for examining the integration of sustainable materials, advanced manufacturing, and Industry 4.0 across sustainability dimensions.

Figure 2 provides a visual summary of the literature identification and selection procedure. Initially, 734 records were obtained from Scopus, 300 from Web of Science, and 411 from IEEE. After applying the filtering and relevance assessments based on predefined criteria, 18 review articles and 138 empirical or conceptual studies remained. Consequently, a final set of 156 articles constitutes the basis for the descriptive analysis presented in this literature review.

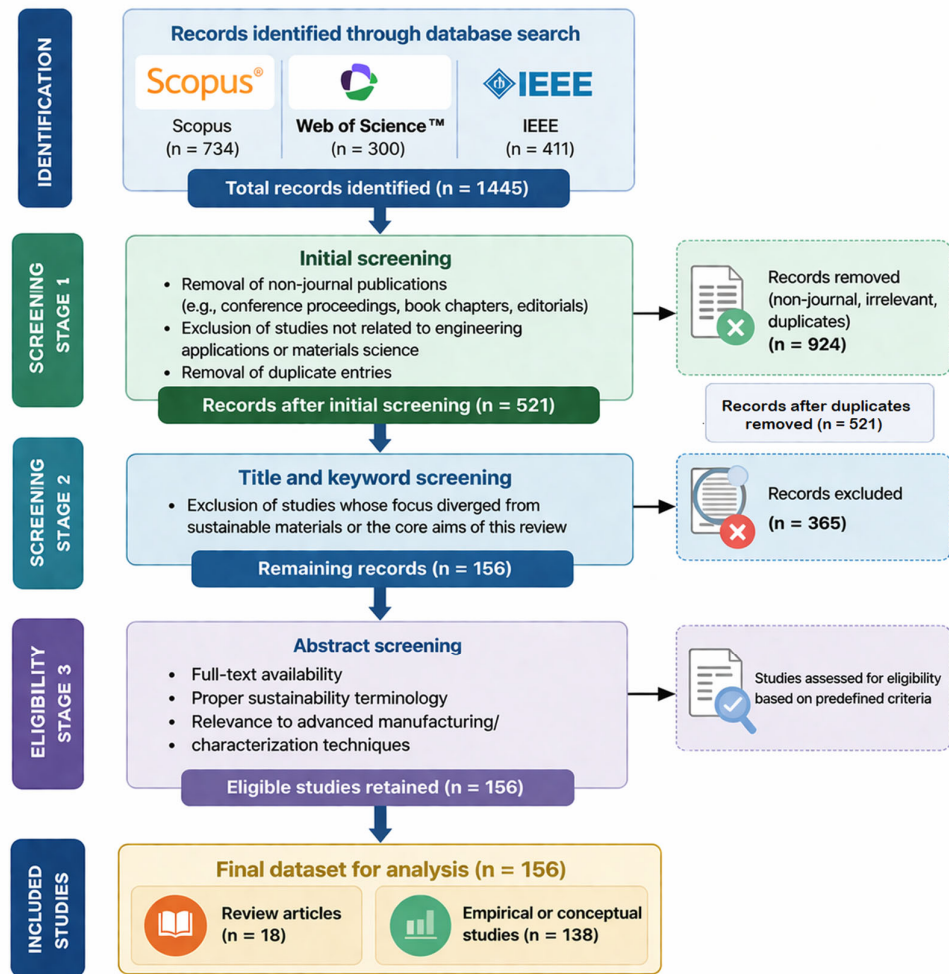


Figure 2. Flow diagram illustrating the PRISMA methodology applied to the literature search.

2.2. Analytical Framework

To analyze the selected papers in more depth and explore their content, an analytical framework was conducted. This analysis combined qualitative indicators with quantitative categorization, thus providing an overview of the integration of sustainable materials and advanced manufacturing technologies to ensure multidimensional sustainability performance (in terms of environmental, social, and economic factors). Specifically, the analytical framework encompassed the following dimensions:

- Temporal distribution of publications: This article discusses the progress of research and its changing trends over time in the literature, a very important topic to follow in the research field of sustainable materials and their applications in advanced manufacturing systems and sustainable performance.
- Methodological distribution of publications: This analysis investigates the range of research designs employed across the selected studies, including conceptual contributions, qualitative inquiries, quantitative empirical analyses, and mixed-method approaches, in order to assess the methodological maturity of the field.
- Journal-wise distribution of publications: This aspect aims to identify the leading academic outlets that have contributed to the development of this research domain, thereby highlighting the most influential journals shaping the discourse.
- Technology-oriented distribution of publications: This dimension provides a structured classification of advanced manufacturing and digital technologies based on

their functional role in supporting sustainable material integration and advancing sustainability objectives.

- Keyword co-occurrence analysis: This dimension explores the interrelationships among key terms used in the literature, allowing for the identification of dominant themes, research clusters, and emerging conceptual linkages within the field.

The purpose of this analytical investigation is to systematically map and characterize the structure of the research field by exploring the ways in which sustainable materials are integrated with advanced manufacturing technologies to improve environmental, social, and economic sustainability outcomes. Through the analysis of the previously defined dimensions, this study enables the identification of prevailing research patterns, including the increasing emphasis on additive manufacturing and machine learning techniques for circular material selection. At the same time, it highlights critical research gaps, notably the limited consideration of social sustainability aspects and the scarcity of longitudinal empirical investigations addressing the biodegradability and recyclability of emerging bio-based composites. These findings provide a foundation for outlining potential avenues for future research.

No statistical aggregation or meta-analytic synthesis was undertaken in this review. Accordingly, all quantitative results reported in the manuscript should be interpreted as context-specific, literature-based observations derived from individual studies rather than as generalized statistical evidence.

3. Results

A total of 156 publications were selected and finalized as the final sample for this literature review, which provided the empirical basis for the analysis and integration of existing knowledge on sustainable materials and their integration with advanced manufacturing technologies, including additive manufacturing and machine learning, including life cycle assessment. The synthesis highlights how sustainable materials, additive manufacturing, machine learning, and life cycle assessment interact to shape sustainability performance across environmental, social, economic, and technological dimensions.

This content analysis led to the development of a conceptual structure that depicts the interactions between sustainable material selection and digital manufacturing tools and their impact on resource efficiency and circularity, which are related to the desired sustainability outcomes.

3.1. Publication Distribution

3.1.1. Temporal Distribution of Publications

Figure 3 illustrates how the number of publications on sustainable materials, advanced manufacturing, and sustainability has evolved from 2015 to 2026. In the earliest period (2015–2017) output was very low, with only three papers in 2015, one in 2016, and none in 2017, indicating that the intersection of these three themes was just beginning to attract attention. A modest rise occurred between 2018 and 2019 (four and three papers, respectively), signaling a slowly growing academic interest. A more substantial increase took place in 2020, which reached eight publications—the first noticeable peak. This upturn may reflect a broader shift in engineering and materials research toward circular economy and low-carbon solutions during that period. The years 2021 and 2022 saw further growth, with 19 and 21 papers respectively, marking a phase where researchers began consolidating empirical case studies and conceptual frameworks that explicitly link sustainable materials with digital manufacturing technologies (e.g., additive manufacturing, machine learning, LCA). Although 2023 experienced a slight dip to 17 papers, the field rebounded strongly in 2024 (23 papers) and reached its highest level so far in 2025

(42 papers). By the time of the search, 15 papers were already indexed in 2026, indicating ongoing research activity in the field and suggesting continued expansion of the literature. Overall, this trend demonstrates a clear and sustained increase in scholarly interest in combining sustainable materials, advanced manufacturing, and sustainability performance. However, as with any bibliometric analysis, these fluctuations should be interpreted with caution, because they can be influenced by external factors such as funding cycles, special issues, or delays between submission and publication. Therefore, this overview serves to provide general context about the field's evolution rather than to establish direct causal explanations.

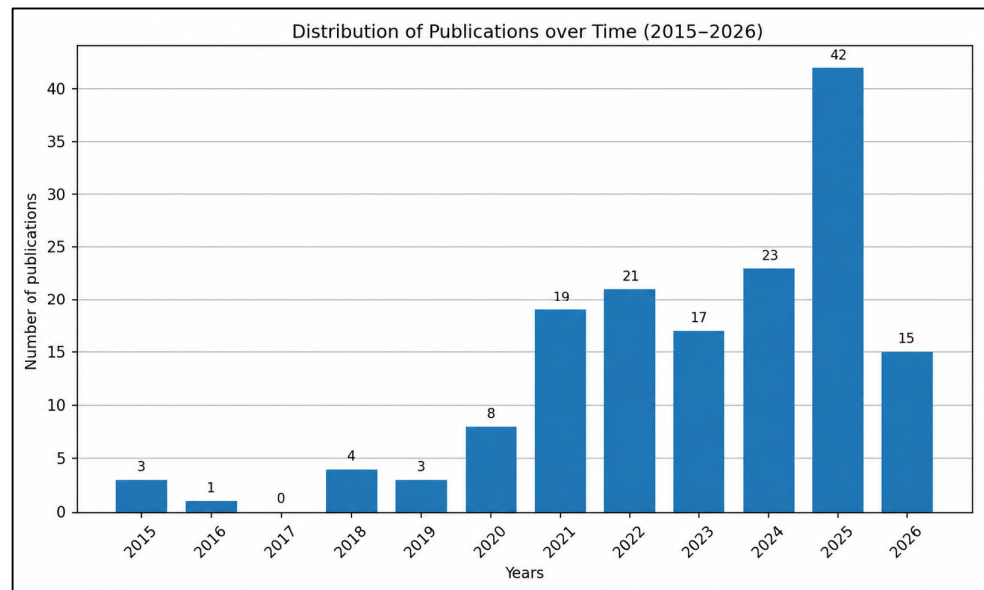


Figure 3. Annual distribution of publications from 2015 to 2026.

3.1.2. Methodological Distribution of Publications

Figure 4 presents the methodological breakdown of the 156 selected papers on sustainable materials, advanced manufacturing, and sustainability performance. The papers were classified into four research types: empirical and case studies, systematic literature reviews and critical syntheses, conceptual and theoretical contributions, and analytical studies (qualitative or quantitative). This typology helps to understand how researchers have approached the intersection of sustainable materials with advanced digital and manufacturing technologies and how they assess environmental, social, and economic outcomes.

The results show that empirical and case studies are the most frequent category. Out of the 156 papers, 138 are original research articles, the majority of which present experimental data, case-based life cycle assessments, process-optimization trials, or material characterization studies. This dominance indicates that research in this field is strongly grounded in practical investigations. Researchers often test bio-based or recycled materials using additive manufacturing or simulation tools, then measure carbon footprint, embodied energy, or recyclability in real or realistic settings. Such studies provide tangible evidence of how sustainable materials perform under specific advanced manufacturing conditions.

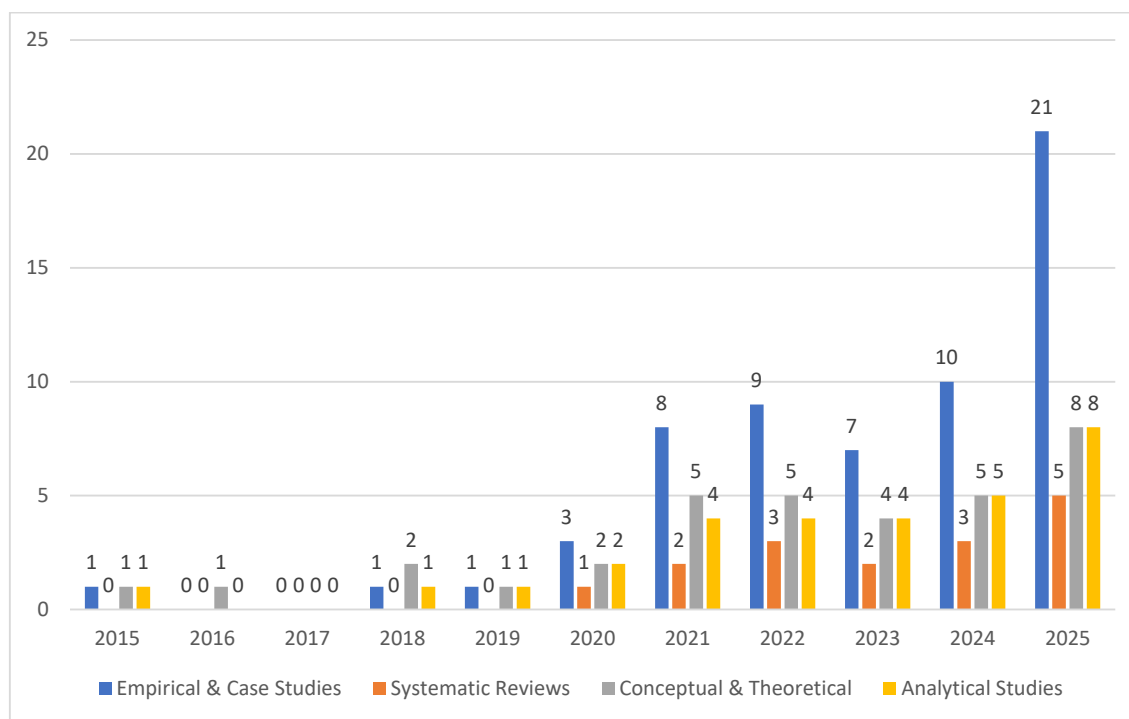


Figure 4. Trends in publication output by research type over time (2015–2025).

Systematic literature reviews and critical syntheses constitute the second most prevalent category, with 18 review papers. These contributions play an essential role in structuring the field. They organize existing knowledge, identify key trends (e.g., the rise in machine learning for material selection), map research gaps (e.g., limited social sustainability indicators), and propose future agendas. Reviews also help consolidate fragmented evidence on topics like circular economy integration or the use of LCA in additive manufacturing.

Conceptual and theoretical contributions appear less frequently but remain meaningful. These papers typically introduce new frameworks, models, or taxonomies that link sustainable materials with Industry 4.0 technologies or sustainability dimensions. Although their number is relatively low, they provide foundational insights that guide subsequent empirical work—for example, by defining a multi-criteria decision framework for material selection under circular economy principles. In this context, MCDM studies generally follow a structured workflow in which criteria are first defined, weights are assigned through expert judgment or pairwise comparison, and alternatives are then ranked using methods such as AHP, TOPSIS, VIKOR, or hybrid combinations. In the reviewed literature, these methods are used to compare material options, evaluate additive manufacturing routes, and support sustainability-oriented process selection. Overall, these workflows transform qualitative sustainability objectives into structured and transparent ranking outputs, thereby enabling reproducible decision support and explicit trade-off analysis.

Finally, analytical studies using purely qualitative or quantitative methods (without full empirical case work) are the least represented category. These investigations often rely on mathematical modeling, simulation only, or survey-based data without experimental validation. Their scarcity suggests that the field prioritizes applied, demonstrative research over purely theoretical or statistical analyses, even though such analytical approaches are important for formalizing trade-offs and validating decision frameworks.

Overall, the methodological distribution reveals a strong applied orientation: most studies test sustainable materials in real or simulated advanced manufacturing environments and evaluate their sustainability performance using life cycle or circularity metrics. Reviews and conceptual papers support this applied core by synthesizing knowledge and offering theoretical guidance. This balance highlights the maturity of the field, where practical demonstrations are backed by systematic organization of the literature and conceptual framing. Future research could benefit from more analytical studies that isolate specific causal relationships—for example, between machine learning parameters and carbon footprint reduction—as well as from more longitudinal empirical work on biodegradability and social sustainability.

3.1.3. Journal-Wise Distribution of Publications

As illustrated in Figure 5, the 156 selected studies are distributed across a diverse set of academic journals, highlighting the interdisciplinary scope of research at the interface between sustainable materials, advanced manufacturing technologies, and sustainability performance. The *Journal of Cleaner Production* is the most prominent outlet, accounting for 36 papers (approximately 23% of the total). This dominance indicates the journal's strong focus on life cycle thinking, circular economy, and environmental impact assessment—core themes of the reviewed literature. The second most frequent source is *Sustainable Production and Consumption*, with 11 papers (about 7%), highlighting the growing attention to sustainable consumption and production patterns. The *International Journal of Production Economics* follows with five papers (3%), while *Industrial & Engineering Chemistry Research* and several other journals—such as *Production Planning & Control*, *Computers & Industrial Engineering*, and *Additive Manufacturing*—each contribute three to four papers. In addition to these leading journals, a substantial share of the literature (over 60% of the journals) appears in sources that have published only one or two relevant articles. Examples include *Materials*, *Polymers*, *IEEE Access*, *Sustainability* (Switzerland), and *Construction and Building Materials*. This broad dispersion confirms that the field draws from multiple disciplines, including materials science, mechanical engineering, industrial engineering, environmental science, and business management. Consequently, no single journal monopolizes the area; instead, the research landscape is fragmented yet rich, with contributions scattered across specialized engineering journals, sustainability-focused periodicals, and interdisciplinary publications. This pattern underscores the complexity and multidisciplinary scope of the domain, where innovations in eco-design, additive manufacturing, and life cycle assessment intersect with broader sustainability goals such as the UN Sustainable Development Goals (SDGs).

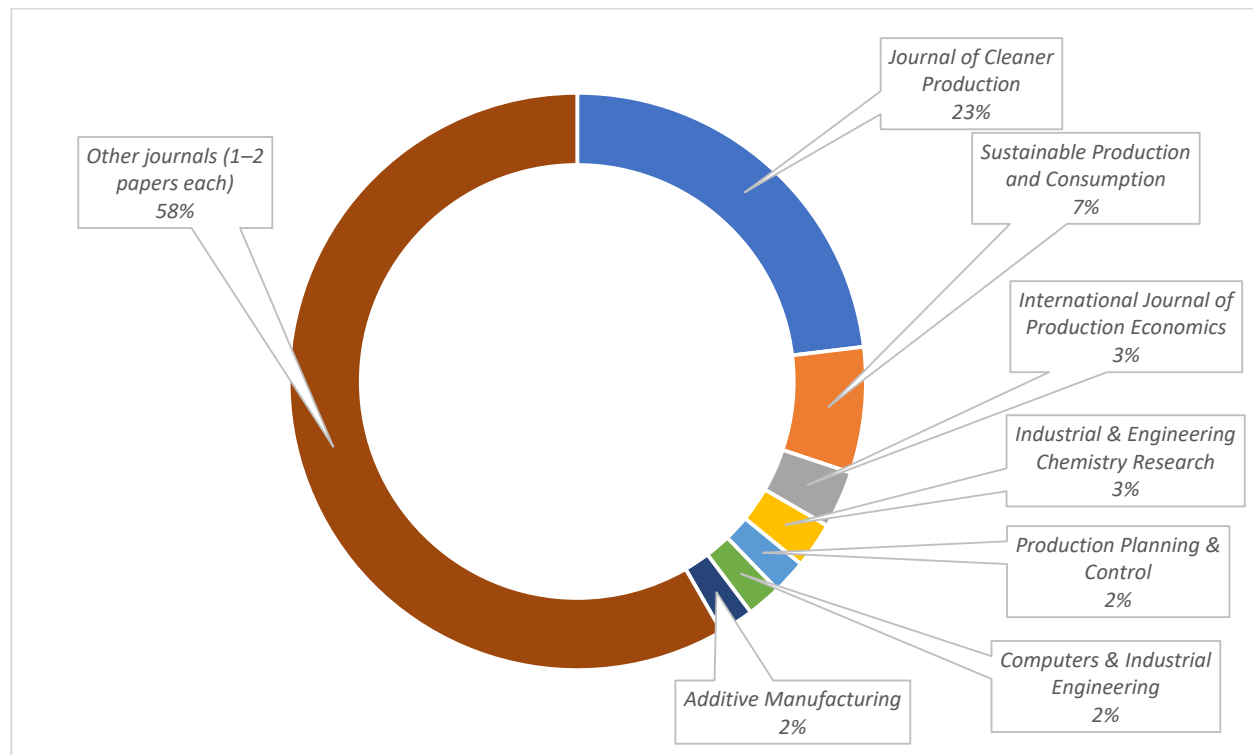


Figure 5. Distribution of selected articles by journal.

3.1.4. Technology-Oriented Distribution of Publications

The analysis of keyword frequencies from the 156 selected papers reveals how different advanced manufacturing and digital technologies are deployed to support sustainable material selection and environmental, social, and economic performance. The results shown in Figure 6 indicate considerable variation in research attention across different technology categories. Industry 4.0 appears as the most frequently cited technology (41 occurrences), reflecting the broad enabling role of digital transformation in connecting sustainable materials with modern production systems. Life cycle assessment (LCA) follows closely (19 occurrences), indicating that environmental accounting remains a central method for evaluating the sustainability impact of material and manufacturing choices. machine learning (15 occurrences) and additive manufacturing (13 occurrences) also feature prominently. The strong presence of additive manufacturing aligns with the growing interest in 3D printing of bio-based, recycled, and biodegradable polymers, where process flexibility can reduce material waste and enable circular design. Machine learning is increasingly used for material informatics, process optimization, and predictive modeling of mechanical properties or carbon footprints. Other technologies such as simulation and modeling, process optimization, and automation appear with lower but consistent frequency, suggesting they are often applied in combination with the dominant categories rather than as standalone solutions. Notably, artificial intelligence (explicitly “AI in Materials”) and digital manufacturing are present but remain less represented, indicating that their integration into sustainable materials research is still emerging. This distribution suggests that the research field is oriented toward reducing waste, improving recyclability, and lowering carbon and energy footprints, as reported across the reviewed studies.

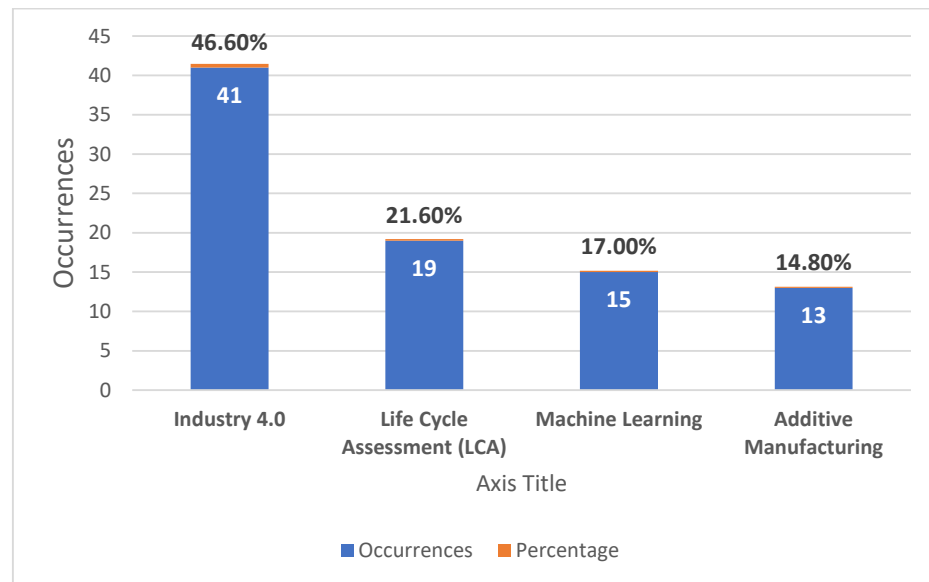


Figure 6. Frequency of key technologies in the reviewed literature.

3.1.5. Keyword Co-Occurrence Analysis

Figure 7 presents the keyword co-occurrence network derived from the final set of 156 articles included in this review. The analysis was performed using VOSviewer (version 1.6.20), which extracted author keywords from the Scopus export and mapped their relationships. In the resulting visualization, larger node sizes correspond to higher keyword frequencies, and different colors indicate distinct thematic clusters.

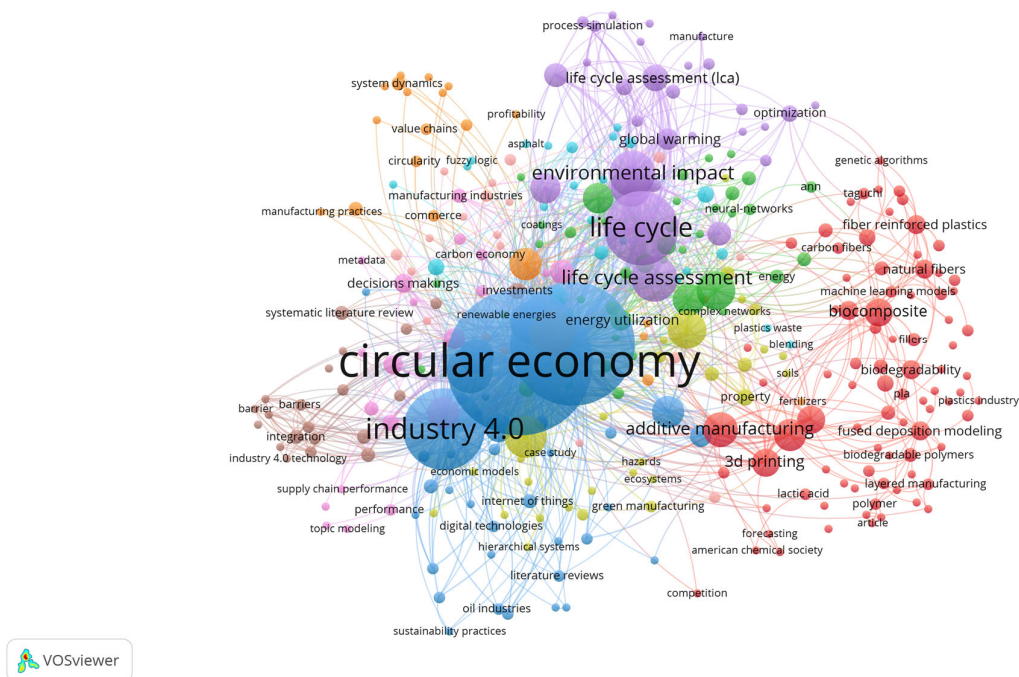


Figure 7. Co-occurrence analysis of keywords in sustainable manufacturing literature (VOSviewer map version 1.6.20).

The most frequently occurring keyword is “circular economy” (91 occurrences), followed by “sustainable development” (73), “industry 4.0” (41), “life cycle” (36), “environmental impact” (19), “life cycle assessment” (19), “sustainability” (19), “supply chains” (19), “decision making” (18), “industrial economics” (17), “ecodesign” (16), “recycling” (15), “machine learning” (15), and “additives” (12). These terms occupy central positions in the network, indicating their foundational role in the literature.

The co-occurrence links reveal several interconnected clusters. One major cluster groups “circular economy” with “recycling”, “ecodesign”, “additives”, and “life cycle”/“life cycle assessment”. This suggests that research frequently examines how product design, material additives, and end-of-life recycling contribute to circular material flows. A second cluster links “industry 4.0” with “machine learning”, “decision making”, “supply chains”, and “industrial economics”. Here, digital enablers are used to optimize manufacturing processes and supply-chain decisions while considering economic and environmental trade-offs. A third cluster revolves around “sustainable development” and “sustainability”, often appearing together with “environmental impact”, indicating that sustainability is evaluated primarily through environmental metrics. Notably, social sustainability terms are absent from the most frequent keywords, revealing a gap in the current literature.

Overall, the keyword co-occurrence analysis shows a research landscape where circular economy principles, Industry 4.0 technologies, and life cycle thinking converge. The network confirms that additive manufacturing (implied via “additives” and related terms) and machine learning are the dominant advanced manufacturing tools being applied to sustainable material challenges. This descriptive mapping also points to future research directions, particularly the need to integrate social sustainability dimensions and to conduct more longitudinal empirical studies on biodegradability and recyclability of novel bio-based composites.

3.2. Content Analysis

Building on the descriptive results, this section synthesizes the principal mechanisms and sustainability implications emerging from the 156 selected studies. The analysis considers publication year, research methodology, the advanced manufacturing or digital technology employed, and the sustainability dimension addressed. The literature shows clear maturation: early work (2015–2018) emphasized material properties and foundational life cycle assessment, whereas more recent studies increasingly combine digital enablers such as machine learning, simulation, and process optimization to improve material selection, reduce waste, and enhance circularity. Several studies also report quantitative outcomes on carbon footprint reduction, embodied energy savings, and economic viability; however, these values are treated here as illustrative, study-specific findings rather than pooled effect sizes, since this review does not perform meta-analysis. To structure the synthesis, this section is organized around two themes: (i) integration mechanisms linking advanced manufacturing and digital technologies to sustainable-material processing, and (ii) contributions to sustainability performance across environmental, social, and economic dimensions.

3.2.1. Integration Mechanisms Between Sustainable Materials and Advanced Manufacturing Technologies

The shift from conventional material selection to sustainable material engineering has increasingly been supported by advanced manufacturing technologies, many of which originate from the Industry 4.0 paradigm. This integration goes beyond waste reduction or process optimization by incorporating simulation modeling, machine learning, automation, and life cycle assessment (LCA) to improve the environmental, social, and

economic performance of material systems. For example, several studies report the use of LCA and simulation methods prior to manufacturing implementation to estimate carbon emissions and embodied energy [109,110].

Analysis of the 156 selected articles reveals three recurring mechanisms: (1) data acquisition and process transparency, (2) intelligent decision-making and workflow enhancement, and (3) automation and human–technology interaction. These mechanisms act jointly to translate sustainability-oriented material innovation into measurable performance improvements. Data acquisition and process transparency improve visibility over material flows, identify environmental hotspots, and reduce implementation uncertainty. Digital monitoring, simulation, and LCA are frequently used to assess alternative material blends and process scenarios before physical implementation, thereby improving design robustness. Intelligent decision-making converts monitoring outputs into operational improvements, with machine learning, optimization algorithms, and AI-supported decision systems used to support material selection, parameter tuning, and trade-off analysis, particularly for variable bio-based or recycled inputs. Automation and human–technology interaction stabilize production, reduce variability, and minimize material losses; however, the literature shows that these gains depend on organizational learning, staff engagement, and leadership support [111]. Multiple investigations show that digital simulation platforms can track resource movement, detect hotspots of non-circularity, and test alternative bio-based or recycled material compositions before physical production [112,113]. Moreover, LCA integrated with additive manufacturing has been reported to reduce material waste and eliminate redundant processing steps, supporting circular economy goals [114]. In a similar manner, artificial intelligence (AI) and real-time monitoring can enhance the traceability of recycled content and improve the reliability of biodegradability assessments [115]. It has been demonstrated by a number of review-based studies that digital tools have a significant impact when embedded within material development workflows, rather than when used as standalone software. A collective analysis of the extant literature indicates that the synergy between sustainable materials and advanced manufacturing is contingent upon organizational learning, staff engagement, and leadership support. These factors have been identified as critical enablers of a successful transformation [116].

To further clarify how machine learning supports parameter optimization in the presence of biomaterial inconsistency, Table 2 compares representative algorithms used in the reviewed literature, highlighting their typical applications, target inconsistencies, and main advantages. These findings suggest that machine learning and LCA are not only decision-support tools but also key enablers of robust material selection under conditions of material variability.

Table 2. Comparison of machine learning algorithms for biomaterial variability.

Algorithm	Typical Use	Biomaterial Inconsistency Addressed	Manufacturing Application	Main Contribution
Random Forest	Prediction and feature importance	Variability in material composition and mechanical properties	Material selection, quality prediction	Handles nonlinear relationships and identifies key variables
Support Vector Machine (SVM)	Classification and regression	Batch-to-batch variation	Property classification, defect prediction	Performs well with small datasets and complex patterns
Artificial Neural Network (ANN)	Nonlinear prediction	Inconsistent input–output relationships	Process parameter optimization	Captures hidden dependencies in material behavior

Gradient Boosting/XGBoost	High-accuracy prediction	Multi-factor variability in bi-omaterial performance	Process tuning, performance prediction	Strong predictive power and robustness
Decision Tree/Hybrid models	Rule-based decision support	Mixed property inconsistency	Sustainable material selection	Easy to interpret and useful for decision-making

Data acquisition and process transparency emerges as the first core mechanism. Among the key objectives of sustainable manufacturing is the identification of material flows using digital value-stream mapping (VSM) or material flow analysis (MFA), making waste and inefficiencies visible [117]. Simulation-based data acquisition tools are the most frequently reported technologies in the selected papers, with “Simulation” and “Modeling” appearing as prominent keywords. The studies demonstrate how simulation can identify congestion points in material processing, support real-time interventions for energy efficiency, and anticipate system behavior to minimize environmental risk [118,119]. In the same way, digitalization of material processing workflows simplifies the application of life cycle monitoring and strengthens transparency. Overall, the findings strongly support the use of data acquisition and monitoring mechanisms alongside sustainable material practices.

Another key mechanism is smarter decision-making and workflow improvements, where the reviewed literature reports on the use of discrete-event simulation and machine learning in decision-making processes, which impacts factors like system responsiveness. Also, the literature reports an increase in staff satisfaction related to material handling after the implementation of an AI-assisted sorting system, leading to a more balanced allocation of human resources [120–122]. AI can further support decision-making within a sustainable manufacturing system structure. For instance, in visual inspection systems based on deep learning technology when used together with lean materials handling approaches there is a huge reduction in reject rates of material since defect detection processes become automatic and more accurate while eliminating waste at the same time. When deep learning technology is used in these processes, there can be an improvement rate of between 95% and 99% [123]. The application of AI-supported sustainable material processes in smart manufacturing requires digital technology integration to make better decisions, predict outcomes, and act in real time. The main components of these processes are digital material flow analysis, AI-supported LCA, digital kanban for materials, and the incorporation of continuous improvement loops [124].

In terms of specific technologies and smart decision-making, AI-based techniques can further improve traditional material flow analysis (MFA), advancing it from a static exercise to a changing source of insights. While conventional MFA depends on human observation and often periodic sampling of data, AI-based MFA systems can pull and analyze changing data on material flows from various manufacturing execution systems. Similarly, researchers can analyze production event logs to identify inefficiencies in material use and provide objective insights into the performance of circularity initiatives. In sum, with the constant updating of material flow maps, these systems can better inform decision-making.

The third identified mechanism includes both automation and collaboration between people and technology. Environmentally responsible production systems focus on getting the most out of resources, following the same steps every time, and always getting better [125]. As a result, Industry 4.0 technologies make it easier to put sustainable material guidelines into practice. Numerous studies indicate that the integration of personnel and technological systems, along with automated operations, enhances the stability of mate-

rial handling processes. Also, combining eco-friendly workflows with mechanized processes increases productivity and shortens cycle times, which improves both operational performance and sustainable workflow practices [126,127]. This progress is due to automated barcode verification systems that ensure that material specifications and batch data match up correctly. This cuts down on wrong material choices and gets rid of unnecessary handling steps, ultimately leading to more efficient logistics operations and contributing to the overall sustainability improvements mentioned. Also, the application of this framework results in exemplary environmental sustainability improvements that include a decline in energy intensity of between 25% and 40%, a decrease of 40% in carbon emissions associated with logistics operations, and increased system uptime of 15%, all pointing towards the framework's potential application [128]. Cross-functional collaboration and the rapid implementation of digital technologies in production environments can be enhanced when sustainable material development is facilitated by digital monitoring of material properties [129]. Research shows that eco-friendly materials and advanced manufacturing can work together through human–system collaboration. This gives production systems the tools they need to deal with more and more complex environmental problems while also strengthening resource-efficient practices at their core.

In addition, advanced manufacturing technologies can improve upon the established methods for sustainable materials. For instance, while material flow analysis relies on manual tracking and spot sampling, material flow analysis could become digitalized if IoT sensors are deployed to gain real-time visibility into material flows and precisely pinpoint non-value-added steps [130]. AI can augment continuous improvement by predicting opportunities to improve material inefficiencies and suggesting focused improvements. Automation has also been utilized to enable error proofing and process control for recycling processes and processing of bio-based materials.

Taken together, many publications describe predictive and proactive approaches to manufacturing management that leverage both sustainable materials and advanced manufacturing. Table 3 presents an overview of research focusing on how data collection, material flow tracking, process transparency, smart decision-making, process optimization, and automation, coupled with human–technology collaboration, drive continuous improvement throughout the entire manufacturing journey. As shown in the table, these papers suggest that advanced manufacturing empowers sustainable materials; however, the strength of this relationship is dependent on the contextual pairing of the technology to particular improvement goals (e.g., reducing carbon footprint, circularity, economic feasibility).

Table 3. Overview of integration mechanisms linking sustainable materials with advanced manufacturing technologies.

Integration Mechanism	Main Advanced Manufacturing/Digital Technologies	Sustainable Materials Context	Sustainability Objectives Supported
Data acquisition, material-flow monitoring, and process transparency	Discrete-event simulation, material flow analysis (MFA), digital product passports, IoT sensors, real-time dashboards, life cycle assessment (LCA) software	Bio-based and recycled material processing, composite manufacturing, construction material supply chains, waste sorting facilities	Material flow visibility, waste identification, circularity tracking, hotspot detection for environmental impact
Decision-making and intelligent process optimization (e.g., ANN, random forest, XGBoost)	Simulation modeling, artificial intelligence (AI), machine learning optimization algorithms	Material selection for eco-design, additive manufacturing parameter optimization, recycled	Evidence-based material choice, process standardization, reduction of carbon footprint and embodied energy,

	(e.g., genetic algorithm, particle swarm), decision-support systems	aggregate concrete formulation, biocomposite development	continuous improvement in circularity
Automation and human–technology interaction	Automated sorting and recycling lines, robotic disassembly, 3D printing (FDM, SLS) for repair/re-manufacturing, collaborative robots, digital twins, blockchain for traceability	End-of-life product processing, polymer recycling, metal powder reuse in additive manufacturing, bio-based composite fabrication	Reduction in non-value-added manual handling, operator engagement, standardized sustainable workflows, learning and capability development for circular economy

To systematically map our findings to RQ1, the causal relationships between the three identified SCM mechanisms and the four sustainability performance dimensions are detailed in Table 4 below.

Table 4. SCM mechanism-to-performance mapping table.

SCM Mechanism	Economic Performance	Environmental Performance	Social Performance	Technological Performance
Data Collection and Process Transparency	Identifies cost inefficiencies and tracks resource expenditure in real time.	Pinpoints energy hotspots and tracks exact carbon footprint across the life cycle.	Monitors workplace conditions and ergonomic data for improved safety.	Creates foundational digital twins and ensures real-time operational visibility.
Intelligent Decision-Making (AI/ML)	Reduces downtime via predictive maintenance and optimizes supply-chain logistics.	Selects optimal bio-based material mixes to lower embodied carbon dynamically.	Adapts operating parameters to minimize worker fatigue and hazardous exposure.	Enables autonomous error correction and continuous process optimization.
Automation and Human–Tech Interaction	Increases labor efficiency and directly reduces material scrap costs.	Lowers overall energy intensity through stabilized, highly precise workflows.	Replaces human labor in physically dangerous or toxic manufacturing roles.	Ensures high-fidelity additive manufacturing and consistent product quality.

3.2.2. Role of Sustainable Materials and Advanced Manufacturing Technologies in Sustainability Performance

Several studies address the integration of sustainable material selection with advanced manufacturing technologies (Industry 4.0) in relation to sustainable production systems [131]. In the same manner, technologies are being designed and implemented to address these requirements and help realize sustainability targets in manufacturing settings. Numerous reports highlight findings with regard to economical, environmental, social and technological sustainability metrics. Henceforth sustainability, within the realm of sustainable manufacturing, will be referred to as the capability of a production system to promote long-term organizational and system health with minimal use of resources and reduced environmental impact [132]. Sustainability is embedded within many continuous improvement philosophies (i.e., Kaizen, lean manufacturing), one of which consists of the continuous efforts to eliminate waste and improve efficiency. Therefore, discussions of sustainability within the realm of sustainable materials and advanced manufacturing pertained to the topics of production processes and material life cycles in the reviewed literature. Additionally, sustainability with regard to sustainable materials and advanced manufacturing is more than blending eco materials and I4.0 together. It focuses on implementation of constant monitoring, communal knowledge and real-time data analysis rather than responding to problems after they occur. A number of research articles highlight the implementation of data-driven decision-making with regard to pairing sustainable materials and I4.0 technologies [133]. By digitally connecting materials and

processes, manufacturing operations are less reliant on spontaneous efforts and able to absorb process variabilities. One of the other key aspects of the sustainable materials–I4.0 integration is the ability to stabilize production processes and make the entire system more predictable. Figure 8 presents an integrated framework in which technological sustainability is not treated as a distinct sustainability pillar. Instead, it is understood as an enabling framework that supports sustainable performance through capabilities such as interoperability, robustness, scalability, digital infrastructure, and process intelligence.

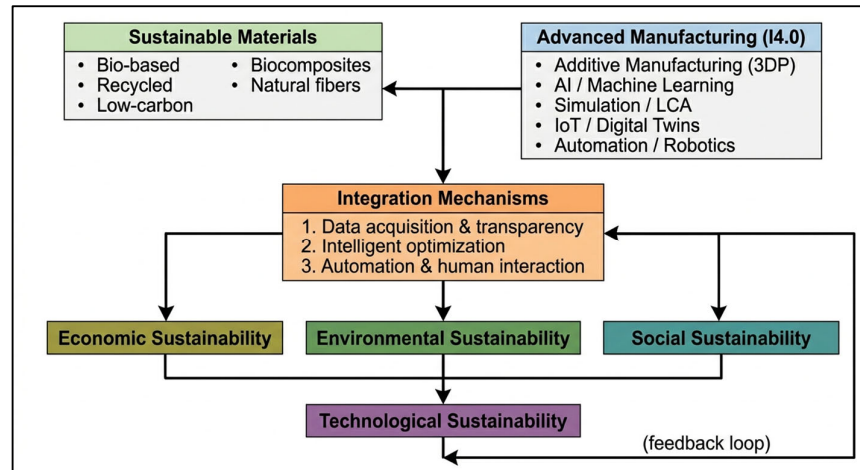


Figure 8. Conceptual and theoretical overview.

- Sustainability of the economy

Empirical studies show that the integration of sustainable materials with advanced manufacturing technologies is associated with benefits in terms of economic sustainability. These findings are discussed in relation to financial performance whilst delivering high-quality products. Recent research highlights the significant impact of Industry 4.0 and the circular economy on improving economic and environmental performance [134].

The adoption of Industry 4.0 technologies, such as the Internet of Things (IoT), cloud computing, big data and artificial intelligence (AI), is associated with improved productivity and the generation of new business opportunities, particularly in the healthcare sector [135]. These technologies also help reduce waste by redirecting systems or workers that deviate from the most efficient pathways. Furthermore, the integration of these technologies into green supply chains promotes green innovation for sustainable products and processes, thereby contributing to a sustainable circular economy.

When it comes to cost reduction, the circular economy, supported by digital transformation, plays a crucial role. For example, in pharmaceutical reverse logistics, digital transformation can lead to substantial savings for a country and ensure a more efficient supply of essential medicines, whilst reducing healthcare costs [136]. Circular economy practices and lean principles, supported by data analysis, improve material waste management and reduce material consumption and energy use. Studies confirm that Industry 4.0 and the circular economy contribute to the reduction in material and energy waste, as well as to lower emissions [137].

Process optimization is also a key factor in economic sustainability. The life cycle assessment of co-firing systems for plastic waste and lignite, for example, confirms the sustainability and benefits in terms of optimization and the conversion of waste into energy [138]. New business models, such as mobile wastewater treatment services, can generate additional financial benefits through the recovery of value-added compounds [139].

Finally, digital monitoring and smart diagnostics, including AI-based quality control, enhance cost control and can reduce material rejection rates [140,141]. The application of AI and machine learning improves operational efficiency and enables more informed decisions regarding material selection.

- Sustainability of the environment

Environmental sustainability within manufacturing systems is recognized as a crucial outcome of process strategies aimed at minimizing ecological impact. Recent studies highlight the integration of sustainable materials and Industry 4.0 (I4.0) into every production stage, noting that industrial activities contribute significantly to global greenhouse gas emissions [128]. This integration is crucial for the transition towards carbon neutrality and resource management [142].

Several key performance indicators (KPIs) for environmental sustainability have been presented, such as CO₂ emissions, waste generation per unit of product, energy consumption per part, and water usage. These metrics are commonly employed to measure environmental performance and progress across different manufacturing sectors [139]. Energy consumption, in particular, has been identified as a critical gap in environmental sustainability, with efforts to optimize it in data centers and industrial processes [137].

Life cycle assessment (LCA) is a fundamental tool for tracking sustainability improvements. The integration of LCA into manufacturing frameworks, supported by advanced technologies, allows for a comprehensive evaluation of environmental performance [143,144]. For instance, LCA has been used to assess the environmental impact of PLA-basalt/hemp biocomposites, demonstrating the benefits of natural fibers [145]. Regionalized LCA models are also being developed to analyze the impact of bio-based materials in construction [146].

Environmental sustainability is also explicitly addressed in waste management and circular economy contexts. The combination of circular material selection with digital tools contributes to reducing hazardous waste generation by facilitating more efficient and data-driven material processing, enabling better classification, monitoring, and ensuring that only the required material quantities are used [147]. I4.0 strengthens the circular economy by reducing waste and promoting advanced sustainability initiatives, particularly in the healthcare sector and in solid-waste management [148,149]. Circular economy solutions are also explored for plastic waste, improving the rheological properties of recycled PET for direct 3D printing [128]. Dynamic system modeling is used to optimize resources and reduce waste in vertical farming, integrating the circular economy for enhanced sustainability [150].

The integration of I4.0 and the circular economy is a growing research area, with studies exploring key drivers, barriers, and mitigation strategies at different organizational levels to enhance sustainable performance [151]. Digital technologies, such as the Internet of Things (IoT), cloud computing, big data, and artificial intelligence (AI), are essential for improving productivity and sustainability by reducing emissions and optimizing resource utilization [152].

- Sustainability on a Social Scale

Although the environmental and economic sustainability dimensions dominate the literature on sustainable materials and advanced manufacturing, social sustainability remains comparatively underrepresented in the reviewed corpus. This imbalance is not only visible in the thematic focus of the articles, but also in the way social issues are distributed across the corpus: they appear sporadically, are rarely developed as primary analytical objects, and are less frequently operationalized than environmental performance indicators. Most studies focus primarily on technical efficiency, carbon footprint reduction, en-

ergy optimization, and circularity performance, while the human and organizational implications of sustainable manufacturing are often treated as secondary outcomes rather than core sustainability objectives. This reveals an important gap in the literature, particularly because the transition toward sustainable and digitalized production systems directly affects workers, skill requirements, workplace organization, and the relationship between industrial facilities and local communities.

In the context of sustainable materials and Industry 4.0 integration, social sustainability may be understood as the ability of manufacturing systems to improve occupational safety, ergonomics, workforce resilience, inclusiveness, stakeholder participation, and quality of working life across the material and production life cycle. In the reviewed corpus of 156 articles, the social dimension is not consistently mapped across studies. Instead, it appears through a limited set of recurring indicators, with occupational safety and ergonomics emerging most frequently, while employee satisfaction, retention, and community acceptance are mentioned less often. Social life cycle assessment (S-LCA) is only marginally represented, suggesting that formal social impact assessment remains limited in this research area.

Several studies indicate that Industry 4.0 technologies can positively influence occupational health and working conditions through automation, intelligent monitoring systems, and human–machine collaboration. In manufacturing environments, collaborative robots, sensor-based monitoring, and AI-assisted control systems can reduce workers' exposure to hazardous substances, repetitive tasks, and physically demanding operations. These technologies can also improve ergonomics by supporting safer workstation design, clearer task allocation, and real-time detection of process deviations, thereby reducing operational stress and contributing to higher employee well-being and job satisfaction. However, these contributions are typically presented as case-specific observations rather than as systematically aggregated social outcomes.

Beyond workplace safety, the literature also shows that social sustainability is closely linked to workforce adaptation and organizational readiness. The introduction of advanced manufacturing technologies and sustainable materials often requires new technical skills, cross-functional collaboration, and continuous digital training. In this respect, social sustainability depends not only on technological deployment but also on the capacity of organizations to support employee upskilling, reduce resistance to change, and promote acceptance of new production practices. Human-centered implementation therefore becomes essential for ensuring that digital and circular transitions are socially viable as well as technically effective.

Stakeholder engagement also emerges as an important dimension of social sustainability in manufacturing systems. The transition toward circular and digitally enabled production requires coordination among managers, engineers, operators, suppliers, and local communities. Research suggests that insufficient participation of internal and external stakeholders can slow implementation, whereas inclusive decision-making processes can improve worker acceptance of automation, strengthen trust in sustainable material strategies, and enhance community acceptance of industrial transformation. In this sense, social sustainability extends from the factory floor to the broader network of actors influenced by manufacturing activities.

Despite these contributions, the literature still lacks standardized indicators for systematically assessing the social impacts of sustainable manufacturing systems. Most studies discuss social aspects descriptively rather than embedding measurable indicators within broader sustainability assessment frameworks. Across the reviewed corpus, the most recurrent indicators include workplace accident rates, ergonomic risk reduction, employee satisfaction and retention, workforce upskilling, acceptance of automation tech-

nologies, stakeholder participation, job creation linked to circular manufacturing initiatives, and community acceptance of sustainable production practices. However, these indicators are not applied consistently across studies, and no single social metric clearly dominates the literature.

This gap persists for several reasons. The field remains strongly oriented toward environmental and technical metrics, such as carbon footprint, energy efficiency, and material circularity, which are easier to quantify and compare across studies. By contrast, social outcomes are highly context-dependent and less standardized, making them difficult to measure using common indicators across sectors, materials, and manufacturing settings. In addition, the research area is largely shaped by engineering and manufacturing disciplines, where labor conditions, community impacts, and equity considerations are not always integrated into study design. As a result, social life cycle assessment and related approaches appear only marginally in the literature. To address this gap, future studies should adopt more concrete and comparable indicators, including worker safety, ergonomics, job quality, skill development, community acceptance, supply-chain fairness, and stakeholder well-being. Mixed-method frameworks combining social LCA, stakeholder analysis, and multi-criteria decision-making could further strengthen the operationalization of social sustainability in advanced manufacturing research.

The keyword co-occurrence analysis further confirms this pattern. Social sustainability terms are not among the most frequent keywords in the corpus, which suggests that the social dimension remains less visible than environmental and technical themes in the literature. This does not mean that social issues are absent, but rather that they are often embedded in broader discussions of process improvement, human-machine interaction, or organizational transformation instead of being treated as explicit sustainability keywords. In addition, social life cycle assessment (S-LCA) appears only marginally in the reviewed studies, indicating that formal social impact assessment is still at an early stage in this research area.

Taken together, the findings suggest that social sustainability is acknowledged in the literature but not yet systematically operationalized. It should therefore be treated not only as an outcome of technological transformation, but also as a critical enabling factor for the successful integration of sustainable materials and Industry 4.0 technologies. Organizational culture, leadership support, employee engagement, and interdisciplinary collaboration strongly influence the effectiveness of digital and circular transformation initiatives.

From a conceptual standpoint, future research should adopt more integrated socio-technical approaches capable of examining environmental, economic, technological, and social sustainability simultaneously. Longitudinal empirical studies are particularly needed to assess how sustainable materials and advanced manufacturing technologies affect employment quality, workforce adaptation, occupational health, inclusiveness, and community acceptance over time. Strengthening the social sustainability dimension would therefore contribute to a more holistic and resilient understanding of sustainable manufacturing systems.

- Sustainability of technology

Having evaluated economic, environmental, and social sustainability in the previous section, now we will examine the concept of technological sustainability by analyzing how sustainable material processes benefit from advanced digital technologies. The literature emphasizes the importance of deploying IoT, big data analytics, and artificial intelligence (AI) enablers of Industry 4.0 to advance the circular economy by limiting waste and improving the flow of materials [139]. Particularly, it is stated that such technologies contribute greatly to enhancing system efficiency through the use of predictive analytics and machine learning models. For example, there were cases when machine learning was applied

to maximize profits while decreasing the negative environmental impacts of manufacturing in areas such as aluminum recycling and solar trucks [114,153].

Moreover, cyber-physical systems and digital twins help increase decision-making speed and perform real-time execution of data, fostering more efficient and transparent communication within the supply chain. In this way, it becomes possible to direct any deviated processes or equipment back to their optimum sustainable paths [154]. In addition to that, blockchain is considered another technology that must be implemented in sustainable manufacturing to avoid its common issues [155].

A number of scientific studies show that additive manufacturing (3D printing) and simulations are among the main technologies driving technological readiness. The ability to design fibrous structures and biodegradable polymers and to predict how they will behave upon decomposition with the help of numerical methods plays an important role in sustainable manufacturing [138]. It becomes possible to make appropriate eco-design decisions early in product development due to PLCA and neural network techniques without the necessity to conduct various scenarios [156].

Summing up, technological sustainability can cover automation and electrification-based models, as well as multi-scale models, which are all crucial for creating a smart circular economy. Such technologies do not function solely as a means to improve efficiency but as pillars of sustainable systems interacting with economic and environmental dimensions.

Figure 9 highlights the various dimensions of sustainability that pertain to the implementation of sustainable manufacturing, including economic, social, technological, and environmental perspectives, together with their respective KPIs.

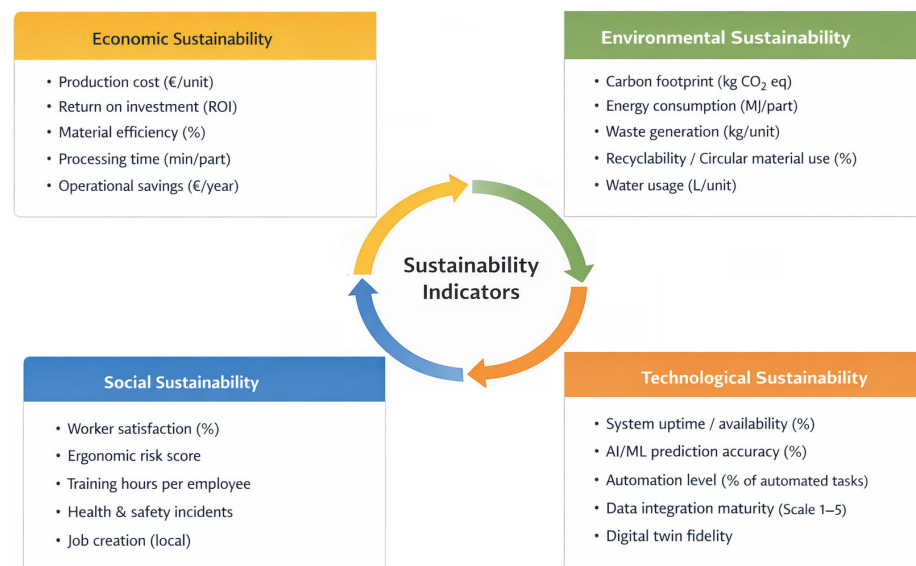


Figure 9. Classification of sustainability indicators in sustainable materials and advanced manufacturing.

4. Discussion

This section discusses the drivers and constraints influencing the integration of sustainable materials and advanced manufacturing (I4.0) toward sustainable production systems. It then presents a proposed framework and highlights potential ideas for further research.

4.1. Enablers of Sustainable Materials—Industry 4.0 Integration

The integration of sustainable materials with Industry 4.0 technologies is primarily enabled by the growing availability of digital tools that improve material visibility, process control, and decision quality. Rather than functioning as isolated technical upgrades, these technologies create the conditions under which sustainable material strategies can be evaluated, tested, and implemented more effectively. In the reviewed literature, the most frequently cited enablers include simulation models, real-time data acquisition systems, analytics platforms, life cycle assessment tools, digital twins, and smart material processing equipment. These tools support manufacturers in mapping material flows, anticipating process behavior, and assessing the implications of alternative production scenarios before implementation.

At the technological level, simulation and digital modeling are particularly relevant because they allow firms to test the behavior of bio-based, recycled, and other sustainable materials under different operating conditions. This is important given the variability often associated with such materials, especially in terms of mechanical consistency, thermal stability, and process sensitivity. By enabling virtual experimentation, these tools reduce uncertainty and improve the feasibility of circular strategies in manufacturing environments. Likewise, real-time data acquisition and advanced analytics enhance traceability and process transparency, thereby supporting more informed operational decisions.

At the organizational level, the integration of sustainable materials and Industry 4.0 is facilitated by strategic alignment, top management commitment, and cross-functional coordination. The literature suggests that digital transformation becomes more effective when sustainability objectives are embedded into managerial priorities rather than treated as separate technical initiatives. In this respect, the role of management is not limited to funding technological investments; it also involves creating an organizational climate that supports experimentation, learning, and collaboration across production, engineering, and sustainability functions.

Human capabilities also represent a key enabling condition. The reviewed studies repeatedly highlight the importance of upskilling, interdisciplinary knowledge, and workforce readiness. Implementing digital tools for sustainable manufacturing requires competencies that combine materials engineering, data interpretation, process optimization, and sustainability assessment. Employees therefore need access to training pathways that strengthen both technical and analytical capabilities. In addition, worker acceptance of new technologies is more likely when employees are involved early in the transformation process and can perceive the practical value of these tools for improving both efficiency and sustainability.

Overall, the literature indicates that the convergence of sustainable materials and Industry 4.0 is enabled by a combination of digital infrastructure, organizational support, and human capability development. These enabling conditions do not guarantee successful implementation, but they create the operational and strategic basis for more transparent, adaptable, and resource-efficient manufacturing systems.

4.2. Challenges and Potential Solutions for Sustainable Materials—Industry 4.0 Integration

Despite the clear potential of integrating sustainable materials with Industry 4.0 technologies, the reviewed literature also reveals several persistent challenges that hinder implementation. These challenges are not limited to one domain; rather, they span technological, economic, organizational, human, and assessment-related dimensions. Addressing them is essential if digital transformation is to support circularity and sustainability rather than create new forms of complexity or environmental burden.

A first major challenge concerns the technological variability of sustainable materials. Bio-based polymers, recycled composites, and biodegradable materials often exhibit heterogeneous properties that complicate process standardization and reduce predictability in manufacturing systems. In additive manufacturing and related digital processes, this variability can affect quality stability, performance repeatability, and process reliability. Another issue is the limited interoperability of data across systems and platforms. Although Industry 4.0 relies heavily on data integration, the literature shows that material-related datasets are often fragmented, inconsistent, or insufficiently standardized. This limits the ability of firms to develop robust predictive models or compare sustainability performance across production contexts.

A second challenge is economic. The adoption of sensors, automation systems, digital twins, analytics software, and other Industry 4.0 components requires substantial upfront investment. These costs are especially burdensome for small and medium-sized enterprises, which often operate with limited financial and technical resources. At the same time, sustainable materials may be more expensive or harder to source consistently, particularly in early commercialization phases. The result is a double economic pressure that can slow down adoption even when the long-term sustainability benefits are clear.

Organizational and human-centered barriers are equally important. Many companies still rely on conventional linear production logics and may lack a clear strategic roadmap for circular and digital transformation. Resistance to change, weak managerial commitment, and limited cross-functional collaboration frequently reduce the pace of implementation. In addition, the use of advanced technologies such as artificial intelligence, simulation, life cycle assessment, and blockchain requires specialized skills that are not yet widespread. Without adequate training, employees may struggle to use these tools effectively or may view them as disruptive rather than enabling.

The literature also highlights limitations in sustainability assessment. Many studies focus on carbon emissions and energy use, while social sustainability, circularity, and long-term durability remain underexplored. This narrow emphasis can lead to incomplete evaluations of the actual contribution of Industry 4.0 to sustainable manufacturing. Moreover, digitalization itself may generate new environmental pressures, such as increased data storage demand, computational energy use, and electronic waste. These risks show that Industry 4.0 should not be assumed to be inherently sustainable.

Several potential solutions emerge from the reviewed studies. First, interoperable digital architectures and standardized material databases are needed to improve traceability and data quality. Digital product passports, blockchain-based traceability systems, and secure cloud infrastructures can also support better life cycle visibility. Second, policy support mechanisms such as subsidies, tax incentives, and green innovation funds can reduce the financial burden of adoption, especially for SMEs. Third, organizations should invest in training, participatory change management, and multidisciplinary capability development to improve technology acceptance and implementation quality. Finally, future research should move toward more integrated assessment frameworks combining LCA, social LCA, circularity indicators, and AI-supported sustainability analytics.

Thus, the integration of sustainable materials and Industry 4.0 should be understood as a transition that is technically promising but institutionally and organizationally demanding. The barriers identified in the literature are not insurmountable, but they require coordinated solutions that combine digital infrastructure, financial support, human capability development, and more comprehensive sustainability evaluation.

4.3. SCM Implementation Roadmap

To address RQ2, this study synthesizes the identified barriers and technological enablers into a three-stage SCM implementation roadmap. The roadmap is intended as a conceptual guide rather than a prescriptive schedule because the pace of implementation will vary according to organizational readiness, company size, sectoral context, resource availability, and existing digital maturity. Accordingly, the short-, medium-, and long-term phases should be interpreted flexibly, rather than as fixed time periods.

Step 1: Foundation and Readiness (Short-Term).

In the initial phase, organizations should establish the basic digital and organizational conditions required for SCM adoption. This includes setting up essential digital infrastructure, such as IoT sensors and data collection systems, and conducting baseline life cycle assessments (LCAs) for current materials and processes. At the same time, firms should secure management commitment, raise awareness of SCM objectives, and begin introductory digital literacy training for operators and technical staff.

Step 2: Integration and Pilot Testing (Medium-Term).

In the second phase, manufacturers should move from preparation to targeted experimentation and integration. This may involve applying machine learning to support sustainable material selection, introducing additive manufacturing in pilot product lines, and using digital tools to improve process monitoring and decision-making. From an organizational perspective, cross-functional teams involving materials engineers, data specialists, production managers, and sustainability staff should be formed to coordinate pilot projects and evaluate their outcomes.

Step 3: Scaling and SCM Convergence (Long-Term).

The final phase involves broader deployment and deeper system integration. At this stage, firms can expand successful pilots across operations, strengthen closed-loop material flows, and integrate automation, circularity, and multidimensional sustainability tracking into routine decision-making. This phase represents the long-term realization of SCM as an integrated socio-technical system, where digital capabilities, circular material practices, and workforce skills are aligned to support continuous improvement and eco-efficient production.

4.4. Development of the Conceptual Framework

The development of the conceptual framework aims to shed light on the research field by clarifying the relationship between sustainable materials and Industry 4.0 and their contribution to sustainable manufacturing performance. In this case, the framework is an integrated, implementation-oriented synthesis derived from the reviewed literature, focusing on operational mechanisms, enabling technologies, barriers, and sustainability outcomes, as shown in Figure 10. The framework has been further refined to more explicitly operationalize the main constructs and clarify their interrelationships. In this framework, technological capabilities are considered enabling mechanisms that support environmental, economic, and social sustainability outcomes, which are treated as dynamically interconnected rather than independent dimensions. The framework also captures feedback effects, suggesting that improvements in one dimension may reinforce or constrain performance in the others over time. Accordingly, the proposed framework pro-

vides a basis for future empirical investigation through case studies, longitudinal analyses, or quantitative modeling approaches. At the same time, the quantitative improvements reported across the reviewed studies, such as reductions in waste, carbon footprint, or processing time, should be interpreted as illustrative, study-specific outcomes rather than generalized effect sizes, since this review does not conduct meta-analytic synthesis.

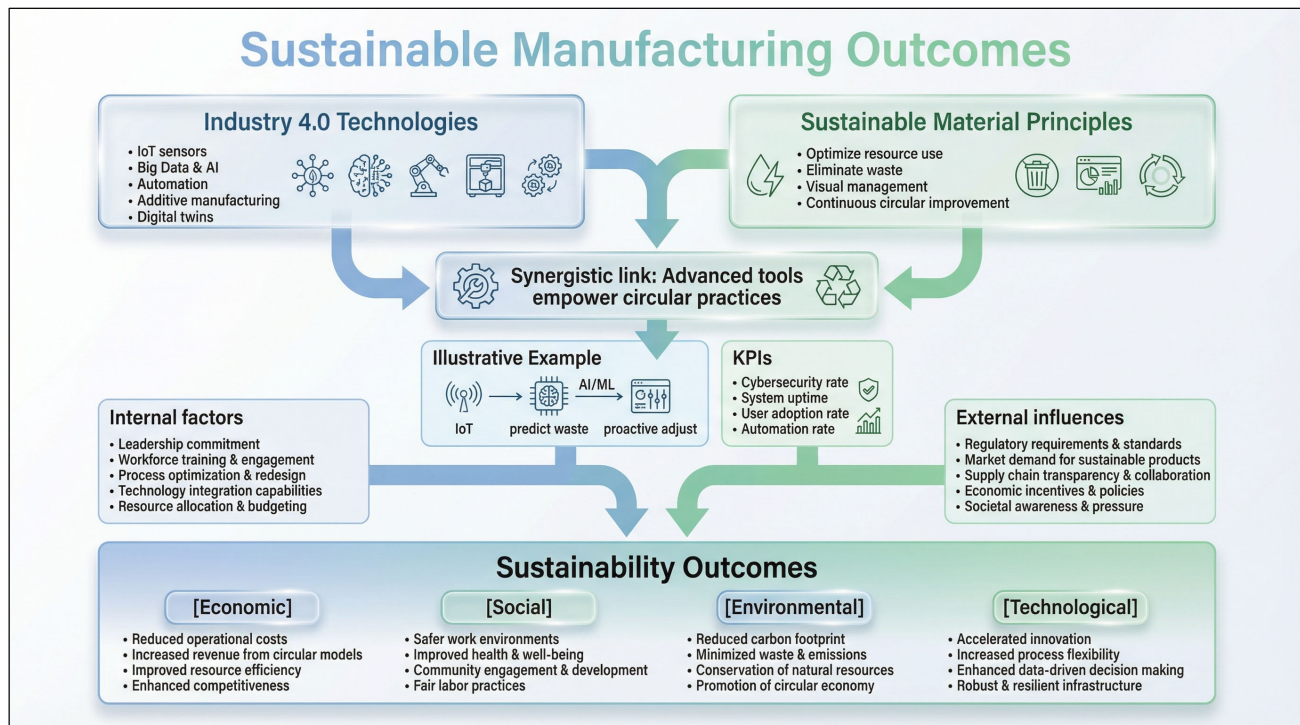


Figure 10. Operational and integrated implementation framework derived from the literature synthesis.

To move beyond a purely descriptive representation, the proposed framework is grounded in socio-technical systems (STS) theory, which provides a robust lens for understanding the interdependence between technology, materials, and human actors in manufacturing environments. From an STS perspective, manufacturing performance cannot be improved by focusing on technological advancement alone. Instead, sustainable production depends on the joint optimization of three interrelated subsystems: the technical subsystem, represented by Industry 4.0 tools and digital infrastructures; the material or ecological subsystem, represented by sustainable, bio-based, or recycled materials; and the social subsystem, represented by human capabilities, organizational readiness, and human–technology interaction. This theoretical positioning is important because it shifts the discussion from a narrow technology-centered view to a broader systemic understanding in which sustainable manufacturing emerges from the coordinated alignment of technical, ecological, and organizational elements. To operationalize this theoretical lens, Table 5 maps representative studies from the reviewed corpus to sensing, seizing, and reconfiguring based on their reported mechanisms and outcomes.

Table 5. Examples of studies illustrating the dynamic capabilities framework.

Representative Study	Main Mechanism/Evidence	Dynamic Capability Dimension	Interpretation
Javaid et al. (2021) [135]	Industry 4.0 tools, digital monitoring, and smart manufacturing applications	Sensing	Illustrates how digital systems improve visibility over processes, materials, and performance conditions.
Kamalakkannan and Kulatunga (2021) [156]	Parametric life cycle assessment for eco-design decisions	Sensing/Seizing	Shows how data collection is transformed into decision support for material and design selection.
Alimohammadi and Behnamian (2025) [136]	Digital transformation in pharmaceutical reverse logistics using multi-objective modeling	Seizing	Demonstrates the use of analytical tools to improve operational and sustainability decisions.
Laskurain-Iturbe et al. (2021) [137]	Circular economy and Industry 4.0 integration in manufacturing	Seizing/Reconfiguring	Highlights how digital tools support strategic adaptation and process redesign.
Tavares et al. (2023) [157]	Additive manufacturing for circular economy and supply-chain restructuring	Reconfiguring	Reflects the redesign of production and supply-chain structures through additive manufacturing.
Jamwal et al. (2022) [155]	Blockchain-enabled sustainable manufacturing and circular economy measures	Reconfiguring	Shows how digital technologies support organizational and process reconfiguration.
Morganti et al. (2025) [119]	Digital twin for wood-for-construction supply-chain and actor-based LCA information	Sensing/Reconfiguring	Demonstrates real-time information capture and system redesign across the supply chain.
Thomsen et al. (2025) [158]	Additive manufacturing for repair through bio-based materials	Reconfiguring	Indicates process and product redesign through circular repair-oriented manufacturing.
Pert and Torres (2025) [159]	Dynamic modeling of circular economy networks	Seizing/Reconfiguring	Shows how system dynamics supports strategic planning and structural adaptation.

Table 5 shows that the three capability dimensions are not isolated concepts but appear as interconnected mechanisms across the reviewed literature. Sensing is most visible in studies emphasizing material-flow monitoring, process transparency, and real-time data acquisition; seizing is reflected in studies using AI, machine learning, optimization, and simulation to support decision-making; and reconfiguring is evident in studies involving automation, digital twins, and human–technology coordination to redesign production and supply-chain structures. This mapping provides an empirical basis for the SCM framework and clarifies how dynamic capabilities are expressed in the corpus.

The theoretical novelty of the framework lies in the way it reconceptualizes the relationship between digitalization and sustainability. In much of the existing literature, Industry 4.0 and circular economy are treated as separate or parallel strategic initiatives, each contributing independently to organizational improvement. In contrast, the proposed framework argues that their relationship is inherently synergistic. More specifically, Industry 4.0 technologies are conceptualized as dynamic capabilities that enable firms to address and compensate for the inherent limitations of sustainable materials. Such limitations may include variability in mechanical properties, inconsistent quality, uncertain supply, or difficulties in processing secondary and bio-based inputs. Within this perspective, digital technologies do not merely coexist with sustainable materials; they

actively facilitate their integration into manufacturing systems by increasing visibility, adaptability, and responsiveness across production processes.

Building on this premise, the framework establishes a clear causal logic among three interrelated integration mechanisms. The first mechanism, data acquisition and transparency, functions as the antecedent condition of the entire process. Through technologies such as IoT sensors, smart monitoring devices, digital tracking systems, and connected platforms, firms are able to capture real-time information on material characteristics, process conditions, machine performance, and waste generation. This enhanced transparency is particularly critical when sustainable materials are used, as these materials often present greater variability than conventional ones. By generating reliable and timely data, this first mechanism creates the informational foundation required for more adaptive and informed decision-making.

The second mechanism, intelligent decision-making and process optimization, transforms raw operational data into actionable insights. Once data are collected and processed, advanced analytics, artificial intelligence, and machine learning tools can be used to identify patterns, predict deviations, optimize process parameters, and support real-time decision-making. At this stage, Industry 4.0 technologies moderate the relationship between sustainable material use and production performance by dynamically adjusting manufacturing settings to maintain quality, efficiency, and consistency. For example, if a recycled material exhibits slight variations in composition or performance, intelligent systems can automatically recalibrate temperature, pressure, speed, or material proportions to accommodate such variations. This mechanism is therefore central to reducing uncertainty and ensuring that the use of sustainable inputs does not compromise operational reliability or final product quality.

The third mechanism, automation and human–technology interaction, represents the operational execution of these optimized decisions on the factory floor. Once production parameters have been defined or adjusted, automated systems, robotic devices, cyber–physical systems, and digitally assisted operators translate those decisions into concrete production actions. However, this mechanism should not be understood as purely technological. In line with STS theory, human actors remain essential to supervising systems, interpreting outputs, handling exceptions, and ensuring continuous improvement. Human–technology interaction thus becomes a key condition for successful implementation, particularly in contexts where flexible adaptation is required. The framework therefore acknowledges that automation alone is insufficient; sustainable manufacturing depends equally on worker involvement, digital skills, training, and organizational support.

By operationalizing these three mechanisms, the framework moves from an illustrative synthesis to an analytical model with explanatory power. It hypothesizes that the successful integration of sustainable materials into sustainable production systems is mediated by Industry 4.0 integration mechanisms and further strengthened or constrained by technological enablers such as interoperability, system robustness, data quality, and cybersecurity. In this sense, sustainable materials constitute the independent variable, while sustainability performance, expressed through environmental, economic, and social outcomes, constitutes the dependent variable. Industry 4.0 mechanisms serve as the mediating pathway through which material sustainability can be translated into measurable manufacturing improvements. This causal structure provides a clearer basis for empirical testing and offers a more rigorous explanation of how and why digital technologies can support sustainable manufacturing transitions.

At the heart of this framework is an effort to address a key problem identified in the scientific literature: how to combine sustainable materials and Industry 4.0 technologies in order to develop genuinely sustainable manufacturing processes. Sustainable materials are often associated with resource efficiency, waste prevention, circular material flows,

and the substitution of virgin resources with renewable or recycled alternatives. At the same time, Industry 4.0 encompasses a range of digital capabilities, including IoT, big data analytics, artificial intelligence, additive manufacturing, digital twins, and automation. When these two streams are integrated, they create the conditions for a more intelligent and circular production model. Digital technologies enhance the traceability, predictability, and controllability of material flows, while sustainable materials provide the ecological basis for reducing environmental impact. Their integration therefore produces a synergistic effect in which digitalization strengthens circularity and circularity gives strategic direction to digital transformation.

A practical example illustrates this interaction clearly. IoT sensors can be used to monitor material flows in real time throughout the production process, tracking the movement, condition, and quantity of both virgin and recycled materials. The resulting data can then be analyzed through AI and machine learning tools to forecast waste generation, detect inefficiencies, and recommend corrective actions before losses occur. In parallel, intelligent systems can optimize production scheduling by taking into account the quantity and quality of recycled materials available at a given moment. Such capabilities enable firms to make proactive decisions rather than reactive adjustments. As a result, manufacturers can reduce raw material consumption, minimize waste, avoid overproduction, and eliminate non-value-added activities such as unnecessary material handling, waiting times, or excessive reprocessing. This makes the production system not only more efficient but also more aligned with circular economy principles.

The technological enablers within this framework can also be assessed through a set of specific key performance indicators. These indicators help evaluate whether the integration of digital technologies effectively supports sustainable material use and broader sustainability objectives. Relevant KPIs may include the number of cybersecurity incidents, which reflects the security and reliability of digital tracking and data exchange systems; system uptime, which indicates the availability of digital infrastructure such as life cycle assessment software, material flow dashboards, or predictive analytics platforms; user adoption rate, which captures the extent to which engineers and operators actively engage with simulation tools, decision-support systems, and AI-based applications; and automation rate, which reflects the level of process digitalization and the reduction in repetitive manual tasks. Together, these indicators allow organizations to monitor both the technical performance and the organizational maturity of technological sustainability initiatives.

Despite its significant potential, the integration of sustainable materials with Industry 4.0 is not without challenges. Several barriers may hinder implementation, including employee resistance to change, technological complexity, inadequate digital infrastructure, and insufficient financial resources. These challenges are shaped by both internal and external factors. Internally, employee attitudes, management commitment, skill levels, and organizational culture influence the willingness and ability of firms to adopt innovative practices. Externally, policy support, market conditions, funding availability, and ecosystem readiness affect the pace and feasibility of transformation. A thorough understanding of these barriers is therefore essential for designing effective implementation strategies and building the infrastructures needed for secure, reliable, and scalable digital solutions.

Among these factors, organizational culture plays a particularly important role. A culture that encourages learning, collaboration, and openness to innovation is more likely to support the successful adoption of advanced technologies and sustainable practices. Such a culture fosters employee engagement, facilitates cross-functional coordination, and strengthens trust in digital systems. Collaboration is especially important because sustain-

able manufacturing requires interaction between multiple actors, including engineers, operators, managers, suppliers, and technology providers. When these actors work together, firms are better positioned to align economic, environmental, social, and technological goals. In this sense, sustainability is not achieved solely through technical investment, but through the development of organizational capabilities that enable people and technologies to work in a complementary and mutually reinforcing way.

Ultimately, the integration of sustainable materials and Industry 4.0 contributes to multidimensional sustainability performance. Economically, it can reduce costs through better resource utilization, lower waste generation, and improved process efficiency. Environmentally, it supports material conservation, circularity, and lower emissions associated with resource extraction and production losses. Socially, it can improve worker safety and job satisfaction by reducing exposure to hazardous substances, minimizing ergonomic risks, and enabling workers to engage in higher-value tasks supported by digital tools. Underpinning these three dimensions, technological enablers strengthen system resilience, adaptability, and process intelligence. The framework therefore highlights that sustainable manufacturing should be understood as a socio-technical transformation in which digital innovation and sustainable material strategies jointly create long-term value.

4.5. Implications and Future Research Directions

The presented outcomes of the research provide different directions for future research in the field of sustainable materials and I4.0 integration which can lead to greener manufacturing practices in the future.

4.5.1. Theoretical Insights

This research adds to the literature by addressing I4.0 technology implementation in material-centric sustainable manufacturing processes. It further develops the extant literature by considering not only the role of I4.0 in increasing the productivity of manufacturing systems, but also in implementing circular economy practices in production facilities. Based on the literature review conducted as part of this research, one may claim that digital technologies create value in the manufacturing sector not only owing to their technical features, but also by engaging in practices linked to the reduction, reuse, and recycling of materials. Moreover, this research provides a theory about the process of integrating sustainable materials into I4.0 by presenting specific pathways, namely data acquisition, intelligent optimization, and automation.

4.5.2. Practical Implications for Manufacturing Management

The results have been identified to have significant practical implications for manufacturing management. Manufacturing managers need to consider digital technologies as facilitators of implementation of sustainable circular material strategies rather than standalone solutions. At the same time, it is crucial to invest in training programs that will develop employees' ability to implement sustainable manufacturing while shifting their mindsets towards embracing this change. Moreover, production staff need to become more competent in using LCA software, simulation programs, and intelligent decision-making solutions. As this study has identified some issues related to implementation of sustainable materials in production in conjunction with I4.0, the obtained results may help in focusing on improving system interoperability for better data-based decision-making related to material circularity.

4.5.3. Further Research Directions

Despite the growing body of literature addressing the integration of sustainable materials and advanced manufacturing technologies, several important research gaps remain unresolved. Future studies should move beyond isolated environmental assessments and adopt a more systemic, interdisciplinary, and longitudinal perspective capable of capturing the complex interactions between digital technologies, circular material systems, and sustainability performance.

First, additional research is required to develop integrated multidimensional assessment frameworks that simultaneously evaluate environmental, economic, social, and technological sustainability. Current studies predominantly focus on environmental indicators such as carbon footprint, embodied energy, and waste reduction, while social dimensions—including worker well-being, occupational safety, skill transformation, ethical governance, and societal acceptance of sustainable materials—remain underexplored. Future investigations should therefore incorporate social life cycle assessment (S-LCA), human-centered manufacturing indicators, and stakeholder-oriented evaluation methods to provide a more balanced sustainability assessment.

Second, future work should emphasize longitudinal empirical studies examining the long-term performance, durability, recyclability, and biodegradability of emerging sustainable materials under real industrial conditions. Most existing investigations rely on laboratory-scale experiments or short-term simulations, which limits the understanding of material behavior throughout multiple life cycles. Longitudinal monitoring using digital twins, IoT-enabled sensing systems, and predictive analytics could provide deeper insights into material aging, reuse potential, and circularity performance over extended operational periods.

Third, the role of artificial intelligence and machine learning in sustainable material engineering remains at an early stage and requires further theoretical and practical development. Existing studies mainly employ AI for process optimization or defect detection; however, future research should investigate explainable AI models for sustainable material selection, autonomous circular manufacturing systems, generative material design, and AI-driven eco-design optimization. In particular, combining machine learning with life cycle assessment (LCA), material flow analysis (MFA), and multi-criteria decision-making (MCDM) methods may enable more dynamic and adaptive sustainability-oriented decision-support systems.

Another important research direction concerns the integration of digital traceability technologies within circular supply chains. Blockchain, digital product passports, and cyber-physical systems have considerable potential to improve transparency, traceability, and accountability across material life cycles. Nevertheless, the literature still lacks robust empirical evidence regarding their scalability, interoperability, cybersecurity implications, and energy consumption. Future studies should therefore examine how these technologies can support closed-loop manufacturing while simultaneously minimizing digital waste and computational energy demand.

Furthermore, research should investigate the organizational and managerial dimensions influencing sustainable manufacturing transformation. While technological capabilities are frequently discussed, limited attention has been given to leadership styles, organizational culture, workforce readiness, and change management strategies required for successful integration of sustainable materials with Industry 4.0 technologies. Future empirical studies could explore how organizational learning, cross-functional collaboration, and employee engagement influence the adoption and effectiveness of circular manufacturing practices.

The scalability of advanced manufacturing technologies for sustainable materials also deserves deeper examination. Although additive manufacturing has demonstrated

promising capabilities for reducing waste and enabling localized production, challenges related to production speed, material standardization, energy intensity, and economic feasibility remain insufficiently understood. Comparative studies across industries such as construction, aerospace, automotive, and healthcare could help identify sector-specific barriers and best practices for scaling sustainable advanced manufacturing solutions.

Additionally, future research should address the policy and governance dimensions of sustainable manufacturing ecosystems. There is a need for studies examining how regulatory frameworks, green procurement policies, carbon taxation mechanisms, and international sustainability standards influence the adoption of sustainable materials and digital manufacturing technologies. Comparative international analyses may further reveal how regional policy environments shape circular economy transitions and sustainable industrial innovation.

From a methodological perspective, future investigations would benefit from employing hybrid research designs that combine bibliometric analysis, simulation modeling, experimental validation, case studies, and real-time industrial data analytics. Such mixed-method approaches could improve the robustness and practical relevance of sustainability assessments while reducing the fragmentation currently observed in the literature.

Finally, future studies should focus on developing integrated predictive frameworks capable of linking sustainable material selection, advanced manufacturing technologies, circular economy principles, and sustainability outcomes within a unified analytical ecosystem. Such frameworks could support proactive decision-making, real-time sustainability optimization, and resilient manufacturing system design, thereby contributing to the transition toward smart, circular, and carbon-neutral industrial systems.

4.5.4. Limitations and Future Scope

This review has several limitations that should be acknowledged. First, the search was restricted to peer-reviewed journal articles published in English, which may have excluded relevant studies published in other languages. Second, conference proceedings, book chapters, editorials, and gray literature were excluded to maintain consistency and methodological rigor, but this may also have led to the omission of emerging or practice-oriented evidence. Third, despite using a systematic search protocol and predefined inclusion criteria, the review remains subject to residual publication bias and selection bias, since studies with stronger or more positive findings are more likely to be indexed and retrieved. Finally, as with all literature reviews, the synthesis reflects the scope and quality of the available evidence at the time of the search. These limitations should be considered when interpreting the findings, and future reviews could broaden the evidence base by incorporating multilingual databases, gray literature, and complementary bibliometric approaches.

5. Conclusions

This literature review examined the growing convergence between sustainable materials and advanced manufacturing technologies within the broader context of sustainable production systems. Based on an analysis of 156 peer-reviewed articles published between 2015 and 2025, the review suggests that the integration of Industry 4.0 technologies with sustainable material strategies is progressively reshaping manufacturing toward more resource-efficient, circular, and data-informed systems. The literature indicates that sustainable manufacturing is no longer limited to substituting conventional materials with bio-based or recycled alternatives; rather, it increasingly depends on the interaction between material innovation, digital technologies, and sustainability-oriented decision-making frameworks.

The reviewed studies indicate that additive manufacturing, artificial intelligence, machine learning, simulation tools, digital twins, and life cycle assessment (LCA) are among the most influential technologies supporting this transition. These technologies are reported to facilitate sustainable material selection, improve process parameter optimization, strengthen traceability, reduce waste generation, and enhance circularity across product life cycles. These studies also report context-specific quantitative improvements in waste reduction, carbon footprint, and processing time. These values are presented as illustrative outcomes from individual studies rather than aggregated effect sizes. Because this review does not apply meta-analytic synthesis, the reported values are presented only to demonstrate the types of benefits observed in specific contexts. Across the literature, three dominant integration mechanisms emerge: (i) data acquisition and process transparency, (ii) intelligent decision-making and process optimization, and (iii) automation combined with human–technology interaction. Together, these mechanisms provide a conceptual basis for understanding how advanced manufacturing may contribute to sustainability performance while also improving operational efficiency and economic viability.

The review also shows that the environmental dimension remains the most extensively investigated sustainability pillar. Most studies focus on reducing carbon emissions, embodied energy, material waste, and resource consumption through digitalized production systems and circular material strategies. LCA emerges as a central methodological tool for evaluating environmental impacts and supporting eco-design decisions. Economic sustainability is likewise associated with productivity gains, waste minimization, process efficiency, and the development of circular business models enabled by Industry 4.0 technologies. By contrast, social sustainability dimensions—including worker well-being, ergonomics, skills development, public acceptance, and organizational readiness—remain comparatively underexplored.

The findings further suggest that the effectiveness of sustainable material–Industry 4.0 integration depends not only on technology, but also on organizational and human factors. Leadership commitment, employee engagement, digital competencies, interdisciplinary collaboration, and organizational culture are repeatedly identified as critical enablers of sustainable transformation. At the same time, implementation barriers such as high costs, interoperability problems, cybersecurity concerns, limited expertise, and resistance to organizational change continue to constrain large-scale adoption, particularly among small and medium-sized enterprises.

From a theoretical perspective, this review contributes an integrated conceptual framework linking sustainable material principles, Industry 4.0 technologies, and multi-dimensional sustainability performance through the proposed Sustainable Circular Manufacturing (SCM) lens. Rather than treating these domains as separate streams of research, the framework clarifies how they interact through distinct mechanisms and implementation conditions. This contribution offers a structured basis for future empirical and conceptual studies and helps move the field beyond descriptive mapping toward a more explanatory understanding of sustainable manufacturing transitions.

Overall, the review suggests that the convergence of sustainable materials and advanced manufacturing technologies represents an important pathway toward smarter and more circular manufacturing systems. However, the field remains fragmented and continues to evolve. Future research should therefore prioritize longitudinal empirical studies, standardized sustainability indicators, stronger integration of social sustainability metrics, ethical governance of AI-driven systems, and interoperable digital infrastructures capable of supporting circular material ecosystems at scale. Such efforts are needed to advance sustainable manufacturing beyond technological optimization toward more resilient, inclusive, and environmentally responsible industrial systems.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AM	Additive Manufacturing
CE	Circular Economy
I4.0	Industry 4.0
IoT	Internet of Things
LCA	Life Cycle Assessment
LR	Literature Review
MFA	Material Flow Analysis
ML	Machine Learning
SDGs	Sustainable Development Goals
SM	Sustainable Manufacturing

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