

REVIEW

A Review on Machine Learning and Digital Twin Enabled Advancements in Biofiller/Fibre-Based Polymer Composites for Sustainable Engineering Applications

Rahul Kumar¹, Faladrum Sharma² and Pradeep Kumar Karsh^{3,*}

¹Department of Mechanical Engineering, School of Engineering (SoE), Dayananda Sagar University, Devarakagalahalli, Harohalli, Kanakapura Road, South Bengaluru Dt., Bengaluru, India

²Centre for Indian Knowledge Systems, Indian Institute of Technology Guwahati, Guwahati, Assam, India

³Department of Mechanical Engineering, Parul Institute of Engineering & Technology, Parul University, Vadodara, India

*Corresponding Author: Pradeep Kumar Karsh. Email: pradeepkarsh@gmail.com

Received: 26 May 2026; Accepted: 05 August 2026; Published: 28 August 2026

ABSTRACT: The increasing environmental concerns after the United Nations' push towards sustainable development goals (SDGs) and depletion of non-renewable resources have accelerated the global pursuit of sustainable materials. Within this framework, bio-based polymer composites have gained considerable attention for their ability to balance mechanical performance, cost-effectiveness, and environmental responsibility. Biofibres/fillers-based polymer composites reinforced with natural fibres like jute, bamboo, coconut coir, pineapple leaf fibre (PALF), and flax offer an attractive combination of mechanical performance, cost-effectiveness, and environmental sustainability. Moreover, additive manufacturing (3D printing), coupled with machine learning, digital twins, and data-driven material design, is transforming the development and optimization of natural fibre-reinforced polymer composites for advanced, sustainable engineering applications and enabled the realization of the material, structure and function paradigm for composite design. This review highlights major developments in bio-based composites through the perspective of integrated modelling strategy and material-design-function philosophy. It also outlines how machine learning and digital twin-based models accelerated the material discovery, prediction, optimization, and sustainability assessment. Using machine learning techniques, prediction of properties, optimization of processes, and detection of defects can be performed in a much faster way. Digital twins provide a virtual representation of components, enabling real-time monitoring, predictive maintenance, virtual testing, and full lifecycle analysis. Moreover, the purpose of this review is to organize the latest progress, highlight the main research gaps, and propose the next steps towards smart, eco-friendly, and Industry 4.0/5.0, compliant composite materials. Also, the integration of life cycle assessment data into digital twin platforms could enable continuous environmental performance assessment throughout the product lifecycle.

KEYWORDS: Natural fibres; machine learning; digital twin; SDGs; additive manufacturing; sustainability

1 Introduction

The shift from petroleum-based polymers/plastics towards renewable, low-carbon alternatives has become more intense in recent years due to the climate emergency, resource depletion, and strict environmental regulations, along with constant push from the UN's sustainable development goals (especially SDG 9, SDG 12 and SDG 13) [1,2]. Bio-based polymers (like Polylactic Acid, Polyhydroxyalkanoates, bio-epoxies) and natural plant-based fibers (flax, jute, hemp, bamboo, sisal, pineapple leaf, coir) offer significant potential for reducing the carbon footprint, environmental toxicity, and waste generation associated with

traditional polymeric materials [3–5]. Although bio-based composites have considerable environmentally friendly benefits, their design and performance optimization rely mainly on experiments and require a lot of time [6]. Simultaneously, advances in machine learning (ML) and materials informatics are reshaping the development, processing, and assessment of bio-based composites by enabling data-driven material design, predictive modelling, and automated process optimization [7,8]. These approaches are gradually replacing trial-and-error methods through a tedious experimentation process. Furthermore, the influence of machine learning extends to predicting the mechanical, thermal, and rheological behavior of novel bio-composite formulations, optimizing fiber/matrix combinations and processing conditions, automating defect detection and quality assurance, and accelerating life cycle assessment (LCA) for sustainability and decision-making [9,10]. Consequently, bio-based composites supported by machine learning (ML) and digital twin (DT) technologies provide a powerful framework for achieving both sustainability and improved performance. ML enables rapid material discovery, property prediction, and process optimization, while DT technology creates a real-time virtual counterpart of the physical system by integrating sensor data, simulation models, and predictive analytics [11]. Therefore, the latest breakthroughs in machine learning and digital twin frameworks offer effective data-driven methods for predictive modeling, process optimization, and life cycle performance assessment. However, the existing literature remains scattered, addressing individual aspects of bio-based composites, machine learning, and digital twin technologies in isolation [12]. Thus, it does not provide a comprehensive and integrated perspective. So, this review stems from the development of machine learning, digital twin technologies, and biofiller/fibre-based polymer composites merging together in the field of sustainable engineering.

The review methodology followed in this study is presented in Fig. 1. The process includes research paper identification, screening, eligibility assessment, study selection, data extraction, thematic classification, and critical synthesis to ensure a state-of-the-art review of Machine Learning and Digital Twin applications in bio-based and hybrid composites.

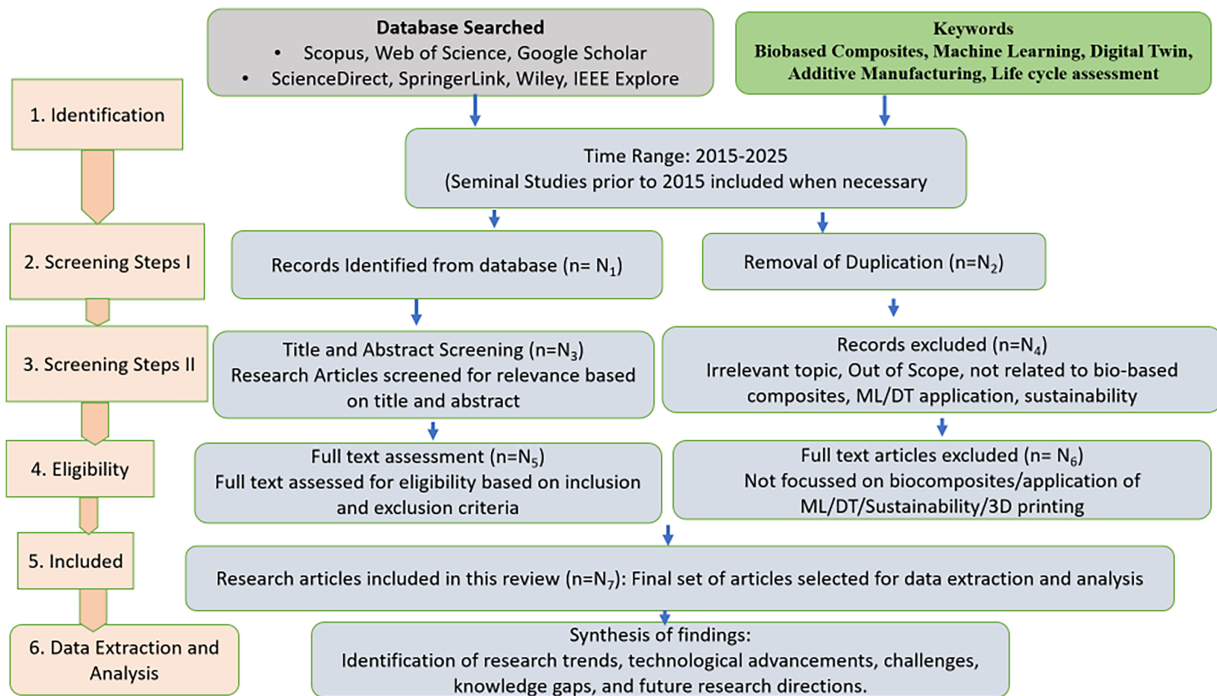


Figure 1: Review methodology.

1.1 Background and Motivation

Hybrid composites are engineered by combining natural fibers with synthetic reinforcements and/or nano-fillers and a polymer matrix material. This combination enhances mechanical strength, thermal stability, and durability over time but potentially reduces environmental sustainability [13]. On the other hand, purely bio-based materials are usually less consistent and perform worse. In addition, they tend to degrade quickly and lose their strength when exposed to changing temperature conditions. These composites are very popular in the automotive and aerospace industries, construction sector, healthcare, and various consumer goods. Weight reduction, environmental friendliness, and better energy efficiency are major reasons driving their adoption across various industries [14,15]. Still, natural fibers vary in quality from batch to batch. This causes uneven (non-uniform) properties and makes them unreliable/worthless over time. Moisture also affects them directly. Therefore, processing of these materials is a complicated task [16,17].

In this regard, digital twin technology enables continuously monitoring of the performance of a product from design to production to its actual use. Machine learning models are capable of forecasting the mechanical response of these materials to different types of stress and load conditions [18]. Also, it identifies defects before they develop into major issues. These digital tool sets raise the level of quality control and are helpful in mapping out the long-term performance of a product without resorting to continuous testing and inspection [19]. The system is able to self-regulate its performance by learning from historical and real-time data. Using this synergetic integration of digital twin and machine learning can enable improving materials design and performance optimization in traditional bio-composites effectively. Also, it makes the final product more reliable and consistent over time.

1.2 Bio-Based Polymer Composites in Sustainable Engineering

Bio-based polymer composites are a great platform for sustainable engineering. Biocomposites are primarily composed of renewable or bio-based constituents. They generally have a lower environmental impact than many conventional composite materials. Also, they could be used for many structural and functional applications, such as composites where natural fibers like flax, hemp, jute, bamboo, or kenaf are bound together by bio-based or partly biodegradable polymers [20,21]. The utilization of these materials reduces the dependence on petroleum-based materials, lowers carbon emissions, and facilitates transition towards a circular economy in engineering and manufacturing. This shift supports several Sustainable Development Goals, especially those related to responsible consumption (SDG 12), climate action (SDG 13), and industrial innovation (SDG 9). The benefits may largely depend on the quality of manufacturing of the materials and their application in real scenarios. Unless the materials are accurately tested in real conditions, the use of these composites in engineering designs may not always result in better performance. This reduces the dependency on fossil fuel in the future, especially if the production processes remain standardized and reliable. In a way, the long-term success is somewhat contingent upon the supply chain stability and regulatory support in major natural fibre based composite markets. Eventually, the wide spread use can change the material selections for different industries [22,23].

1.3 Role of Machine Learning and Digital Twins in Advanced Sustainable Materials

Recently, researchers and industry professionals have begun to focus on how machine learning can be combined with digital twins to create new bio-based advanced materials [24]. In fact, developing better materials such as plant-fibre reinforced polymer composites or hybrid composite types nowadays relies heavily on smart software tools rather than the conventional way of lengthy and tedious laboratory experimentation. The traditional methods involve many cycles of specimen preparation, testing of the fabricated samples, and extensive waiting time [25]. Besides that, these methods waste lots of time and money.

Nevertheless, this is a different scene when machine learning is combined with continuous virtual feedback to form models that can predict the results before going for physical experiments.

These technologies enable real-time monitoring of sustainable material development, simulation of underlying material behaviour, and prediction of service life under various loading conditions [26]. It is no longer the case that final decisions are made by assumption because the data patterns are extracted from the previously manufactured and tested samples. Operations become less wasteful in terms of raw materials since initially low amount is thrown away. Moreover, sustainability is also making headway as less waste is produced during trials [27]. Furthermore, the costs are reduced as precision eliminates the need for excess. As the ML and DT system learns from historical and real-time data, design selection becomes progressively more accurate, resulting in enhanced performance, reduced uncertainty, and optimized material and process configurations [28].

1.4 Scope and Objectives of the Review

The scope of this review is to comprehensively explore the integration of bio-based and hybrid polymer composites with machine learning (ML) and digital twin (DT) technologies for sustainable engineering applications and life cycle assessment. It also describes how machine learning (ML) and digital twin (DT) technologies can address variability, process uncertainty, and property prediction in bio-based and hybrid polymer composites. It further attempts to identify challenges and limitations along with future research directions.

2 Bio-Based Polymer Composites: Materials and Processing

Bio-based polymer composites are processed through various manufacturing techniques and approaches depending on different types of biopolymers.

2.1 Bio-Polymers: Types and Characteristics

The various types of bio-based polymers are:

- Polylactic Acid (PLA): It is a widely adopted thermoplastic polymer in consumer goods and packaging due to stiffness and easy processing. Nowadays, artificial intelligence (AI) assisted reactive blending and reinforcement prediction tools are being used to improve toughness and heat resistance of this polymer.
- Polyhydroxyalkanoates (PHAs): These are fully biodegradable thermoplastic polymers where AI models help optimize compositional addition, carbon-source utilization, and molecular weight distribution to reduce costs.
- Bio-Epoxy and Bio-Polyesters: These are another important class of bio-based polymers. AI-enabled molecular modelling accelerates the development of lignin- or plant-oil-based resins with tailored glass transition temperatures, crosslink densities and cure cycles.

2.2 Natural Fibers and Bio-Fillers

Various types of natural fibres are coir, bamboo, hemp, sisal, jute, banana, wood, cotton, silk, and pineapple leaf, etc. Their sources of origin are presented in Fig. 2. Mostly, natural fibres are classified based on their sources of origin, like plant-based (bamboo, sisal, banana, etc.) and animal-based (Silk, wool, etc.). Furthermore, plant-based fibres can be divided on the basis of the part of the tree (stem, fruit, leaf, etc.) used for extracting the fibres. The details about all fibres are presented in Table 1. The hydrophilicity, variability, and moisture sensitivity limit the engineering uses of these fibres. The interfacial adhesion and moisture absorption problems can be suppressed by chemical treatment [29]. In addition, natural fibres generally

begin to thermally degrade within the temperature range of 180°C–250°C, depending on their chemical composition, while many biopolymers exhibit limited thermal stability during prolonged processing. Elevated temperatures may result in degradation of cellulose, hemicellulose, and lignin components, moisture loss, discoloration, and deterioration of fibre–matrix interfacial adhesion [30]. Artificial intelligence (AI) can be used to play a supporting role in automated fiber property classification using machine vision, machine learning-based prediction of fiber–matrix adhesion, and optimization of alkali, silane, and enzymatic treatments [31,32]. Moreover, the machine learning models can correlate fiber microstructure with composite mechanical performance, thus reducing experimental workload.

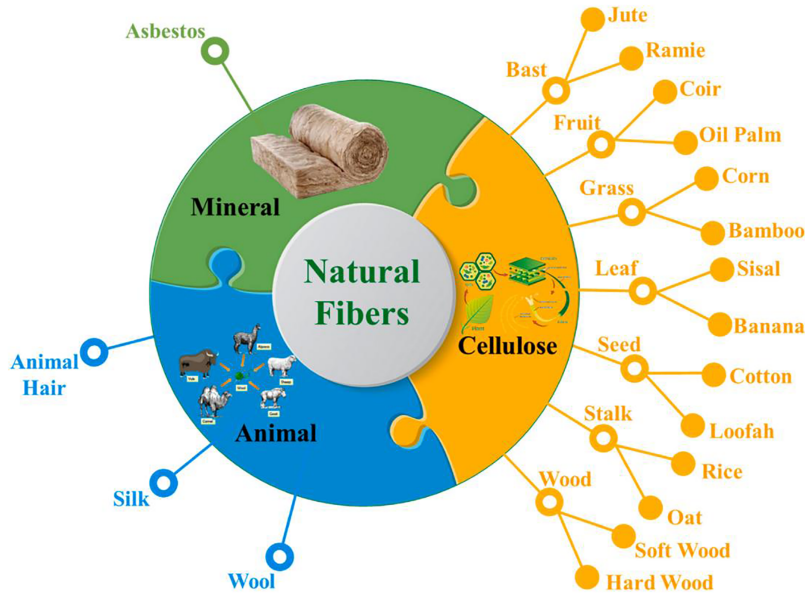


Figure 2: Types of natural fibres according to their sources of origin [adapted from [33] under a creative commons (CC) license].

Table 1: Chemical composition and mechanical properties of natural fibers.

Fiber	Cellulose (%)	Hemicellulose (%)	Lignin (%)	Moisture (%)	Density (g/cm ³)	Tensile Strength (MPa)	Elongation at Break (%)	Young's Modulus (GPa)
Coir	27–50	0.15–20	30–45	9–11	1.2–1.5	186–345	3–7	2–8
Bamboo	70–74	12–14	10–12	13–20	0.45–0.99	540–630	1–3	11–17
Hemp	53–91	4–18	1–21	12	1.4–1.6	310–750	2–4	30–60
Sisal	47–78	10–24	7–14	8–23	1.3–1.55	385–725	2–3	9–38
Jute	58–64	20–24	11–15	12–14	1.3–1.5	393–773	1.2–1.8	13–26.5
Banana	71	13	7	11–14	0.75–0.95	355–384	2–6	20–51
Flax	62–72	18–20	2–5	2.6–8	1.4–1.5	343–2000	1.2–3.3	27–103
Pineapple	70–82	18.8	14–15	11.8	1.4–1.5	413–1627	1.6–3	34–82

2.3 Hybrid Bio-Based Composite Material System

Hybrid bio-based composite material systems combine bio-based polymers with multiple types of natural, synthetic, or nano-scale reinforcements to achieve enhanced mechanical, thermal, and functional performance while maintaining sustainability benefits. Several authors have explored the utilization of different natural fibres along with graphene/other fillers in the development of hybrid polymer composites [34,35].

Unlike conventional single-reinforcement composites, hybrid systems exploit the synergistic effects of different reinforcements, enabling improved strength-to-weight ratio, damage tolerance, and durability. This approach addresses the inherent limitations of purely bio-based composites, such as lower stiffness, moisture sensitivity, and variability in natural fibers. In hybrid bio-based composites, bio-derived polymer matrices such as bio-epoxy, PLA, and PHA are reinforced with combinations of natural fibers, synthetic fibers (e.g., glass or carbon), and nano-fillers (e.g., nanocellulose, graphene, MXene, or nano-clays).

2.4 Manufacturing Techniques

The manufacturing methods have a profound effect on the strength, quality, and environmental footprint of bio-based and hybrid bio-based composites. Polymers derived from biological sources and natural fibers are susceptible to changes in temperature, humidity, and various stages of processing. Hence, choosing the right method and making fine adjustments are indispensable for manufacturing stable and reliable biofibre reinforced polymer composite structures. Also, new processing methods combined with the digital twin and machine learning offer enhanced control and higher productivity for manufacturing these composites. The behavior of materials in real-world applications often deviates from the results observed in a controlled laboratory environment. This discrepancy needs regular observation of the manufacturing process. An active system of surveillance can help identify problems at the earliest stage. On the contrary, passive systems may reveal minor alterations in performance over a period of time. An ongoing evaluation of the data ensures the delivery of results meeting the expected standards consistently. Conventional composite manufacturing techniques such as compression molding, resin transfer molding (RTM), vacuum-assisted resin infusion, and hand lay-up are widely employed for bio-based composites [36].

2.4.1 Compression and Injection Molding

Compression and injection moulding are important techniques for thermoplastic material processing. Compression molding is particularly suitable for thermoplastic bio-based matrices, offering good dimensional accuracy and high production rates. In the last few decades, various authors investigated the mechanical properties of compression- and injection-molded biopolymer composites [37]. The compression and injection moulding set-up is demonstrated in Figs. 3 and 4, respectively. Compression moulding can accommodate both short and long fibres, offering improved mechanical properties. Injection moulding and extrusion are primarily used for short-fibre composites due to their ability to process discontinuous reinforcements efficiently [38,39].

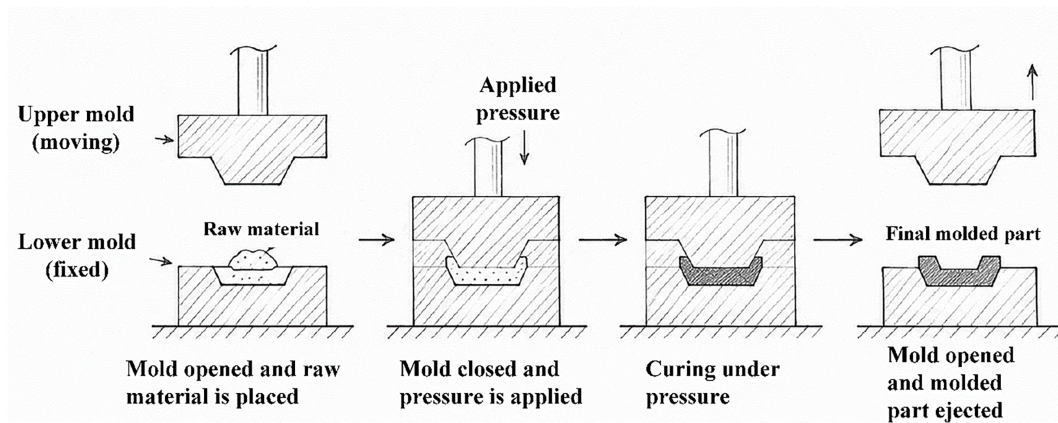


Figure 3: Compression moulding.

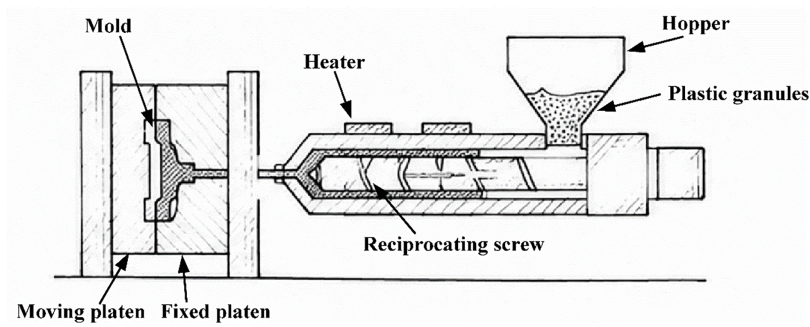


Figure 4: Injection molding.

2.4.2 Resin Transfer Molding (RTM)

Resin Transfer Molding (RTM) is one of the most important processing techniques for thermoset polymers. RTM is a closed-mold composite manufacturing technique widely used for producing high-quality bio-based and hybrid bio-based composite components with good surface finish and controlled fiber volume fraction. In the RTM method, dry fiber preforms comprising natural fibers, synthetic fibers, or their hybrids are placed inside a rigid, matched mold. A low-viscosity resin is injected under controlled pressure. The resin impregnates the fiber preform, followed by curing within the closed mold to form the final composite samples. Processes such as resin transfer moulding (RTM) are particularly suitable for continuous-fibre composites, providing superior strength and stiffness through controlled fibre orientation [40]. The RTM process is shown in Fig. 5.

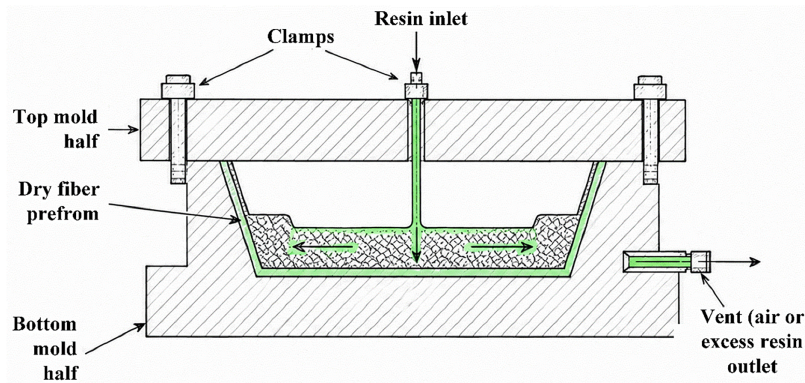


Figure 5: Resin Transfer Molding (RTM).

2.4.3 Additive Manufacturing (3D Printing)

Additive manufacturing (AM), commonly referred to as 3D printing, has emerged as a transformative technique for fabricating bio-based and hybrid bio-based composite materials. It offers unprecedented design flexibility, material efficiency, and sustainability advantages [41]. In bio-based composites, the AM process primarily employs thermoplastic matrices such as polylactic acid (PLA), polyhydroxyalkanoates (PHA), and bio-based polyesters, often reinforced with natural fibers (e.g., bamboo, flax, jute) or nano-fillers (e.g., cellulose nanocrystals, graphene, MXenes). Fused filament fabrication (FFF), popularly known by its trademark name, fused deposition modeling (FDM), is the most widely used AM technique for these composites. In FDM, a filament material is melted and extruded through a nozzle to form successive layers as shown in Fig. 6. Additive manufacturing techniques can process short fibres and, increasingly,

continuous-fibre reinforcements, enabling the fabrication of complex composite structures with tailored properties [42].

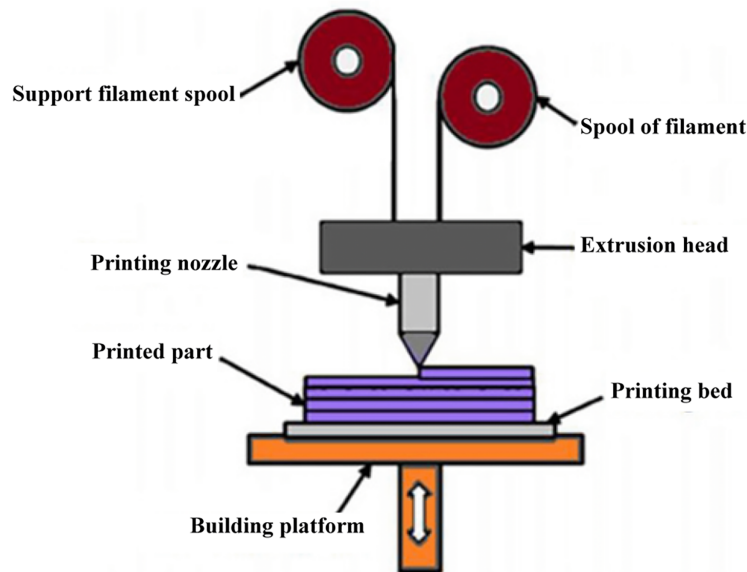


Figure 6: Fused deposition modeling-based 3D printing [adapted from [43] under a creative commons (CC) license].

3 Sustainability and Environmental Impact

The sustainability and environmental impact of biofibre-reinforced polymer composites are highly effective and serve as key considerations in the development and application of bio-based and hybrid composite materials. Unlike conventional composites derived from petroleum-based polymers and synthetic fibers, bio-based composites utilize renewable resources such as plant-based polymers/fibres like wheat gluten, natural fibers, and biodegradable fillers. The use of plant-based polymers significantly reduces dependence on fossil fuels and lowers the overall carbon footprint. The integration of sustainable materials with advanced manufacturing processes and digital twin-enabled optimization further enhances their environmental performance while meeting engineering requirements.

3.1 Life Cycle Assessment (LCA) of Bio-Based Composites

The conventional way of conducting life cycle assessment (LCA) is a very sluggish, time-consuming, and data-intensive process. In bio-based composites, the LCA process typically begins with an assessment of raw material sourcing. Natural fibers such as flax, jute, bamboo, or hemp absorb carbon during growth, providing a carbon-capturing and storing benefit, while bio-based polymers such as polylactic acid (PLA) or polyhydroxyalkanoates (PHA) derived from renewable feedstocks that reduce dependence on fossil fuels. The manufacturing stage is another key factor, as energy consumption, resin synthesis, fiber treatment, and composite processing (e.g., compression molding, resin transfer molding, or additive manufacturing) can significantly influence the overall environmental footprint. Process optimization, including waste reduction and energy-efficient curing, contributes to lower impacts and improved sustainability performance.

Researchers used different methods to conduct LCA. For example, Seile et al. [44] used a cradle-to-gate approach for evaluating LCA of flax and hemp fiber-reinforced PLA composites with glass fiber-reinforced polyamide composites. The cradle-to-gate approach considers environmental impacts from raw material procurement to the completion of the manufacturing process. The authors employed the CML (Centrum

voor Milieukunde Leiden, developed at Institute of Environmental Sciences at Leiden University) impact assessment method, which quantifies environmental impacts through indicators such as global warming, acidification, and eutrophication. The carbon footprints of flax fibre reinforced PLA, hemp fibre reinforced PLA and glass fibre reinforced polyamide composites were reported as 1.19, 1.70, and 9.14 kg CO₂ equivalent per kg of composite, respectively. Recupido et al. [45] employed cradle-to-gate LCA based on the CML method to evaluate the environmental impacts of producing bio-based polyurethane foams reinforced with functionalized hemp fibres and rice husk-derived silica fillers. Conventional LCA provides valuable insights into the environmental impacts. However, by integrating machine learning and a digital twin model, the improvement in life cycle assessment can be achieved through predicting hotspots in carbon emissions and energy usage, automating inventory data estimation for bio-composites, evaluating end-of-life scenarios (composting, recycling, biodegradation), and recommending optimal feedstocks based on region-specific agricultural data. Fig. 7 illustrates a schematic representation of the enhancement of LCA through the integration of machine learning and digital twin models.

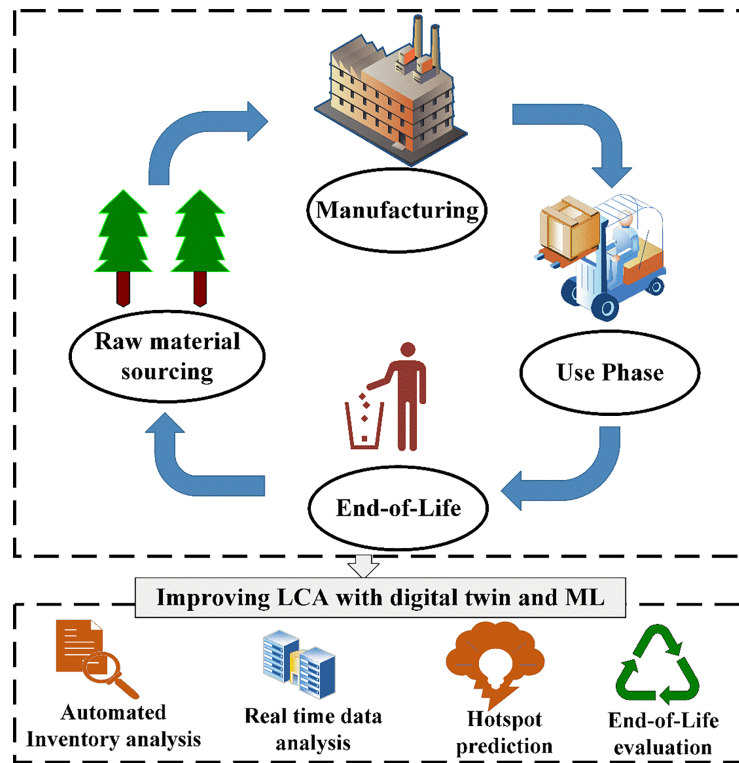


Figure 7: Life cycle assessment of bio-based composites.

3.2 Carbon Footprint and Energy Consumption

Carbon footprint and energy consumption are key indicators for evaluating the environmental performance of bio-based and hybrid composites. The carbon footprint tracks all greenhouse gas (GHG) emissions from a material or product over its entire life, starting with raw material extraction, processing, manufacturing, shipping, use, and final disposal. Bio-based composites typically reduce carbon emissions compared to their conventional petroleum-based counterparts. Natural fibers like flax, jute, bamboo, and hemp take in carbon dioxide while growing, removing carbon from the atmosphere and partially balancing out emissions from later steps of processing. Bio-based polymer matrices derived from corn starch or sugarcane help in reducing dependency on fossil fuels and lower overall greenhouse gas emissions. The amount of energy

used for producing these composites is influenced by the methods of fiber preparation, resin production, shaping, and curing times. Conventional techniques like compression molding and resin transfer molding require very precise heat and pressure adjustments that lead to increased energy consumption. 3D printing constructs objects layer by layer, thus reducing the amount of energy used and waste created. In fact, energy savings up to 30% of the total energy have been reported [46]. Hybrid composite materials combining natural and synthetic reinforcements can effectively balance better mechanical properties with a lower carbon footprint provided that the share of renewable materials is increased to the highest possible level.

3.3 Biodegradability and End-of-Life Scenarios

Biodegradability and handling of materials at the end of their life are critical considerations in the design and development of bio-based and hybrid composites. These materials come from renewable sources. Unlike traditional petroleum-based ones, some break down naturally in certain environments. This helps in reducing long-term waste and pollution. Therefore, knowing the degradation process is important. Proper disposal plans must be put in place. Without them, the environmental benefits do not fully materialize. The right end-of-life choices help ensure the materials perform well over time. Some decompose after use that reduces landfill burden. Designing with this in mind supports better outcomes for ecosystems. For instance, PLA–flax fibre composites have demonstrated reduced environmental impacts compared to glass-fibre-reinforced plastics when managed through composting or recycling pathways. Likewise, natural-fibre-reinforced composites used in automotive interior components can contribute to landfill reduction and resource conservation when appropriate recovery strategies are implemented [47].

3.4 Alignment with UN's SDGs and Circular Economy

Bio-based and hybrid composites are playing a role in advancing key sustainability targets while aligning with circular economy ideas, with a focus on smarter use of materials, less trash/waste, and better production habits. The substitution of petroleum-derived polymers and synthetic reinforcements with renewable, bio-based, and biodegradable alternatives offers significant environmental advantages, including lower greenhouse gas emissions, reduced depletion of resources, and cleaner production processes [48]. These changes grow more meaningful when biocomposites industries incorporate them thoughtfully in circular economy strategies that prioritize resource recovery, material efficiency, and sustainable lifecycle management. As they are sourced from plants, these substances help Sustainable Development Goal (SDG 12) by using less oil-based stuff while encouraging smarter ways to get raw inputs. When used in vehicles or bridges, lighter green composites tie into SDG 13—less weight means less fuel burnt, fewer planet-warming gases released over time. Smart factory methods paired with live data tracking also link to SDG 9, pushing fresh thinking in how things are built without wasting effort or supplies. The typical SDG alignment of bio-based composites is presented in Fig. 8.

Circular economy principles are embedded in the lifecycle management of bio-based composites. The various applications of natural fibre-based composites and their circular economic integration are demonstrated in Fig. 9. Materials are designed for reusability, recyclability, or biodegradability, thus ensuring that resources are continuously cycled and waste is minimized. Hybrid composites are optimized to balance performance with environmental considerations, enabling the reuse of fibers and polymers, energy recovery, or disposal at the end of life.

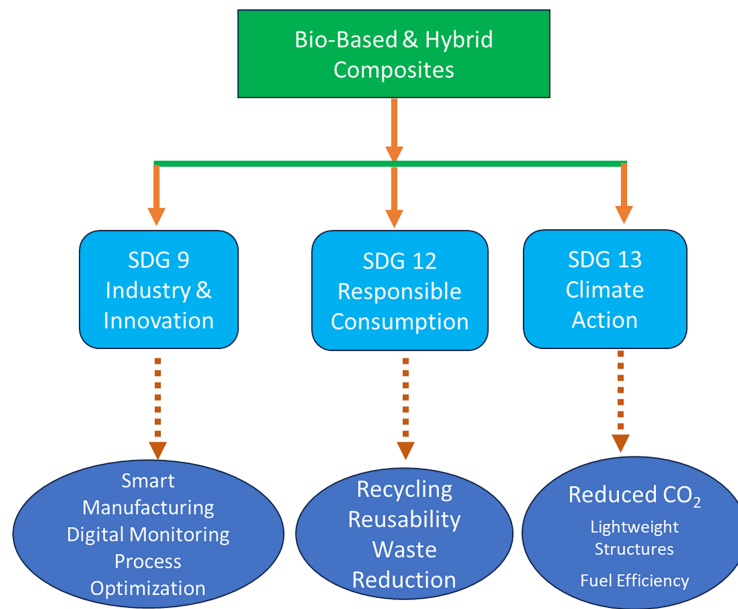


Figure 8: SDG alignment of bio-based composites.

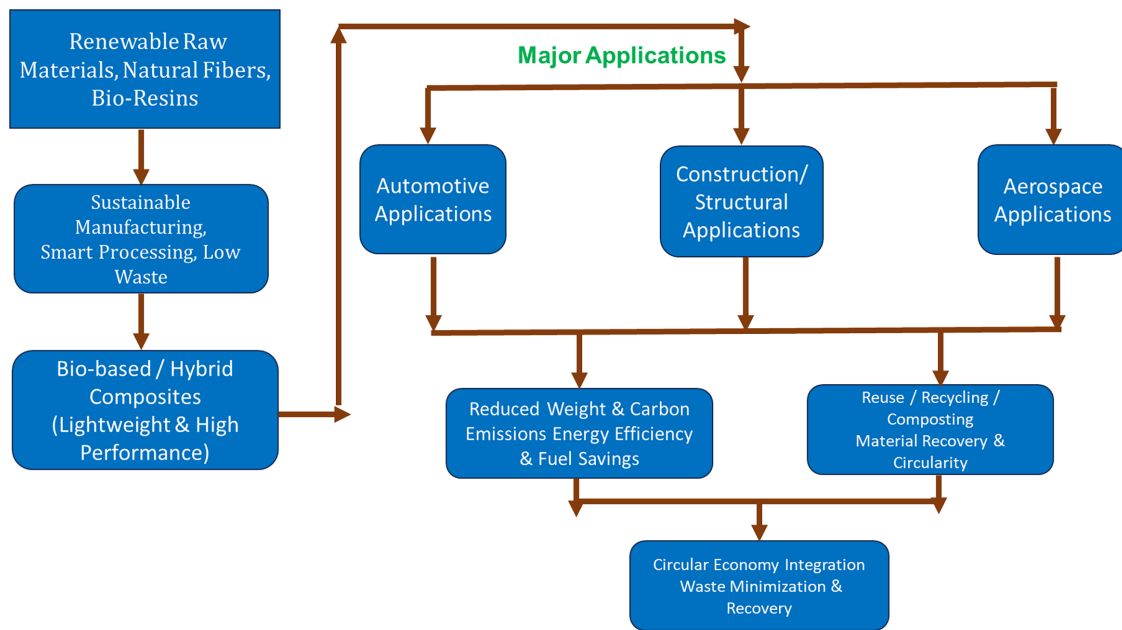


Figure 9: Natural fibres-based composites and their circular economic integration.

4 Machine Learning Techniques in Bio-Based Polymer Composites

Natural fibre composites are characterized by variation in weight % of their fibre reinforcements, mixing of different types of reinforcements, and the diverse ways in which they respond to manufacturing steps. This results in slow and variable methods that depend on trial and error. Such conventional approaches usually require a lot of time and mostly show variation in results. In this regard, Machine learning

presents a quicker alternative for manufacturing, processing, and operating the entire life cycle of bio-based polymer composites. It is also capable of forecasting the behavior of composites more dependably in different situations, thus enhancing the accuracy of mechanical properties without the need for extensive physical testing.

4.1 Overview of Machine Learning Algorithms

Machine learning methods can be broadly categorized into two groups: supervised and unsupervised. Fig. 10 represents various types of Machine Learning Algorithms. In addition to traditional methods such as regression, support vector machines (SVM) and artificial neural networks (ANN) are frequently employed in the prediction of material properties and modelling of processes. The features may be the fiber orientation type, polymer composition, temperature during curing or application of pressure-force in the final stage. All these variables can be linked to the output variables such as the material's tensile strength, stiffness or heat resistance [49].

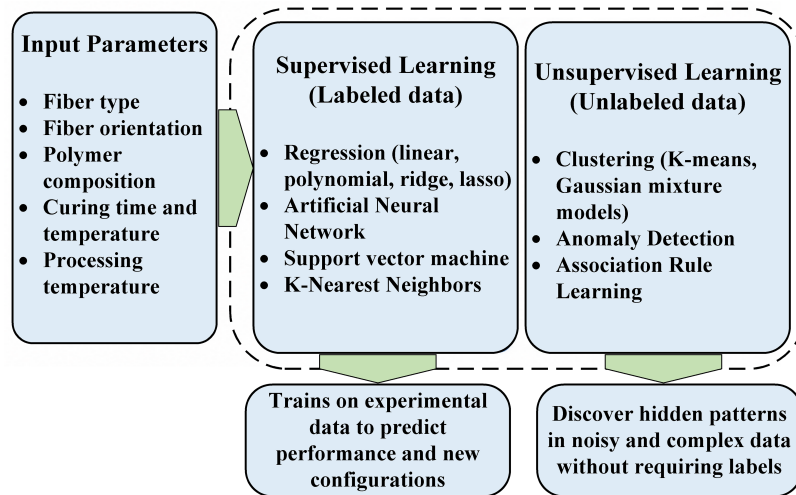


Figure 10: Various types of machine learning algorithms.

These models train on the manufacturing process parameters and laboratory experimental data to forecast the performance of previously unexplored material configurations, thereby reducing the need for extensive manufacturing trials. Unsupervised machine learning techniques such as clustering, autoencoders, and principal component analysis are widely utilized to identify hidden patterns, correlations, and outliers/anomalies in highly complex and noisy datasets without needing labelled data [25]. These techniques allow not only the extraction of features of a material and the reduction of the number of variables but also the classification of materials and the detection of defects. Owing to this, manufacturing defects like porosity, fibre misalignment, and microstructural variations can be identified at an early stage. In addition, they can be used for process monitoring and to improve the structure-property relationship. These capabilities are a powerful combination of gathering experimental observations through data-driven analysis that allows accelerating novel material design and its optimization.

4.2 Machine Learning-Based Property Prediction

Bio-based composite materials made from biopolymers and natural fibers often exhibit considerable differences. This is due to variability in natural fibers, the use of different reinforcement mixtures, and the

influence of processing on the testing results. Therefore, methods like trial-and-error or simple mathematical models do not serve as reliable tools for anticipating the behavior of these materials. Machine learning assists in predicting such properties as strength, wear resistance, and other mechanical performance traits by uncovering hidden patterns in how the input parameters vary with respect to the outputs. Some researchers have used regression, artificial neural networks, and support vector machines in an attempt to predict mechanical performance [50]. The research works indicate these methods are more effective than traditional methods when dealing with the complex behavior of bio-composite materials in practice. Among various studied models, the ANN-based method yielded the best predictive accuracy (75.5% to 89.8%) as compared to SVR and RF-based methods (68.1% to 85.6%) [51,52]. They can also be expected to make better predictions in the future if more and more data is made available to them for training. The comparison of different machine learning models utilized for biocomposites mechanical properties prediction is represented in Table 2.

Table 2: Comparison of machine learning approaches for predicting mechanical properties of composite materials.

Sl. No.	Composite System	ML Technique	Property Predicted	Performance Metric	Main Outcome	Limitation	Reference
1	Geopolymers	ANN, SVR, RF	Compressive strength	R ² , RMSE, MAE	ANN highest accuracy	Dataset dependency	[51]
2	Fibre-reinforced composites	ANN, SVR, RF, DT	Tensile, flexural, impact properties	Accuracy, RMSE	ANN superior for nonlinear relationships	Generalization challenges	[52]
3	Laminated FRP composites	ANN, ML optimization	Mechanical behaviour	R ² , error metrics	Effective for optimization and prediction	Limited experimental datasets	[12]
4	Composite materials	ANN, RF, SVR, ensemble methods	Multiple properties	Statistical indices	Comparative evaluation of ML algorithms	Lack of unified benchmarks	[53]
5	Fibre-reinforced polymers	CNN	Stress field and mechanical response	Prediction accuracy	Rapid prediction from microstructure images	Requires image datasets	[54]

4.3 Mechanical Properties

Some supervised machine learning techniques used to forecast the change and development of mechanical properties include artificial neural networks, support vector regression, and random forests. These modeling approaches are supported by the data collected through laboratory experiments, computer simulations, or sensors installed on the actual parts [55]. After data collection, patterns and relationships in the samples are identified, and the material behaviour is predicted in new circumstances without the assistance of expensive physical testing. Consequently, the number of physical tests required in the development phase is minimized. Models based on ANNs are capable of forecasting mechanical properties like tensile strength, Young's modulus, and impact strength. The authors indicated that the findings were extremely accurate [56]. For example, ANN models have been successfully employed to predict the tensile strength, Young's modulus, flexural strength, and impact resistance of fibre-reinforced composites. In a

comparative study by Anwar et al. [51], ANN-based models predicted compressive strength with accuracies ranging from 75.5% to 89.8%, outperforming SVR and RF models, which achieved accuracies between 68.1% and 85.6%. Similarly, Sharma et al. [52] reported that ANN models achieved coefficients of determination (R^2) exceeding 0.90 for predicting tensile and flexural properties of composite materials, demonstrating excellent agreement between predicted and experimental values. Kibrete et al. [50] further highlighted that ANN and deep learning models commonly achieve prediction errors below 10% for key mechanical properties such as tensile strength and elastic modulus when trained on sufficiently large datasets.

4.4 Thermal and Viscoelastic Properties

Machine learning techniques are becoming increasingly effective for predicting the thermal and viscoelastic properties of bio-based and hybrid polymer composites. Thermal conductivity, specific heat capacity, coefficient of thermal expansion, glass transition temperature, storage modulus, loss modulus, and damping behavior are critical properties of materials in and outdoors that determine long-term performance. These properties are likely to affect the longevity and service life of materials when exposed to varying environmental conditions. Such models minimize the reliance on physical tests, and this method generally leads to enhanced precision when adequate training data are available [57].

Kibrete et al. [50] reported that Artificial Neural Network (ANN)-based models can effectively predict thermomechanical properties of composite materials, often achieving coefficients of determination (R^2) exceeding 0.90. Similarly, Sorour et al. [12] reviewed the application of machine learning techniques for fiber-reinforced polymer composites and highlighted that ANN, Support Vector Regression (SVR), and Random Forest (RF) models provide highly accurate predictions of thermal and viscoelastic properties, with prediction errors generally below 10% when adequate training data are available. Furthermore, Liu et al. [11] demonstrated that machine learning models can successfully capture complex nonlinear relationships between material composition and thermal behavior, enabling reliable prediction of properties such as thermal conductivity, glass transition temperature, and storage modulus. More recently, Zhu et al. [58] reviewed over a decade of machine learning applications in composite materials and concluded that ANN and deep learning models consistently outperform traditional empirical approaches in predicting thermomechanical responses, often achieving prediction accuracies above 90%.

4.5 Moisture Absorption and Degradation Behavior

Besides the impact on material strength and durability, there is also an increase in moisture content and swelling after the composite samples have been submerged in water. Natural fibres are hydrophilic, and the water content in the composite made them swell. This facilitated the loosening of the interfacial bonds, thereby resulting in the deterioration of the materials. This is one of the main reasons for faster performance deterioration. It would have taken a great deal of time if every test case for material performance evaluation was run. Due to such demands, resources are depleted one after another. Whereas machine learning is very silent here, it is already helping. Predictions on the effects of dampness become more and more precise. Besides that, design decisions can be better made without running many experiments. Also, lifespan predictions become more dependable. Support vector machines were quite successful with one set [59].

4.6 Machine Learning Driven Process Optimization

Machine learning assists in refining the way the manufacturing of bio-based and hybrid polymer composites is done. These materials are highly sensitive to changing conditions such as temperature, pressure, curing time, fiber alignment, pressure applied and resin flow. Overall, these factors determine strength,

heat resistance, and durability. Artificial neural networks, support vector regression, and random forests are examples of models frequently used to map process inputs to final outputs like tensile strength, impact resistance, thermal stability, and void content [60]. These models apprehend every performance alteration. Even a slight change in resin flow can have a big impact on the final product. That's why it is critical to carry out testing for each parameter. In Such case, predictive models enable efficient process optimization, reduce experimental trials, and improve the consistency and quality of the manufactured composites. In addition, environmental factors such as moisture, temperature, and UV exposure significantly influence the long-term durability of natural fibre composites, highlighting the need to consider these effects during material design and performance evaluation [61].

4.7 Defect Detection and Quality Control Using Machine Learning

Defect detection and quality control are critical challenges in the manufacturing of bio-based and hybrid polymer composites due to the heterogeneity of natural fibers, variability in hybrid reinforcement, and sensitivity of bio-based polymers to processing conditions. Fig. 11 presents an overview of defect detection and quality control using machine learning techniques.

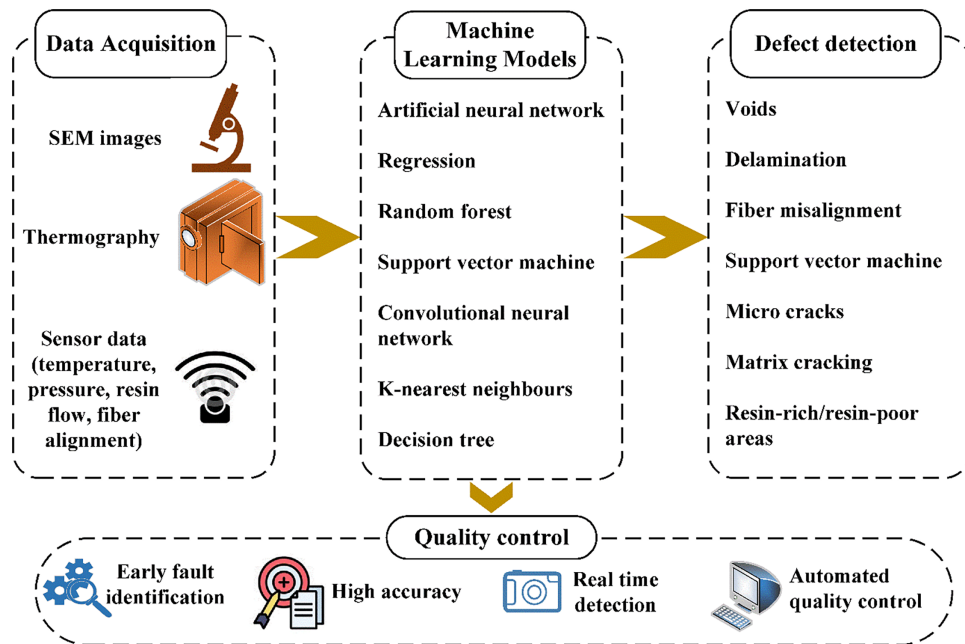


Figure 11: Defect detection and quality control using machine learning.

The supervised learning and deep learning algorithms, including convolutional neural networks, artificial neural networks, and support vector machines, are widely employed for defect detection. These models are trained on datasets obtained from imaging techniques (e.g., scanning electron micrography, ultrasound, thermography) or sensor data capturing parameters such as temperature, pressure, resin flow, and fiber alignment [62]. By learning complex patterns in the data, these machine learning models can identify anomalies such as voids, delamination, fiber misalignment, resin-rich or resin-poor areas, and microcracks, often in real time and with higher accuracy than conventional methods. Beldar et al. have applied a convolutional neural network model for detecting the defect/voids/cracks in carbon fibre-reinforced epoxy composites [63].

5 Digital Twin Framework for Bio-Based Polymer Composites

The digital twin (DT) framework for bio-based polymer composites represents an advanced cyber-physical system that integrates physical materials, virtual models, and real-time data to enhance material design, manufacturing, performance prediction, and sustainability. Bio-based polymer composites offer a good option over traditional synthetic plastics, and more researchers are focusing on these eco-friendly materials. Digital twin technology provides a practical way to connect the real-world composite with its virtual version. The DT system updates in real time, and changes in performance are tracked automatically. Monitoring happens without interrupting operations, and both versions stay synchronized as conditions shift. Users can make decisions based on live data, and the feedback loops keep things accurate and responsive.

5.1 Concept and Architecture of Digital Twins

The concept of digital twin evolved from preceding forms of digital representations, namely digital model and digital shadow. A digital model is a static virtual representation of a physical entity without any exchange of data between the physical and virtual environments. A digital shadow enables one-way data flow from the physical system to the digital representation. It allows the virtual model to reflect changes occurring in the physical counterpart. Hence, the data transfer in digital shadow is a one-way process. However, a digital twin forms a two-way connection. The information continuously flows between the physical and virtual entities [64]. A digital twin is essentially a virtual copy of a physical object that not only represents it but is also capable of tracking the changes in it over time. Fig. 12 represents the digital twin flow diagram. It collects real-time information from the actual system and modifies its status accordingly. Different from standard models, this one is not fixed, as it continuously changes based on the behavior of the regulated and controlled entity. It allows for uninterrupted monitoring, forecasting, and improvement of operations. In the case of advanced materials, it is the connecting point between the physical world and the digital tools.

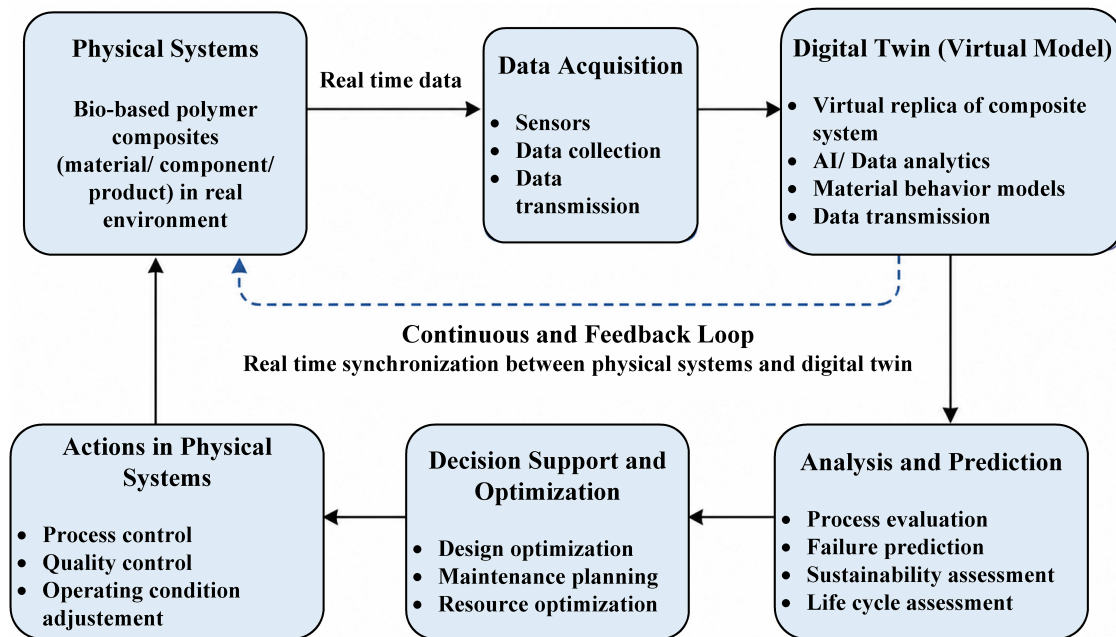


Figure 12: Digital twin flow diagram.

Thanks to real-time performance measurement, engineers are always capable of quick reactions to the given scenarios. Owing to a digital twin, the process of continuous monitoring and adjustment has been made much more precise and efficient. Using this approach will lead to the improvement of the design and the life of the materials.

5.2 Data Acquisition and Sensor Integration

Sensor integration and data acquisition are fundamental components of a Digital Twin framework, as they facilitate the continuous exchange of information between real-world systems and their virtual counterparts, enabling accurate monitoring, simulation, and decision-making. It is undoubtedly one of the best approaches towards linking real-world activities with their digital counterparts. A typical data acquisition system in an additive manufacturing setup is depicted in Fig. 13. To handle high-performance materials and their manufacturing, the process of data acquisition encompasses not only the collection of live data, but also the historical data related to the material's characteristics, manufacturing environment/parameters, and other influences. Moreover, if the input signals are sufficiently reliable and continuous, the model can produce accurate results and reveal a comprehensive understanding.

On the other hand, sensor integration primarily refers to the joining of sensors to the physical system to accurately monitor the key parameters not only during the manufacturing process but also during the product's usage. For example, temperature sensors are used for keeping an eye on the curing process and changes in heat, whereas strain gauges and fiber-optic sensors are means to examine the material's deformation and the response to the loads. Pressure sensors are commonly used to measure and control processing parameters, while humidity sensors are more suitable for assessing exposure to environmental conditions. In the manufacturing of composites, *in-situ* monitoring techniques provide real-time information. These are very important factors when working with materials with highly variable composition and properties. Digital twin models driven by datasets are developed using machine learning and statistical methods to identify patterns and establish relationships mainly based on experimental, sensor, and operational data. Some of the popular methods are artificial neural networks, support vector machines, Gaussian process regression, and deep learning architectures. The sensor technologies and data acquisition methods used in Digital Twin frameworks for composite manufacturing and monitoring is depicted in Table 3.

Table 3: Sensor technologies and data acquisition methods used in Digital Twin frameworks for composite manufacturing and monitoring.

Sl. No	Sensor Type/Data Source	Parameter Monitored	Application in Composite Manufacturing	Role in Digital Twin	References
1	Temperature Sensors (Thermocouples, RTDs)	Temperature, curing profile	Monitoring resin curing, thermal cycles, and process optimization	Prediction of curing behavior, thermal degradation, and process control	Tao et al. [65], Fuller et al. [66], Leng et al. [18]
2	Strain Gauges	Strain, deformation	Monitoring structural response during manufacturing and service	Stress analysis, damage initiation, and structural integrity assessment	Giurgiutiu [67], Farrar and Worden [68]
3	Fiber-Optic Sensors (FBG)	Strain, temperature, crack initiation	<i>In-situ</i> monitoring of composite structures	Real-time structural health monitoring and damage detection	Di Sante [69], Kuang et al. [70], Peters [71]
4	Pressure Sensors	Mould pressure, resin flow pressure	Compression moulding, RTM, injection moulding	Process optimization and defect prediction	Tao et al. [65], Leng et al. [18]

(Continued)

Table 3 (continued)

Sl. No	Sensor Type/Data Source	Parameter Monitored	Application in Composite Manufacturing	Role in Digital Twin	References
5	Humidity Sensors	Moisture content, environmental exposure	Durability assessment of natural-fibre composites	Moisture absorption and degradation prediction	Fuller et al. [66], Leng et al. [18]
6	Vibration Sensors (Accelerometers)	Dynamic response, vibration characteristics	Monitoring operational performance	Predictive maintenance and fatigue analysis	Farrar and Worden [68], Giurgiutiu [67]
7	Operational Manufacturing Data	Process parameters (speed, pressure, temperature)	Smart manufacturing systems	Real-time optimization and adaptive control	Tao et al. [65], Fuller et al. [66], Leng et al. [18]
8	Simulation Data (FEA/CFD)	Stress, temperature, flow behavior	Virtual process modelling	Scenario analysis and Digital Twin calibration	Kritzinger et al. [64], Leng et al. [18]

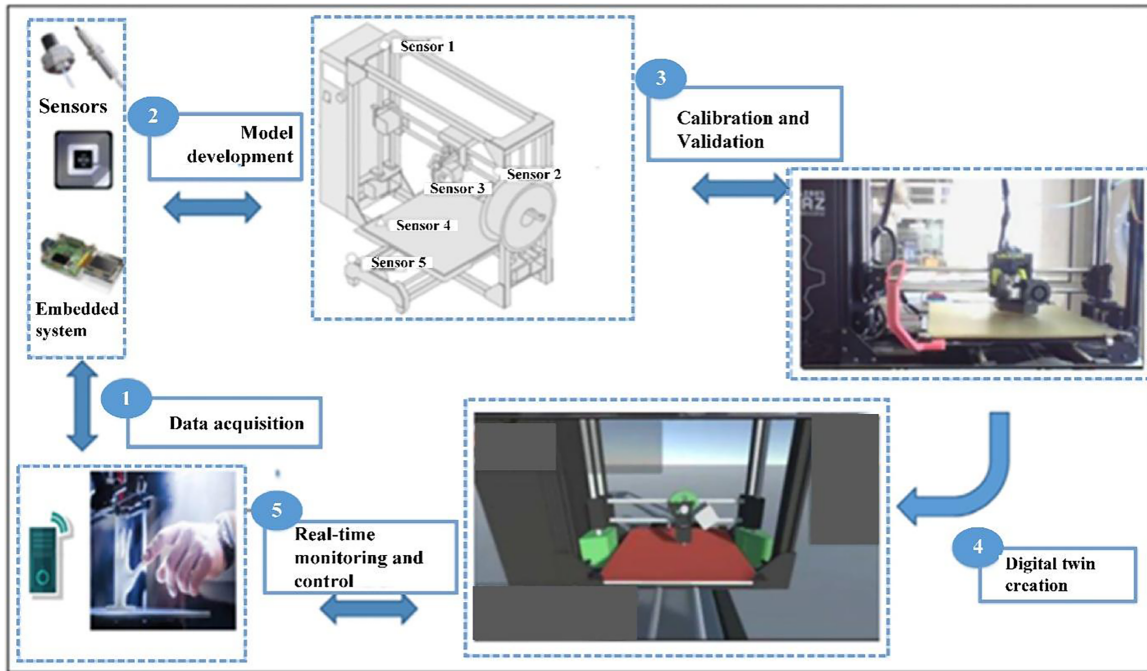


Figure 13: Data acquisition through a digital twin system in an additive manufacturing setup [adapted from Ref. [72] under a creative commons (CC) license].

5.3 Real-Time Monitoring and Predictive Maintenance

One significant advantage of digital twin technology is real-time monitoring and predictive maintenance. They facilitate continuous assessment of the system's health and enable prompt decision-making during operations. The actual physical system is connected to its digital counterpart via a live link. This allows the team to monitor the progress of key performance indicators as they are being developed. Unusual deviation from expected behavior is immediately detected. Sensors and data acquisition devices continuously collect data such as temperature, strain, vibration, load, and weather conditions. Predictive maintenance is

far more than just assessing the present situation. It relies on the combination of historical data and live data to predict future performance and potential component failures. The system is capable of warning the operators just before a breakdown occurs.

6 Integration of Machine Learning and Digital Twins

Machine learning enhances digital twin systems by injecting them with intelligence, the ability to change, and forecasting capabilities. Digital twins leverage machine learning to analyze data, detect complex patterns, and enhance their performance over time. The fusion is very effective in complex, nonlinear systems with uncertainties, varying conditions, and material differences. In the system, there will be automatic modifications based on real-time data. Improvements in performance are the result of continuous feedback loops. Such modifications take place without the need for human intervention. In contrast to changing environments, digital twins are capable of real-time response. The outcomes accurately correspond to real operating conditions.

Machine Learning Enhanced Digital Twin Models

Machine learning-enhanced digital twin models have been shown to significantly outperform traditional ones. They bring together physics-based simulations and machine learning to identify patterns in sensor, experimental, and real-time operational data. The algorithms learn the behavior of physical systems under different conditions rather than being based only on the equations that have been previously formulated. This capability enables the Digital Twin to adapt to changing conditions, manage uncertainties, and continuously improve the accuracy of its predictions over time. It appears that this is especially helpful for materials that are naturally diverse or that show nonlinear behaviour. Moreover, this methodology enhances the accuracy and promptness of responses in complicated environments. Fig. 14 depicts the working of the machine learning-enhanced digital twin for a physical system.

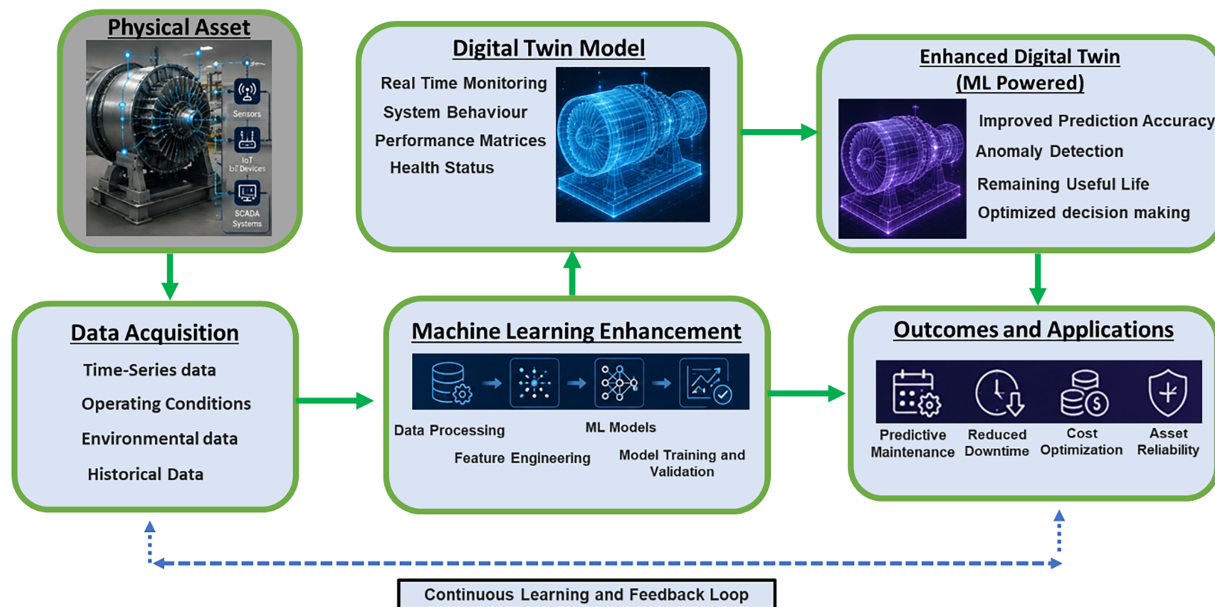


Figure 14: Machine learning enhanced digital twin models.

The comparison of various machine learning-enhanced digital twin frameworks for different material and manufacturing applications is presented in Table 4.

Table 4: Comparison of machine learning-enhanced digital twin frameworks for material and manufacturing applications.

SI No.	Application/ System	ML Technique	Digital Twin Function	Performance Improvement/ Numerical Results	Key Findings	Limitations	Reference
1	Smart manufacturing systems	ANN, Data Analytics	Process monitoring and optimization	Prediction accuracy >90% for process-state estimation	ML improves adaptability and predictive capability compared to conventional DT models	Requires large volumes of sensor data	Tao et al. [65]
2	Industrial digital twins	ANN, Deep Learning	Real-time decision support	Reduction in prediction errors by 15%–30% compared with physics-only models	Hybrid DT models improve responsiveness to changing operating conditions	High computational requirements	Fuller et al. [66]
3	Industry 4.0 manufacturing	Deep Neural Networks (DNN)	Process optimization and predictive maintenance	Downtime reduction of 20%–40% through predictive analytics	Integration of ML enables adaptive and self-learning Digital Twins	Data quality significantly affects performance	Leng et al. [18]
4	Composite materials and structures	ANN, Surrogate ML Models	Mechanical property prediction	R ² values exceeding 0.90 for strength and stiffness prediction	ML-enhanced DTs capture nonlinear material behavior more effectively than physics-based models alone	Limited availability of standardized datasets	Liu et al. [11]
5	Fiber- reinforced polymer composites	ANN, SVR, RF	Mechanical behavior prediction	ANN models achieved R ² > 0.90 in most reported studies	ANN consistently outperformed conventional statistical models	Potential overfitting with small datasets	Sorour et al. [12]

(Continued)

Table 4 (continued)							
SI No.	Application/ System	ML Technique	Digital Twin Function	Performance Improvement/ Numerical Results	Key Findings	Limitations	Reference
6	Composite materials (Review of ML studies)	ANN, CNN, Deep Learning	Multi-property prediction and optimization	Prediction accuracies frequently exceeded 90%	Deep learning models improve predictive performance and scalability	Need for larger open-access datasets	Zhu et al. [58]
7	Composite materials	ANN, SVM, RF	Property prediction and material design	Prediction errors generally below 10%	ML algorithms successfully model complex material-property relationships	Interpretability remains a challenge	Kibrete et al. [50]
8	Composite materials	ANN, SVR, RF, DT	Mechanical property prediction	ANN accuracy: 75.5%–89.8%; SVR/RF: 68.1%–85.6%	ANN demonstrated superior capability in capturing nonlinear relationships	Generalization across composite systems remains difficult	Sharma et al. [52]

7 General Review on Machine Learning, Sustainable Materials and Digital Twin

7.1 State of the Art: Digital Twin and Machine Learning

Digital twin (DT) frameworks have proven highly effective in modeling complex material degradation and structural life cycles where direct data collection is challenging. He et al. [73] developed an intelligent digital twin framework to predict and calibrate the corrosion fatigue life of suspension bridge suspender wires. By integrating mechanism-driven, sensor-driven, and probabilistic information fusion (combining entropy-based constraints with Bayesian updating), their model reduced fatigue life uncertainty by 88% and highlighted that neglecting interval bounds leads to prediction discrepancies of up to 54%. Similarly extending DTs to complex structural materials, Antonini et al. [74] introduced an experimental–computational pipeline to model commercial coronary bioresorbable polymer scaffolds when direct material properties are absent. Utilizing the Parallel Rheological Framework calibrated via parametric unit simulations, their workflow effectively matched full-device experimental radial forces while significantly minimizing computational overhead.

A significant portion of recent literature focuses on leveraging DTs to overcome the inherent unpredictability and defect rates of additive manufacturing (AM) technologies. At a foundational level, digital twin ecosystems support virtual testing and remote management by leveraging open-source controllers and external sensors to synchronize positional, temperature, and runtime data instantly, offering an affordable path to retrofit legacy 3D printers [75]. In more advanced setups, continuous data sharing between physical and virtual entities allows artificial intelligence to detect defects and dynamically adjust process settings [76]. For instance, in robotic laser-directed energy deposition, a multi-sensor fusion architecture combining acoustic, infrared thermal, visual, and laser line scanning data enables machine learning algorithms to map 3D defects and automate toolpath updates for self-correcting, cleaner production [77]. To structure this evolution, Osho et al. [78] introduced a modular “4R” model (Representation, Replication, Reality, and Relational), utilizing an FDM 3D printer to validate the early sensing stages required to transition a physical asset into a self-aware, autonomous digital twin.

Beyond localized process control, digital twins are increasingly used to optimize entire production chains, hybrid manufacturing configurations, and underlying cost structures. Anderson and van Der Merwe [79] combined time-driven activity-based costing with digital twinning to manage equipment capacity constraints in AM. By simulating standard times alongside random variations, their framework enables operators to dynamically recalculate production expenses in real time. On the factory floor, Barnowski et al. [80] utilized a comprehensive digital twin for the virtual commissioning of a multifunctional laser robot cell that integrates cutting, joining, and AM without tool changes, drastically reducing commissioning times and production errors. For hybrid manufacturing, Dvorak et al. [81] demonstrated a CNC machining DT for wire arc additively manufactured preforms, integrating structured light scanning and dynamic milling measurements to validate post-machining geometry and surface quality. More broadly, Jain and Narayanan [82] established that DT-enabled machine learning approaches streamline entire manufacturing ecosystems—reducing worker transit through optimized layouts, accelerating prototyping times from weeks to hours, and exposing hidden operational wastes.

Kantaros and Ganetsos [83] evaluated the cooperative coupling of Cyber-Physical Systems (CPS), Digital Twins, and 3D printing within the Industry 4.0 paradigm. They underscored how this triple integration drives mass customization and industrial competitiveness, though its widespread scalability remains throttled by security vulnerabilities and a lack of universal communication protocols. As these technologies mature, research has shifted toward macro-level integration frameworks and the systemic challenges of deployment. Addressing these systemic gaps, Psarommatis and May [84] conducted a systematic review

targeting Zero-Defect Manufacturing (ZDM). They observed that current DT implementations suffer from a lack of structured, standardized approaches, subsequently proposing a standardized design methodology to guide both academic and industrial practitioners toward reliable, cross-domain DT deployment.

Liu et al. [85] reviewed digital twin concepts, technologies, and industrial applications, emphasizing the need for clearer and industry-oriented definitions. Kritzinger et al. highlighted that digital twin research is still evolving, with major focus on production planning and control in manufacturing systems [64]. Tao et al. proposed digital twin-driven frameworks for product design, manufacturing, and service, demonstrating their practical industrial potential through case studies [86]. Cai et al. integrated manufacturing and sensor data to develop digital twin virtual machine tools for cyber-physical manufacturing, validating the concept using a 3-axis milling machine. Together, these studies establish digital twins as key enablers of Industry 4.0, supporting intelligent manufacturing, real-time monitoring, optimization, and predictive decision-making [87]. Lee et al. [88] discussed the role of Cyber-Physical Systems (CPS) in smart manufacturing, where real-time synchronization between physical factories and digital systems enables efficient, collaborative, and resilient operations. Rosen et al. emphasized the importance of modularity, connectivity, autonomy, and digital twins as the key drivers of future manufacturing systems [89]. Fang et al. proposed a digital twin-based job shop scheduling method that improves real-time and precise production scheduling through dynamic resource updates and interactive scheduling strategies, validated using a prototype system [90]. Together, these studies highlight the growing integration of CPS and digital twins for intelligent, adaptive, and optimized manufacturing environments.

Negri et al. [91] analyzed the evolution of digital twin concepts from aerospace to Industry 4.0 manufacturing and proposed a dedicated DT definition through the MAYA project. Schleich et al. [92] introduced a reference model based on Skin Model Shapes to serve as a digital twin throughout product design, manufacturing, and lifecycle management. Fuller et al. [66] reviewed digital twin applications across manufacturing, healthcare, and smart cities while discussing enabling technologies, challenges, and future research directions. Grieves [93] originally introduced the digital twin concept as a virtual representation of a produced system, enabling comparison between design intent and actual manufactured output to improve design-execution integration. David et al. [94] explored the use of digital twins in flexible manufacturing system education based on Kolb's Experiential Learning theory, demonstrating their potential in enhancing practical learning environments. DebRoy et al. discussed the current status and research needs of first-generation digital twins for additive manufacturing, emphasizing computationally efficient and high-fidelity models for predicting AM process behavior [95]. Knapp et al. developed a digital twin for laser-based directed energy deposition additive manufacturing to accurately predict thermal behavior, microstructure, cooling rates, SDAS, and hardness, validated using Stainless Steel 316L and Alloy 800H [96]. Qi and Tao reviewed the integration of big data and digital twin technologies, highlighting their complementary roles in cyber-physical integration, predictive maintenance, and smart manufacturing transformation [97].

Alajmi [98] reviewed the application of digital twins in improving the performance, sustainability, and manufacturing of fibre-reinforced polymers (FRPs), emphasizing real-time monitoring, predictive analysis, and eco-friendly composite production. Fernández-León et al. [99] developed a digital twin for resin transfer moulding (RTM) that uses deep learning and sensor data to detect resin flow defects in real time with high accuracy and rapid response. Attaran et al. [100] reviewed the role of digital twins in Industry 4.0, highlighting their applications in simulation, performance prediction, manufacturing optimization, logistics, and supply chain management. Xu et al. [101] proposed an AI-based digital twin framework for composite structures using deep neural networks to predict displacement and stress fields in real time, significantly reducing computational time while enabling scalable lifecycle analysis and smart manufacturing.

Zhang et al. [102] proposed a digital twin framework for robotics-based smart manufacturing systems that enables automatic and flexible system reconfiguration through a five-dimensional fusion model and reusable service function blocks. Aivaliotis et al. [103] developed a physics-based methodology for creating digital twins for predictive maintenance, validated using an industrial robot digital model for monitoring and analysis applications. Zambal et al. [104] introduced a digital twin-based manufacturing database for carbon fiber composite structures, integrating sensor data to evaluate mechanical properties, safety margins, and reduce rework in aircraft component manufacturing. Hürkamp et al. [105] demonstrated a simulation-based digital twin for thermoforming over-moulded thermoplastic composites, where reduced-order modeling and machine learning enabled real-time temperature prediction, bond quality monitoring, and inline quality control. Hughes et al. [106] utilized a digital twin model in Siemens NX to optimize composite laminate structures under thermal and fatigue loading, achieving improved stiffness and a 13% reduction in material usage through optimized reinforcement design. Chinesta et al. [107] discussed the evolution from traditional simulations to virtual, digital, and hybrid twins, emphasizing the transition from big-data to smart-data paradigms for advanced engineering analysis. Liu et al. [108] proposed DFMTR, a digital twin-based few-shot meta-transfer learning framework for defect detection in Carbon Fiber Reinforced Plastics structures, significantly improving damage classification and localization using limited real data. Li et al. [109] investigated digital twin technology for crack detection and modulus degradation prediction in CFRP laminates using fatigue testing, μ -CT imaging, and Lamb wave analysis, enabling real-time structural monitoring and residual life prediction.

Li et al. [110] proposed a hierarchical digital twin framework for microwave-assisted fused filament fabrication of continuous carbon fiber reinforced thermoplastics, enabling real-time monitoring, belt slippage detection, and predictive maintenance for improved printing reliability and efficiency. Ghnatios et al. [111] developed an AI-assisted digital twin for polymerization of recyclable Elium[®] Resin and carbon fiber composites, combining simulation and neural networks to accurately predict curing behavior and resin evolution. Shehab et al. [112] reviewed the application of digital twins in carbon fiber composite recycling, emphasizing enhanced monitoring, automation, and process efficiency while identifying challenges in data management and system validation. Kamble et al. [113] investigated digital twins in sustainable manufacturing supply chains, highlighting the role of IoT, cloud computing, and blockchain in enabling intelligent, integrated, and sustainable supply chain management frameworks. Hürkamp et al. [114] developed a digital twin framework for fiber-reinforced thermoplastic (FRTP) composite manufacturing using thermoforming and injection over-molding, where FEM simulations and machine learning were combined to predict bond strength and detect process-related defects. Polini and Corrado [115] proposed a digital twin tool for managing geometrical deviations in composite assemblies by integrating manufacturing, assembly, and inspection data to improve product precision and lifecycle quality tracking. Ball and Badakhshan [116] reviewed the use of digital models, shadows, and twins in sustainable manufacturing, emphasizing their role in optimizing resource productivity and reducing environmental impact while identifying gaps between industrial practice and academic research. Baalbergen et al. demonstrated the application of digital twins in out-of-autoclave thermoplastic composite manufacturing, showing improvements in process optimization, efficiency, waste reduction, and energy savings throughout the production lifecycle [117].

Cimino et al. [118] investigated the integration of digital twins with Manufacturing Execution Systems (MES) in Industry 4.0 manufacturing, identifying gaps in real-time interaction, monitoring, optimization, and maintenance services while proposing a practical DT-enabled assembly line implementation for closed-loop production control. Leng et al. [18] reviewed digital twin applications in smart manufacturing system design and proposed the FSBCIP framework to support efficient simulation, early error detection, and intelligent system development. Zheng et al. [119] analyzed Industry 4.0 technologies across manufacturing

lifecycle processes, highlighting the extensive adoption of IoT, Big Data Analytics, and Cloud Computing in production scheduling, control, and supply chain management. Macchi et al. [120] explored the role of digital twins in asset lifecycle management, emphasizing their growing importance in supporting monitoring, analysis, and data-driven decision-making for industrial assets. Xie et al. [121] proposed a digital twin-driven framework for managing the complete lifecycle of cutting tools by integrating IoT, cloud computing, big data, and AI to support continuous tool improvement, virtual testing, and smart manufacturing services. Hearley et al. [122] developed an automated framework for composite material digital twins that combines AI-based microscopy segmentation and Bayesian optimization to generate realistic microstructure models, enabling accurate prediction of composite damage and efficient multiscale material analysis.

7.2 State of the Art: Sustainable Materials

Driven by a 2022 UN mandate to replace petroleum-based plastics, Olonisakin et al. [123] examined advanced biopolymer blends (e.g., PLA, PHAs, PBS, PBAT, and TPS) reinforced with natural fillers. They noted that incorporating specialized compatibilizers is essential to balance the cost-to-performance ratio in industrial recycling systems. However, market adoption remains limited by confusing eco-labels and ambiguous degradation timelines [124]. To establish clear environmental baselines, Cosate de Andrade et al. [125] conducted a life cycle assessment comparing three end-of-life pathways for PLA. Their findings indicated that mechanical recycling carries the lowest environmental burden, followed by chemical recycling and composting, with grid electricity consumption serving as the primary source of environmental impact across all three pathways. Karan et al. [126] and Ali et al. [127] evaluated large-scale biorefinery concepts that convert solar-driven biomass (plants, microalgae, cyanobacteria) or organic biowaste into biofuels and biodegradable plastics. This global shift is moving rapidly across chemical packaging supply chains, with nations like China and India expected to spearhead production growth [128].

To circumvent time-consuming physical testing during fabrication, Nasrin et al. [129] evaluated the integration of machine learning algorithms within polymer-based 3D printing. Because layer-by-layer extrusion introduces hidden defects and heat-driven molecular irregularities, smart data-driven models are being increasingly used to accurately forecast mechanical outputs and optimize printing parameters. Comprehensive reviews by Siakeng et al. [130] and Ilyas et al. [131] detailed recent progress in the design, synthesis, and biodegradation of natural fiber-reinforced PLA composites. While PLA provides high rigidity, its industrial scale-up has faced hurdles like brittleness and rapid crystallization; current efforts are heavily targeting 3D and stimuli-responsive 4D printing applications to expand its engineering utility. Agumba et al. [132] addressed fiber–matrix incompatibility by utilizing a lignin-based resin paired with fiber mercerization (alkali treatment) in compression-molded jute fiber biocomposites. This approach yielded increases of 37.7% in flexural strength and 72.9% in flexural modulus, accompanied by improved hydrophobicity and thermal stability due to reduced void content. Structural anisotropy was explored by Hasan et al. [133], who evaluated hot-pressed flax woven fabric composites with PLA and PP matrices. Lengthwise flax/PLA configurations achieved a high tensile strength of 128.6 MPa, whereas widthwise flax/PP proved weaker but offered superior bending resistance, underscoring the critical influence of fiber orientation on final properties. Broadly addressing these trends, reviews by Khalid et al. [134], Kumar et al. [135], and general automotive studies [33] emphasize that while NFRPCs utilizing jute, flax, hemp, or sisal offer favorable strength-to-weight ratios, their growth relies on resolving moisture absorption, thermal sensitivity, and processing variations. Computational modeling and targeted fiber treatments (e.g., silane coatings) are presented as key solutions to accelerate industrial adoption.

Sweat et al. [136] developed a physics-based digital twin framework to reconstruct crystal-scale microstructures of PAN and pitch-based carbon fibers. Merging transmission electron microscopy (TEM)

and X-ray scattering data, the framework quantitatively linked local crystal characteristics to micromechanical properties, identifying key structural defects like skin-core misalignment to offer a new path for performance customization. Addressing advanced functionality, a high-performance structural supercapacitor was engineered using graphene nanoplatelet-coated woven carbon fiber composites [137]. The coated configurations achieved a threefold increase in specific capacitance alongside enhanced energy and power densities, successfully illuminating LEDs while maintaining a stable Young's modulus through optimized fiber compaction. Moving toward intelligent systems, Kaufmann et al. [138] investigated natural fiber-reinforced hybrid composites that combine bio-based and synthetic fibers to balance environmental and structural needs. Their review highlighted the integration of chemical modifications to improve durability alongside the emergence of smart hybrid composites equipped with embedded sensors and actuators for real-time engineering diagnostics.

7.3 State of the Art: Machine Learning for Material Behavior, Process Optimization and Additive Manufacturing

Attariani et al. [139] used an anisotropic heat transfer model governed by the Hunt criterion to study a synchronized circular laser array in powder bed fusion. Their simulations revealed that optimizing laser overlap promotes up to 45% equiaxed grain formation in Ti-6Al-4V alloys, eliminating highly anisotropic columnar microstructures. At the macro-scale, Large Format Additive Manufacturing (LFAM) of short carbon-fiber (CF) reinforced ABS often suffers from thermal warpage. To mitigate this, a coupled multiscale DT framework combined Mean-Field homogenization with Finite Element Analysis (FEA) to predict elastic properties within a 7.8% discrepancy margin of experimental values, offering a pathway to mitigate thermal residual stresses [140]. Taylan et al. [141] compared multiple ML algorithms including artificial neural networks (ANN), support vector regression (SVR), and polynomial chaos expansion (PCE) to predict polymer filament flow properties in FDM, identifying PCE as the most accurate model for tailoring rheological formulations. To maximize structural capacity, Alhaddad et al. [142] integrated an ANN with an Artificial Bee Colony (ABC) evolutionary algorithm to map seven key printing parameters, successfully maximizing the ultimate tensile strength (UTS) of fiber-reinforced polymer composites. The convergence of artificial intelligence and AM opens up opportunities for high-value customization and circular economy paradigms across multiple high-tech domains [143,144]. Kannan et al. [145] explored sustainable AM by aligning materials science with AI/ML predictive optimization. Their research emphasized that tuning processing parameters is critical for the printability and thermal resistance of renewable, bio-based composites.

8 Applications in Sustainable Engineering

Digital twin technology, combined with machine learning techniques, has been extensively utilized in sustainable engineering. This includes the entire range of actions from designing to producing, operating, and managing environmentally friendly systems throughout their life cycles. By facilitating instant monitoring of systems, predictions based on data analysis, and optimization, digital twins can help save resources, lower the carbon footprint, and improve the dependability of systems. In the area of smart manufacturing, digital twins help in finding greener ways of production that result in less material wastage, lower energy consumption, and fewer defective products. Natural fibre-based hybrid polymer composites combine lightweight structures, tunable properties, and sustainability, making them attractive for diverse applications. However, their widespread adoption depends on meeting performance, durability, safety, and environmental requirements.

8.1 Automotive and Electric Vehicle Components

Digital twin systems allow the creation of virtual prototypes that accurately represent real components and performance. This concept is certainly applicable to the automotive and electric vehicle (EV) sectors, whereby engineering, production, and maintenance can be enhanced through intelligent decisions based on DT systems. However, it should also be noted that this technology depends on simulation and analytics capabilities and requires integration with shop-floor and field study for success.

8.2 Aerospace and Lightweight Structures

Digital twin-enabled machine learning along with integrated bio-based hybrid polymer composites are quite important in aerospace and lightweight structural systems. These areas need high performance, weight reduction, and sustainability. Hybrid bio-based composites in aerospace can be used for structural panels, interior components, secondary load-bearing elements, and non-critical aerodynamic surfaces. Digital twins are essential in aerospace applications of bio-based composites as they allow real-time monitoring, predictive maintenance, and analysis of lifecycle performance.

8.3 Construction and Infrastructure Applications

Bio-based hybrid polymer composites as eco-friendly materials are being used more and more in construction and infrastructure projects to improve sustainability, durability, and structural performance. The construction industry needs materials that are light, corrosion-resistant, have good thermal stability, and can resist prolonged exposure to environmental factors. With the use of natural fibers and the aid of computational tools, bio-based composites can be a greener substitute to traditional concrete, steel, and synthetic composites. They will also contribute to resilient and sustainable infrastructure development. In construction, the applications of bio-based composites include beam panels cladding, flooring, and facade systems. But if combined with digital twin technology and machine learning, it will be faster and easier to select the right fibers and biocomposites.

9 Challenges and Limitations

Even though bio-based and hybrid polymer composites merged with digital twin and machine learning technologies have significant potential to transform the manufacturing industry, there are still several challenges and limitations for their mass adoption and on-the-ground implementation. Besides that, challenges such as the variability of materials, limitations of processing, predictive modeling, and integration complexities should be resolved to a large extent for sustainable, high-performance composite systems to be more efficient. One significant challenge is the natural variability of the bio-based materials. The mechanical properties, moisture absorption, and dimensional stability of natural fibers can differ significantly from one another due to their growth in different environments, aging, and methods of extraction. Additional challenges include the lack of standardized Digital Twin (DT) ontologies for bio-based composites and the limited availability of open-source datasets for Machine Learning (ML) model training and validation.

9.1 Data Availability and Quality Issues

Among the biggest obstacles to the deployment of machine learning and digital twin systems in the field of bio-based and hybrid polymer composites are data availability and quality. Production of accurate predictive models, the design of process methodologies, the identification of defects, and environmental impact assessment, along with a dependence on having high-quality and representative datasets. Data quality and consistency are also major points of concern. The great variability in the properties of natural fibers, the batches of bio-polymers, and the combinations of hybrid reinforcements may give rise to inconsistencies.

Moreover, the differences in experimental setup, sensor calibration, units of measurement, and atmospheric conditions add even more to the problem of dataset uniformity. Grieves and Vickers [19] emphasized the need for standardized data exchange mechanisms to enable seamless integration of physical and virtual systems.

9.2 Scalability and Industrial Adoption

The scalability and industrial adoption of bio-based and hybrid polymer composites, integrating machine learning and digital twin technologies, is still a major challenge. The materials and technologies have shown very promising potential in the lab and pilot-scale tests, but transferring them into large-scale industrial production still faces various technical, economic, and logistical issues that have to be resolved for widespread implementation. Bio-based composites, especially hybrid systems, require very fine control of fiber alignment, matrix impregnation, curing, and additive manufacturing parameters. It is challenging to ensure consistent quality at larger scales due to the variability of natural fibers and the hybrid reinforcement structures being very sensitive to changes.

9.3 Cost and Computational Constraints

The cost and computational constraints really limit the uptake of bio-based and hybrid polymer composites coupled with machine learning and digital twin technologies. Cost constraints come from a number of different areas, like the raw materials used in bio-based composites (high-quality natural fibers, bio-polymers, and hybrid reinforcements). Besides that, processing methods like resin transfer molding, compression molding, and additive manufacturing might need precise control, special equipment, and energy-intensive operations, which would collectively further push up production costs.

Computational constraints are also a significant challenge. Digital twins are based on real-time simulations of complex physical, thermal, mechanical, and chemical phenomena that are capable of running computationally intensive finite element models or multiscale analyses. When these are supplemented with ML algorithms for predictive modeling, defect detection, or process optimization, the computational requirements can increase substantially. Liu et al. [11] reported that most ML applications in composites rely on small and application-specific datasets, restricting model generalization and robustness. Kibrete et al. [50] and Zhu et al. [58] further noted that the lack of publicly available composite material databases remains a major obstacle to the development of reliable and transferable ML models.

10 Future Research Directions

The integration of bio-based sustainable polymer composites with machine learning (ML) and digital twin technologies presents immense opportunities, but it also highlights several areas that require further research and development to fully exploit their potential. The future research section has been expanded to include specific research gaps, such as the lack of standardized Digital Twin ontologies for bio-composites, limited availability of open-source datasets for ML training, challenges in multi-scale modeling and real-time monitoring, and the need for DT-integrated life cycle assessment (LCA) frameworks.

10.1 AI/ML-Driven Materials Design

Artificial intelligence and machine learning are getting more and more recognition as game-changing tools for designing and developing bio-based and hybrid polymer composites. Usually, material design depends a lot on trial-and-error experiments, which take up a lot of time and utilize intensive resources. These methods allow a data-driven approach that can quickly go through a huge design space, find the best material combinations, and accurately predict performance results. These materials designed by these methods also make it possible to do multi-objective optimization, i.e., considering different properties such

as tensile strength, impact resistance, thermal stability, biodegradability, and cost all at the same time. The future of bio-composites integrated with machine learning and digital twin is illustrated in Fig. 15.

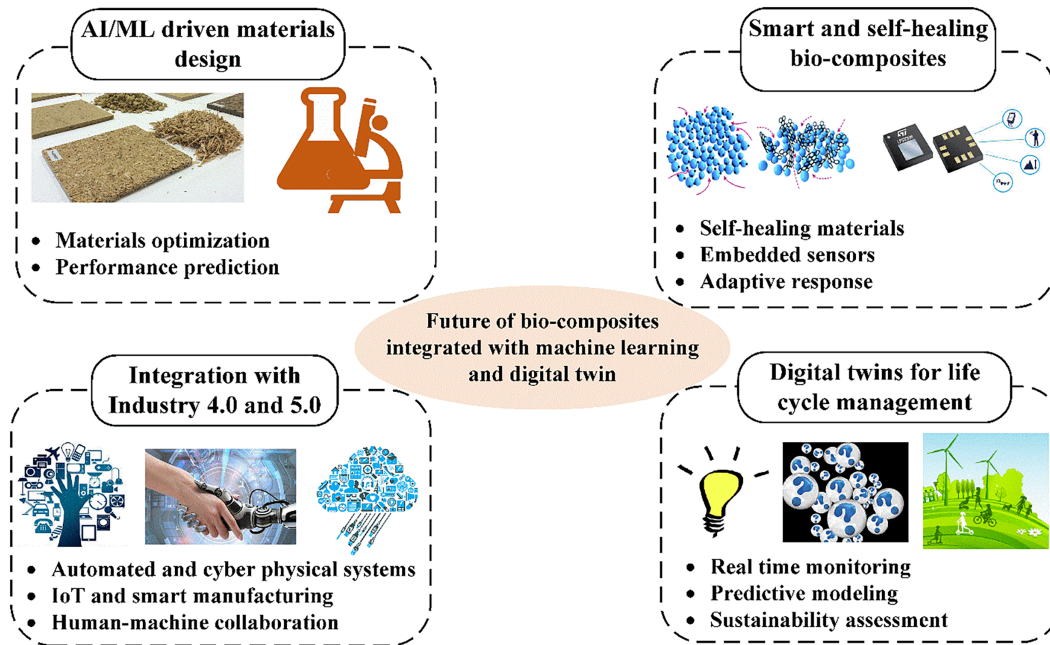


Figure 15: Future research directions.

10.2 Smart and Self-Healing Bio-Composites

The creation of intelligent and self-healing bio-based and hybrid polymer composites is a new area of material engineering that holds great hope for the sustainable development of materials. Smart composites are materials capable of identifying, responding, and adjusting to changes in the environment such as variations in temperature, humidity, stress, or even damage. On the other hand, self-healing composites have an internal mechanism to repair microcracks or damage automatically; therefore, the service life can be lengthened, and reliability improved. To make smart bio-based composites, one can use responsive polymer matrices, embedded sensors, or functional fillers. Self-healing bio-composites are generally made by including microcapsules, vascular networks, or reversible chemical bonds in the polymer matrix.

10.3 Integration with Industry 4.0 and Industry 5.0

Introducing bio-based and hybrid polymer composites into Industry 4.0 and emerging Industry 5.0 paradigms is considered a major step towards sustainable, smart, and human-friendly manufacturing. Industry 4.0 highlights automation, cyber-physical systems, the internet of things (IoT), and data-driven decision-making; on the other hand, Industry 5.0 is oriented towards collaboration between humans and machines, customization, sustainability, and societal impact.

10.4 Digital Twins for Complete Product Life Cycle Management

Digital twins have the potential to revolutionize the way entire life cycles of bio-based and hybrid polymer composites are controlled, starting from material design and manufacturing to in-service performance and end-of-life scenarios. By having a virtual model of a composite part that is an exact replica of its physical counterpart at the same time, digital twins open the door to a whole range of activities like

forecasting through modeling, checking conditions, enhancing performance, and evaluating sustainability over the life cycle of the product. At the design and development stage, digital twins coupled with machine learning can accurately imitate behaviors such as mechanical, thermal, viscoelastic, and moisture-related changes of bio-based composites experiencing different operational conditions. The integration of real-time Life Cycle Assessment (LCA) with Digital Twin frameworks is another emerging research area. Current DT implementations primarily focus on process optimization and performance monitoring, while environmental indicators such as carbon footprint, energy consumption, recyclability, and end-of-life impacts are rarely incorporated into real-time decision-making. Leng et al. [18] and Grieves & Vickers [19] identified sustainability-driven Digital Twins as a promising direction for future smart manufacturing systems. Integrating LCA data into DT platforms could enable continuous environmental performance assessment throughout the product lifecycle.

11 Conclusions

This review work has presented a critical and comprehensive review of the application of machine learning along with digital twin in advancing the utilization of biofiller/fibre reinforced polymer composites towards sustainable development. The principal findings and key conclusions derived from the current review work are outlined below.

- Bio-based and hybrid polymer composites have the potential to revolutionize both sustainable and high-performance engineering application if combined with machine learning (ML) and digital twin technologies.
- Such materials merge natural, biodegradable, and lightweight fibers with synthetic reinforcements or nano-fillers, delivering improved mechanical, thermal, and functional properties alongside reduced environmental loads.
- By using machine learning techniques, prediction of properties, optimization of process parameters, and detection of defects can be performed, thereby expediting the discovery of new material compositions, accurately predicting mechanical, thermal, viscoelastic, and moisture behaviors, and reducing manufacturing defects.
- Digital twins provide a virtual representation of components, enabling real-time monitoring, predictive maintenance, virtual testing, and full lifecycle analysis.

Acknowledgement: The authors would like to acknowledge Dayananda Sagar University, Main Campus, Harohalli, Parul University and IIT Guwahati for giving necessary facilities to carry out the research work.

Funding Statement: The authors received no specific funding for this study.

Author Contributions: The manuscript is conceptualized, written, edited and reviewed by Rahul Kumar. Faladrum Sharma and Pradeep Kumar Karsh participated in the editing, figure and table making and reviewing the manuscript. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials: Not applicable.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Mohanty AK, Vivekanandhan S, Pin JM, Misra M. Composites from renewable and sustainable resources: challenges and innovations. *Science*. 2018;362(6414):536–42. doi:10.1126/science.aat9072.
2. Kumar R, Jagadish, Zindani D, Bhowmik S. Tensile properties prediction of WFRP composite based on machine learning and ANN models: an experimental and statistical approach. *J Mater Eng Perform*. 2026;1–14. doi:10.1007/s11665-026-13924-w.
3. Gonçalves R, Serra J, Reizabal A, Correia DM, Fernandes LC, Brito-Pereira R, et al. Biobased polymers for advanced applications: towards a sustainable future. *Prog Polym Sci*. 2025;162:101934. doi:10.1016/j.progpolymsci.2025.101934.
4. Ajayi NE, Rusnakova S, Ajayi AE, Ogunleye RO, Agu SO, Amenaghawon AN. A comprehensive review of natural fiber reinforced Polymer composites as emerging materials for sustainable applications. *Appl Mater Today*. 2025;43:102666. doi:10.1016/j.apmt.2025.102666.
5. Faruk O, Bledzki AK, Fink HP, Sain M. Biocomposites reinforced with natural fibers: 2000–2010. *Prog Polym Sci*. 2012;37(11):1552–96. doi:10.1016/j.progpolymsci.2012.04.003.
6. Pickering KL, Efendy MGA, Le TM. A review of recent developments in natural fibre composites and their mechanical performance. *Compos Part A Appl Sci Manuf*. 2016;83(10):98–112. doi:10.1016/j.compositesa.2015.08.038.
7. Kumar VV, Santos TF, Santos CM, Nzeyimana BS, Shahin K, Jeevan Rao H, et al. Artificial intelligence and machine learning approaches for composite materials: recent developments and applications. *Polym Compos*. 2026;47(12):10636–63. doi:10.1002/pc.71029.
8. Dinita A, Rosca CM, Tanase M, Stancu A. A comprehensive review on bridging the research gap in AI-driven material simulation for FRP composites. *Comput Model Eng Sci*. 2025;144(1):147–99. doi:10.32604/cmesci.2025.066276.
9. Alagulkshmi R, Ramalakshmi R, Veerasimman A, Palani G, Selvaraj M, Basumatary S. Advancements of machine learning techniques in fiber-filled polymer composites: a review. *Polym Bull*. 2025;82(7):2059–89. doi:10.1007/s00289-025-05638-1.
10. Martínez A, Fan J, Miller SA. Machine learning in life cycle assessment and low carbon material discovery: challenges and pathways forward for the construction industry. *Resour Conserv Recycl*. 2026;224(18):108567. doi:10.1016/j.resconrec.2025.108567.
11. Liu X, Tian S, Tao F, Du H, Yu W. How machine learning can help the design and analysis of composite materials and structures? arXiv:2010.09438. 2020.
12. Sorour SS, Saleh CA, Shazly M. A review on machine learning implementation for predicting and optimizing the mechanical behaviour of laminated fiber-reinforced polymer composites. *Heliyon*. 2024;10(13):e33681. doi:10.1016/j.heliyon.2024.e33681.
13. Jawaid M, Abdul Khalil HPS. Cellulosic/synthetic fibre reinforced polymer hybrid composites: a review. *Carbohydr Polym*. 2011;86(1):1–18. doi:10.1016/j.carbpol.2011.04.043.
14. Ramesh M, Palanikumar K, Reddy KH. Plant fibre based bio-composites: sustainable and renewable green materials. *Renew Sustain Energy Rev*. 2017;79(18):558–84. doi:10.1016/j.rser.2017.05.094.
15. Ullah S, Akhter Z, Palevicius A, Janusas G. Review: natural fiber-based biocomposites for potential advanced automotive applications. *J Eng Fibres Fabr*. 2025;20(1):15589250241311468. doi:10.1177/15589250241311468.
16. Mohanty AK, Misra M, Drzal LT. Natural fibers, biopolymers, and biocomposites. Boca Raton, FL, USA: CRC Press; 2005.
17. Dhakal HN, Zhang ZY, Richardson MOW. Effect of water absorption on the mechanical properties of hemp fibre reinforced unsaturated polyester composites. *Compos Sci Technol*. 2007;67(7–8):1674–83. doi:10.1016/j.compscitech.2006.06.019.
18. Leng J, Wang D, Shen W, Li X, Liu Q, Chen X. Digital twins-based smart manufacturing system design in Industry 4.0: a review. *J Manuf Syst*. 2021;60(9):119–37. doi:10.1016/j.jmsy.2021.05.011.

19. Grieves M, Vickers J. Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems. In: Kahlen J, Flumerfelt S, Alves A, editors. Transdisciplinary perspectives on complex systems. Cham, Switzerland: Springer; 2016.
20. Kumar R, Kumar K, Bhowmik S, Sarkhel G. Tailoring the performance of bamboo filler reinforced epoxy composite: insights into fracture properties and fracture mechanism. J Polym Res. 2019;26(2):54. doi:10.1007/s10965-019-1720-x.
21. Kumar R, Kumar K, Bhowmik S. Assessment and response of treated *Cocos nucifera* reinforced toughened epoxy composite towards fracture and viscoelastic properties. J Polym Environ. 2018;26(6):2522–35. doi:10.1007/s10924-017-1150-y.
22. Mohanty AK, Misra M, Drzal LT. Sustainable bio-composites from renewable resources: opportunities and challenges in the green materials world. J Polym Environ. 2002;10(1):19–26. doi:10.1023/A:1021013921916.
23. La Rosa AD, Recca G, Summerscales J, Latteri A, Cozzo G, Cicala G. Bio-based versus traditional polymer composites. A life cycle assessment perspective. J Clean Prod. 2014;74(7):135–44. doi:10.1016/j.jclepro.2014.03.017.
24. Butt J, Mohaghegh V. Combining digital twin and machine learning for the fused filament fabrication process. Metals. 2023;13(1):24. doi:10.3390/met13010024.
25. Karuppusamy M, Thirumalaisamy R, Palanisamy S, Nagamalai S, El Sayed Massoud E, Ayrilmis N. A review of machine learning applications in polymer composites: advancements, challenges, and future prospects. J Mater Chem A. 2025;13(22):16290–308. doi:10.1039/d5ta00982k.
26. Li X, Li G, Bi Z. Digital twins to predict crack propagation of sustainable engineering materials under different loads. Machines. 2024;12(2):125. doi:10.3390/machines12020125.
27. Jamwal A, Agrawal R, Sharma M, Kumar A, Kumar V, Garza-Reyes JAA. Machine learning applications for sustainable manufacturing: a bibliometric-based review for future research. J Enterp Inf Manag. 2022;35(2):566–96. doi:10.1108/jeim-09-2020-0361.
28. Ghanem R, Soize C, Mehrez L, Aitharaju V. Probabilistic learning and updating of a digital twin for composite material systems. Int J Numer Meth Eng. 2022;123(13):3004–20. doi:10.1002/nme.6430.
29. Kabir MM, Wang H, Lau KT, Cardona F. Chemical treatments on plant-based natural fibre reinforced polymer composites: an overview. Compos Part B Eng. 2012;43(7):2883–92. doi:10.1016/j.compositesb.2012.04.053.
30. Neto JSS, de Queiroz HFM, Aguiar RAA, Banea MD. A review on the thermal characterisation of natural and hybrid fiber composites. Polymers. 2021;13(24):4425. doi:10.3390/polym13244425.
31. Yin BB, Liew KM. Machine learning and materials informatics approaches for evaluating the interfacial properties of fiber-reinforced composites. Compos Struct. 2021;273(4):114328. doi:10.1016/j.compstruct.2021.114328.
32. Xia C, Pan Z, Fei Z, Zhang S, Li H. Vision based defects detection for Keyhole TIG welding using deep learning with visual explanation. J Manuf Process. 2020;56(8):845–55. doi:10.1016/j.jmapro.2020.05.033.
33. Elfaleh I, Abbassi F, Habibi M, Ahmad F, Guedri M, Nasri M, et al. A comprehensive review of natural fibers and their composites: an eco-friendly alternative to conventional materials. Results Eng. 2023;19(3):101271. doi:10.1016/j.rineng.2023.101271.
34. Thakur VK, Thakur MK, Raghavan P, Kessler MR. Progress in green polymer composites from lignin for multifunctional applications: a review. ACS Sustain Chem Eng. 2014;2(5):1072–92. doi:10.1021/sc500087z.
35. Kuilla T, Bhadra S, Yao D, Kim NH, Bose S, Lee JH. Recent advances in graphene based polymer composites. Prog Polym Sci. 2010;35(11):1350–75. doi:10.1016/j.progpolymsci.2010.07.005.
36. Ashrith HS, Jeevan TP, Xu J. A review on the fabrication and mechanical characterization of fibrous composites for engineering applications. J Compos Sci. 2023;7(6):252. doi:10.3390/jcs7060252.
37. Gorrepotu SR, Debnath K, Mahapatra RN, Srivatsan TS. A critical review on mechanical and morphological characteristics of injection molded biodegradable composites. Polym Compos. 2022;43(12):8634–72. doi:10.1002/pc.27096.
38. Iqbal RM, Ahammad R, Arifuzzaman M, Islam MS, Islam MM. Manufacturing and properties of jute fiber-reinforced polymer composites—a comprehensive review. Materials. 2025;18(5):1016. doi:10.3390/ma18051016.
39. Ning H, Lu N, Hassen AA, Chawla K, Selim M, Pillay S. A review of long fibre thermoplastic (LFT) composites. Int Mater Rev. 2020;65(3):164–88. doi:10.1080/09506608.2019.1585004.

40. Bittrich L, Seuffert J, Dietrich S, Uhlig K, Lisboa TV, Kärger L, et al. On the resin transfer molding (RTM) infiltration of fiber-reinforced composites made by tailored fiber placement. *Polymers*. 2022;14(22):4873. doi:10.3390/polym14224873.
41. Parandoush P, Lin D. A review on additive manufacturing of polymer-fiber composites. *Compos Struct*. 2017;182:36–53. doi:10.1016/j.compstruct.2017.08.088.
42. Yu K, Dunn ML. Design and extrusion-based 3D printing of continuous fiber composites: status, challenges, and opportunities. *Langmuir*. 2024;40(17):8751–9. doi:10.1021/acs.langmuir.4c00139.
43. Mogan J, Harun WSW, Kadirgama K, Ramasamy D, Foudzi FM, Sulong AB, et al. Fused deposition modelling of polymer composite: a progress. *Polymers*. 2023;15(1):28. doi:10.3390/polym15010028.
44. Seile A, Spurina E, Sinka M. Reducing global warming potential impact of bio-based composites based of LCA. *Fibers*. 2022;10(9):79. doi:10.3390/fib10090079.
45. Recupido F, Lama GC, Ammendola M, De Luca Bossa F, Minigher A, Campaner P, et al. Rigid composite bio-based polyurethane foams: from synthesis to LCA analysis. *Polymer*. 2023;267(7):125674. doi:10.1016/j.polymer.2023.125674.
46. Oladunni OJ, Lee CKM, Ibrahim ID, Olanrewaju OA. Advances in sustainable additive manufacturing: a systematic review for construction industry to mitigate greenhouse gas emissions. *Front Built Environ*. 2025;11:1535626. doi:10.3389/fbuil.2025.1535626.
47. Le Duigou A, Pillin I, Bourmaud A, Davies P, Baley C. Effect of recycling on mechanical behaviour of bio-compostable flax/poly(l-lactide) composites. *Compos Part A Appl Sci Manuf*. 2008;39(9):1471–8. doi:10.1016/j.compositesa.2008.05.008.
48. Kamarudin SH, Mohd Basri MS, Rayung M, Abu F, Ahmad S, Norizan MN, et al. A review on natural fiber reinforced polymer composites (NFRPC) for sustainable industrial applications. *Polymers*. 2022;14(17):3698. doi:10.3390/polym14173698.
49. Qiu C, Yang J. Machine learning applications in composites: manufacturing, design, and characterization. In: *Machine learning in materials informatics: methods and applications*. Washington, DC, USA: American Chemical Society; 2022. p. 65–85.
50. Kibrete F, Trzepieciński T, Gebremedhen HS, Woldemichael DE. Artificial intelligence in predicting mechanical properties of composite materials. *J Compos Sci*. 2023;7(9):364. doi:10.3390/jcs7090364.
51. Anwar MK, Qurashi MA, Zhu X, Shah SAR, Siddiq MU. A comparative performance analysis of machine learning models for compressive strength prediction in fly ash-based geopolymers concrete using reference data. *Case Stud Constr Mater*. 2025;22(21):e04207. doi:10.1016/j.cscm.2025.e04207.
52. Sharma H, Arora G, Singh MK, Ayyappan V, Bhowmik P, Rangappa SM, et al. Review of machine learning approaches for predicting mechanical behavior of composite materials. *Discover Appl Sci*. 2025;7(11):1238. doi:10.1007/s42452-025-07616-8.
53. Dev B, Rahman MA, Islam MJ, Rahman MZ, Zhu D. Properties prediction of composites based on machine learning models: a focus on statistical index approaches. *Mater Today Commun*. 2024;38(1):107659. doi:10.1016/j.mtcomm.2023.107659.
54. Sun Y, Hanhan I, Sangid MD, Lin G. Predicting mechanical properties from microstructure images in fiber-reinforced polymers using convolutional neural networks. *J Compos Sci*. 2024;8(10):387. doi:10.3390/jcs8100387.
55. Li C, Zheng K. Methods, progresses, and opportunities of materials informatics. *InfoMat*. 2023;5(8):e12425. doi:10.1002/inf2.12425.
56. Pathan MV, Ponnusami SA, Pathan J, Pitisongsawat R, Erice B, Petrinic N, et al. Predictions of the mechanical properties of unidirectional fibre composites by supervised machine learning. *Sci Rep*. 2019;9(1):13964. doi:10.1038/s41598-019-50144-w.
57. Shanmugam V, Babu K, Kannan G, Mensah RA, Samantaray SK, Das O. The thermal properties of FDM printed polymeric materials: a review. *Polym Degrad Stab*. 2024;228:110902. doi:10.1016/j.polymdegradstab.2024.110902.
58. Zhu J, Bai R, Xu Y, Wang J, He L, Lei Z, et al. Application of machine learning to mechanical properties of composite materials: a ten-year review (2015–2025). *Eng Appl Artif Intell*. 2026;169:114068. doi:10.1016/j.engappai.2026.114068.

59. Thanikodi S, Meena M, Dwivedi YD, Aravind T, Giri J, Samdani MS, et al. Optimizing the selection of natural fibre reinforcement and polymer matrix for plastic composite using LS-SVM technique. *Chemosphere*. 2024;349(1):140971. doi:10.1016/j.chemosphere.2023.140971.
60. Vignesh V, Kumar SS, Mohan AMA, Arasu IV, Nagaprasad N, Krishnaraj R. Machine learning-based estimation and optimization of phoenix Dactylifera Seed Powder reinforced vinyl ester bio-composites. *Sci Rep*. 2026;16(1):6663. doi:10.1038/s41598-026-37202-w.
61. Musthaq MA, Dhakal HN, Zhang Z, Barouni A, Zahari R. The effect of various environmental conditions on the impact damage behaviour of natural-fibre-reinforced composites (NFRCS)—a critical review. *Polymers*. 2023;15(5):1229. doi:10.3390/polym15051229.
62. Nagata F, Habib MK, Watanabe K. Design and implementation of convolutional neural network-based SVM technique for manufacturing defect detection. *Int J Mechatron Autom*. 2021;8(2):53. doi:10.1504/ijma.2021.115240.
63. Beldar P, Chandramore R, Jagtap S, Bendale D. Enhanced convolutional neural networks for defect detection in fiber-reinforced composites: a hyperparameter optimization approach. *J Eng Appl Sci*. 2025;72(1):125. doi:10.1186/s44147-025-00698-6.
64. Kritzing W, Karner M, Traar G, Henjes J, Sihn W. Digital twin in manufacturing: a categorical literature review and classification. *IFAC-PapersOnLine*. 2018;51(11):1016–22. doi:10.1016/j.ifacol.2018.08.474.
65. Tao F, Zhang H, Liu A, Nee AYC. Digital twin in industry: state-of-the-art. *IEEE Trans Ind Inf*. 2019;15(4):2405–15. doi:10.1109/tii.2018.2873186.
66. Fuller A, Fan Z, Day C, Barlow C. Digital twin: enabling technologies, challenges and open research. *IEEE Access*. 2020;8:108952–71. doi:10.1109/ACCESS.2020.2998358.
67. Giurgiutiu V. *Structural health monitoring of aerospace composites*. Cambridge, MA, USA: Academic Press; 2016.
68. Farrar CR, Worden K. *Structural health monitoring: a machine learning perspective*. Hoboken, NJ, USA: John Wiley & Sons, Inc.; 2012.
69. Di Sante R. Fibre optic sensors for structural health monitoring of aircraft composite structures: recent advances and applications. *Sensors*. 2015;15(8):18666–713. doi:10.3390/s150818666.
70. Kuang KSC, Quek ST, Koh CG, Cantwell WJ, Scully PJ. Plastic optical fibre sensors for structural health monitoring: a review of recent progress. *J Sens*. 2009;2009(1):312053. doi:10.1155/2009/312053.
71. Peters K. Polymer optical fiber sensors—a review. *Smart Mater Struct*. 2011;20(1):013002. doi:10.1088/0964-1726/20/1/013002.
72. Ahsan MM, Liu Y, Raman S, Siddique Z. Digital twins in additive manufacturing: a systematic review. *Internet Things*. 2025;33(2):101692. doi:10.1016/j.iot.2025.101692.
73. He Y, Ma Y, Huang K, Wang L, Zhang J. Digital twin Bayesian entropy framework for corrosion fatigue life prediction and calibration of bridge suspender. *Reliab Eng Syst Saf*. 2024;252(5):110456. doi:10.1016/j.ress.2024.110456.
74. Antonini L, Berti F, Isella B, Hossain D, Mandelli L, Pennati G, et al. From the real device to the digital twin: a coupled experimental-numerical strategy to investigate a novel bioresorbable vascular scaffold. *PLoS One*. 2021;16(6):e0252788. doi:10.1371/journal.pone.0252788.
75. Gunasegaram DR, Murphy AB, Matthews MJ, DebRoy T. The case for digital twins in metal additive manufacturing. *J Phys Mater*. 2021;4(4):040401. doi:10.1088/2515-7639/ac09fb.
76. Ben Amor S, Elloumi N, Eltaief A, Louhichi B, Alrasheedi NH, Seibi A. Digital twin implementation in additive manufacturing: a comprehensive review. *Processes*. 2024;12(6):1062. doi:10.3390/pr12061062.
77. Chen L, Yao X, Liu K, Tan C, Moon SK. Multisensor fusion-based digital twin for *in-situ* quality monitoring in additive manufacturing. *Proc Des Soc*. 2023;3:2755–64. doi:10.48550/arXiv.2304.05685.
78. Osho J, Hyre A, Pantelidakis M, Ledford A, Harris G, Liu J, et al. Four Rs framework for the development of a digital twin: the implementation of representation with a FDM manufacturing machine. *J Manuf Syst*. 2022;63:370–80. doi:10.1016/j.jmsy.2022.04.014.
79. Anderson AM, van Der Merwe A. Time-driven activity-based costing related to digital twinning in additive manufacturing. *South Afr J Ind Eng*. 2021;32(1):37–43. doi:10.7166/32-1-2271.

80. Barnowski D, Dahmen M, Farkas T, Petring D, Petschke U, Pootz M, et al. Multifunctional laser processing with a digital twin. *Procedia CIRP*. 2022;111(8):822–6. doi:10.1016/j.procir.2022.08.091.
81. Dvorak J, Cornelius A, Corson G, Zamoski R, Jacobs L, Penney J, et al. A machining digital twin for hybrid manufacturing. *Manuf Lett*. 2022;33:786–93. doi:10.1016/j.mfglet.2022.07.097.
82. Jain S, Narayanan A. Digital twin-enabled machine learning for smart manufacturing. *Smart Sustain Manuf Syst*. 2023;7(1):111–28. doi:10.1520/ssms20220035.
83. Kantaros A, Ganetsos T. Integration of cyber-physical systems, digital twins and 3D printing in advanced manufacturing: a synergistic approach. *Am J Eng Appl Sci*. 2024;17(1):1–22. doi:10.3844/ajeassp.2024.1.22.
84. Psarommatis F, May G. A literature review and design methodology for digital twins in the era of zero defect manufacturing. *Int J Prod Res*. 2023;61(16):5723–43. doi:10.1080/00207543.2022.2101960.
85. Liu M, Fang S, Dong H, Xu C. Review of digital twin about concepts, technologies, and industrial applications. *J Manuf Syst*. 2021;58:346–61. doi:10.1016/j.jmsy.2020.06.017.
86. Tao F, Cheng J, Qi Q, Zhang M, Zhang H, Sui F. Digital twin-driven product design, manufacturing and service with big data. *Int J Adv Manuf Technol*. 2018;94(9):3563–76. doi:10.1007/s00170-017-0233-1.
87. Cai Y, Starly B, Cohen P, Lee YS. Sensor data and information fusion to construct digital-twins virtual machine tools for cyber-physical manufacturing. *Procedia Manuf*. 2017;10(3):1031–42. doi:10.1016/j.promfg.2017.07.094.
88. Lee J, Bagheri B, Kao HA. A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manuf Lett*. 2015;3:18–23. doi:10.1016/j.mfglet.2014.12.001.
89. Rosen R, von Wichert G, Lo G, Bettenhausen KD. About the importance of autonomy and digital twins for the future of manufacturing. *IFAC-PapersOnLine*. 2015;48(3):567–72. doi:10.1016/j.ifacol.2015.06.141.
90. Fang Y, Peng C, Lou P, Zhou Z, Hu J, Yan J. Digital-twin-based job shop scheduling toward smart manufacturing. *IEEE Trans Ind Inf*. 2019;15(12):6425–35. doi:10.1109/tii.2019.2938572.
91. Negri E, Fumagalli L, Macchi M. A review of the roles of digital twin in CPS-based production systems. *Procedia Manuf*. 2017;11:939–48. doi:10.1016/j.promfg.2017.07.198.
92. Schleich B, Anwer N, Mathieu L, Wartzack S. Shaping the digital twin for design and production engineering. *CIRP Ann*. 2017;66(1):141–4. doi:10.1016/j.cirp.2017.04.040.
93. Grieves M. Digital twin: manufacturing excellence through virtual factory replication. White Paper. 2014:1–7.
94. David J, Lobov A, Lanz M. Leveraging digital twins for assisted learning of flexible manufacturing systems. In: *Proceedings of the 2018 IEEE 16th International Conference on Industrial Informatics (INDIN)*; 2018 Jul 18–20; Porto, Portugal. p. 529–35.
95. DebRoy T, Zhang W, Turner J, Babu SS. Building digital twins of 3D printing machines. *Scr Mater*. 2017;135:119–24. doi:10.1016/j.scriptamat.2016.12.005.
96. Knapp GL, Mukherjee T, Zuback JS, Wei HL, Palmer TA, De A, et al. Building blocks for a digital twin of additive manufacturing. *Acta Mater*. 2017;135(3):390–9. doi:10.1016/j.actamat.2017.06.039.
97. Qi Q, Tao F. Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. *IEEE Access*. 2018;6:3585–93. doi:10.1109/access.2018.2793265.
98. Alajmi A. Twinning the future: implementing digital twin technology in the optimisation of fibre-reinforced polymers. *MATEC Web Conf*. 2024;401(11):11005. doi:10.1051/matecconf/202440111005.
99. Fernández-León J, Keramati K, Baumela L, González C. A digital twin for smart manufacturing of structural composites by liquid moulding. *Int J Adv Manuf Technol*. 2024;130(9):4679–97. doi:10.1007/s00170-023-12637-x.
100. Attaran M, Attaran S, Celik BG. The impact of digital twins on the evolution of intelligent manufacturing and Industry 4.0. *Adv Comput Intell*. 2023;3(3):11. doi:10.1007/s43674-023-00058-y.
101. Xu X, Wang G, Yan H, Zhang L, Yao X. Deep-learning-enhanced digital twinning of complex composite structures and real-time mechanical interaction. *Compos Sci Technol*. 2023;241:110139. doi:10.1016/j.compscitech.2023.110139.
102. Zhang C, Xu W, Liu J, Liu Z, Zhou Z, Pham DT. Digital twin-enabled reconfigurable modeling for smart manufacturing systems. *Int J Comput Integr Manuf*. 2021;34(7–8):709–33. doi:10.1080/0951192X.2019.1699256.
103. Aivaliotis P, Georgoulas K, Arkouli Z, Makris S. Methodology for enabling digital twin using advanced physics-based modelling in predictive maintenance. *Procedia CIRP*. 2019;81:417–22. doi:10.1016/j.procir.2019.03.072.

104. Zambal S, Eitzinger C, Clarke M, Klintworth J, Mechin PY. A digital twin for composite parts manufacturing: effects of defects analysis based on manufacturing data. In: Proceedings of the 2018 IEEE 16th International Conference on Industrial Informatics (INDIN); 2018 Jul 18–20; Porto, Portugal. p. 803–8.
105. Hürkamp A, Lorenz R, Ossowski T, Behrens BA, Dröder K. Simulation-based digital twin for the manufacturing of thermoplastic composites. *Procedia CIRP*. 2021;100:1–6. doi:10.1016/j.procir.2021.05.001.
106. Hughes DJ, Keir S, Meggs C. Digital twin methodology for compression moulded thermoplastic composite optimisation. In: Proceedings of the 14th International Conference on Flow Processes in Composite Materials (FPCM-14); 2018 May 30–Jun 1; Luleå, Sweden. p. 14–5.
107. Chinesta F, Cueto E, Abisset-Chavanne E, Duval JL, El Khaldi F. Virtual, digital and hybrid twins: a new paradigm in data-based engineering and engineered data. *Arch Comput Meth Eng*. 2020;27(1):105–34. doi:10.1007/s11831-018-9301-4.
108. Liu C, Chen Y, Xu X. Structural digital Twin for damage detection of CFRP composites using meta transfer Learning-based approach. *Expert Syst Appl*. 2025;261:125458. doi:10.1016/j.eswa.2024.125458.
109. Li Q, Zhao G, Li J, Li S, Yan W, Tian X, et al. An *in-situ* predictive method for modulus degradation in composite structures with fatigue damage: applications in digital twin technology. *Mech Syst Signal Process*. 2025;237(3):113090. doi:10.1016/j.ymssp.2025.113090.
110. Li N, Link G, Jelonnek J, Ong SK. Digital twins towards microwave-assisted 3D printing of continuous carbon fiber reinforced composites. *Procedia CIRP*. 2023;119:158–63. doi:10.1016/j.procir.2023.03.088.
111. Ghnatios C, Gérard P, Barasinski A. An advanced resin reaction modeling using data-driven and digital twin techniques. *Int J Mater Form*. 2022;16(1):5. doi:10.1007/s12289-022-01725-0.
112. Shehab E, Kazhymurat T, Jyeniskhan N, Amantayeva A, Meirbekov A, Singh S, et al. Developing a digital twin for carbon fiber composites recycling: challenges and future research direction. *Adv Sci Technol*. 2022;116(6):61–6. doi:10.4028/p-h01m30.
113. Kamble SS, Gunasekaran A, Parekh H, Mani V, Belhadi A, Sharma R. Digital twin for sustainable manufacturing supply chains: current trends, future perspectives, and an implementation framework. *Technol Forecast Soc Change*. 2022;176(11):121448. doi:10.1016/j.techfore.2021.121448.
114. Hürkamp A, Gellrich S, Ossowski T, Beuscher J, Thiede S, Herrmann C, et al. Combining simulation and machine learning as digital twin for the manufacturing of overmolded thermoplastic composites. *J Manuf Mater Process*. 2020;4(3):92. doi:10.3390/jmmp4030092.
115. Polini W, Corrado A. Digital twin of composite assembly manufacturing process. *Int J Prod Res*. 2020;58(17):5238–52. doi:10.1080/00207543.2020.1714091.
116. Ball P, Badakhshan E. Sustainable manufacturing digital twins: a review of development and application. In: *Sustainable design and manufacturing*. Singapore: Springer; 2022. p. 159–68.
117. Baalbergen EH, de Marchi JA, Offringa A, Hengeveld S, Troost B, He K, et al. Applying digital twin technology in thermoplastic composites production: supporting process monitoring, optimization and automation for real-time efficiency and smart quality control. Amsterdam, The Netherlands: Netherlands Aerospace Centre; 2020. Report No.: NLR-TP-2020-406.
118. Cimino C, Negri E, Fumagalli L. Review of digital twin applications in manufacturing. *Comput Ind*. 2019;113:103130. doi:10.1016/j.compind.2019.103130.
119. Zheng T, Ardolino M, Bacchetti A, Perona M. The applications of Industry 4.0 technologies in manufacturing context: a systematic literature review. *Int J Prod Res*. 2021;59(6):1922–54. doi:10.1080/00207543.2020.1824085.
120. Macchi M, Roda I, Negri E, Fumagalli L. Exploring the role of digital twin for asset lifecycle management. *IFAC-PapersOnLine*. 2018;51(11):790–5. doi:10.1016/j.ifacol.2018.08.415.
121. Xie Y, Lian K, Liu Q, Zhang C, Liu H. Digital twin for cutting tool: modeling, application and service strategy. *J Manuf Syst*. 2021;58(1):305–12. doi:10.1016/j.jmsy.2020.08.007.

122. Hearley BL, Pineda EJ, Bednarczyk BA, Baker JR, Wilson LG. Towards the development of multiscale digital twins for fiber-reinforced composite materials using machine learning. *Appl Sci.* 2026;16(8):3666. doi:10.3390/app16083666.
123. Olonisakin K, Mohanty AK, Thimmanagari M, Misra M. Recent advances in biodegradable polymer blends and their biocomposites: a comprehensive review. *Green Chem.* 2025;27(38):11656–704. doi:10.1039/d5gc01294e.
124. Manu T, Nazmi AR, Shahri B, Emerson N, Huber T. Biocomposites: a review of materials and perception. *Mater Today Commun.* 2022;31(10):103308. doi:10.1016/j.mtcomm.2022.103308.
125. de Andrade MF C, Souza PMS, Cavalett O, Morales AR. Life cycle assessment of poly(lactic acid) (PLA): comparison between chemical recycling, mechanical recycling and composting. *J Polym Environ.* 2016;24(4):372–84. doi:10.1007/s10924-016-0787-2.
126. Karan H, Funk C, Grabert M, Oey M, Hankamer B. Green bioplastics as part of a circular bioeconomy. *Trends Plant Sci.* 2019;24(3):237–49. doi:10.1016/j.tplants.2018.11.010.
127. Ali SS, Abdelkarim EA, Elsamahy T, Al-Tohamy R, Li F, Kornaros M, et al. Bioplastic production in terms of life cycle assessment: a state-of-the-art review. *Environ Sci Ecotechnol.* 2023;15:100254. doi:10.1016/j.es.2023.100254.
128. Ciriminna R, Pagliaro M. Biodegradable and compostable plastics: a critical perspective on the dawn of their global adoption. *ChemistryOpen.* 2020;9(1):8–13. doi:10.1002/open.201900272.
129. Nasrin T, Pourkamali-Anaraki F, Peterson AM. Application of machine learning in polymer additive manufacturing: a review. *J Polym Sci.* 2024;62(12):2639–69. doi:10.1002/pol.20230649.
130. Siakeng R, Jawaid M, Ariffin H, Sapuan S, Asim M, Saba N. Natural fiber reinforced polylactic acid composites: a review. *Polym Compos.* 2019;40(2):446–63. doi:10.1002/pol.201900272.
131. Ilyas RA, Sapuan SM, Harussani MM, Hakimi MYAY, Haziq MZM, Atikah MSN, et al. Polylactic acid (PLA) biocomposite: processing, additive manufacturing and advanced applications. *Polymers.* 2021;13(8):1326. doi:10.3390/polym13081326.
132. Agumba DO, Park G, Woong Kim J, Kim J. Biobased natural fiber-reinforced composites derived from lignin-based resin and mercerized jute fibers. *Mater Lett.* 2024;360:136055. doi:10.1016/j.matlet.2024.136055.
133. Hasan KMF, Horváth PG, Markó G, Alpár T. Thermomechanical characteristics of flax-woven-fabric-reinforced poly(lactic acid) and polypropylene biocomposites. *Green Mater.* 2022;10(1):1–10. doi:10.1680/jgrma.20.00052.
134. Khalid MY, Al Rashid A, Arif ZU, Ahmed W, Arshad H, Ali Zaidi A. Natural fiber reinforced composites: sustainable materials for emerging applications. *Results Eng.* 2021;11(6):100263. doi:10.1016/j.rineng.2021.100263.
135. Kumar R, Bhargav C, Bhowmik S. Bamboo fibre reinforced thermoset and thermoplastic polymer composites: a short review. *AIP Conf Proc.* 2018;1992:020018. doi:10.1063/1.5049114.
136. Sweat R, Park JG, Liang R. Digital twin for microstructure-property analysis. *Materials.* 2020;13(19):4231. doi:10.3390/ma13194231.
137. Sánchez-Romate XF, Del Bosque A, Artigas-Arnaud J, Muñoz BK, Sánchez M, Ureña A. A proof of concept of a structural supercapacitor made of graphene coated woven carbon fibers: EIS study and mechanical performance. *Electrochim Acta.* 2021;370:137746. doi:10.1016/j.electacta.2021.137746.
138. Kaufmann J, Temesgen AG, Cebulla H. A comprehensive review on natural fiber reinforced hybrid composites processing techniques, material properties and emerging applications. *Discov Mater.* 2025;5(1):227. doi:10.1007/s43939-025-00419-z.
139. Attariani H, Petitjean SR, Dousti M. Digital twin of laser array for powder bed fusion. *Int J Adv Manuf Technol.* 2022;123(5):1433–40. doi:10.1007/s00170-022-10223-1.
140. Castelló-Pedrero P, García-Gascón C, García-Manrique JA. Multiscale numerical modeling of large-format additive manufacturing processes using carbon fiber reinforced polymer for digital twin applications. *Int J Mater Form.* 2024;17(2):15. doi:10.1007/s12289-024-01811-5.
141. Taylan O, Abdullah T, Baik S, Yilmaz MT, Alidrisi HM, Qurban RO, et al. Evolutionary machine learning for rheological behavior of PBS. *Polym Bull.* 2024;81(10):8663–83. doi:10.1007/s00289-023-05106-8.
142. Alhaddad W, He M, Halabi Y, Almajhali KYM. Optimization of AM fiber composites using ANN and ABC Structures. 2022;46(3):1781–95. doi:10.1016/j.istruc.2022.10.134.

143. Hassan M, Misra M, Taylor GW, Mohanty AK. A review of AI for optimization of 3D printing of sustainable polymers and composites. *Compos Part C Open Access*. 2024;15:100513. doi:10.1016/j.jcomc.2024.100513.
144. Roy A, Ahmed MJ, Mondol LC. AI-enhanced additive manufacturing. *J Primeasia*. 2024;5(1):1–9. doi:10.25163/primeasia.5110247.
145. Kannan G, Kurien RA, Khoklang K, Sriamornsak P, Suttiruengwong S. Biodegradable polymers and biocomposites in sustainable additive manufacturing: a review. *Int J Biol Macromol*. 2025;333(2):148611. doi:10.1016/j.ijbiomac.2025.148611.