International Journal of Advanced Engineering Application (IJAEA)
Volume 3 Issue 11 Nov 2026
ISSN :3048-6807

Artificial Intelligence in Polymer Composites: A Review of Machine Learning Applications

Emekwisia, Chukwudubem C.[1*], Oyesetan, Kolade O.[2], Onuoha, Precious C.[3], Eso, John T.[4], Nwakama, Precious O.[5], Eshikhogie, Eshiozemogie L.[6]

[1]Department of Metallurgical and Materials Engineering, Nnamdi Azikiwe University, Awka, Nigeria. [2]Division of Electronic Engineering, Jeonbuk National University, South Korea.
[3]Council for the Regulation of Engineering in Nigeria (COREN), Abuja, Nigeria.
[4]Department of Civil Construction and Environmental Engineering, North Carolina State University, Raleigh, USA.
[5]Department of Research and Development, Obimo (Suzhou) Technology Co. Ltd, Kunshan, China.
[6]Department of Natural Resources and Environmental Design, North Carolina Agricultural and Technical State University, Greensboro, USA.
[*]Corresponding Email: cc.emekwisia@unizik.edu.ng

Abstract

Polymer matrix composites (PMCs) have become important structural and functional materials because their matrix chemistry, reinforcement type, architecture, interface, and processing history can be tailored to meet application-specific requirements. Nevertheless, the development of reliable composite systems remains difficult because material performance emerges from coupled phenomena spanning molecular, microstructural, laminate, component, and environmental scales. Conventional experimental campaigns are consequently expensive and time-consuming, while high-fidelity numerical simulations can become computationally demanding when many formulation and process variables must be explored simultaneously. Machine learning (ML) and broader artificial intelligence (AI) methods provide a complementary approach by learning relationships from experimental, computational, imaging, and process-monitoring data and using those relationships for prediction, optimization, classification, and inverse design. This review synthesizes recent developments in AI-assisted polymer-composite research, with emphasis on literature published from 2018–2024. The review covers material design and selection, mechanical and functional-property prediction, multiscale modelling, manufacturing-process optimization, additive manufacturing, defect detection, damage prognosis, fire performance, tribology, explainable AI, physics-informed learning, and digital-twin-oriented workflows. The literature indicates that ML is most mature for tabular prediction problems and increasingly capable in image-based inspection and surrogate modelling of expensive simulations. However, apparently high prediction accuracy does not necessarily establish generalizability: many studies are limited by small datasets, correlated observations, inconsistent testing protocols, leakage between training and test sets, narrow material families, and insufficient external validation. Accordingly, AI should be viewed as a decision-support and acceleration layer rather than a replacement for materials science, mechanics, or experimental validation.

Keywords: ***Polymer Matrix Composites, Machine learning, Artificial Intelligence, Property Prediction, Process Optimization.***

INTRODUCTION

Polymer matrix composites are engineered combinations of a polymeric continuous phase and one or more reinforcing or functional phases. Thermosetting matrices such as epoxy, polyester and vinyl ester are widely used where dimensional stability and high specific performance are required, whereas thermoplastics such as polypropylene, polyamide, polyether ether ketone (PEEK) and polylactic acid (PLA) offer melt-processability, toughness and, in many cases, improved opportunities for recycling. Reinforcements may be continuous or discontinuous carbon and glass fibres, aramid fibres, natural fibres, particles, platelets, nanotubes or hybrid architectures. The resulting property set is not simply the weighted average of constituent properties; it depends on interfacial bonding, fibre orientation,

dispersion, porosity, residual stress, curing or cooling history, environmental exposure and the geometry of the manufactured component.

The multivariable nature of composite performance makes design particularly suitable for materials-informatics approaches. A formulation that increases stiffness may reduce impact resistance, while a process change that improves consolidation may increase cycle time or induce residual stress. Similarly, a higher fibre volume fraction can improve load transfer only when impregnation and orientation remain adequate. Materials informatics has been proposed as a means of converting heterogeneous materials data into descriptors and predictive relationships, thereby enabling rapid screening of candidate systems and more systematic exploration of design spaces (Ramprasad et al., 2017; Butler et al., 2018). The central opportunity is not merely faster regression but the construction of an iterative workflow in which data acquisition, modelling, experimentation and design continuously inform one another.

The expansion of machine learning has changed the way materials researchers can approach such relationships. Rather than specifying an explicit analytical form for every interaction, supervised learning algorithms infer mappings between input variables and target properties. Tree ensembles can model nonlinear tabular data; support-vector regression can perform effectively when datasets are relatively small; neural networks can approximate complex functions; convolutional neural networks can learn spatial features from images; and sequence models can represent time-dependent process signals. Materials-intelligence ecosystems further combine databases, descriptors, surrogate models, high-throughput computation and active learning to reduce the cost of navigating large materials spaces (Batra et al., 2021).

Within polymer composites, the need for such methods is particularly evident because the same material may be affected by composition, processing, microstructure and service environment. A useful predictive model therefore has to distinguish genuine material relationships from experimental noise and laboratory-specific effects. Recent reviews have documented growing ML activity in reinforced composites, laminated fibre-reinforced polymers, high-performance composites and polymer-composite process simulation (Cassola et al., 2022; Dev et al., 2024; Liu, M. et al., 2024; Sorour et al., 2024; Wang et al., 2024). These studies collectively indicate that ML can support prediction and optimization, but they also emphasize data quality, validation and transferability as persistent barriers.

Another important development is the shift from isolated prediction to lifecycle integration. AI can be used at the material-design stage to screen formulations, during processing to predict flow or cure behaviour, during inspection to identify defects, and during service to diagnose damage or estimate remaining performance. In additive manufacturing, real-time imaging and process signals can be linked to automated decisions, creating the basis for closed-loop control. In this context, AI is increasingly discussed alongside digital twins and Composites 4.0, where models of materials and manufacturing processes are connected to physical production systems (Belnoue & Hallett, 2024; Jin et al., 2024).

Despite these advances, the literature remains fragmented. Some studies focus on one property, one reinforcement system, or one manufacturing route, while others focus on a specific algorithm. A model reporting an R^2 above 0.95 may still have limited engineering value if the test set is randomly split from nearly identical experiments, if the model has only been tested within a narrow composition range, or if the experimental protocol differs between laboratories. Consequently, a critical review must consider not only predictive accuracy but also dataset size, descriptor quality, validation strategy, physical plausibility, uncertainty and domain of applicability.

This review therefore examines AI and ML across the polymer-composite lifecycle. The objectives are to: (i) summarize the main AI architectures used for polymer-composite research; (ii) synthesize applications in material design and property prediction; (iii) evaluate AI-assisted processing, additive manufacturing and quality control; (iv) discuss physics-informed and explainable approaches; (v) identify methodological weaknesses that restrict reproducibility and generalization; and (vi) propose research directions toward multimodal, sustainable and closed-loop composite development.

METHODOLOGY

Literature Databases and Search Strategy

A structured literature-review strategy was employed. The search scope emphasized peer-reviewed research and review articles addressing machine learning, artificial intelligence, materials informatics, polymer composites, fibre-reinforced polymers, composite manufacturing, defect detection, additive manufacturing, physics-informed learning, explainable AI and inverse materials design. Major scholarly publisher databases and indexing platforms were considered, including ScienceDirect, Nature, Springer and related bibliographic records. Search strings combined material terms ("polymer composite", "fibre-reinforced polymer", "nanocomposite", "CFRP", "GFRP") with computational terms ("machine learning", "artificial intelligence", "deep learning", "neural network", "support vector", "random forest", "XGBoost", "physics-informed neural network", "explainable AI") and application terms ("property prediction", "process optimization", "defect detection", "damage prognosis", "additive manufacturing"). Similar structured searches have been reported in recent composite-ML reviews.

Inclusion and Exclusion Criteria

Priority was given to peer-reviewed studies that clearly connected an AI/ML method with a polymer, fibre-reinforced polymer, nanocomposite, or closely related composite system and that reported sufficient methodological information to understand the inputs, outputs, validation approach or application context. Reviews were included where they provided systematic synthesis of an application area. Studies focused exclusively on metals or ceramics were not used as evidence for polymer-composite-specific performance, although foundational materials-informatics papers were retained where they establish general principles directly applicable to polymer systems. Conference abstracts, records without sufficient bibliographic information, duplicate publications and claims that could not be independently verified were excluded from the expanded reference list.

Synthesis Approach and Limitations

The synthesis was qualitative rather than a statistical meta-analysis because the selected studies use different composite chemistries, feature spaces, target properties, sample sizes, validation schemes and performance metrics. Direct pooling of reported R^2, RMSE or accuracy values would therefore risk creating a misleading numerical ranking. Instead, studies were organized according to the role of AI in the composite lifecycle: material design, property prediction, process modelling, defect inspection, service-life prediction, and emerging physics-informed or explainable approaches. Particular attention was paid to whether a reported result was experimentally validated, whether the model was tested on independent data, and whether the study addressed the limitations of data-driven extrapolation.

RESULTS AND DISCUSSION

FUNDAMENTALS OF POLYMER COMPOSITES

Polymer Matrices and Reinforcement Architecture

The matrix controls environmental resistance, chemical compatibility, viscoelastic behaviour, processing window and a substantial part of the composite's damage tolerance. Thermosets form cross-linked networks during cure and are widely used for structural laminates because they can provide good dimensional stability and fibre impregnation. Thermoplastics can be remelted and reshaped and are increasingly attractive for rapid processing and recycling.

Elastomeric matrices occupy another design space in which flexibility, damping and recoverability are more important than high modulus. These distinctions matter for AI because matrix identity is not simply a categorical label: molecular structure, molecular weight, cure state, glass-transition temperature, viscosity and processing history may all act as relevant descriptors (Gomez-Flores et al., 2024).

Reinforcement architecture introduces an additional hierarchy. Continuous fibres generate highly directional stiffness and strength, short fibres create orientation-dependent discontinuous reinforcement, while particulate and nanoscale fillers influence interfacial, electrical, thermal, barrier or tribological properties. Natural fibres add further variability because fibre geometry, moisture content, chemical treatment and biological origin may vary substantially. Hybrid composites can therefore contain several interacting descriptor families. The literature on ML-assisted composite design emphasizes that data hygiene and careful representation of material and process variables are essential because a model cannot infer a relationship that has been poorly encoded or confounded in the training data (Chen et al., 2023; Gomez-Flores et al., 2024).

Process–Structure–Property Relationships

Composite properties emerge from a chain linking formulation to processing, microstructure and performance. For a fibre composite, resin viscosity influences impregnation; impregnation influences void content; voids and fibre waviness influence stress concentration and damage initiation; and the resulting microstructure influences strength and fatigue life. In thermosets, temperature and time determine cure kinetics, while in thermoplastics the thermal history controls crystallinity, residual stress and interlayer bonding. Additive manufacturing introduces deposition direction, raster angle, layer height, nozzle temperature and print speed as additional variables. A robust AI workflow should therefore avoid treating composition as the only determinant of performance (Cassola et al., 2022; Zhao et al., 2024).

Key Performance Indicators

Mechanical indicators commonly include tensile strength, tensile modulus, flexural strength, impact resistance, interlaminar shear strength, fracture toughness and fatigue life. Thermal indicators include glass-transition temperature, thermal conductivity, coefficient of thermal expansion and decomposition behaviour. Tribological indicators include coefficient of friction and wear rate. Functional composites may also be assessed for electrical conductivity, electromagnetic shielding, sensing capability and flame retardancy. Because these outputs have different physical meanings and noise characteristics, algorithm selection and validation should be matched to the target rather than selected solely because a model performed well in another application (Dev et al., 2024).

MACHINE LEARNING TECHNIQUES USED IN POLYMER COMPOSITES

Artificial Neural Networks and Multilayer Perceptrons

Artificial neural networks (ANNs) approximate nonlinear relationships through interconnected layers of weighted transformations. In composite research, multilayer perceptrons are useful when the inputs are numerical descriptors such as fibre fraction, fibre length, matrix ratio, curing temperature and processing pressure. Their strength is flexibility, but they can overfit small experimental datasets. This makes regularization, cross-validation and independent testing especially important. Deep networks become advantageous when the data are sufficiently large or when structured inputs such as images, spectra or process histories are available (LeCun et al., 2015).

Support Vector Machines and Regression

Support vector machines and support vector regression (SVR) are particularly useful when datasets are small or moderately sized and nonlinear relationships can be represented through kernel functions. Their optimization framework controls model complexity, but performance depends on feature scaling and hyperparameter selection. In composite research, SVR is attractive when expensive experiments limit sample size. The appropriate conclusion is not that SVR is universally superior, but that it can provide a strong baseline when the dataset is too small to justify a large neural architecture (Dev et al., 2024; Sorour et al., 2024).

Random Forest, Gradient Boosting and XGBoost

Tree-based ensembles are widely suited to tabular composite datasets because they capture nonlinear interactions without requiring strong assumptions about the functional form. Random Forest averages many decision trees, reducing variance and providing useful measures of feature importance. Gradient boosting constructs trees sequentially to reduce residual error, while XGBoost adds regularization and computational optimizations. A 2024 study of treated jute/glass/epoxy composites used a large experimental dataset and reported XGBoost as the strongest among the compared models for predicting mechanical properties, illustrating the value of relatively rich datasets and feature-importance analysis (Beldar & Kadbhane, 2024).

Convolutional and Sequence Models

Convolutional Neural Networks (CNNs) are designed for spatially structured data and have therefore become important for micrographs, ultrasonic C-scans, thermographic images and X-ray computed tomography. Recurrent architectures and long short-term memory networks can represent sequential process data such as temperature, pressure or sensor signals. The most useful applications combine these architectures with domain knowledge rather than treating images or time series as isolated pattern-recognition problems. For example, an image classifier can identify a defect, but an engineering system must still determine whether the defect is acceptable, how it affects structural integrity and what process condition produced it (Helwing et al., 2022; Daghigh et al., 2024).

Physics-Informed Machine Learning

Physics-informed neural networks (PINNs) incorporate governing equations, constitutive relationships, boundary conditions or conservation laws into model training. This can be valuable in composites because experimental datasets are often sparse while the governing physics are partially known. PINNs have been investigated in solid mechanics, including constitutive modelling, inverse problems and damage prediction, with the objective of constraining solutions to physically admissible regions (Raissi et al., 2019; Hu et al., 2024). For composite manufacturing, physics-informed learning can potentially encode heat transfer, resin flow, cure kinetics and mechanical equilibrium rather than relying solely on empirical correlations. Amini Niaki et al. (2021) demonstrated this principle for coupled heat transfer and resin cure in an autoclave composite-tool system.

Explainable AI and Uncertainty

Explainable AI (XAI) is important when predictions must be interpreted by materials engineers. SHAP values, permutation importance, partial-dependence analysis and local surrogate explanations can identify which features contribute to a prediction. SHAP provides a principled additive attribution framework, whereas LIME constructs local approximations around individual observations (Lundberg & Lee, 2017; Ribeiro et al., 2016). Explanation, however, should not be confused with causality. A feature may be highly predictive because it is correlated with another process variable or because it identifies a laboratory batch. Uncertainty estimates are similarly necessary because a high point prediction without an indication of model confidence can encourage unsafe extrapolation. A comparative overview of these architectures is provided in Table 1.

Table 1. Summary of Machine-Learning Architectures Commonly Applied to Polymer-Composite Research.

Architecture	Typical Composite Inputs	Suitable Outputs/tasks	Principal Strengths	Main Caution	Reference
ANN/MLP	Formulation, fibre fraction, process variables	Strength, modulus, thermal properties	Flexible nonlinear mapping	Overfitting with small datasets	LeCun et al., 2015; Ding et al., 2022
SVR	Scaled tabular descriptors	Mechanical/thermal/tribological properties	Effective for limited datasets	Sensitive to kernel and hyperparameters	Dev et al., 2024; Sorour et al., 2024
RF/XGBoost	Composition + process + environment	Property prediction, ranking, classification	Strong tabular performance and feature importance	Can memorize narrow domains	Beldar & Kadbhane, 2024; Liu et al., 2022
CNN	Micrographs, CT, thermography, C-scans	Defect detection/segmentation	Learns spatial features automatically	Needs representative labelled images	Helwing et al., 2022; Daghigh et al., 2024
LSTM/sequence models	Temperature/pressure/time histories	Process-state prediction	Captures temporal dependence	Requires sufficiently informative sequences	Lu et al., 2023; Cassola et al., 2022
PINN/hybrid models	Sparse data + governing equations	Field prediction, inverse problems	Can impose physical constraints	Training can be difficult and computationally expensive	Amini Niaki et al., 2021; Hu et al., 2024

AI FOR POLYMER COMPOSITE MATERIAL DESIGN

Data Representation and Descriptor Engineering

The first step in AI-assisted material design is converting a composite into a representation that a model can use. Basic descriptors include matrix type, reinforcement type, fibre volume or weight fraction, fibre length, aspect ratio and orientation. More advanced representations include molecular fingerprints, chemical descriptors, surface-treatment variables, interfacial properties, pore statistics and microstructural descriptors. For image-based approaches, raw microscopy or tomography can be used directly or converted into lower-dimensional descriptors. Descriptor selection should balance physical relevance, measurement reliability and availability at the point where a prediction will be deployed. (Lu & Jayaraman, 2024). The materials-informatics literature emphasizes that descriptors determine the hypothesis space available to a learning model. A descriptor that ignores orientation cannot directly represent anisotropic stiffness unless the relevant information is encoded elsewhere. Similarly, a model trained on nominal fibre

content may incorrectly attribute variability caused by fibre dispersion to composition. Consequently, feature engineering in composites is not a purely computational step; it is part of the materials-science formulation of the problem (Ramprasad et al., 2017; Schmidt et al., 2019).

Forward Prediction and Inverse Design

Forward models predict a property from a specified material formulation. Inverse design reverses the direction: the desired property is specified and the algorithm searches for material combinations likely to achieve it. Inverse design is particularly attractive for polymeric materials because the number of possible structures and formulations can be extremely large. Machine-learning-assisted polymer discovery has demonstrated that a limited experimental dataset can be used to screen large hypothetical spaces before selected candidates are synthesized and tested (Wu et al., 2019; Kumar et al., 2019). The same logic can be extended to composites by defining a target vector containing strength, toughness, conductivity, thermal stability or cost and searching for combinations that satisfy several constraints simultaneously.

Multiscale Modelling

A major challenge in composite design is connecting molecular or constituent information to component-scale performance. Recent multiscale ML work on carbon-fibre-reinforced polymers illustrates the potential to connect lower-scale information with macroscopic mechanical properties more efficiently than repeated high-fidelity simulation alone (Zhao et al., 2024). In a practical workflow, molecular descriptors may characterize the resin, micromechanical models may represent fibre–matrix interaction, and laminate-level models may describe orientation and stacking sequence. ML can serve as a surrogate between these levels, but the interfaces between scales must be explicitly validated (Friederich et al., 2021).

Multi-Objective Optimization

Composite design is rarely a single-objective problem. Increasing stiffness may increase cost, density or brittleness, while improving flame resistance may alter viscosity or processing. Multi-objective algorithms such as genetic algorithms, particle swarm optimization and Bayesian optimization can explore trade-offs. The goal is to identify a set of feasible designs rather than one universally optimal formulation. This is consistent with the broader shift from one-property optimization toward materials systems that satisfy mechanical, thermal, environmental, economic and manufacturing constraints simultaneously (Wu et al., 2019; Kumar et al., 2019).

AI FOR PROPERTY PREDICTION

Mechanical Properties

Mechanical-property prediction is currently one of the most established applications of ML in polymer composites. Tensile strength, modulus, flexural strength, interlaminar properties and failure responses can be related to fibre content, orientation, laminate configuration, matrix characteristics and processing variables. Reviews of laminated FRP literature report extensive use of ANN, support-vector, tree-based and evolutionary approaches for mechanical-property prediction and optimization (Sorour et al., 2024). The principal value of these models is rapid screening, particularly when the same experimental campaign would otherwise require numerous specimen batches.

Deep-learning models can also connect microstructure to mechanical response. For example, DNN approaches have been used to predict macroscopic properties and microscopic cracking behaviour in unidirectional fibre-reinforced polymer composites using experimentally validated computational data (Ding et al., 2022; Li et al., 2022). Such approaches are promising because they reduce the need to prescribe simplified microstructural descriptors, but they

also create a new requirement: the generated or measured microstructures must represent the variability encountered in real materials.

Fatigue and Durability

Fatigue prediction is more challenging than static-property prediction because the response depends on load history, stress ratio, environment, damage accumulation and manufacturing defects. ML can learn nonlinear relationships between these variables and fatigue life, but random splitting of repeated measurements from the same specimen family can inflate apparent accuracy. For polymeric systems, random-forest modelling has demonstrated the ability to predict fatigue life from test conditions and identify influential factors (e.g., Kishino et al., 2023). In structural composites, the same concept should be extended using specimen-level or batch-level splits so that the test set represents genuinely new material states.

Environmental Degradation

Service conditions such as water, humidity, temperature and alkaline exposure can alter polymer matrices and interfaces. XGBoost-based models have been investigated for predicting long-term performance of pultruded FRP composites exposed to water, humidity and alkaline solutions, demonstrating how environmental variables can be incorporated into residual-strength and modulus prediction (Liu et al., 2022). Such models are potentially valuable for maintenance planning, but long-term extrapolation remains a major concern because service data often cover only a fraction of the lifetime of interest.

Thermal and Fire Performance

Thermal conductivity, glass transition and fire response are influenced by polymer chemistry, filler type, filler loading and microstructure. ML has been used to accelerate polymer and composite design in this area. For flame-retardant systems, recent studies have used random forests and other models to predict ignition and heat-release parameters, while other work has used ML to guide the design of organic flame retardants for epoxy composites (Jafari et al., 2024; Chen et al., 2023). These applications illustrate the value of ML as a screening mechanism, but experimentally validated fire testing remains indispensable because flammability is governed by coupled chemical and transport phenomena (Wiśniewska et al., 2024).

Tribological Properties

Tribological behaviour is often strongly nonlinear because friction and wear depend on load, sliding speed, temperature, counterface, reinforcement and transfer-film formation. ANN models have been shown to predict tribological responses of polymer-composite systems from composition and operating conditions, while gradient-boosting approaches have been applied to PTFE composites (Zhao et al., 2023; Wang et al., 2023). These examples suggest that ML can support tribomaterial screening and reduce the number of experiments needed to map operating conditions. Nevertheless, model transfer between tribometers, counterface materials and test standards should be demonstrated before industrial deployment. Table 2 summarizes the principal property domains, descriptors, algorithms and validation priorities discussed above.

Table 2. Property Domains, Common Descriptors, Machine-Learning Approaches and Validation Priorities in Polymer Composites.

Property Domain	Common Descriptors	Common ML Approaches	Validation Priority	Citation

Tensile/flexural	Fibre fraction, orientation, matrix, cure, process	RF, XGBoost, ANN, SVR	Independent material batch	Sorour et al., 2024; Ding et al., 2022; Beldar & Kadbhane, 2024
Fatigue	Stress ratio, frequency, load, architecture, environment	RF, ANN, sequence models	Specimen/batch-level split	Kishino et al., 2023; Sorour et al., 2024
Thermal	Filler fraction, matrix chemistry, dispersion, temperature	ANN, SVR, tree ensembles	Out-of-range uncertainty	Lu & Jayaraman, 2024; Dev et al., 2024
Tribology	Load, speed, temperature, filler and matrix	ANN, GBR, SVR	Counterface/test-condition transfer	Wang et al., 2023; Dev et al., 2024
Fire	Polymer chemistry, additive identity/loading, formulation	RF, ANN, interpretable ML	Experimental fire-test confirmation	Jafari et al., 2024; Chen et al., 2023; Wiśniewska et al., 2024
Durability	Humidity, water, temperature, exposure time	XGBoost, RF, hybrid models	Long-term external validation	Liu et al., 2022; Gomez-Flores et al., 2024

AI FOR MANUFACTURING OPTIMIZATION

Resin Transfer Moulding and Process Simulation

Manufacturing-process simulation is an important target for ML because composite mould filling and curing can require repeated numerical calculations. Variables include resin viscosity, permeability, inlet pressure, temperature, fibre architecture, cure kinetics and tool geometry. A review by Cassola et al. (2022) shows that ML has been explored for forming, flow and other process-simulation problems and can act as a surrogate for computationally expensive calculations. More recent work has demonstrated image-based surrogate modelling of composite mould filling, showing that ML can approximate process fields with substantially lower computational cost than exhaustive simulation under the studied conditions (Belnoue & Hallett, 2024).

Injection and Compression Moulding

For injection and compression processes, ML can map process parameters to filling quality, warpage, residual stress or cycle time. The key challenge is that process variables interact strongly: changing temperature can alter viscosity and cooling rate simultaneously, while pressure may affect both consolidation and dimensional stability. A useful AI optimization framework should therefore be multi-objective and constrained by feasible process windows. Surrogate models are especially attractive when coupled to optimization algorithms because they can replace thousands of repeated simulations during the search stage. Published work on composite process simulation identifies computationally efficient process models as an important basis for process-window exploration and digital manufacturing; this evidence supports the use of validated simulation/ML surrogates, while application-specific moulding predictions still require validation (Belnoue & Hallett, 2024; Cassola et al., 2022).

Additive Manufacturing of Polymer Composites

Additive manufacturing creates a data-rich environment in which nozzle temperature, speed, layer height, raster orientation, fibre path and thermal history can be recorded. ML can use these variables to predict strength, interlayer bonding, porosity and geometric accuracy (Thomas et al., 2022). In continuous-fibre additive manufacturing, deep-learning-assisted defect detection has been coupled with closed-loop adjustment of process parameters, illustrating a transition from passive inspection to active process control (Lu et al., 2023). Reviews of ML and XAI in additive manufacturing further show that interpretability is important when process decisions must be justified to operators and engineers.

Digital Twins and Closed-Loop Control

A digital twin can be understood as a dynamic computational representation linked to a physical system. In composite manufacturing, the twin may combine process sensors, finite-element or process models, ML surrogates and inspection data. AI can update the virtual representation as new measurements arrive, while the model can recommend process adjustments. Reviews of AI-integrated digital twins and additive manufacturing identify this combination as an emerging pathway for process optimization, quality monitoring and lifecycle management (Jin et al., 2024). For composites, however, the digital twin should not be reduced to a dashboard; it requires traceable data, validated models and defined decision rules.

AI FOR DEFECT DETECTION AND QUALITY CONTROL

Defect Types and Inspection Modalities

Composite defects include voids, porosity, delamination, fibre waviness, resin-rich regions, dry spots, cracks, inclusions and poor interlayer bonding. Their detectability depends on the inspection modality. Optical imaging is effective for accessible surfaces, while ultrasonic C-scans can reveal internal discontinuities. X-ray computed tomography provides three-dimensional information about pores and damage, and infrared thermography can detect thermal anomalies associated with subsurface defects. Each modality creates a different data structure, and the AI model should be designed accordingly.

Computer Vision and Deep Learning

CNN-based approaches can classify, detect and segment defects from images. Segmentation is particularly useful when the size and spatial distribution of a defect matter, because a simple image-level label does not provide information about location or morphology. Deep learning has been applied to X-ray CT data for segmentation of fatigue-damage mechanisms in fibre-reinforced polymers, reducing dependence on manually designed image-processing rules (Helwing et al., 2022). Reviews of defect-detection research similarly identify deep learning as a rapidly expanding area while emphasizing the importance of representative datasets and interpretable validation (Daghigh et al., 2024).

Real-Time Inspection and Human Oversight

For production use, inspection speed and false-alarm rates are as important as accuracy. A model that is highly accurate offline but too slow for an automated line has limited practical value. Transfer learning can reduce training requirements when a related dataset exists, but the transferred features may not remain valid across imaging equipment, surface conditions or material systems. Human oversight therefore remains important, particularly when the consequence of a missed defect is safety-critical. The preferred architecture is often human-in-the-loop rather than fully autonomous classification (Daghigh et al., 2024; Lu et al., 2023).

From Detection to Damage Prognosis

Detection identifies an anomaly; prognosis estimates its likely effect on future performance. This distinction is crucial for structural composites because not every visible or ultrasonic indication has the same structural significance. AI-based prognosis can combine defect size, location, loading history, environmental exposure and prior damage observations to estimate remaining performance. Such models must be linked to fracture mechanics, fatigue mechanics or validated structural testing rather than treated as purely statistical classifiers (Daghigh et al., 2024; Helwing et al., 2022).

EXPLAINABLE, PHYSICS-INFORMED AND HYBRID AI

Explainable AI for Materials Interpretation

A central criticism of AI in materials engineering is that accurate predictions can be difficult to interpret. In composite design, engineers often want to know whether the model is responding to fibre content, orientation, matrix chemistry, processing temperature or a hidden batch variable. SHAP-based explanations can rank feature contributions across a dataset, while local explanations can identify the variables driving a particular prediction. These tools are most useful when paired with domain knowledge and sensitivity analysis. An explanation should be tested for stability and plausibility rather than accepted simply because it is visually persuasive (Lundberg & Lee, 2017; Ribeiro et al., 2016).

Physics-Informed Learning

Physics-informed learning addresses a complementary problem: even if a model is predictive, it may violate known physical constraints. A model for thermal behaviour should not predict impossible trends merely because they appear in noisy training data. PINNs and related hybrid approaches incorporate governing equations or constitutive information into the optimization process. Reviews of PINNs in solid mechanics show applications in constitutive modelling, inverse identification and damage assessment, while also documenting challenges such as computational cost, loss balancing and sensitivity to discontinuities (Hu et al., 2024).

Hybrid ML–Mechanics Frameworks

The most defensible strategy for many composite applications may be hybrid rather than purely data-driven. Classical micromechanics can provide physically meaningful baselines, finite-element models can generate high-fidelity synthetic data, and ML can learn the residual error or act as a fast surrogate. This arrangement can reduce data requirements while preserving known relationships. The multiscale CFRP work reported by Zhao et al. (2024) illustrates the broader potential of coupling ML with multiscale representations. The objective should be to use AI where it is strongest—interpolation, pattern extraction and rapid approximation—while retaining mechanics where governing principles are well established.

Uncertainty Quantification and Domain of Applicability

Prediction uncertainty is essential for engineering decisions. A model trained on carbon/epoxy laminates should not automatically be trusted for a natural-fibre thermoplastic composite. This is the domain-shift problem emphasized in materials-informatics research. Ensemble methods, conformal prediction, Gaussian-process approaches and probabilistic neural networks can provide useful uncertainty estimates. More importantly, the system should identify when a new observation lies outside the training distribution. A prediction with high uncertainty is not a failure of AI; it is information that a new experiment or higher-fidelity simulation is needed (Hu et al., 2024; Gomez-Flores et al., 2024).

CURRENT CHALLENGES AND METHODOLOGICAL BOTTLENECKS

Small and Heterogeneous Datasets

Composite experiments are expensive, and published datasets often contain tens rather than thousands of observations. Even when the nominal sample count is large, observations may be strongly correlated because several measurements come from the same batch or specimen. Heterogeneity across laboratories further introduces differences in materials, equipment and testing standards. This limits the reliability of random train/test splits and makes external validation essential (Gomez-Flores et al., 2024; Dev et al., 2024).

Data Leakage and Validation

Data leakage occurs when information from the test set indirectly enters model training. In composites, this can happen when replicate specimens, nearly identical processing conditions or images from the same scan are distributed across both training and test sets. A model may then appear highly accurate while having little ability to predict a genuinely new batch. Grouped splitting by specimen, batch, material family or laboratory is often more realistic (Gomez-Flores et al., 2024; Sorour et al., 2024).

Standardization of Composite Data

A reusable composite dataset should include material identity, supplier or batch where relevant, reinforcement architecture, processing route, environmental conditioning, test standard, specimen geometry and measurement uncertainty. Without such metadata, two values that appear comparable may have been produced under different conditions. Standardization therefore has greater importance than simply increasing the number of records (Ramprasad et al., 2017; Batra et al., 2021).

Black-Box Interpretability

Deep networks can achieve strong predictive performance but may not reveal why a prediction was made. This is problematic where materials decisions have safety implications. XAI can improve transparency, but explanation methods have their own assumptions and can be unstable. Interpretability should therefore be assessed as part of model validation (Lundberg & Lee, 2017; Ribeiro et al., 2016).

Cross-System Generalizability

A model can fail when transferred from one matrix, reinforcement, manufacturing route or testing laboratory to another. Transfer learning and domain adaptation may reduce this problem, but they require enough overlap between source and target domains. Models should report the composition and process range over which they were trained (Gomez-Flores et al., 2024; Wang et al., 2024).

Physical Consistency

Purely statistical models can reproduce correlations that conflict with known mechanics. Physics-informed or hybrid models can reduce this risk, but they introduce additional modelling complexity. The appropriate level of physics should depend on the problem: a simple tabular screening task may not require a PINN, whereas field prediction governed by conservation equations may benefit strongly from physical constraints (Hu et al., 2024; Amini Niaki et al., 2021).

Reproducibility and Software Dependence

Hyperparameters, preprocessing, random seeds, data splits and feature definitions can substantially influence model performance. Published studies should therefore provide enough information for independent reproduction, preferably including data dictionaries and code where possible. Reproducibility is especially important for reviews because reported performance values are otherwise difficult to compare (Dev et al., 2024; Sorour et al., 2024).

RESEARCH GAPS AND FUTURE DIRECTIONS

Multimodal AI

Future composite AI systems should combine numerical composition and process data with microscopy, tomography, spectroscopy, thermal histories and mechanical-test curves. A multimodal model could, for example, relate fibre orientation images and processing history directly to strength and damage tolerance. The principal challenge is aligning observations collected at different scales and times. Metadata and standardized identifiers will be essential (Lu & Jayaraman, 2024; Batra et al., 2021).

Active Learning and Autonomous Experimentation

Active learning can select the next experiment that is expected to provide the greatest information or improve a target property. Rather than testing formulations uniformly, an AI system can propose candidates, receive experimental results, update the model and choose the next batch. This reduces wasted experiments and is particularly attractive for high-dimensional composite formulation spaces. However, active learning must include safety and manufacturability constraints so that the algorithm does not propose physically impossible or impractical experiments (Batra et al., 2021; Ramprasad et al., 2017).

Generative AI and Inverse Composite Design

Generative models such as variational autoencoders and generative adversarial networks can represent and generate candidate structures. In polymer composites, this could extend from molecular design to fibre architecture, porous structures, lattice-reinforced systems and graded multifunctional materials. Generative design should nevertheless be constrained by manufacturability, constituent availability, environmental stability and structural mechanics. A generated candidate is a hypothesis requiring physical validation, not an automatically verified material (Wu et al., 2019; Kumar et al., 2019).

Sustainable and Circular Composite Design

Sustainability provides an important future application for AI because material selection increasingly involves multiple lifecycle criteria. Models could simultaneously optimize mechanical performance, embodied energy, recycled content, recyclability, cost and service life. Bio-based fibres and agro-waste fillers introduce additional variability that may be managed through data-driven quality classification. For thermoset composites, AI could also support sorting, degradation-process optimization and recovery-route selection. However, the cited Jafari et al. (2024) and Chen et al. (2023) studies address machine-learning-assisted fire-retardant design; they do not directly validate end-of-life or circularity performance. Such lifecycle applications should therefore be treated as proposed research directions until supported by dedicated evidence.

Digital Twins and Composites 4.0

The integration of process simulation, sensor data, AI surrogates and inspection information provides a route toward digital twins for composite production. A mature system would maintain a traceable digital record from formulation through manufacture and service. Deviations in process conditions could trigger predictions of likely defects, while inspection results could update the virtual model. Current work on composites process models emphasizes the need

for faster simulation and better integration with digital manufacturing systems, providing a foundation for this direction (Belnoue & Hallett, 2024; Jin et al., 2024; Cassola et al., 2022).

Standards for Reporting AI in Composite Research

A practical reporting standard should include dataset size, independent units of observation, feature definitions, missing-data treatment, preprocessing, train/validation/test strategy, hyperparameters, performance metrics, uncertainty, external validation and domain of applicability. For image models, the number of specimens and images should be distinguished because many images may originate from one physical specimen. For time-series data, windows derived from the same experiment should not be split across training and test sets. These reporting practices would make future reviews more comparable and would reduce the risk of inflated performance claims (Gomez-Flores et al., 2024; Dev et al., 2024).

INTEGRATED FRAMEWORK FOR AI-ASSISTED POLYMER COMPOSITE DEVELOPMENT

The evidence synthesized in this review supports an integrated lifecycle framework rather than isolated AI applications. At the first stage, material and process descriptors are collected and standardized. At the second stage, baseline statistical and physics-based models establish a reference. At the third stage, ML models are trained and compared using grouped or external validation. At the fourth stage, explainability and uncertainty analysis determine whether the model has learned plausible relationships and whether new cases lie within its domain. At the fifth stage, the model is coupled to optimization or active learning to propose candidate formulations and process settings. Experimental testing then closes the loop by confirming or rejecting the predictions (Belnoue & Hallett, 2024; Jin et al., 2024; Gomez-Flores et al., 2024).

Such a framework changes the role of AI from a standalone prediction engine to an experimental planning and decision-support layer. The most valuable system may not be the model with the highest test-set R^2; it may be the model that identifies a smaller number of informative experiments, provides uncertainty estimates, explains the dominant variables and transfers successfully to a new material family. This distinction is particularly important for polymer composites because the objective is ultimately reliable material development rather than numerical prediction for its own sake (Batra et al., 2021; Wang et al., 2024). The corresponding roles of AI across the composite lifecycle are summarized in Table 3.

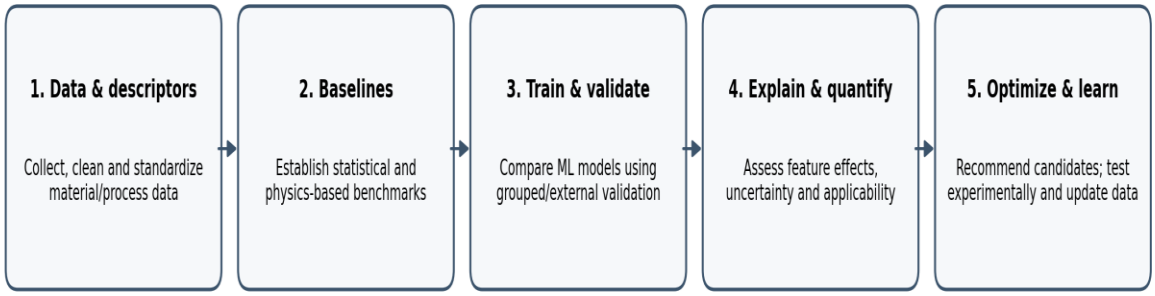


Figure 2. Proposed five-stage integrated framework for AI-assisted polymer-composite development.

Table 3. Integrated lifecycle framework for AI-assisted polymer-composite development.

Lifecycle Stage	AI role	Required Data	Human/physics Role	Expected Output	Citation
Material formulation	Screening and inverse design	Matrix, reinforcement, chemistry, ratios	Define feasible chemistry and processing window	Candidate formulations	Wu et al., 2019; Kumar et al., 2019; Zhao et al., 2024
Process planning	Surrogate modelling/optimization	Temperature, pressure, speed, geometry	Set equipment and physical constraints	Process window	Cassola et al., 2022; Jin et al., 2024
Manufacturing	Monitoring and control	Sensor streams, images, process history	Approve corrective actions	Stable process and lower defect risk	Lu et al., 2023; Jin et al., 2024
Inspection	Detection/segmentation	CT, ultrasonic, optical, thermal images	Assess engineering significance	Defect map/classification	Helwing et al., 2022; Daghigh et al., 2024
Service	Damage/prognosis	Load, environment, inspection history	Fracture/fatigue assessment	Condition estimate	Liu et al., 2022; Daghigh et al., 2024
End-of-life	Sorting/recovery optimization	Composition, contamination, degradation state	Select recovery route	Circular material pathway	Proposed application; dedicated lifecycle evidence needed

CONCLUSION

Artificial intelligence and machine learning are becoming significant tools for polymer-composite research because they can approximate nonlinear relationships, accelerate simulation, identify patterns in complex inspection data and support multi-objective design. This review demonstrates applications spanning material formulation, mechanical and functional-property prediction, environmental durability, fire performance, tribology, process simulation, additive manufacturing, defect detection and damage assessment. Tree-based methods remain particularly useful for structured experimental datasets, while deep learning is increasingly important for images, time series and high-dimensional representations. Physics-informed and hybrid approaches provide an avenue for combining the flexibility of ML with the constraints of mechanics and transport phenomena. The principal limitation is not a lack of algorithms but the quality and representativeness of the available data. Small datasets, inconsistent test protocols, data leakage, narrow material domains and limited external validation can produce apparently impressive but poorly transferable models. Consequently, future research should prioritize standardized data structures, grouped validation, uncertainty quantification, explainable models and experimentally validated transfer. The most promising direction is a closed-loop workflow in which AI proposes, physics constrains, experiments validate, and new data continuously improve

the model. Such integration can shorten development cycles while preserving the central role of materials science, engineering judgement and experimental evidence.

REFERENCES

1. Amini Niaki, S., Haghighat, E., Campbell, T., Poursartip, A., & Vaziri, R. (2021). Physics-informed neural network for modelling the thermochemical curing process of composite-tool systems during manufacture. Computer Methods in Applied Mechanics and Engineering, 384, 113959. https://doi.org/10.1016/j.cma.2021.113959
2. Batra, R., Song, L., & Ramprasad, R. (2021). Emerging materials intelligence ecosystems propelled by machine learning. Nature Reviews Materials, 6, 655–678. https://doi.org/10.1038/s41578-020-00255-y
3. Belnoue, J. P.-H., & Hallett, S. R. (2024). Process models: A cornerstone to composites 4.0. Composites Part B: Engineering, 283, Article 111621. https://doi.org/10.1016/j.compositesb.2024.111621
4. Beldar, P. R., & Kadbhane, S. (2024). Utilizing machine learning to forecast mechanical characteristics of NaOH-treated jute fiber reinforced composite materials. Materials Letters, 377, 137411. https://doi.org/10.1016/j.matlet.2024.137411
5. Butler, K. T., Davies, D. W., Cartwright, H., Isayev, O., & Walsh, A. (2018). Machine learning for molecular and materials science. Nature, 559, 547–555. https://doi.org/10.1038/s41586-018-0337-2
6. Cassola, S., Duhovic, M., Schmidt, T., & May, D. (2022). Machine learning for polymer composites process simulation – a review. Composites Part B: Engineering, 246, 110208. https://doi.org/10.1016/j.compositesb.2022.110208
7. Chen, Z., Yang, B., Song, N., Liu, Y., Rong, F., Zhang, X., Chen, T., Zhang, Q., Jiang, J., Chen, T., Yu, Y., & Liu, L. X. (2023). Machine learning-enabled rational design of organic flame retardants for enhanced fire safety of epoxy resin composites. Composites Communications, 44, 101756. https://doi.org/10.1016/j.coco.2023.101756
8. Daghigh, V., Daghigh, H., Lacy, T. E., Jr., & Naraghi, M. (2024). Review of machine learning applications for defect detection in composite materials. Machine Learning with Applications, 18, 100600. https://doi.org/10.1016/j.mlwa.2024.100600
9. Dev, B., Rahman, M. A., Islam, M. J., Rahman, M. Z., & Zhu, D. (2024). Properties prediction of composites based on machine learning models: A focus on statistical index approaches. Materials Today Communications, 38, 107659. https://doi.org/10.1016/j.mtcomm.2023.107659
10. Ding, X., Hou, X., Xia, M., Ismail, Y., & Ye, J. (2022). Predictions of macroscopic mechanical properties and microscopic cracks of unidirectional fibre-reinforced polymer composites using deep neural network (DNN). Composite Structures, 302, 116248. https://doi.org/10.1016/j.compstruct.2022.116248
11. Friederich, P., Häse, F., Proppe, J., & Aspuru-Guzik, A. (2021). Machine-learned potentials for next-generation matter simulations. Nature Materials, 20, 750–761. https://doi.org/10.1038/s41563-020-0777-6
12. Gomez-Flores, A., Cho, H., Hong, G., Nam, H., Kim, H., & Chung, Y. (2024). A critical review on machine learning applications in fiber composites and nanocomposites: Towards a control loop in the chain of processes in industries. Materials & Design, 245, 113247. https://doi.org/10.1016/j.matdes.2024.113247
13. Helwing, R., Hülsbusch, D., & Walther, F. (2022). Deep learning method for analysis and segmentation of fatigue damage in X-ray computed tomography data for fiber-reinforced polymers. Composites Science and Technology, 230, 109781. https://doi.org/10.1016/j.compscitech.2022.109781

14. Hu, H., Qi, L., & Chao, X. (2024). Physics-informed neural networks (PINN) for computational solid mechanics: Numerical frameworks and applications. Thin-Walled Structures, 205, 112495. https://doi.org/10.1016/j.tws.2024.112495
15. Jafari, P., Zhang, R., Huo, S., Wang, Q., Yong, J., Hong, M., Deo, R., Wang, H., & Song, P. (2024). Machine learning for expediting next-generation of fire-retardant polymer composites. Composites Communications, 45, 101806. https://doi.org/10.1016/j.coco.2023.101806
16. Jin, L., Zhai, X., Wang, K., Zhang, K., Wu, D., Nazir, A., Jiang, J., & Liao, W.-H. (2024). Big data, machine learning, and digital twin assisted additive manufacturing: A review. Materials & Design, 244, 113086. https://doi.org/10.1016/j.matdes.2024.113086
17. Kishino, M., Matsumoto, K., Kobayashi, Y., Taguchi, R., Akamatsu, N., & Shishido, A. (2023). Fatigue life prediction of bending polymer films using random forest. International Journal of Fatigue, 166, Article 107230. https://doi.org/10.1016/j.ijfatigue.2022.107230
18. Kumar, J. N., Li, Q., Tang, K. Y. T., Buonassisi, T., Gonzalez-Oyarce, A. L., & Ye, J. (2019). Machine learning enables polymer cloud-point engineering via inverse design. npj Computational Materials, 5, 73. https://doi.org/10.1038/s41524-019-0209-9
19. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521, 436–444. https://doi.org/10.1038/nature14539
20. Li, M., Zhang, H., Li, S., Zhu, W., & Ke, Y. (2022). Machine learning and materials informatics approaches for predicting transverse mechanical properties of unidirectional CFRP composites with microvoids. Materials & Design, 224, 111340. https://doi.org/10.1016/j.matdes.2022.111340
21. Liu, M., Li, H., Zhou, H., Zhang, H., & Huang, G. (2024). Development of machine learning methods for mechanical problems associated with fibre composite materials: A review. Composites Communications, 49, 101988. https://doi.org/10.1016/j.coco.2024.101988
22. Liu, X., Liu, T., & Feng, P. (2022). Long-term performance prediction framework based on XGBoost decision tree for pultruded FRP composites exposed to water, humidity and alkaline solution. Composite Structures, 284, 115184. https://doi.org/10.1016/j.compstruct.2022.115184
23. Lu, L., Hou, J., Yuan, S., Yao, X., Li, Y., & Zhu, J. (2023). Deep learning-assisted real-time defect detection and closed-loop adjustment for additive manufacturing of continuous fiber-reinforced polymer composites. Robotics and Computer-Integrated Manufacturing, 79, 102431. https://doi.org/10.1016/j.rcim.2022.102431
24. Lu, S., & Jayaraman, A. (2024). Machine learning for analyses and automation of structural characterization of polymer materials. Progress in Polymer Science, 153, 101828. https://doi.org/10.1016/j.progpolymsci.2024.101828
25. Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. In I. Guyon et al. (Eds.), Advances in Neural Information Processing Systems (Vol. 30). Curran Associates.
26. Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, 378, 686–707. https://doi.org/10.1016/j.jcp.2018.10.045
27. Ramprasad, R., Batra, R., Pilania, G., Mannodi-Kanakkithodi, A., & Kim, C. (2017). Machine learning in materials informatics: Recent applications and prospects. npj Computational Materials, 3, 54. https://doi.org/10.1038/s41524-017-0056-5
28. Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?": Explaining the predictions of any classifier. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 1135–1144. https://doi.org/10.1145/2939672.2939778

29. Schmidt, J., Marques, M. R. G., Botti, S., & Marques, M. A. L. (2019). Recent advances and applications of machine learning in solid-state materials science. npj Computational Materials, 5, 83. https://doi.org/10.1038/s41524-019-0221-0
30. Sorour, S. S., Saleh, C. A., & Shazly, M. (2024). A review on machine learning implementation for predicting and optimizing the mechanical behaviour of laminated fiber-reinforced polymer composites. Heliyon, 10(13), e33681. https://doi.org/10.1016/j.heliyon.2024.e33681
31. Thomas, A. J., Barocio, E., & Pipes, R. B. (2022). A machine learning approach to determine the elastic properties of printed fiber-reinforced polymers. Composites Science and Technology, 226, 109293. https://doi.org/10.1016/j.compscitech.2022.109293
32. Wang, Q., Wang, X., Zhang, X., Li, S., & Wang, T. (2023). Tribological properties study and prediction of PTFE composites based on experiments and machine learning. Tribology International, 188, 108815. https://doi.org/10.1016/j.triboint.2023.108815
33. Wang, Y., Wang, K., & Zhang, C. (2024). Applications of artificial intelligence/machine learning to high-performance composites. Composites Part B: Engineering, 285, 111740. https://doi.org/10.1016/j.compositesb.2024.111740
34. Wiśniewska, P., Movahedifar, E., Formela, K., Naser, M. Z., Vahabi, H., & Saeb, M. R. (2024). The chemistry, properties and performance of flame-retardant rubber composites: Collecting, analyzing, categorizing, machine learning modeling, and visualizing. Composites Science and Technology, 250, 110517. https://doi.org/10.1016/j.compscitech.2024.110517
35. Wu, S., Kondo, Y., Kakimoto, M.-A., Yang, B., Yamada, H., Kuwajima, I., Lambard, G., Hongo, K., Xu, Y., Shiomi, J., Schick, C., Morikawa, J., & Yoshida, R. (2019). Machine-learning-assisted discovery of polymers with high thermal conductivity using a molecular design algorithm. npj Computational Materials, 5, 66. https://doi.org/10.1038/s41524-019-0203-2
36. Zhao, Y., Lin, L., & Schlarb, A. K. (2023). Artificial neural network accomplished prediction on tribology – A promising procedure to facilitate the tribological characterization of polymer composites. Wear, 532–533, Article 205106. https://doi.org/10.1016/j.wear.2023.205106
37. Zhao, G., Xu, T., Fu, X., Zhao, W., Wang, L., Lin, J., Hu, Y., Du, L. (2024). Machine-learning-assisted multiscale modeling strategy for predicting mechanical properties of carbon fiber reinforced polymers. Composites Science and Technology, 248, 110455. https://doi.org/10.1016/j.compscitech.2024.110455 Conversion and Management, 178, 146-177.