Artificial Intelligence and Machine Learning in Composite Materials: A Comprehensive Literature Review and Bibliometric Analysis

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Peer-reviewed Version of Record: Fu, H., Eskandariyun, A., Portales Picazo, P., Johnson, K. A., Morton, A., Wynn, M., and Zobeiry, N. (2026). Artificial intelligence and machine learning in composite materials: A comprehensive literature review and bibliometric analysis. *Composites Part A: Applied Science and Manufacturing, 210, 110092.* https://doi.org/10.1016/j.compositesa.2026.110092

Abstract

Artificial intelligence (AI) and machine learning (ML) are transforming composites research and engineering by augmenting experimental testing and physics-based simulation with data-driven models for analysis, design, prediction, and optimization. This paper presents a comprehensive, quantitative review of the field by performing a bibliometric analysis of 1,474 AI/ML-enabled publications from 2010–2025 across seven leading composites journals, followed by an in-depth review of over 200 representative studies. Following a systematic methodology, we develop a taxonomy that maps composite research topics to AI/ML methods to investigate cross-cutting trends, impactful and emerging topics and methods, as well as country-level publication patterns and method adoption. The analysis shows that Mechanics & Failure dominates publication volume (>700 papers, ~50% of AI/ML-enabled composite publications), while Sustainability exhibits the highest citation impact relative to its small volume. In contrast, thermal protection and thermo-mechanical topics emerge as high-novelty areas with lower impact. Methodologically, literature remains dominated by artificial neural networks (ANNs, ~26%), followed by clustering methods (~14%), with increasing use of probabilistic approaches such as Gaussian process regression (GPR) and vision-based convolutional neural networks (CNNs). Beyond trend mapping, critical gaps are identified, including a lack of leakage-safe validation, a significant "virtual-to-real gap" despite high accuracy metrics, and limited generalization under distribution shift. These issues are largely rooted in the inherently stochastic nature of composite response, driven by material and process variability. In response, emerging directions increasingly prioritize physics-informed learning, probabilistic modeling and uncertainty quantification, transfer learning, and Bayesian updating enabled by sparse sensing.

Keywords: Literature Review; Artificial intelligence; Process and properties; Physics-informed learning; Uncertainty quantification

Glossary

ABS: Acrylonitrile Butadiene Styrene
AE: Acoustic emission
AFP: Automatic fiber placement
AI: Artificial intelligence
AM: Additive manufacturing
ANN: Artificial neural network
BLF: Buckling load factor
BO: Bayesian optimization
BVID: Barely visible impact damage
CAE: Convolutional autoencoder
CAI: Compression-after-impact
CFRP: Carbon fiber-reinforced polymer
CNN: Convolutional neural network
CNT: Carbon nanotube
CT: X-ray computed tomography
CycleGAN: Cycle-consistent generative adversarial network
DAE: Denoising autoencoder
DE: Differential evolution
DIC: Digital image correlation
DL: Deep learning
DOC: Degree of cure
DOE: Design of experiment
DT: Decision tree
DVC: Digital volume correlation
EKI: Ensemble Kalman inversion
FDM: Fused deposition modeling
FEA: Finite element analysis
FFF: Fused filament fabrication
GAN: Generative adversarial network
GCN: Graph convolutional network
GFRP: Glass fiber–reinforced polymer
GNN: Graph neural network
GPR: Gaussian process regression
GAF: Gramian angular field
HTC: Heat transfer coefficient
HVI: High-velocity impact
ICA: Independent Component Analysis
IGA: Isogeometric analysis
ILSS: Interlaminar shear strength
IR: Infrared
KNN: K-nearest neighbors
KRG: Kriging
LASSO: Least absolute shrinkage and selection operator
LCM: Liquid composite molding
LightGBM: Light gradient boosting machine
LIME: Local interpretable model-agnostic explanations
LSTM: Long short-term memory
LVGP: Latent variable Gaussian process
MCMC: Markov chain Monte Carlo
MD: Molecular dynamics
ML: Machine learning
MSE: Mean squared error
MuTINN: Multiscale thermodynamics-informed neural network
NDE: Non-destructive evaluation
NURBS: Non-uniform rational B-splines
PA: Nylon/Polyamide
PC: Polycarbonate
PCA: Principal component analysis
PCE: Polynomial chaos expansion
PDE: Partial differentiation equation
PEEK: Polyether-ether-ketone
PIDON: Physics-informed DeepONet
PINN: Physics-informed neural network
PINO: Physics-informed neural operator
PSO: Particle swarm optimization
R^2: Coefficient of determination
RBF: Radial basis functions
ResNet: Residual neural network
RF: Random forest
RMSE: Root mean squared error
RNN: Recurrent neural network
RSM: Response surface methodology
RUL: Remaining useful life
RVE: Representative volume element
SOM: Self-organizing map
SHAP: SHapley additive explanations
SHM: Structural health monitoring
SVR: Support vector regression
SVM: Support vector machine
SWGPR: Spatially-weighted GPR
U-Net: U-shaped convolutional neural network
UQ: Uncertainty quantification
ViT: Vision transformer
XAI: Explainable artificial intelligence
XGBoost: eXtreme gradient boosting
YOLO: You only look once

1. Introduction

Scientific and engineering domains have seen a surge of artificial intelligence (AI) and machine learning (ML) applications over the past decade. Similarly, AI/ML-enabled publications in composites have grown significantly and now account for more than 7% of annual output in major composites journals (>300 papers per year; see Section 2). While part of this growth reflects the broader expansion of AI/ML across disciplines, the composites community has also driven significant domain-specific advances in response to unique challenges and needs.

Despite the wide adoption of composites, significant challenges remain in manufacturing, design, optimization, and certification. In the aerospace industry, for example, material development, process qualification, and part certification based on the “building block” approach typically span a decade before adoption [1, 2]. In response, major progress has been made in the development of high-fidelity, multi-scale, and multi-physics simulation tools. However, complex model calibration and high computational cost often limit their applicability for design-space exploration and optimization. Additionally, the inherently stochastic nature of composites, stemming from material and process uncertainty, orthotropic/anisotropic behavior, and often nonlinear, multi-mode damage and failure, further compounds these challenges.

To address these limitations, AI/ML is increasingly utilized in composites studies to augment experimental testing and physics-based simulation with fast, data-driven surrogates, enabling, in some cases, near-real-time evaluation and prediction [3-5]. Beyond accelerating forward analysis, AI/ML is reshaping how the field tackles ill-posed inverse problems, such as inferring process parameters, internal damage states, or spatially varying boundary conditions from sparse sensor data, which are often impractical to solve with traditional methods [6-8]. In parallel, generative and inverse-design applications are emerging, including reconstructing full stress–strain responses from limited observables and generating microstructural features that satisfy target performance constraints [9-12]. Additionally, the growth of image- and time-series-based models is expanding AI/ML use in inspection, monitoring, and process control, where models are trained on data from thermography, X-ray computed tomography (CT), digital image correlation (DIC), acoustic emission (AE), and guided waves [13-17]. Finally, the field is shifting toward physics-informed learning, probabilistic learning, transfer learning, and uncertainty quantification, which are essential for bridging the “virtual-to-real gap” and developing deployable models [2, 18-22].

Recent AI/ML-enabled studies now span the full composites lifecycle, organized in this review under four primary categories: Material Design & Properties, Processing & Manufacturing, Mechanics & Performance, and Structural Health Monitoring (SHM) & Sustainability. Among these, Mechanics & Failure dominates publication volume with more than 50% of the AI/ML-enabled literature [3, 23]. The specific AI methods used in different categories are strongly application dependent. While Mechanics & Performance studies primarily use artificial neural networks (ANNs) [24, 25], along with substantial use of clustering [16, 26], strong applications of convolutional neural networks (CNNs) are observed in image- and signal-based studies such as Defects & Quality, and SHM [8, 27, 28]. While Processing & Manufacturing studies show a more distributed mix of AI/ML methods, noticeable applications of probabilistic approaches such as Gaussian process regression (GPR), and uncertainty quantification (UQ) are observed [29, 30].

Despite several valuable application- and/or methodology-focused literature reviews [3, 31-35], a comprehensive new review is justified for several reasons. First, the rapid expansion of literature has produced a fragmented landscape that is increasingly difficult to synthesize, particularly for emerging technologies and novel composites applications [36]. Second, the field is transitioning from black-box surrogates toward physics-integrated models, including physics-informed features and architectures [18], physics-informed neural networks (PINNs) [19, 37], operator learning [5], and more recently, generative frameworks [9, 11], which are not consistently captured by older taxonomies. Third, the central challenge for AI in composites has shifted from training accuracy to reliability under uncertainty [2, 4]. High reported metrics are often inflated by validation leakage, narrow sampling, or neglecting panel-to-panel and batch-to-batch variability, limiting practical applicability [20, 38].

Accordingly, this paper presents a comprehensive overview of AI/ML applications in composites using a combination of quantitative bibliometric analysis of AI/ML-enabled publications across seven leading composites journals from 2010–2025, followed by an in-depth technical review of more than 200 selected publications. The details of the approach are discussed in Section 2, followed by macro-observations from the bibliometric analysis in Section 3 on trends, impact, novelty, country-level patterns, and method adoption. Sections 4–7 complement these high-level observations with an in-depth technical review of selected papers covering the four categories of research discussed above. Finally, we connect macro-trends to technical details in Section 8 by identifying critical gaps in reliability, generalization, and validation, and by outlining emerging directions.

2. Literature Review Methodology

To establish a representative baseline for the integration of AI/ML within the composites domain, we conducted a systematic bibliometric analysis. The workflow consisted of five distinct stages: (1) data acquisition, (2) keyword-based filtration, (3) taxonomy development, (4) visualization, and (5) in-depth critical review:

- *Data Acquisition*: The search was restricted to seven high-impact journals of the field: Composites Part

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A: Applied Science and Manufacturing, Composites Part B: Engineering, Composites Science and Technology, Composite Structures, Polymer Composites, Journal of Reinforced Plastics and Composites, Composites Communications. For the temporal scope, we targeted all publications from 2010 to the present. This initial query yielded a total of 50,361 publications, as plotted yearly in Figure 1 with an average of approximately 4,000 combined publications per year over the past five years.

- *Keyword-based filtration*: Next, a targeted filtration was applied to identify studies explicitly utilizing AI/ML. A comprehensive Boolean search query was executed on publication titles and abstracts. At a high level, keywords related to different categories, including general AI/ML, deep learning (DL), deterministic and probabilistic ML methods, and supervised, unsupervised, and dimensionality-reduction methods, were considered in this search. The query resulted in 1,474 publications since 2010 (1,615 since 1988), representing the core dataset for this review. This indicates a steady growth in the share of AI/ML-related publications in composites, as shown in Figure 1, with a sharp rise beginning around 2019 and reaching 305 publications in 2025, or approximately 7.1% of total publications.
- *Taxonomy development*: For keyword analysis, two-tiered taxonomies were developed: one defining composites research context (e.g., process modeling, defect characterization, mechanical performance) and one defining AI/ML methodologies. These taxonomies were implemented as YAML structures. A custom Python script was subsequently deployed to parse the title and abstract of each paper, mapping the content to one or more categories within these taxonomies.
- *Visualization*: Categorized data were processed using Python to generate structured inputs, which were then visualized in Flourish Studio to identify trends and patterns.
- *In-depth critical review*: The authors down-selected approximately 210 papers for in-depth technical review. This final selection focused on studies spanning different sub-categories of both composites research and AI/ML methods. In addition, special attention was paid to highly cited papers, as well as papers published in the last two years, to capture emerging trends.

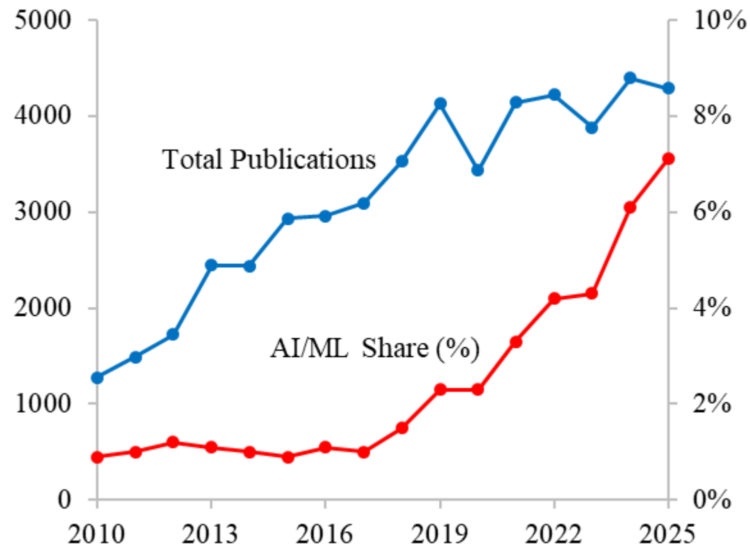

Figure 1: Yearly total publications of seven composite journals since 2010 (Composites Part A, Composites Part B, Composites Science and Technology, Composite Structures, Polymer Composites, Journal of Reinforced Plastics and Composites, Composites Communications), and AI/ML publications as a percentage of total publications.

3. The Big Picture

As shown in Figure 2, AI/ML has now been integrated across the composites lifecycle, consistent with the proposed taxonomy in this study comprising Material Design & Properties, Processing & Manufacturing, Mechanics & Performance, and SHM & Sustainability. Under these four top-level categories, seventeen sub-categories are identified, demonstrating that AI/ML tools span a broad range of applications, including design, testing, analysis, and optimization. Among these sub-categories, Mechanics & Failure has the largest footprint, comprising more than 700 publications, or approximately 50% of the total AI/ML publications since 2010. In contrast, sub-categories such as Bonding & Joining, Thermo-mechanical Properties, and Sustainability each contain fewer than ten dedicated studies.

Figure 3 shows the taxonomy of AI/ML methods for composite-related publications defined in this study. Overall, six top-level categories and twenty-one sub-categories were defined based on keyword analysis of papers published between 2010 and 2025. Across all sub-categories, ANNs are the most widely used method, appearing in approximately 26% of the publications. This is followed by clustering methods (e.g., k-means, ~14%), linear models (e.g., LASSO, ~11%), GPR/PCE/UQ (Gaussian process regression, polynomial chaos expansion, and uncertainty quantification, ~9%), and CNNs (~8%).

Here we define impact as the average number of citations per paper per year within a given topic. Novelty is defined as the percentage of papers published in a topic since 2023 relative to the total number of papers published in that topic since 2010. Based on these metrics, composites sub-categories are compared in

Figure 4, where Sustainability emerges as the highest-impact topic, but with comparatively lower novelty. In contrast, Thermal Protection, Fatigue & Creep, and Thermo-mechanical Properties show high novelty but lower impact, consistent with emerging application areas. By publication volume, Mechanics & Failure remains the dominant topic, reflecting sustained activity with moderate impact and novelty. Among the remaining topics, Functional Properties stands out with high impact but moderate novelty.

Figure 5 illustrates the annual publication count (2010–2025) of AI/ML-enabled composites studies, broken down by topic. From 2010 to ~2018, overall activity remained low, with most publications concentrated on Mechanics & Failure. A clear inflection point appears around 2019, followed by broad-based growth across most topics. In 2025, Mechanics & Failure accounts for approximately 54% of AI/ML publications, while the other top six categories, Defects & Quality, Impact & Crash, Material Design, Nanocomposites, Functional Properties, and Manufacturing, account for roughly 30% of publications combined.

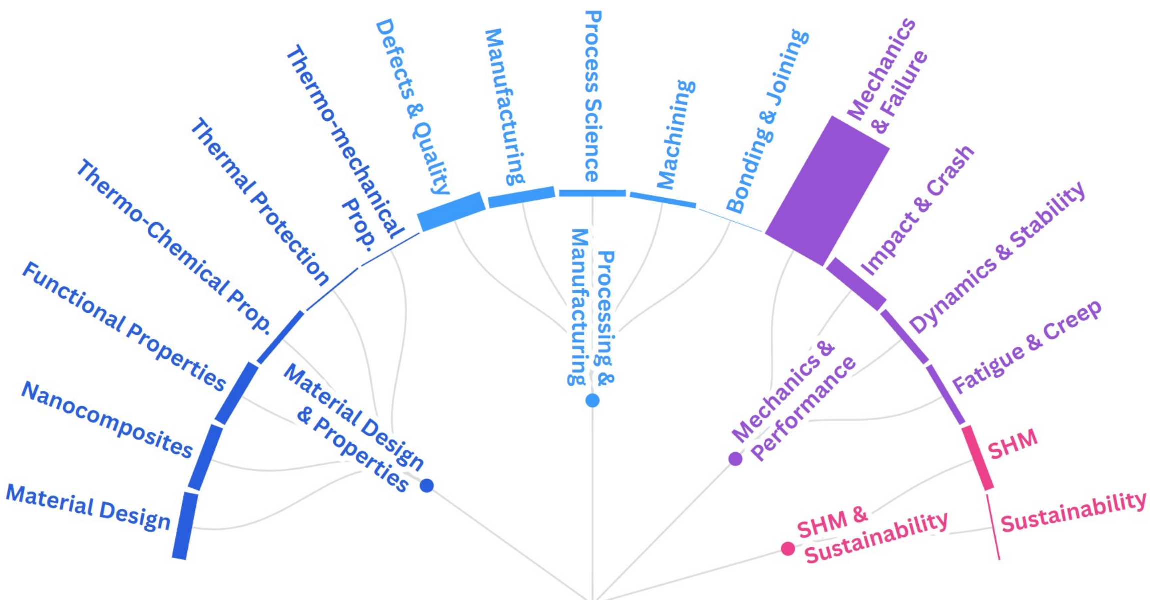

Figure 2: Taxonomy of composites research topics for AI/ML-enabled studies. Segment sizes are proportional to the number of AI/ML-related composite publications from 2010–2025.

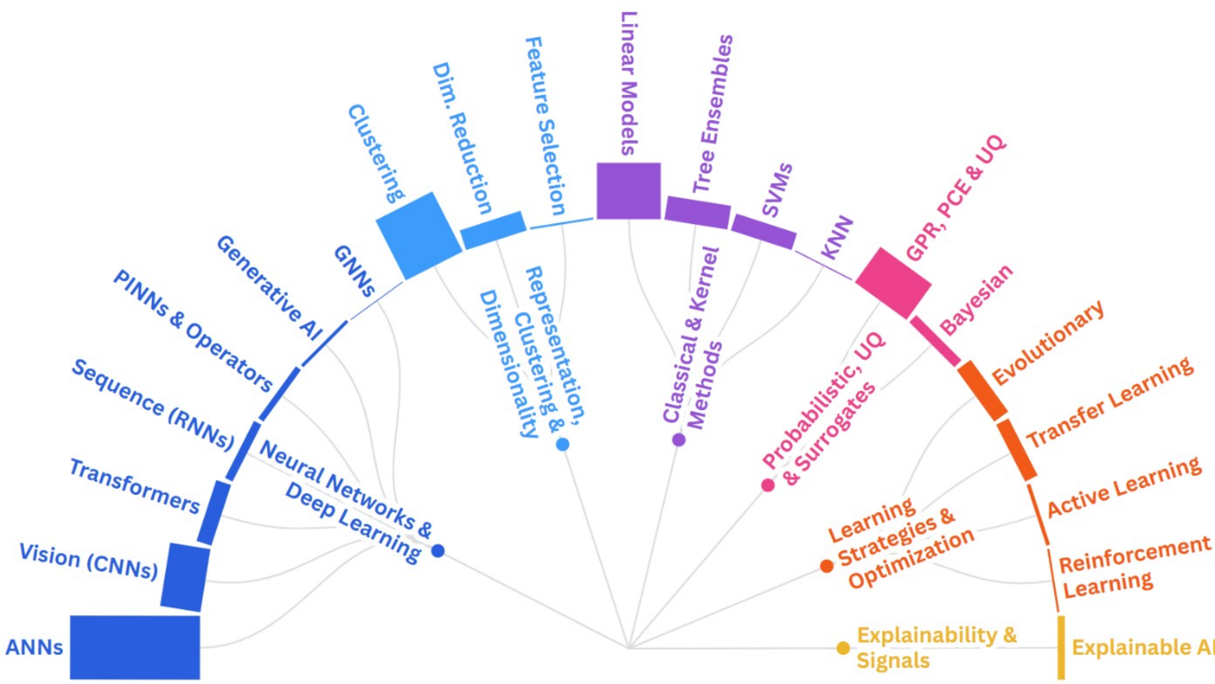

Figure 3: Taxonomy of AI/ML methods for composites research. Segment sizes are proportional to the number of composite-related publications using each method from 2010–2025.

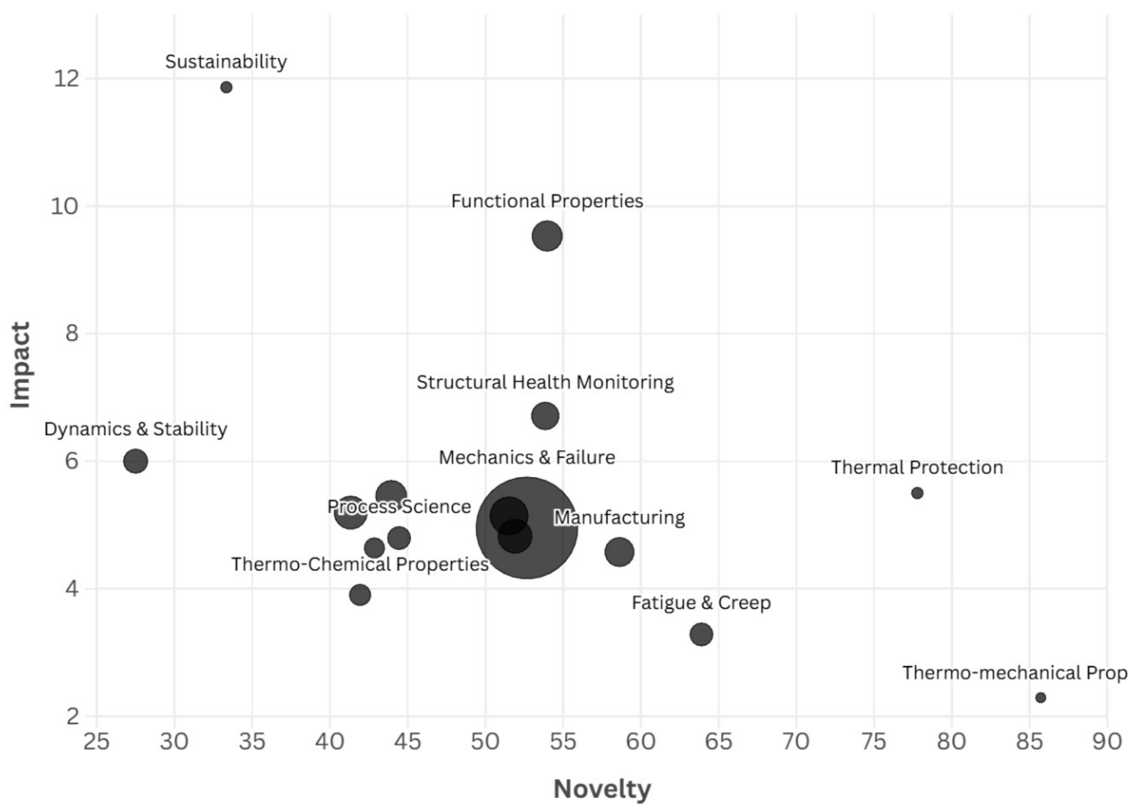

Figure 4: Impact–novelty map for AI/ML in composites (2010–2025). Impact is defined as average citations

per paper per year, and novelty is defined as the fraction of papers published since 2023. Bubble size denotes the total number of publications in each topic.

Figure 6 shows a 2D heatmap highlighting hotspots between composite topics and AI/ML methods. It reveals clear concentration patterns: a small number of topic–method combinations dominate the literature, while many others show relatively modest activity. The strongest interaction occurs between Mechanics & Failure and ANNs with 160 publications, followed by clustering with 99 publications and linear models with 72 publications. In categories such as Defects & Quality and SHM, vision-based methods (e.g. CNNs) are the dominant approach, consistent with image-based workflows. In Nanocomposites, while ANNs and linear models remain dominant, several AI/ML methods, including dimensionality reduction, support vector machine (SVM), and Bayesian approaches, are notably absent. Other topics, such as Manufacturing and Process Science, show more distributed engagement across multiple ML approaches.

Figure 7 and Figure 8 together provide a global perspective on AI/ML applications for composites. Figure 7 summarizes publication counts by country, showing strong concentration in a small set of contributors. China leads with 647 publications, followed by the United States (174), India (129), the United Kingdom (119), and Iran (89). A second tier includes South Korea (77), Australia (67), Germany (64), Canada (50), France (45), Turkey (44), and Italy (44). Across Europe and the United Kingdom, the combined total is approximately 520 publications, indicating a substantial regional footprint. Figure 8 shows how selected high-output countries utilize different AI/ML methods in composites research. Across all countries, ANNs dominate. China shows substantial use of vision (e.g. CNNs), while the United States and the United Kingdom show comparatively higher use of GPR, PCE, and UQ methods relative to their total volume. India and Iran rely primarily on ANNs and linear models, with more limited use of vision and UQ-focused approaches.

In terms of AI/ML approaches for composites, in the past three years (2023-2025), several cross-cutting directions have emerged. First, physics-informed learning, including PINNs and neural operators, has appeared in recent composites studies, driven by the need for physics-aware and PDE-governed surrogates. Second, transfer learning is becoming a practical pathway to reuse trained models for new material systems, geometries, and sensing modalities, especially where labeled data are scarce. Third, active learning and Bayesian optimization (BO) are increasingly used to reduce experimental and simulation effort using targeted evaluations. Fourth, uncertainty-aware and explainable workflows are moving to the forefront, particularly in SHM, process control, impact, fatigue, and certification-relevant decision-making. Finally, early generative approaches are being explored to augment data (e.g., microstructures, fields, and signals), though robust validation remains a key limitation.

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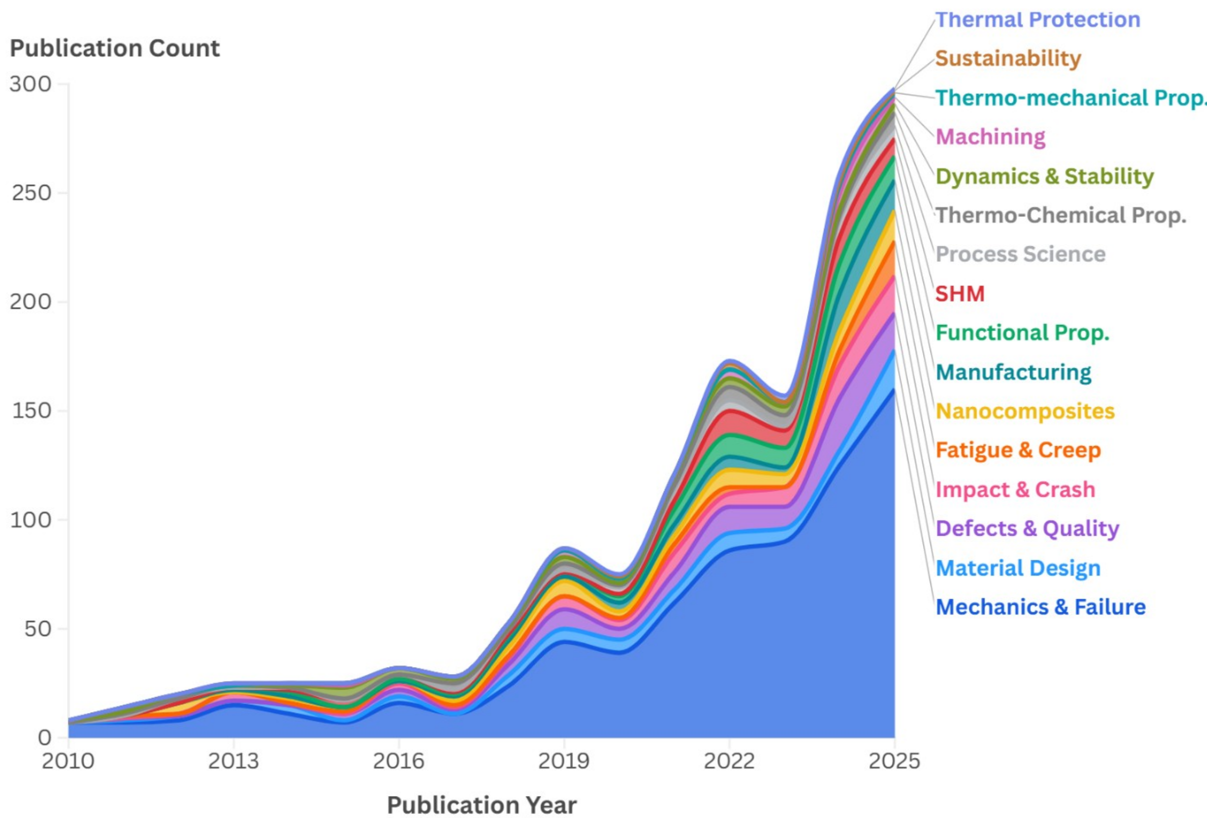

Figure 5: Annual publication counts of AI/ML-enabled composites studies by topic (2010–2025).

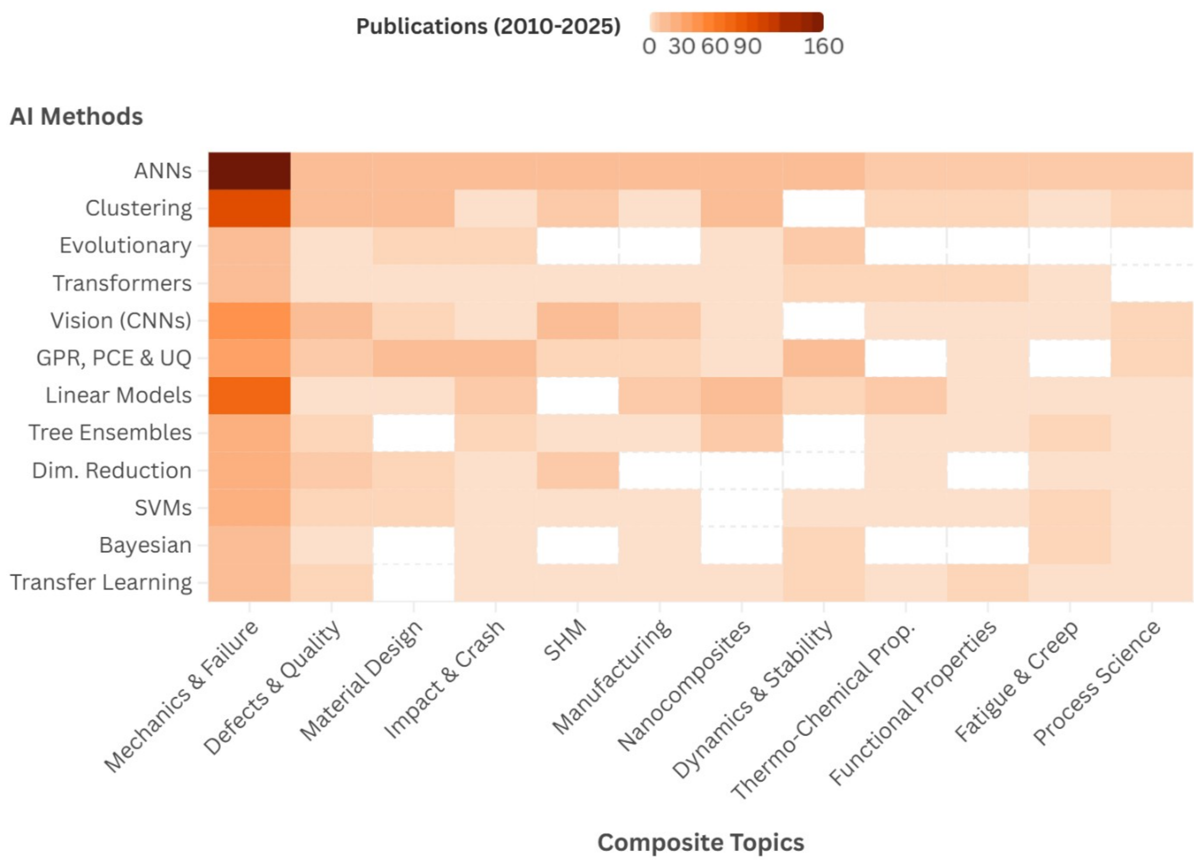

Figure 6: Number of publications (2010–2025) reporting the use of specific AI/ML methods across major composite research topics.

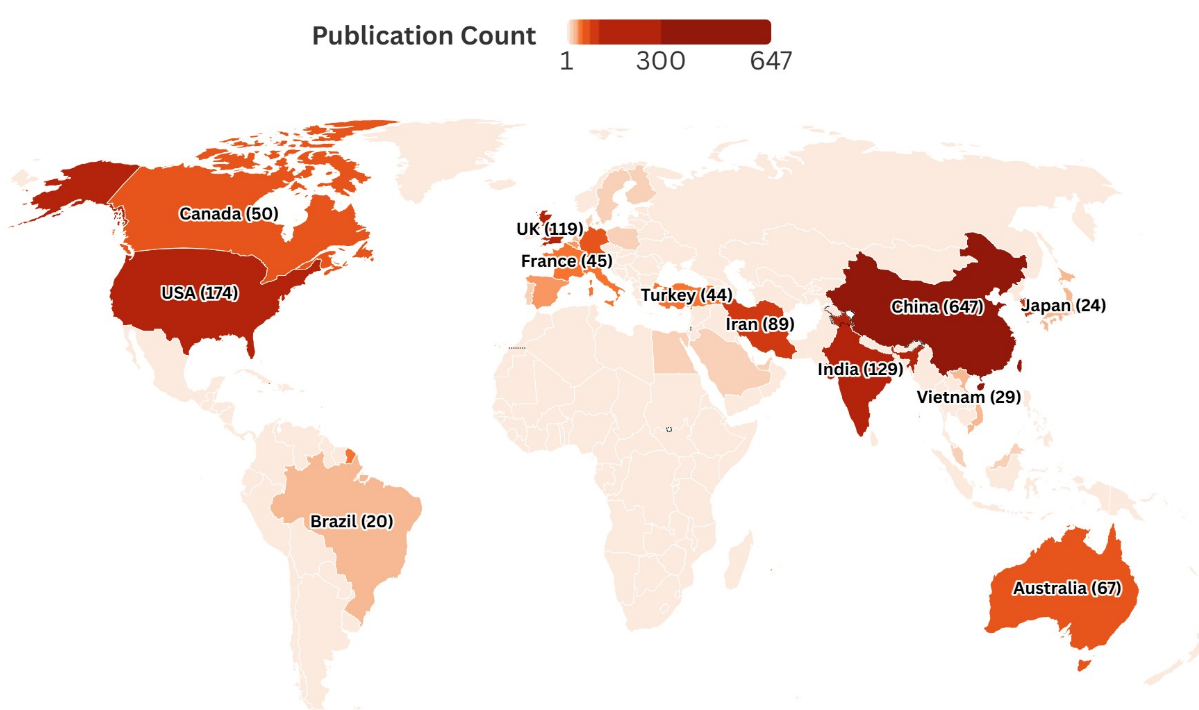

Figure 7: Global distribution of AI/ML-enabled composites publications by country (2010–2025).

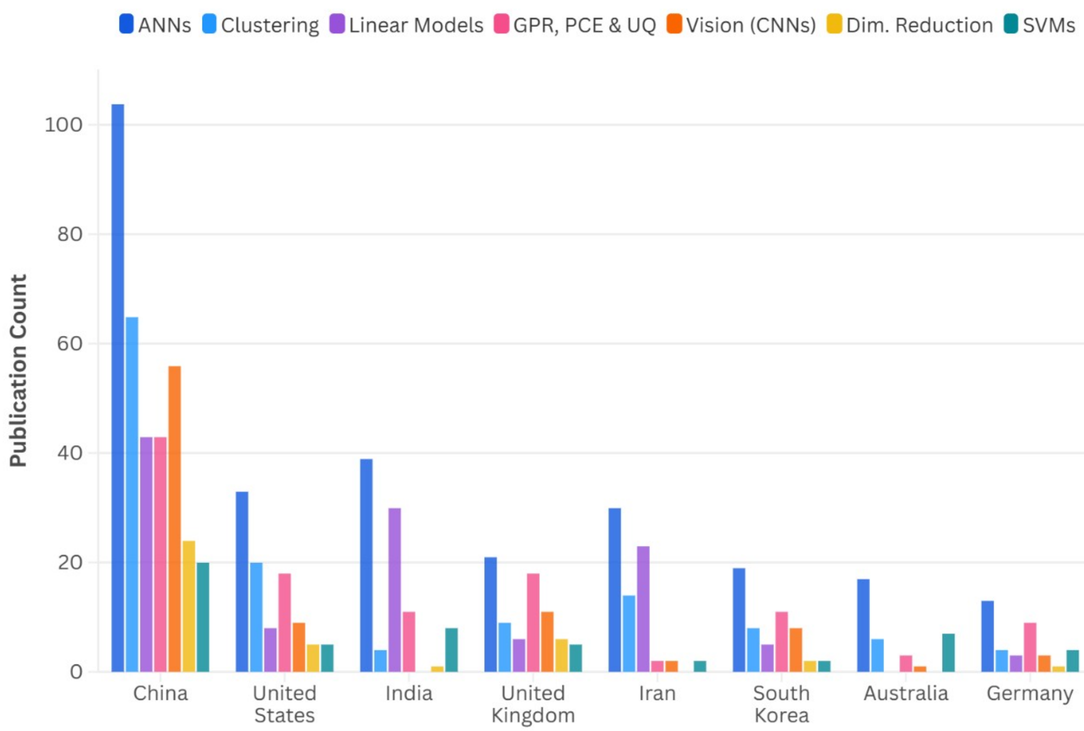

Figure 8: AI/ML method breakdown for selected high-output countries in AI/ML-enabled composites research (2010–2025).

4. Material Design and Properties

Under Material Design and Properties, the dominant research activity concentrates in Material Design, Nanocomposites, and Functional Properties, while thermally focused topics represent emerging directions with lower publication volume. Table 1 summarizes the main AI/ML methods and primary objectives across these sub-categories. In this section, we provide an in-depth review of the Material Design and Nanocomposites sub-categories, while also reviewing Microstructure Segmentation and Generation as an important cross-cutting enabler, given the growing reliance on image-based datasets.

4.1 Material Design

Establishing accurate structure-property relationships is essential to the design and optimization of composites. In structural composites, mechanical behavior, damage tolerance, and overall durability depend on the interactions between the constituent properties and the internal architecture across multiple length scales. Microscale features such as fiber orientation, phase topology, void morphology, and interfacial bonding govern the macroscopic composite response [39, 40]. Because these composites involve complex architecture, the resulting behavior is typically nonlinear, anisotropic and path-dependent, and cannot be captured reliably by closed-form analytical models [18]. High-fidelity numerical simulations can address these challenges but are typically computationally prohibitive for iterative design and optimization [41, 42].

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Table 1: Summary of AI/ML methods and primary research objectives for the Material Design and Properties category.

Sub-Category	Top 3 AI Methods (paper counts)	Primary Research Objectives
Material Design	ANNs (18) GPR, PCE & UQ (15) Clustering (10)	• Inverse design of auxetics and metamaterials. • Optimize woven designs and stacking sequences. • Topology optimization for lattice truss structures.
Nanocomposites	Clustering (11) Linear Models (11) ANNs (10)	• Quantify nanoparticle dispersion and clustering. • Model interfacial characteristics and debonding. • Predict thermal conductivity and EMI shielding.
Functional Properties	ANNs (8) Explainable AI (4) Transformers (4)	• Enhance sensing and energy harvesting. • Recognize multimodal signals. • Monitor dielectric breakdown and permittivity.
Thermo-Chemical Prop.	Linear Models (8) ANNs (7) Transformers (3)	• Monitor cure kinetics and glass transition. • Measure resin content and porosity. • Analyze pyrolysis and chemical reaction kinetics.
Thermo-mechanical Prop.	Transfer Learning (2) ANNs (1) Dim. Reduction (1)	• Predict cure-induced warping and deformations. • Program CTE and bi-functional responses. • Assess thermal stability of 3D-printed parts.
Thermal Protection	ANNs (1) Evolutionary (1) Tree Ensembles (1)	• Predict ablation recession and surface roughness. • Optimize flame retardancy and heat release. • Classify surface degradation in extreme heat.

AI/ML has emerged as an attractive complementary approach to enable microstructure-aware surrogate modeling, inverse design, and rapid prediction of properties directly from compositional, micro- and macro-structural features. For example, for two-phase and multiphase microstructures, where effective stiffness and strength are controlled by the spatial distribution and topology of the phases, convolutional neural networks (CNNs) trained on grayscale structural images have demonstrated the ability to predict stiffness and strength with errors below 3%, capturing the influence of spatial arrangement and phase morphology [40]. For damage analysis in woven and textile ceramic matrix composites (CMC), physics-informed recurrent neural networks (RNN) surrogate models have been developed [18, 41]. These ML models capture key deformation mechanisms and predict full nonlinear stress-strain responses with $R^2 > 0.99$, achieving orders-of-magnitude speedups (up to $\sim 10^7$ - $10^8 \times$) relative to high-fidelity generalized method of cells approaches.

AI/ML has also accelerated the optimization of composite material architectures. For functionally graded composites, where ceramic-to-metal gradation must simultaneously manage stiffness distribution, thermal-stress mitigation, and manufacturability, 3D-CNN surrogate models trained on non-uniform rational B-splines (NURBS)-represented microstructures have replaced repeated 3D isogeometric analysis (IGA) evaluations, enabling multi-objective optimization of graded fields [39]. These models have reported values of R^2 = 0.9998, allowing optimized designs with improvements of up to 43% in the fundamental

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frequency.

In architected bio-inspired composites, where toughness and pseudo-ductility emerge from discontinuities, crack-deflection features, and staggered morphologies, BO with GPR has been shown to increase composite toughness by more than 100%, identifying optimal geometrical configurations with only limited FE simulation data [43]. Similarly, BO was used to design staggered platelet composites with 12% improved toughness after only five additional experiments [44]. BO has also been applied to maximize fracture energy in bioinspired helicoidal composites [45]. An adaptive Kriging-based Bayesian updating for laminated structures was proposed [46]. A latent variable Gaussian process (LVGP) that encodes discrete microstructure classes into a continuous latent space to support multiscale topology optimization was reported [47].

In structural architectures, dual graph neural networks (GNNs) have been developed to predict lattice truss deformation and stress-strain response, generalizing to unseen configurations [48]. SVMs have been applied to analyze filament deformation in 3D cementitious printing, identifying yield stress and nozzle speed as the dominant factors [49].

4.2 Nanocomposites

Recent studies on polymer nanocomposites using AI/ML indicate that simulation-driven surrogate modeling is now the dominant approach, where multiscale representative volume element (RVE)–FEM or MD datasets are used to train fast regressors for thermal or multifunctional design. These include carbon nanotube (CNT)- or graphene-based composites being modeled using ANN–particle swarm optimization (PSO), GPR, SVM, decision trees (DT), and RSM surrogates to rapidly predict thermal conductivity under uncertainty [50-56].

A second category integrates simulation and experiments for inverse characterization, where ML extracts hidden interphase or morphology parameters, such as dielectric interface properties or CNT waviness, by aligning FE predictions with measurements [57-59]. A third trend uses experimental or literature-derived datasets to train predictive models for mechanical strength, EMI shielding, or sensing performance, with ensembles, ANNs, and SVMs enabling rapid screening and revealing key material/design factors [60-62].

Unsupervised learning also appears in microstructure characterization, where clustering and density-estimation methods quantify dispersion or agglomeration without labels [63]. Finally, AI/ML increasingly serves as a reduced-order component inside multiphysics simulations, accelerating electromechanical MEMS modeling, EMI/EM designs, and ablation response prediction with compact ANN surrogates [64-67]. Explainable AI tools such as Shapley additive explanations (SHAP) and local interpretable model-agnostic explanations (LIME) have also been used to interpret thermal conductivity predictions in graphene nanocomposites, relating eXtreme gradient boosting (XGBoost) feature importance back to physical filler phenomena [68].

4.3 Microstructure Segmentation and Generation

With the recent advances in deep learning, AI is increasingly used for automated microstructure segmentation, quantitative feature extraction, and synthetic microstructure generation in composites research. This subsection focuses on AI-enabled microstructure analysis workflows using imaging data (e.g., X-ray micro-computed tomography (CT), optical, and electron microscopy) to support structure–property modeling and materials design.

CT-based workflows aim to reconstruct physically realistic micromechanical models by converting volumetric scans into digital representations. Traditional thresholding-based segmentation has largely been replaced by semantic segmentation, primarily U-Net style CNNs, that classify fibers, matrix, and voids on a voxel basis [69-73]. Reported segmentation accuracies above 95% are common, but validation is often limited to a small number of high-quality scans or simulated datasets with fewer demonstrations under varied industrial conditions.

Phase-level labeling has proven insufficient for predictive modeling, particularly in textile composites, motivating instance segmentation approaches that resolve individual yarn and tow identities. Synthetic CT generation for training Mask R-CNN architectures and pseudo-labeling strategies enable yarn-resolved RVE construction without exhaustive manual labeling. This substantially improves annotation efficiency but introduces dependence on realistic synthetic data and heuristic segmentation logic (e.g., via morphological tracking) [69, 74, 75]. Watershed post-processing approaches further isolate tows in tightly packed laminates, but segmentation errors propagate nonlinearly into reconstructed geometry, limiting confidence in subsequent micromechanical predictions. In the cited CT-digital twin studies, segmentation offsets at tow boundaries, orientation field interpolation, and partial volume artifacts are repeatedly highlighted as key sources of geometric uncertainty, which are expected to propagate nonlinearly into stiffness and damage predictions.

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CT compensation further extends applicability into industrial imaging regimes. Cycle-consistent generative adversarial network (CycleGAN)-based super-resolution artificially restores fiber-scale contrast from noisy or time-compressed CT scans. This reduces acquisition time in exchange for inference uncertainty with limited guarantees against hallucinated microstructural features [76]. Comparable workflows using CNN segmentation on degraded CT imagery achieve scan time reductions of about 80% while preserving average stiffness prediction accuracy, although strong grayscale nonuniformity and feature blurring remain persistent limitations [73].

Orientation-aware reconstructions enhance digital twins by integrating CNN slice classification, semantic segmentation, and object detection with physics-based orientation estimation to reconstruct woven RVEs from minimal angle CT datasets [77]. Complementary digital twin approaches embed porosity fields and tow distortions directly into FE models to improve prediction of stiffness degradation and damage initiation, but these frameworks remain tightly coupled to scan quality assumptions and limited weave libraries [71, 72, 78]. Generative adversarial network (GAN)-generated RVEs can expand training coverage by synthesizing statistically consistent microstructures, although training instability and hallucinated correlations remain key challenges [79]. Hybrid segmentation feature models enable experimental textile RVE extraction with improved experimental and FE agreement, but at limited scalability [80].

5. Processing and Manufacturing

AI/ML methods are increasingly being integrated into composites manufacturing, helping break the speed–fidelity trade-off in process simulation and decision-making by enabling high-fidelity predictions at near-real-time cost. The primary motivation is to accelerate process simulations, enable in-situ inspection and anomaly detection, and reduce cost while mitigating process-induced defects through optimization and control. In this domain, AI/ML is most commonly used to (i) develop high-speed surrogate models for coupled thermo-chemo-mechanical and flow analyses, (ii) interpret sparse in-situ sensing for defect detection and quality assurance, and (iii) support closed-loop process control under uncertainty. Consistent with the taxonomy defined earlier, Processing and Manufacturing is organized into five sub-categories (Table 2): Manufacturing, Defects & Quality, Process Science, Machining, and Bonding & Joining. For Manufacturing, we focus on automatic fiber placement (AFP) and additive manufacturing (AM) as representative case studies where AI/ML supports design-space exploration, process optimization, and defect detection. For Defects & Quality, applications range from in-situ detection of layup defects (e.g., gaps and overlaps) to image-based quantification of porosity and fiber misalignment, and process-induced deformation (PID). Process Science covers AI/ML-enabled research on process characterization and process simulation for processes such as resin infusion/RTM–VARTM and autoclave curing (e.g., cure cycle optimization). Machining and Bonding & Joining are summarized in Table 2, given their smaller publication footprint.

5.1 Manufacturing: Automatic Fiber Placement

AFP has emerged as a manufacturing process that can produce high-performance composite structures by enabling the precise and repeatable placement of composite tows onto complex mold surfaces [81]. AI/ML tools are increasingly used across the AFP workflow, including (i) modeling and design optimization, (ii) process parameter optimization, and (iii) in-process defect detection and mitigation.

Table 2: Summary of AI/ML methods and primary research objectives for the Processing and Manufacturing category.

Sub-Category	Main AI Methods (paper counts)	Primary Research Objectives
Manufacturing	ANNs (12) Linear Models (6) Vision-CNNs (6)	• Control parameters for AM/3D printing. • Optimize automated fiber placement (AFP) paths. • Automate structural repairs and toolpaths.
Defects & Quality	Vision-CNNs (19) Clustering (13) ANNs (11)	• Predict defect formation (e.g., gaps/overlaps). • In-situ inspection using machine vision. • Quantify porosity and fiber misalignment.
Process Science	ANNs (5) Clustering (3) GPR, PCE & UQ (3)	• Simulate resin flow/RTM filling patterns. • Optimize cure cycles for thick laminates. • Predict thermal histories during fabrication.
Machining	ANNs (10) Linear Models (9) SVMs (2)	• Predict cutting forces and tool wear. • Minimize drilling-induced delamination. • Optimize waterjet/laser cutting parameters.
Bonding & Joining	ANNs (1) Dim. Reduction (1)	• Detect weak adhesion and "kissing bonds". • Predict residual strength of bonded joints. • Optimize weld parameters for hybrid joints.

One of the primary advantages of AFP is the ability to steer fibers along curvilinear paths, enabling variable-stiffness composite structures with optimized performance [82]. However, the design of these structures often requires high-fidelity FE evaluations, making iterative optimization costly. AI/ML addresses this challenge through surrogate models (e.g., radial basis functions (RBF), Kriging, and ANNs) that approximate physics-based simulations at a fraction of the cost [83]. For example, RBF-based surrogate models were used to optimize the buckling load factor (BLF) of a composite wingbox subject to the Tsai–Wu failure criterion [82]. ANNs have also been used to build surrogates that quantify the impact of AFP defects, supporting the reduction of knockdown factors and potentially less restrictive design allowables [84]. BO has also been applied to identify improved designs with fewer expensive evaluations [85].

The quality and performance of AFP parts are highly dependent on key process parameters, including heating temperature, layup speed, and compaction pressure [81]. Traditionally, parameter optimization relies on extensive and costly trial-and-error experimentation or time-consuming simulations. ML

 VOR: doi.org/10.1016/j.compositesa.2026.110092

accelerates this step by training on data from physical experiments, numerical simulations, or multiscale models [81, 86, 87]. For instance, ANNs can be trained on experimental data to predict the thermal history during fabrication, enabling monitoring and process optimization with reduced experimental iteration [88]. More advanced approaches, such as theory-guided machine learning, aim to improve generalization beyond the training range and reduce data requirements relative to purely data-driven models [89].

Despite advances in process control, defects such as gaps, overlaps, wrinkles, twists, position error, and foreign object debris (FOD) can still occur during AFP production and compromise structural integrity [90]. In-process inspection is therefore essential, enabling defect detection and repair during layup. AFP inspection systems commonly rely on profilometry-derived point clouds (e.g., laser or structured light scanning) and machine vision [28, 91-94]. CNNs have been used for automated defect classification and, more recently, for near-real-time forecasting of defect formation [28]. As these models move closer to certification-relevant workflows, explainable AI is being explored to interpret model decisions (e.g., DeepSHAP, integrated gradients, and Grad-CAM variants) [95].

5.2 Manufacturing: Additive Manufacturing

AM of composites is dominated by FDM/FFF processing of reinforced thermoplastics (e.g., PEEK, ABS, and PLA), where part quality is governed by a high-dimensional set of process parameters such as printing speed, nozzle/bed temperature, and layer thickness. The coupled interactions of thermo-chemical-flow processes combined with phase changes, drive nonlinear changes in mechanical response, microstructure evolution, surface quality, and distortion, motivating AI/ML for rapid process–property mapping, optimization, and monitoring.

Response surface methodology (RSM) with design of experiment (DOE) remain common baselines for AM design-space exploration, including optimization of ceramic slurry/binder formulations [96], FFF parameters and composition in PLA-based composites [97], Box–Behnken designs for process–property correlation in PA6/CNT systems [98] and fiber-reinforced PC composites [99]. Beyond polynomial RSM, NN- and tree-based models have been used as surrogates for process optimization and dimensional quality prediction, such as for PETG-CF [100] and ABS/GF systems [101]. Additionally, CNNs combined with evolutionary search have been demonstrated for parameter optimization in continuous carbon fiber-reinforced polymer (CFRP) printing [102].

Computer vision techniques have also been applied for image segmentation and in-situ monitoring in composite AM. For example, porosity in 3D-printed CF-ABS parts was estimated using K-means clustering benchmarked against global and local thresholding on synthetic images [103]. The comparison showed that k-means achieved the highest accuracy. X-CT validation further supported ML-based porosity

 VOR: doi.org/10.1016/j.compositesa.2026.110092

quantification as a cost-effective alternative for composites.

5.3 Defects & Quality

AI/ML-enabled quality assurance is increasingly positioned as an in-process capability that links sensing to actionable metrics, including defects such as gaps/overlaps, wrinkles, porosity, and fiber misalignment. As discussed in Section 4.3, image-based quantification workflows (e.g., porosity and fiber misalignment from CT or microscopy) play a central role in defect quantification. Deep learning architectures, such as you-only-look-once (YOLOv8) and U-Net (CNN-based detection/segmentation), as well as hierarchical models such as PointNet++, enable in-situ inspection and classification of defects such as wrinkles and twists [94, 104]. More recently, workflows have shifted from post-process analysis toward in-process forecasting, where integrated long short-term memory (LSTM)–CNN architectures predict the formation of fiber twists before they are fully deposited, enabling proactive corrections [28].

Another key AI/ML application for composites process optimization is predicting process-induced deformation (PID), such as spring-in, warpage, and other distortions [105]. For composites, residual stresses develop during processing, leading to part deformation upon demolding [106]. Excess PIDs are often mitigated through tool compensation, shimming, and iterative rework [107]. Stochastic FE–trained ANN surrogates enabled sensitivity analysis of PID with respect to material and process parameters [108], enabling PID mitigation via process optimization [29, 109]. For example, a theory-guided GPR framework optimized cure cycles and layups using limited targeted experiments [29], while spatially-weighted GPR (SWGPR) fused multi-fidelity data to enable accurate spring-in predictions [4]. CNN-based surrogates predicted full-field deformation maps with high accuracy in seconds [110]. Beyond final-state prediction, CNN–LSTM models have been used to predict deformation history throughout curing [111], and physics-guided GPR models have quantified uncertainty in cure-induced spring-in while supporting efficient multivariate sensitivity analysis [112].

5.4 Process Science

In composites manufacturing, high-fidelity multiphysics process simulation models remain essential, but their costly characterization and calibration campaigns, combined with computational cost, often limit their applications to design-space exploration, process optimization, and defect mitigation. In resin infusion and liquid composite molding (RTM/VARTM/LCM), AI/ML mitigates flow variability by enabling near-real-time inference of permeability, porosity, and race-tracking from in-process sensing using ANN surrogates with Bayesian inversion or ensemble Kalman inversion (EKI) [113]. Gradient-boosting models (XGBoost/LightGBM) enable rapid quality diagnosis and defect localization [114], while PINN-based formulations support real-time monitoring of through-thickness permeability variations [37].

Thermo-chemical and thermo-mechanical analyses of temperature, cure-state evolution and material properties have also been studied using AI/ML, including PINN-based solvers for 1D thermoset curing [19, 115]. AI/ML is increasingly used to stabilize ill-posed inverse manufacturing problems where boundary conditions or internal state variables are not directly measurable. This includes RNN and classification models for multi-objective optimization of the cure cycle [116], as well as Bayesian inference frameworks that can estimate local heat-transfer coefficients (HTCs) and effective air temperatures from limited thermocouple data while quantifying uncertainty [117]. AI/ML is also used to accelerate process simulations, including combined theory-guided ANNs and reduced-order modeling frameworks to accelerate process simulations for complex aerospace components [118], and theory-guided GPRs to drastically accelerate the optimization of cure cycles and layups for thick laminate [29].

AI/ML also enables real-time monitoring and control during manufacturing, including property-tracking frameworks that infer prepreg property evolution during cure from in-situ measurements [19, 88, 119]. For example, theory-guided ANNs have been used to predict transient temperature fields in AFPs to support online, model-based heat-source control [89].

Kinetics characterization is fundamental in composites process simulation, enabling process optimization and defect mitigation [30, 120]. AI/ML accelerates kinetics characterization via computationally efficient surrogates, physics-informed PDE solvers, adaptive controllers, and continuous-learning architectures that support expanding kinetics databases [41, 120, 121]. Physics-informed frameworks, including physics-informed neural networks (PINNs), neural operators (PINOs), and physics-informed DeepONet (PIDON), embed governing PDEs to reduce repeated FE simulations and enable fast, physically consistent prediction of temperature and degree-of-cure (DOC) evolution [120, 122, 123]. Neural-network surrogates and hybrid genetic-algorithm–neural-network (GA–NN) approaches have been used to replace repeated FE evaluations in cure-cycle optimization.

Process characterization often requires extensive testing. Active-learning frameworks can substantially improve data efficiency. For example, active-learning GPR has characterized multi-stage pyrolysis reactions in ceramic-matrix composites with only a few targeted tests, while enabling accurate transfer learning to new material systems with minimal additional testing [30]. Beyond data efficiency, robust generalization across chemistries remains challenging for empirical kinetics models. Continuous-learning architectures, such as ATANets and FENets, mitigate this limitation by retaining prior kinetics knowledge, enabling scalable kinetics databases with stable accuracy [124]. Similarly, for pyrolysis and ablation, ANNs enable fast inference of boundary conditions (e.g., blowing rate and wall enthalpy) from internal temperature histories, stabilizing otherwise ill-posed inverse problems [67].

6. Mechanics and Performance

Mechanics and Performance of composites constitute the most extensive domain of AI application, accounting for the highest volume of research since 2010. Driven by the need to decode highly non-linear failure behaviors and spatiotemporal damage progression, AI models—led by a massive volume of ANN and clustering studies—are replacing high-fidelity but slow Finite Element Analysis (FEA). These data-driven tools are utilized to estimate design allowables [1, 125], predict compression-after-impact (CAI) strength [20], and perform remaining useful life (RUL) prognosis under fatigue loading [126]. The transition toward inverse design [127] allows researchers to input target performance metrics, such as specific energy absorption [128], to generate optimized material architectures and stacking sequences that were previously computationally inaccessible. A summary of the sub-categories, AI methods and their objectives for Mechanics and Performance category is listed in Table 3. In this section, we focus on three sub-categories of Mechanics & Failure, Impact & Crash, and Fatigue & Creep for a detailed review.

Table 3: Summary of AI/ML methods and primary research objectives for the Mechanics and Performance category.

Sub-Category	Main AI Methods (paper counts)	Primary Research Objectives
Mechanics & Failure	ANNs (160) Clustering (99) Linear Models (72)	• Predict progressive damage and failure surfaces. • Discover data-driven failure criteria. • Characterize material properties.
Impact & Crash	ANNs (17) GPR, PCE & UQ (13) Linear Models (9)	• Evaluate energy absorption and crashworthiness. • Detect and localize impact damage events. • Predict compression-after-impact (CAI) strength.
Dynamics & Stability	ANNs (10) GPR, PCE & UQ (10) Evolutionary (10)	• Quantify stochastic vibration and buckling loads. • Optimize resonance margins and modal responses. • Analyze aeroelastic flutter and stability.
Fatigue & Creep	ANNs (6) Tree Ensembles (4) Bayesian (3)	• Predict the remaining useful life (RUL). • Simulate time-dependent stiffness degradation. • Analyze viscoplastic and creep behavior.

6.1 Mechanics and Failure

Mechanical properties, damage, and failure remain the most widely studied topics in composites using AI/ML. These studies use various data sources (experimental, numerical, hybrid, and physics-guided/PDEs) and modeling approaches (accelerated forward surrogates, inverse analysis of ill-posed problems, failure-criterion discovery, multiscale coupling, and uncertainty quantification).

For example, using experimental data, SVM has been used for FRP-RC beam failure-mode classification [129]. U-Net-based segmentation has also been applied to nano-enhanced carbon fibers to support interfacial shear-strength analysis, with emphasis on mode identification and interfacial failure characterization [130]. In contrast, many studies leverage single-scale FE simulations to train surrogate regression models, including bonded-joint residual strength prediction via GPR [131], failure-angle approximation for composite plies using ANN-based replacements of iterative criteria [132], and pressure-vessel failure-factor prediction using deep neural ensembles [133]. At higher fidelity, multiscale FE and micromechanics-driven datasets enable surrogate modeling of complex failure envelopes. Examples include 3D RVE-based ANN prediction of biaxial and triaxial failure surfaces [134, 135], and Bayesian-optimized identification of anisotropic SMC failure criteria [136].

Recent studies on composite failure prediction can be grouped into four themes: (1) surrogate acceleration of failure models using ANNs [132, 133, 137, 138], (2) discovery of failure criteria using deep learning or sparse regression [134, 139, 140], (3) multiscale ML –FE coupling for progressive failure prediction [134-136, 141], and (4) probabilistic and uncertainty-aware frameworks incorporating Bayesian inference, Gaussian-process surrogates, or probability-embedded failure metrics [129, 131, 135, 142].

FE-only studies primarily use parametric simulations to build forward surrogates for design and optimization. These studies exploit FE sweeps to learn predictors of ballistic performance [143], transverse or effective moduli from micromechanical RVEs [144, 145], buckling loads [146, 147], or multiscale structural responses [148-150]. These models are typically deployed inside optimization loops, such as GRNN–NSGA-II layup optimization [151] or GA-based design searches [148, 152].

In contrast, hybrid experimental and numerical datasets enable ML models to perform tasks that are prohibitively expensive or impossible to perform with FE alone. Examples include cohesive law identification from pull-out tests [153], 3D defect reconstruction from 2D DSPSS fields using TL-enhanced 3D CNNs [154], crack sizing from shearography [155], and GAN-assisted recovery of PBX material-parameter distributions [156]. Bayesian CNNs and hybrid surrogates have also been used to quantify strength-uncertainty using DIC fields [157] and to reduce extrapolation uncertainty through transfer learning [133].

Multiscale simulation frameworks use ML to reduce the cost of hierarchical modeling. In concurrent FE^2 strategies, microscale RVEs are solved in tandem with the macroscale problem. In woven and twisted textile composites, this approach has been accelerated through ML meta-models and microstructure-aware surrogates, including macro–micro simulations [141] and FE–FFT framework enriched with stochastic yarn-scale variability from micro-CT [158]. Similar concepts appear in global–local FE^2 pipelines, where physics-guided NNs reduce repeated microscale solves, as demonstrated for an aeroelastic wingbox design [159], and in extreme-rate loading, where multiscale FE is paired with ML to predict underwater-explosion response [160].

A complementary class of methods employs hierarchical multiscale homogenization, using ML surrogates to replace expensive micro-to-macro mappings. Examples include surrogate-based stochastic stiffness prediction [161], parametrically upscaled continuum-damage models linking micromechanics to macro constitutive behavior [162], and molecular-to-continuum property mapping from MD simulations using data-driven predictors [163]. Hybrid ML–homogenization approaches have likewise been applied to thermal transport in nanocomposites [50].

Beyond property prediction, ML increasingly supports constitutive-law discovery and viscoelastic process modeling. Symbolic regression has been used to derive multiaxial yield functions directly from atomistic simulations [164], while LSTMs capture multiscale viscoelastic behavior during forming and curing of woven CFRPs [165]. Across these areas, multiscale ML papers are increasingly combining data-driven models with probabilistic modeling of microstructure uncertainty, employing random-field descriptions, Monte Carlo sampling, principal component analysis (PCA)-based microstructure encoding, and physics-guided models to propagate variability from micro- to macro-scale behavior [158, 159, 163].

6.2 Impact and Crash

Impact and crash problems are dominated by heterogeneous, largely internal damage evolution and limited observability, motivating AI/ML for (i) damage detection and localization from sparse sensing and NDE,

(ii) surrogate modeling for rapid impact response prediction, and (iii) inverse design and optimization for improved energy absorption.

Low-velocity impact (LVI) is typically associated with barely visible impact damage (BVID), where AI models are increasingly employed to detect damage states from sparse NDE data. For example, K-means clustering was used to classify impact-induced damage and associated load-bearing capacity in flax/coral bio-composite laminates using quasi-static indentation and acoustic-emission data [166]. In another example, FE-assisted AE analysis used differential evolution (DE) and PCA to support clustering and classification of impact damage mechanisms in CFRP laminates [167].

Image-based learning has also been used to infer LVI-BVID. Using surface profiles paired with internal damage measurements from tool-drop LVI tests, logistic regression, ridge regression, and random forest (RF) were used to predict impactor shape and delamination metrics (area and length) [168]. Related extensions include decision-tree multi-task learning [169] and compression-after-impact (CAI) studies [170]. In addition, self-monitoring smart composite fabrics have been used to train CNN models for failure characterization and to infer impact location and impact energy [171]. Attention-enhanced YOLOv5s and U-Net models have also been applied to μCT images to detect microcracks and extract key features in 3D angle-interlock woven composites [172].

Spatiotemporal attention-enhanced ANNs have been developed to correlate the BVID thermographic pattern in CFRP to impact energy [173]. Sensor-based monitoring has also combined electrical resistance and energy absorption to track impact damage, with K-means clustering and PCA to successfully identifying damage types such as delamination, matrix cracking and fiber breakage [174]. Similarly, strain signals and load signals could be used to train CNN models to identify impact localization and reconstruct impact time-history [175].

High-velocity impact (HVI) involves penetration-dominated and mixed-mode failure. In such cases, AI/ML is used for rapid damage assessment and surrogate-assisted design of impact-resistant architectures and process settings. For example, RSM with a Box-Behnken design was used to study fabric architecture and processing conditions to improve the ballistic energy absorption in Kevlar/Polypropylene woven composites [176]. In another study, ANNs trained on FE simulations enabled surrogate-based optimization of auxetic-core sandwich panels under impact loading [177]. Furthermore, impact resistance of SiC-Bamboo fiber/epoxy composites was improved via ANN-assisted process optimization, with interlaminar shear strength (ILSS) and impact resistance as outputs [178]. L27 design of experiment was employed to vary the SiC filler percentage, stirring duration and bamboo fiber layers and the outputs were ILSS and impact resistance. ANN was trained and used for parameter optimization.

6.3 Fatigue and Creep

Fatigue life prediction and endurance-limit screening remain central to the design of composite structures. However, self-heating of polymer composites during fatigue testing often limits the test frequency to 1–5 Hz, substantially extending test duration relative to metals [179-181]. In addition, substantial scatter is commonly reported in both static and fatigue data [180, 182]. Recent AI/ML applications therefore are focused on reducing the test burden and quantifying uncertainty.

In-situ IR imaging has been coupled with ANNs for online fatigue prognosis [25]. In carbon/epoxy laminates, ANN models based on stress concentration factors, loading levels, stacking sequences, and self-temperature-rise features outperform baseline methods such as decision trees and gradient boosting [25]. To account for progressive stiffness degradation and uncertainty, physics- and data-driven fatigue life prediction methods have been developed using stochastic stiffness-degradation models with BO [183].

Based on fatigue damage evolution in glass fiber-reinforced polymer (GFRP) laminates, laser-ultrasonic Lamb-wave velocity provides a data-rich, in-situ proxy for damage progression. Accordingly, Lamb-wave measurements were coupled with five physics-based sub-models, combined with Markov chain Monte Carlo (MCMC) for inverse parameter identification in each model [184]. The resulting posteriors were then used to calibrate and stack the sub-models into a master meta-model, enabling fatigue-life prediction with credible-interval (CI) criteria and validation against both stiffness-based and Lamb-wave-based experiments [184]. Related work used convolutional autoencoder (CAE) models for wave feature extraction and RNNs for fatigue loading condition recognition [185].

In self-sensing hybrid FRP composites, electrical resistance monitoring provides an in-situ signal that evolves with damage accumulation. Accordingly, LSTM models were trained to predict remaining fatigue life directly from resistance histories, without explicit stress or strain inputs [186]. Carbon fiber sensor tows enabled real-time monitoring, with resistance trends correlating with fatigue cycling across stress levels [186]. Similarly, CNT-based electrical resistance was linked to in-situ residual-strength prediction in fatigued glass/epoxy, and stacked ensembles outperformed individual regressors (e.g., ridge regression, K-nearest neighbors (KNN), DT, RF, XGBoost, and support vector regression (SVR)) [187].

7. Structural Health Monitoring and Sustainability

SHM and sustainability comprise a relatively small fraction of AI/ML-enabled composites research; however, they exhibit outsized impact, particularly for sustainability, as reflected by the citation metrics (see Figure 4). In SHM, AI/ML enables near-real-time integrity assessment from sparse acoustic-emission (AE) and guided-wave data, using CNN-based models with Bayesian inference for uncertainty-aware diagnosis. In sustainability-focused studies, AI/ML accelerates structure–property screening and qualification of bio-based and recycled composites. The details of this category are summarized in Table 4.

Table 4: Summary of AI/ML methods and primary research objectives for the SHM and Sustainability category.

Sub-Category	Main AI Methods (paper counts)	Primary Research Objectives
Structural Health Monitoring	ANNs (13) Vision CNNs (10) Clustering (7)	• Detect and locate damage via AE and Lamb waves. • Categorize failure modes using signal similarities. • Optimize sensor placement for monitoring,
Sustainability	Linear Models (3) ANNs (2) Vision CNNs (1)	• Predict bio-composite tensile strength. • Characterize recycled part behavior. • Optimize bio-based/green formulations.

7.1 Structural Health Monitoring

AE has been a popular NDI method used for structural health monitoring of composite structures. Recent studies increasingly use AI/ML to map AE, guided-wave, and ultrasonic signals to damage state. This includes CNN-based classification and localization using AE scalograms [188], CNN-based evaluation of breathing debonds from non-linear guided-wave signals [189], and Lamb wave-based damage detection in CFRP panels [17]. Additionally, denoising autoencoders (DAEs) have been used to improve ultrasonic damage imaging of complex CFRP composite structures [190], and signal-to-image encodings with Gramian angular field (GAF) have been coupled with CNNs for guided-wave damage detection [191].

Using aircraft-wing FE models informed by real flight loading and strain data, CNNs have been trained for damage detection and localization [192]. Physics-guided CNNs (PGCNNs) combine physics-model outputs with data-driven predictions via physics-constrained loss functions, achieving >90% accuracy across most studied CFRP layups [193]. For sensor placement and sparse sensing design, GPR surrogates have been used for vibration-based damage detection [194]. Related work combined Kriging-based mode-shape reconstruction with Lichtenberg optimization for sensor placement [195].

7.2 Sustainability

In sustainability and recyclability, AI/ML is mainly used for rapid property screening and process–structure –property mapping in bio-based and recycled composites [196-199]. For bio-based systems, regression and tree-based models (e.g., ANN, SVM, RF) have linked processing and morphology to mechanical performance [200]. For recycled thermoplastic composites, thermodynamics-informed, data-driven multiscale models such as the multiscale thermodynamics-informed neural network (MuTINN) capture local anisotropy and porosity effects with low error while reducing multiscale computation time by >90% [197]. Separately, CNNs trained on surface images have been used to predict tensile response and

 VOR: doi.org/10.1016/j.compositesa.2026.110092

interrogate fracture mechanisms in recycled CFRP composites [201]. To study the recyclability of thermoset composites, RSM was used to investigate the relationship between processing variables and material properties [196]. Overall, the literature remains fragmented, motivating standardized datasets and protocols for more transferable sustainability models.

8. Critical Evaluation and Research Gaps

8.1 Deployment Reliability and Methodological Maturity

AI/ML for composites should be evaluated under different expectations than many other materials, particularly for engineering and manufacturing deployment. Composites exhibit inherently stochastic responses due to material variability and process uncertainty, compounded by multiscale structure, orthotropic/anisotropic behavior, and nonlinear, multi-mode failure. In certification, this necessitates extensive testing and simulation to map variability across panel-to-panel and batch-to-batch scatter, environmental effects, geometric complexity, process-induced defects, and impact damage (BVID/VID).

Consequently, the central AI challenge for composites is not training or test accuracy, but deployment reliability, as stochasticity emerges under conditions beyond the training data distribution. Across many reviewed studies, surrogate models are trained on deterministic forward FE simulations, achieving near-unity agreement with the FE solver and primarily serving to accelerate numerical analysis (e.g., [202, 203]). However, this does not imply deployment reliability, as the aforementioned sources of variability are often outside the training distribution, leading to a virtual-to-real gap [81].

Currently, two recurring limitations reflect the field's maturity. First, most studies treat variability as generic additive noise (often Gaussian), rather than modeling mechanistic drivers. Recent work, however, is beginning to address this: Du et al. [20] decoupled aleatoric and epistemic uncertainty for compression-after-impact using a Bayesian ResNet, showing that epistemic uncertainty spikes at specific impact energies where training data are sparse. Additionally, Reiner [2] shows that MCMC-based Bayesian estimation is highly prior-sensitive, and that generic (e.g., Gaussian) priors can bias composite strength predictions.

Second, the field is still dominated by complex AI models trained in small independent-data regimes, often relying on only a handful of panels or manufacturing batches. To compensate, recent studies are exploring two fronts: virtual sample generation [204-206], and transfer learning [30, 207]. However, both require guardrails. For virtual sample generation, the assumed priors must be scrutinized, as they can bias predictions [2]. For transfer learning, negative transfer can occur when source and target domains are misaligned [22].

8.2 Generalization and Validation

Generalization in composites beyond the training zone is achievable only if simulation-based datasets capture the underlying physics with accurately calibrated stochastic parameters, and if experimental datasets are sufficiently large to capture the sources of uncertainty discussed above and represent the relevant distributions. As such, limited generalization typically stems from (i) low-fidelity and/or poorly calibrated models, and/or (ii) distribution shift in practice.

A recurring weakness in ML models trained on experiments is that test/validation data are often drawn from the same panel or batch. Coupon-level random splits can therefore leak information, since coupons from the same panel share process history and, frequently, defect statistics. For simulation-driven studies, in contrast, many datasets do not explicitly incorporate realistic priors. In addition, for many composite applications, developing truly high-fidelity numerical models remains challenging.

As such, high training accuracy metrics such as R^2 or RMSE are not sufficient. Robust conclusions require leakage-safe evidence of generalization, which in turn requires group-based splits by panel/batch/specimen, with the held-out set nested outside the hyperparameter-tuning and cross-validation loops. In addition, interpretability is increasingly used as supporting evidence, with methods such as SHAP/LIME and Sobol index analysis providing “grey-box” transparency that is valuable for certification [38, 68, 208].

To improve model robustness, physics integration is increasingly utilized in the composites literature. This includes a wide range of approaches, including physics-based features [209], physics-based kernels and architectures [29], and physics-based losses [18], including PINNs [37, 210]. Recent publications indicate that the field is moving beyond standard PINNs, as they often struggle with nonlinear, long-time dynamics such as exothermic curing reactions. This has motivated methods such as neural operators to learn families of solutions for rapid evaluation and real-time optimization [5], as well as co-training of coupled state variables and temporal domain decomposition [19].

8.3 Applied AI for Composites

Given that composite certification is built around statistical allowables (A- and B-basis), models that report only point estimates without uncertainty are not decision-grade. As such, uncertainty quantification (UQ) must be utilized as a decision guardrail. For example, Du et al. [20] demonstrated that model uncertainty can be used to trigger when additional testing or inspection is needed. This also requires prediction-interval checks and separation of epistemic uncertainty (uncertainty from limited data and model inadequacy) from aleatory uncertainty (intrinsic panel-to-panel and batch-to-batch scatter).

Lifecycle drift, and therefore distribution shift, is unavoidable, for example due to aging of fabrication equipment and material/process changes. As such, deployment of AI models for composites requires integration of sparse sensing and the capability for fine-tuning or Bayesian updating. Related to this, Mello and Gomes [195] highlighted the importance of sensor placement optimization under sparse sensing conditions.

Deployed models may be used in a variety of applications, including inverse problems to infer defects or boundary conditions, or more broadly for optimization. Inverse problems are often mathematically ill-posed with non-unique solutions, necessitating forward-consistency checks and calibrated prediction intervals. Interestingly, the field is moving toward “full-response inverse design.” For example, Ferdousi et al. [9] used cGANs to generate microstructures matching specific stress–strain responses, while Sun et al. [11] and Chen et al. [21] utilized VAEs and transfer-learning-guided GANs, respectively, for laminate design under manufacturing constraints.

9. Conclusions

This paper presented a comprehensive review of applications of AI/ML for composite materials, focusing on papers published in seven major journals in the field between 2010 and 2025, amounting to 1,474 AI/ML-enabled publications out of a total of 50,361 publications. This review followed a systematic approach, first conducting a comprehensive bibliometric analysis of all publications, followed by an in-depth technical review of over 200 selected papers spanning representative studies.

The initial analysis revealed a major inflection point around 2019, where the share of AI/ML-enabled publications increased sharply from an annual level of about 1% to around 7.1% in 2025 (over 300 publications in 2025 across the seven major journals). The bibliometric analysis revealed a field with uneven research activity, where Mechanics and Failure dominates the landscape, accounting for approximately 54% of the AI/ML-enabled publications in 2025. This category is largely focused on the application of ANNs as fast surrogates for forward FE simulations. While this research category sits in the mid-range of the novelty (defined as the fraction of publications after 2023) and impact (defined as annual average citations) spectrum, the Sustainability topic exhibits the highest impact with low novelty at one end of the spectrum. In contrast, thermal-related research, including thermal degradation and thermo-mechanical properties, shows high novelty with low impact at the other end of the spectrum, consistent with hallmarks of emerging topics.

However, despite the rapid expansion of research and applications across a wide range of topics using diverse AI/ML methods, this critical evaluation uncovers a significant “virtual-to-real” gap in the literature. Most existing models are trained either on data generated from high- and/or low-fidelity FE simulations in a deterministic manner, or on relatively small experimental datasets, without accounting for the inherent stochasticity of composites arising from material variability and process uncertainty. As a result, panel-to-panel and batch-to-batch variability, as well as the use of stochastic models with realistic priors, remains largely neglected, undermining generalization and deployment reliability of developed models.

To bridge this gap, emerging trends in the literature include physics-integrated learning, the use of stochastic FE simulations, and probabilistic ML models coupled with UQ. These advances are further complemented by recent workflows that leverage sparse in-situ sensing, which make practical fine-tuning and retraining feasible. In combination, these directions target major shortcomings of current models for composites: limited reliability under variability and distribution shift (addressed through UQ and probabilistic modeling, combined with in-situ sparse sensing), and limited generalization (addressed through physics-integrated formulations). Together, these methods can help overcome key barriers to applied AI in composites by enabling data-driven models that streamline complex engineering workflows, including aerospace design, certification, and qualification of composite structures.

Acknowledgement

The authors gratefully acknowledge financial support from the University of Washington, Seattle, WA. We also thank Mr. Luohaoran Wang, a former student in our group, for valuable discussions on AI applications in the sustainability and recyclability of composite materials. In addition, we appreciate Dr. Caleb Schoenholz for providing insightful feedback on the initial draft of the manuscript, particularly regarding physics-informed machine learning approaches for process-induced deformation, a topic he previously investigated as a PhD student in our group.

Author contributions: CRediT

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