

Hybrid Automotive Composites with Artificial Intelligence Based Optimization-Advances, Challenges and Future Directions

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Abstract. Modern vehicle designs increasingly employ hybrid automotive composites to reduce weight, enhance performance, and improve sustainability. The growing complexity of hybrid material systems due to multi-reinforcement architectures and process–structure–property linkage has highlighted the limits of classical trial-and-error and physics-based optimization. This review investigates the development of hybrid automotive composites and how Artificial Intelligence (AI)–based optimization is influencing material design, manufacturing, and the service life of composite products and components. These developments include AI aided material selection, hybrid configuration optimization, process parameter tuning, defect prediction, digital twins, and sustainability design frameworks. A systematic assessment is provided of major issues such as performance–recyclability trade-off, data insufficiency, lack of standard datasets, and model interpretability limitations. The review also highlights critical research gaps and future directions towards explainable, lifecycle-aware and autonomous AI-based composite systems. An industrial prospect is also discussed, where proper pathways for scalable, certifiable and sustainable deployment of AI-enabled hybrid composites in the next-generation automotive applications are highlighted.

Keywords: hybrid composite architectures, automotive lightweight materials, digital twins, explainable machine language, sustainable composites, process–structure–property relationships, circular economy design.

1.Introduction

1.1 Evolution of Automotive Composites

1.1.1 Transition from Monolithic to Hybrid Composites

Automotive materials have evolved from monolithic metals towards increasingly advanced hybrid composite systems to overcome the limitations of individual materials used. The automotive industry initially relied mainly on steels and aluminum alloys for vehicle structures because of their strength, ductility and established processing technologies. However, their relatively high density limits further weight reduction [1, 2]. This was followed by the introduction of fibre-reinforced polymer (FRP) composites, especially glass fibre–reinforced polymers (GFRP), which offered superior specific strength and corrosion resistance, but presented challenges with impact tolerance, recyclability and environmental burden [3, 4]. The emergence of hybrid automotive composites comprising metals combined with FRPs or different fibre types, and multi-reinforcement metal matrix composites to exploit synergistic behavior has been motivated by these limitations [2, 5, 6]. A combined reinforcement of SiC and graphite in a micron-sized hybrid system was found suitable for automotive structural applications [7]. Fibre-metal laminates, natural/synthetic fibre hybrids, and hybrid metal matrix composites are used to tailor stiffness, toughness, durability, and mitigate brittleness or cost penalties associated with monolithic systems [8–10]. This change illustrates a shift to multiple functionalities and balanced performance in the material design of automotive engineering [4, 11].

1.1.2 Lightweighting, Performance, and Sustainability Drivers

The rapid development of hybrid automotive composites has been driven by lightweighting, performance and sustainability requirements. The pressure for stricter fuel economy and emission regulations is compounded by the global trend of electrification. Therefore, the demand for materials that can reduce vehicle mass without losing durability has intensified, despite their relatively high cost, thereby supporting their use in automotive applications [5, 12]. Hybrid composites allow the placement of low-density polymers or natural fibres with high-strength, synthetic fibres or metals to gain stiffness, crashworthiness, fatigue, and energy absorption properties that outperform those of monolithic materials [2, 10, 13]. Natural fibres, recycled reinforcements and agro-waste particulates are increasingly being incorporated in composites so as to reduce embodied energy, cost and life-cycle environmental impact [4, 6, 9]. Advances in processing, interface engineering, and life-cycle assessment further support this transition. This has made hybrid automotive composites important for lightweight, high-performance and sustainable vehicle design [11, 12].

1.2 Need for Artificial Intelligence (AI)-Based Optimization

1.2.1 Complexity of Hybrid Material Systems

Due to the integration of different fibres, matrices, and reinforcements, hybrid automotive composites exhibit complex characteristics, including pronounced anisotropy, heterogeneous interfaces and strong process-structure-property coupling. Research indicates that multi-reinforcement systems lead to non-linear interactions between the

material composition, process parameters, and functional performances (mechanical strength, wear behavior, and surface integrity) [14]. The situation becomes more complex when considering competing automotive requirements, including lightweighting, crashworthiness, manufacturability, and sustainability, as well as multiphysics effects during processing and service [15-17]. As a result, conventional linear or reductionist approaches cannot effectively navigate the high-dimensional and counterintuitive design space.

1.2.2 Limitations of Trial-and-Error and Conventional Modelling

Conventional techniques such as trial and error experimentation and physics-based modelling approaches cannot capture the complex, non-linear interdependencies between variables and are increasingly inadequate for optimizing hybrid automotive composites. Single-objective optimization often results in sub-optimal trade-offs, such as enhanced wear resistance at the cost of machinability or surface quality [14]. In addition, high-fidelity numerical models are computationally intense and rely on simplifying assumptions that can reduce prediction accuracy under industrially relevant conditions [16, 17]. The combinatorial explosion of design variables makes it impractical to exhaustively experiment, necessitating the need for AI-driven, data-centric optimization frameworks for robust and efficient composite design. As depicted in Table 1, AI-based analysis can offer advantages over conventional optimization methods [15].

Table 1. Comparative Analysis of AI vs. Traditional Methods

Aspect	Traditional Methods	AI-Driven Methods	Advantage of AI
Computational Cost	High (Iterative Finite Element Analysis (FEA) loops)	Low (Once trained, surrogate models can provide rapid evaluations)	Enables exploration of vast design spaces impracticable with FEA.
Optimality	Often converges to local minima.	Better at finding global optima	Can identify non-intuitive, higher-performance designs within the defined design space.
Handling Uncertainty	Often separate, post hoc analysis (e.g., Monte Carlo).	Integrated directly into the optimization	More efficient and robust reliability-based design.
Manufacturability Integration	Often checked after design, leading to redesign loops.	Can be embedded as constraints within the AI optimization.	Manufacturability can be incorporated as a design constraint, reducing iterations.
Design Interpretation	Based on engineer's intuition from simulation results.	Provides data-driven insights via Explainable AI (XAI) on parameter influence.	Supports faster and more objective decision-making; and can improve user trust.
Knowledge Leverage	Relies on expert experience and documented standards.	Large language models (LLMs) can support cross-disciplinary knowledge synthesis and workflow automation	Can accelerate knowledge transfer and workflow development.

1.3 Scope, Objectives, and Structure of the Review

This review provides an overview of hybrid automotive composites developed using combinations of dissimilar reinforcements, matrices and manufacturing processes aimed at improving mechanical performance, lightweighting potential and sustainability. The main aim of the review is to critically assess how AI-based optimization frameworks are influencing composite materials design, manufacturing, performance prediction and service life. The review synthesizes current knowledge on hybrid composite architectures and processing routes, and state-of-the-art AI and machine-learning (ML) tools being applied across the composite lifecycle. It also highlights contradictions, challenges, and research gaps restricting industrial adoption of hybrid composites. Finally, it outlines near- and long-term research opportunities aligned with automotive sustainability and digitalization goals. The article begins with the fundamentals of hybrid composites and their manufacturing methods, followed by discussions of AI techniques and applications, sustainability issues, industrial case studies, challenges, and future recommendations and concludes with perspectives.

2. Hybrid Automotive Composites: Fundamentals and Classification

2.1 Definition and Design Philosophy of Hybrid Composites

Hybrid automotive composites are defined as advanced engineered material systems consisting of two or more different reinforcements such as natural fibres, synthetic fibres, metals and/or nano-scale fillers purposely incorporated in a polymer matrix or integrated structural assembly to exhibit performance that exceeds that of monolithic materials can offer [1, 18]. Hybrid composites are designed to exploit the complementary mechanical, physical and environmental properties of both fibrous and metallic materials. This combination can improve lightweighting

potential, strength, stiffness, durability, cost effectiveness and sustainability than can be achieved through conventional single-fibre composites or purely metallic structures. The design philosophy is application-driven and system-oriented, and aims to achieve optimal load sharing, tailored stiffness distribution and multifunctionality, rather than maximisation of a single property [19, 20]. In automotive engineering, this philosophy is usually implemented by the combination of natural and synthetic fibres, where carbon or glass fibres are used as the high-performance materials responsible for carrying the primary loads, and natural fibres provide insulation and reduce environmental impacts [1]. Hybridisation may also concern metal–composite systems, where metals ensure impact resistance, torque transmission and joint integrity, while FRPs improve specific stiffness and dynamic response [19]. The emphasis on fibre selection, volume fraction, orientation, stacking sequence and interfacial compatibility in hybrid composites from a materials design perspective serves to efficiently transfer stress, delay damage initiation and improve damage tolerance [20]. Consideration of manufacturability, durability, and lifecycle performance supports the consideration of hybrid automotive composites as smart materials for modern vehicle lightweighting and sustainability designs [18].

2.1 Types of Hybridization

2.1.1 Fibre–Fibre Hybrids

Fibre–fibre hybridization refers to the mixing of two or more fibre types in a common matrix. This is the most studied and widely used type of hybridization in automotive composites to exploit the complementary mechanical and functional properties of different fibres. Standard configurations are carbon-glass, glass-aramid and synthetic-natural fibre hybrids. Here, high-stiffness fibres carry the primary load whereas ductile or sustainable fibres provide toughness, impact resistance and cost efficiency. The stacking sequence, fibre orientation and volume fraction have a strong influence on the hybrid effect and control stress redistribution and gradual damage evolution. Experimental studies show that well-designed fibre-fibre hybrids can suppress brittle failure modes and delay crack propagation, resulting in increased energy absorption under impact loading. Natural-synthetic fibre hybrids also yield weight savings and environmental advantages, particularly for semi-structural components in automobiles. While hybridization can provide significant synergistic benefits, poor architectural design or interfacial incompatibility can reduce their merits [21–23].

2.1.2 Fibre–Matrix Hybrids

Interfacial performance, damage tolerance, and overall composite performance enhancement can be accomplished by hybridization of polymer matrix and fibre reinforcement. In automotive composites, this approach has involved modifying the thermoset or thermoplastic matrix through polymer blending, elastomer toughening or particulate and nano-scale additives while retaining conventional fibre architectures. The matrix plays a key role in governing stress transfer, delamination resistance, and failure mechanisms. Strong fibre-matrix interface adhesion improves stiffness and strength. Controlled interfacial debonding and fibre pull-out promote energy dissipation. Research shows that by optimizing the resin matrix chemistry, it is possible to drastically improve impact resistance and fatigue performance without modifying the fibre content. Poor compatibility between fibres and modified matrices can negate improvements in mechanical properties. Hybridization of fibre and matrix offers an important design control variable for lightweight, crashworthy, and manufacturable automotive composite structures [23–25].

2.1.3 Multi-Scale and Nano-Hybrid Systems

Multi-scale and nano-hybrid composites represent an innovative hybrid approach involving the integration of various scales of reinforcing materials, starting from macro-scale fibres to nano-scale fillers. In general, hybrid composites consist of fibres that serve as the primary source of rigidity and strength, and nano-scaled materials like silica, nanoclay, carbon nanotubes, and graphene that provide toughness and resistance to cracks in the matrix. Adding nano-reinforcements helps to fill in microcracks, limit the growth of even larger cracks, and stabilize the exponential growth of damage. This ultimately leads to improvements in flexural, impact, and fatigue properties. Studies based on morphology show that the properties of the composite benefit from uniform nanoparticle dispersion along with strong interfacial bonding. In the absence of them, performance can degrade due to agglomeration. Multi-scale hybrid composites have the potential to simultaneously improve lightweighting, durability, vibration damping, and environmental resistance of automotive applications. Although promising, barriers to large-scale industrial deployments include processing scalability, control of dispersion, and cost [23–25].

2.2 Common Materials Used in Automotive Applications

2.2.1 Natural, Synthetic, and Recycled Fibres

In automotive composite systems, natural, synthetic and recycled fibres are selected to meet the demands for lightweighting, mechanical performance, cost-effectiveness and sustainability [25, 26]. Natural fibres such as flax, hemp, jute, kenaf, sisal, coir and wood fibres have gained popularity in interior and semi-structural automotive components due to their low density, renewability, biodegradability and relatively favourable specific stiffness and strength [27–29]. Additionally, natural fibres possess beneficial vibration damping and acoustic insulation properties, which are valuable for automotive interior applications [27, 30]. In contrast, synthetic fibres (glass, carbon and aramid

fibres) continue to be widely used in load-bearing and performance-critical automotive components due to their superior absolute strength, stiffness, thermal stability and durability [26, 29, 31]. However, the high energy consumption, non-renewable origin and recycling difficulties associated with synthetic fibres have led to increased research into the use of recycled fibres (reclaimed glass fibres, recycled carbon fibres and recycled polymeric fibres) [32-34]. These recycled fibres support circular economy strategies by minimising material waste and embodied energy while providing adequate mechanical performance in non-critical automotive components [35, 36].

2.2.2 Thermoset versus Thermoplastic Matrices

The polymer matrix plays a decisive role in determining the mechanical performance, processing characteristics, and End-of-Life (EoL) options of automotive composites, with thermoset and thermoplastic systems being the two principal categories [26, 30]. Thermoset matrices such as epoxy, polyester, vinyl ester, phenolic, and polyurethane resins are widely used in automotive applications due to their high stiffness, dimensional stability, chemical resistance, and strong fibre–matrix adhesion resulting from their crosslinked molecular networks [29, 35, 37]. These properties make thermosets suitable for structural and semi-structural components where temperature and mechanical stability are critical. However, the irreversible curing process limits the recyclability and repairability of thermosets posing sustainability concerns [27, 36]. On the other hand, thermoplastics like polypropylene, polyethylene, polyamide, polycarbonate, polyethylene terephthalate, and bio-polymers such as polylactic acid exhibit properties such as reprocessability, high-impact resistance, compatibility with high-volume manufacturing techniques (injection, compression molding, etc.) [28, 32, 38]. Although challenges remain because of higher melt viscosity and fibre–matrix interfacial bonding issues, particularly for natural fibres, thermoplastics are becoming increasingly popular, due to their recyclability as well as vehicle EoL legislations and circular economy [31, 33, 34].

3. Manufacturing Techniques for Hybrid Automotive Composites

3.1 Conventional Manufacturing Processes

3.1.1 Compression Molding

In the manufacture of hybrid automotive composites, compression molding is one of the most widely used technologies due to its maturity, fast cycle times and suitability for mass production [39-41]. Figure 1 depicts a schematic of compression molding.

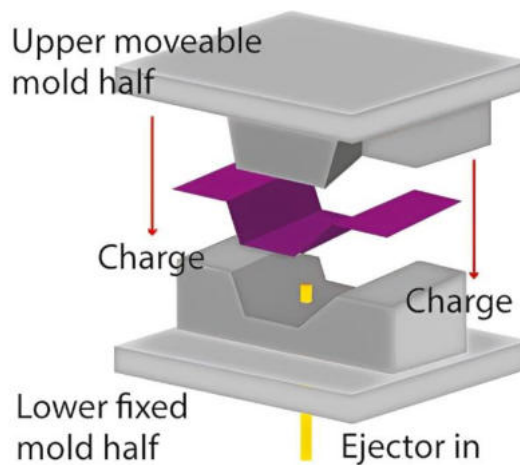


Fig. 1 - Schematic Representation of Compression Molding [42]

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Thermoset and thermoplastic hybrid systems may also be used for the process (sheet molding compound, long-fibre thermoplastic, hybrid fibre mat). Different natural and synthetic fibre reinforcements can be combined in a single component [40, 41]. Because compression molding offers good surface finish, dimensional stability, and relatively high fibre volume fractions, it is suitable, for semi-structural and structural automotive components [39, 43]. It is possible to modify hybrid architectures through strategies of charge placement and localized reinforcement to increase stiffness, impact resistance and weight reduction [41, 44]. Nonetheless, fibre reorientation caused by resin flow, non-uniform impregnation, and limited control over complex fibre architectures can cause mechanical anisotropy as well as variations in hybrid laminates [43-45].

3.1.2 Resin Transfer Moulding (RTM)

RTM is an established closed mold technology for high-quality hybrid automotive composites with defined fibre architecture and size precision [39, 40]. Figure 2 shows a schematic of RTM. In RTM, dry hybrid fibre architectures consisting of glass, carbon, and/or natural fibres, among others, are infiltrated with a low-viscosity thermosetting resin with pressure/vacuum assistance [41, 43]. By using this procedure, the fibre wet-out, void content and surface finish are superior to those obtained with open-mold processes [40, 44]. RTM has particular suitability for load-bearing automotive components, especially with fibres placed subject to loading, and high structural integrity [39, 45]. However permeability mismatches between dissimilar fibres, long cycle times, and the need for accurate resin rheology control and injection strategy remain a challenge for high volume automotive applications [43-45].

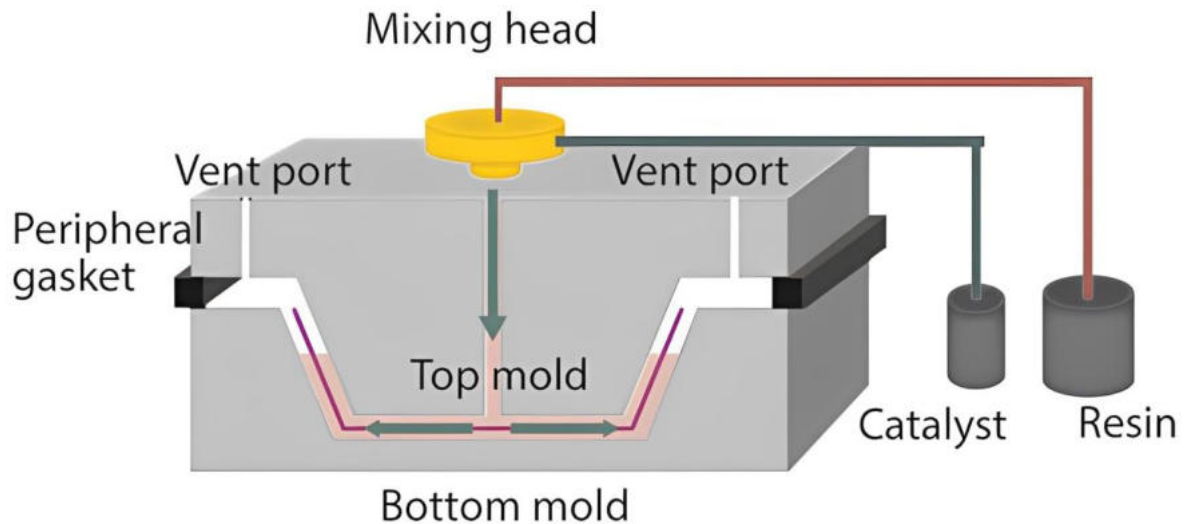


Fig. 2. - Schematic Representation of RTM [42]

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3.1.3 Injection Molding and Thermoforming

Injection molding and thermoforming are mainly used in the production of hybrid automotive composites based on thermoplastic materials, where high productivity and recyclability are important requirements [40, 46]. Injection molding is also used in the production of more intricate components through the use of short- or long-fibre-reinforced thermoplastics, enabling high levels of automation, dimensional accuracy, and functional integration [41, 46]. Figure 3 shows a schematic of injection molding. Hybrid structures are typically achieved by overmolding ribs and fastening features onto continuous fibre-reinforced laminates or metallic inserts and provide opportunities for lightweight design and assembly consolidation [44, 47]. Thermoforming shapes pre-consolidated hybrid composite sheets into geometry under controlled heat and pressure while maintaining continuous reinforcement and allowing for rapid cycle times to be achieved [46, 48]. There are, however, significant limitations to the mechanical performance and reliability of injection-molded and thermoformed hybrid components due to fibre breakage, orientation variability, and interfacial bonding quality [46-48].

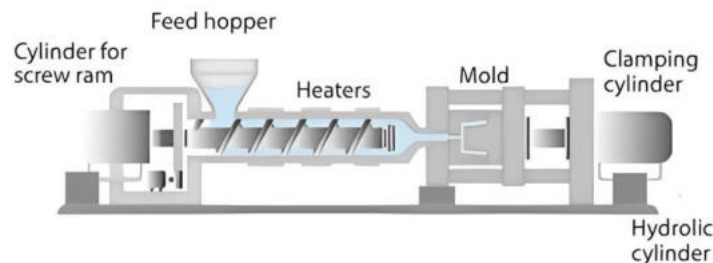


Fig. 3 - Schematic Representation of Injection Molding [42]

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3.2 Advanced and Smart Manufacturing Approaches

3.2.2 Automated Fibre Placement (AFP)

AFP enables precise, programmable placement of continuous fibre tows with controlled orientation and stacking, which is of great value to hybrid composites in automotive parts [43, 44]. AFP makes it possible to hybridize materials at specific localized areas by using high-performance fibres, especially carbon, only in load-carrying areas, while using less expensive fibres, such as glass or natural fibres, in less demanding areas [41, 45]. It is also possible with AFP to optimize material use and maximize structural efficiency while improving stiffness-to-weight ratios [44, 46]. AFP can also reduce labour requirements compared with traditional lay-up methods [43, 47]. However, AFP is relatively expensive, with slower deposition rates, while there is also need for downstream consolidation processes, including RTM and/or compression molding, that can restrict use of AFP in automotive manufacturing [46–48].

3.2.3 Additive Manufacturing (AM) and Hybrid AM

AM is a promising method for the fabrication of hybrid composites to develop tooling, inserts, cores and local reinforcement [46, 47]. AM allows for complex geometries, functional integration, and fast prototyping with less material waste [48]. Hybrid AM approaches combine additive processes with standard composite manufacturing routes. For example, hybrid processes could entail using printed polymer features with RTM or compression molded fibre-reinforced laminates [45, 47]. These strategies improve design freedom and part consolidation, but issues of anisotropy, interfacial bonding and repeatability continue to inhibit large-scale structural automotive applications [46–48].

3.2.4 Digital Twins in Composite Manufacturing

Digital twins connect physical production systems for hybrid composites with virtual process models, offering a promising step towards smart manufacturing of automotive composites [48, 49]. Digital twins that combine sensor information with simulations of resin flow, curing, thermal behavior, and fibre deformation allow process predictions and defect mitigation [45, 47, 49]. In the hybrid composite manufacturing process, these tools are especially useful for optimizing heterogeneous materials, permeability variations and complex interfacial interactions of two or more dissimilar material constituents [44, 48]. Digital twins can reduce the trial and error experimentation, increasing quality assurance and improving process robustness throughout the production life cycle [47, 49]. The performance of these techniques largely depends on reliable material models, dependable in-situ monitoring, and thorough experimental validation [48, 49].

4 AI-Based Optimization Techniques in Hybrid Composite Design

4.1 Overview of AI and ML Methods

4.1.2 Artificial Neural Networks (ANNs)

ANNs are widely used ML methods capable of modelling complex and strongly nonlinear relations, not necessarily relying on physical models of governing equations [50, 51]. Although these methods were inspired by biological neural structures, including layered connections of artificial neurons with input, hidden, and output layers, their learning capability facilitates adaptable structures with weighted connections and nonlinear activation functions [52, 53]. Backpropagation methods of error minimization are generally applied in training ANN models [50, 54]. Due to their flexibility, ANN models are generally well-suited in dealing with complex multivariate, noisy, and multimodal data patterns in many engineering tasks [51, 55]. However, ANN predictions are sensitive to network architecture, learning rate, and training data [53, 56]. Therefore, regularized hyperparameter settings of ANN models are critical in order to obtain statistically reliable and generalizable predictions [55, 57].

4.1.3 Support Vector Machines (SVMs)

SVMs are a type of supervised learning algorithms based on the structural risk minimization principle which enhances generalization capability [50, 53]. The main aim of SVMs is to create an optimal hyperplane in a high dimensional space that maximizes the margin between the data points [52, 54]. SVMs utilize kernel functions for nonlinear problems to implicitly map input data into higher dimensional spaces, thereby modelling complex relationships [51, 55]. By virtue of the margin-based learning framework, SVMs are reasonably robust to overfitting and work well when the number of samples is not too large but the dimensionality is high [53, 56]. SVMs are less susceptible to local-minimum problems than ANNs and their solutions are more stable and repeatable [50, 57]. However, kernel selection and parameter tuning greatly affect their predictive performance, and for large datasets, they have substantial computational complexity, limiting their applicability in big data applications [54, 55].

4.1.4 Decision Trees and Ensemble Models

Decision trees are a rule-based ML method that recursively divides the input feature space into homogeneous sub-groups according to criteria such as information gain or impurity reduction [51, 52]. Due to their sequential nature, decision trees have clear rules that make them easy to interpret. Therefore, they are suitable for applications where the ability of a model to explain its reasoning is important [53, 57]. Individual decision trees can be unstable and prone to

overfitting. This is especially the case if the data used is noisy or complex [50, 54]. To overcome these limitations and improve the predictive accuracy and generalization performance, ensemble learning approaches like random forests, bagging and boosting utilize multiple decision trees [55, 56]. Aggregating the predictions of a number of weak models helps ensemble models reduce the effects of both bias and variance and increase the robustness to the uncertainties associated with the data [51, 57]. In addition, these models allow the calculation of the feature importance and have been shown to outperform standalone models of ANN and SVM in predicting tasks in engineering applications [52, 56].

4.2 Deep Learning and Physics-Informed AI

4.2.2 Convolutional Neural Networks (CNNs) for Microstructure Analysis

Deep learning methods are increasingly applied in microstructure analysis, especially CNNs, which are capable of automatically capturing spatial features from high-dimensional image data [58]. In materials and structural engineering, CNNs enable the analysis of microstructural characteristics such as grain morphology, porosity distribution, crack initiation sites, and damage localization, all of which have crucial effects on macroscopic mechanical and fatigue behavior [59, 60]. Through learning directly from either microscopy images or spatially resolved simulation outputs, CNNs are able to capture complex non-linear correlations between microstructural heterogeneity and material response that are difficult to represent through manually engineered descriptors [60]. By incorporating a stress-strain field, energy dissipation maps, or representative volume element data, CNN-based surrogate models can efficiently establish the microstructure-property link and reduce computational cost, thus complementing traditional physics-based constitutive modelling [58, 61].

4.2.3 Hybrid Data-Driven-Physics-Based Models

Beyond purely data-driven learning, hybrid data-driven-physics based models are a major step towards applying deep learning to engineering and materials problems [58, 61]. ML architectures, training datasets or loss functions can be formulated to incorporate governing physical principles like energy conservation, thermodynamic consistency, damage irreversibility or fatigue evolution laws [59, 62]. This incorporation of physical constraints restricts the solution space of deep neural networks, reduces overfitting, and improves extrapolation to unseen loading or processing conditions [60, 63]. Hybrid methods have shown strong generalisation ability in the literature and also substantial savings in computational cost as compared to fully resolved numerical simulations [58]. By combining mechanistic knowledge with the expressive power of deep learning, physics-informed hybrid models can provide robust, interpretable, and scalable surrogate solutions for multiscale materials modelling, structural analysis, and fatigue life prediction [61-63].

4.3 Optimization Algorithms

4.3.2 Genetic Algorithms (GAs)

GAs are optimization methods based on population evolution. GAs are based on the principle of natural selection. This principle favours the selection of fitter solutions for reproduction. Similarly, this algorithm is based on chromosome-based representations. Genetic and evolution-based algorithms are responsible for generating new offspring [64-70]. The fact that they do not rely on derivatives makes it possible for them to explore complex, nonlinear and multimodal search spaces where gradient information may not be available or uncertain [65, 68]. GAs are readily applied in engineering and ML optimization problems with mixed discrete-continuous variables, complex constraints and multiple local optima [66, 69]. The stochastic nature of GAs provides a stochastic search mechanism which promotes global search and is against to premature convergence, while selection pressure enables gradual exploitation of promising regions [64, 68]. Depending on population size, encoding schemes, and parameters of genetic operators, GA performance depends strongly on these setting, which is often empirical tuning [65, 69]. In addition, the convergence of GAs can be relatively slow for high-dimensional problems, motivating hybridization with swarm-based or probabilistic optimization approaches [66, 70].

4.3.3 Particle Swarm Optimization (PSO)

PSO is a swarm-intelligence-based metaheuristic inspired from social-behavior observed in animal groups such as bird flocks or fish schools [64-70]. Particles in PSO are candidate solutions that move in the search space by updating their velocities and positions through both personal best experience and shared global knowledge [65, 69]. According to [64, 68], this mechanism for information sharing can strike an efficient balance between exploitation and exploration. Moreover, unlike GAs, the mechanism has a relatively simple structure and requires fewer control parameters. PSO usually shows quicker convergence and smaller computational cost, making it appealing for large-scale and real-time optimization problems [65, 70]. Despite this, its performance depends on inertia weights, acceleration coefficients, and swarm topology and insufficient diversity can lead to premature convergence [66, 68]. As a result, numerous studies have investigated on adaptive and hybrid PSO variants to boost reliability and robustness [69, 70].

4.3.4 Bayesian Optimization (BO)

BO is a probabilistic, model-based optimization approach for cases in which objective-function evaluations are costly, noisy, or limited [68-70]. The surrogate model constructed by BO is often based on a Gaussian process, which approximates the objective function and quantifies predictive uncertainty [66, 69]. Thus, acquisition functions guide the sequential selection of new points to evaluate by balancing the exploration of uncertain regions with the exploitation of promising solutions [65, 68]. This strategy, which accounts for predictive uncertainty, allows for high sample efficiency and rapid convergence with far fewer evaluations than population-based heuristics [64, 70]. BO is particularly useful for hyperparameter tuning as well as experimental design in ML and engineering applications [66, 70]. However, the scalability of the approach may be limited in high-dimensional spaces because of the complexity of the surrogate model, which motivates various hybridizations of BO with GA or PSO so as to leverage complementary strengths [67–69].

5 AI Applications Across the Composite Lifecycle

5.1 Material Selection and Hybrid Configuration Optimization

AI has become a key enabler for the material selection and configuration optimization of hybrid automotive composites, where lightweighting, mechanical performance, durability and manufacturability must be considered simultaneously. AI-driven frameworks can efficiently navigate the high-dimensional design space resulting from the complex combinations of matrices, fibres, fillers, geometries, volume fractions, orientations and AM parameters, by learning robust structure–property and process–structure–property relationships from experimental, simulation, and microstructural image data [71, 72]. Predicting the mechanical properties of materials through computational modelling is a common practice in materials science. Supervised ML, deep learning, and hybrid ML–physics models can substantially reduce trial-and-error testing through accelerated screening and ranking of candidate material systems in terms of target metrics such as specific stiffness, strength, energy absorption, and fatigue resistance [71]. Moreover, the implementation of inverse design and optimization strategies, along with ML surrogates, makes it possible to optimize configurations (fibre orientation, stacking sequence, thickness distribution, etc.) autonomously while maintaining their physical plausibility via physics-based validation [71, 72]. Collectively, these approaches will accelerate design iterations, enhance performance trade-offs, and facilitate the design of custom-tailored, high-performance, and sustainable hybrid automotive composite architectures [71, 72].

5.2 Process Parameter Optimization and Defect Prediction

The use of AI has become increasingly important for process parameters optimization and defect prediction of hybrid automotive composite manufacturing due to the coexistence of material heterogeneity, complex processing routes and stringent quality requirements. Surrogate models based on ANNs and ensemble learners are computationally inexpensive alternatives to high-fidelity finite element simulations that can rapidly optimize curing cycles, fibre placement strategies and consolidation parameters while reducing the use of trial-and-error experiments significantly [15]. Table 2 summarizes the prevalent methodologies of the AI-based composite-process optimization. These methodologies mostly consist of ANNs, SVMs and hybrid surrogate frameworks, since they can capture strong nonlinearities between manufacturing variables and quality responses [15].

Table 2. AI Methodologies for Composite Design and Optimization [15]
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Methodology Category	Specific Techniques	Primary Function in Composite Design	Key Advantages	References
Surrogate Modelling & Global Optimization	ANN-GA, ANN-PSO, PSO-ANN	Replaces costly FEA simulations; identifies global or near-global optima for stacking sequences and dimensions.	Can substantially reduce computational cost; effective for high-dimensional, non-linear problems.	[73, 74]
Hybrid & Advanced Predictive Models	Adaptive Neuro-Fuzzy Inference System (ANFIS)-GA, ANFIS-PSO, ANN-Non-Dominated Sorting Genetic Algorithm II (NSGA-II)	Predicts complex behaviors such as buckling and fatigue life while accounting for imperfections.	High accuracy (high R^2 and low root mean squared error); handles uncertainty and multi-objective optimization.	[75, 76]
XAI	SHapley Additive exPlanations (SHAP), Partial Dependence Plots	Interprets black-box models; identifies critical design	Can improve engineering trust; enables informed	[77-79]

	(PDPs), Counterfactual Analysis	parameters and their influence.	design adjustments; supports certification.	
Uncertainty & Design Allowables	XGBoost, Random Forests, Gaussian Processes	Predicts statistical distribution of material properties (e.g., notched strength, fire-retardant behavior) for reliable design.	Establishes statistical design allowables computationally; manages material and process variability.	[80-84]
LLMs	Generative Pre-trained Transformer 4 (GPT-4) with LangChain, MechGPT, CompCap for Multimodal LLMs (MLLMs)	Automates process planning; integrates cross-disciplinary knowledge; interprets multimodal data.	Automates workflows; enhances knowledge retrieval and synthesis; bridges design and documentation.	[85-87]

Temperature, pressure, resin flow, fibre orientation, and curing time are among the process parameters that can affect the performance of these parts. Robust process windows can be identified by these models minimizing voids and promoting uniform impregnation and the required mechanical properties under loading conditions encountered in automotive applications [88]. At the same time, defect prediction frameworks using AI use deep learning architectures particularly CNNs to identify delamination, porosity, fibre misalignment, and interfacial defects with in-line sensor data, as well as non-destructive evaluation methodologies (e.g. thermography, ultrasonics, X-ray computed tomography) [89, 90]. Integration of XAI further allows identification of dominant process variables responsible for defect formation, supporting closed-loop control and real-time corrective action [15]. AI-enabled approaches equipped with Industry 4.0 and Quality 4.0 paradigms allow a transition from reactive post-process inspection to predictive quality control, scalable, reliable, and sustainable hybrid automotive composite manufacturing [89].

5.3 Mechanical, Thermal, and Impact Property Prediction

AI has proven to be an effective and robust framework for predicting the mechanical, thermal and impact properties of hybrid automotive composites. These materials are complex because of their heterogeneous and multiscale reinforcements with nonlinear damage behavior. A variety of supervised ML models such as ANNs, support vector regression, random forest ensembles, and decision-tree-based algorithms have been widely adopted for the prediction of tensile, flexural, fatigue, and fracture properties by learning their nonlinear correlations with constituent properties, processing conditions, and microstructure features [91, 92]. Data-driven methods can provide improved predictive performance than empirical or physics-based models, particularly in the case of hybrid system models with natural and synthetic fibres, where experimental datasets are scarce or expensive to obtain [91]. AI-based prediction has also been extended from mechanical properties to the prediction of thermophysical properties, namely thermal conductivity, degradation temperature, and thermomechanical stability, using the output from the Thermogravimetric Analysis and Dynamic Mechanical Analysis tests along with the compositional variables [92]. Deep learning models may also allow for the direct extraction of the structure–property relationship from microstructural images. These models can capture of fibre orientation, interfacial quality, and filler dispersion on coupled thermal–mechanical performance [91]. AI-based models have proven to be effective in predicting impact strength, energy absorption, and damage tolerance under dynamic loading. They are useful in crashworthiness design thereby enabling more efficient virtual screening of hybrid composite configurations. [92, 93] When combined, these AI-based predictive tools aid in multi-property assessment in a unified manner, thus expediting material selection, and optimization of performance of next-generation hybrid automotive composites, while diminishing experimental burden and reducing development time significantly [91-93].

5.4 Structural Health Monitoring (SHM) and Damage Detection

AI-enabled SHM is emerging as an integral technique for damage assessment in hybrid automotive composites, thereby supporting a shift towards continuous monitoring instead of periodic inspection. The integration of multi-source information, including vibration response, acoustic emission, strain, ultrasonic, and thermographic data, with ML and deep learning algorithms, respectively, can enable AI-based SHM systems to identify, locate, and categorize complex damage states of matrix cracking, delamination, fibre failure, and barely visible impact damage with high accuracy [90, 94-96]. The use of vibration- and strain-based monitoring with supervised and unsupervised learning can help in identifying the stiffness degradation by looking at the changes in modal parameters under noisy operational conditions [90, 96]. Deep learning architectures such as CNNs, recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and autoencoders can enhance SHM capability through automated feature extraction, temporal damage tracking, and anomaly detection with reduced dependence on labeled data [94]. Furthermore, AI-driven data fusion systems that blend different types of non-destructive testing improve diagnostic robustness and

reduce false positives associated with single-sensor strategies [90, 96]. The scalable and adaptable solutions from these AI-empowered SHM systems improve safety, enable predictive maintenance, and support improved design decision-making of lightweight structures with self-learning capabilities, for hybrid automotive composites with various loading and environmental conditions [94-96].

6 Sustainability, Circular Economy, and Environmental Impact

6.1 AI-Driven Eco-Design of Hybrid Composites

Eco-design for hybrid automotive composites involves incorporating environmental objectives at the material thereby reducing the need for modifications at later design stages. In contrast to traditional design frameworks focusing on mechanical performance, AI-based design frameworks can optimize stiffness, strength and weight along with other environmental parameters, such as embodied energy, recyclability, etc. Utilization of ML and evolutionary algorithms assists in the exploration of large design spaces made of fibre type, stacking sequence, matrix and hybridization ratio, ultimately leading to the identification of eco-efficient solutions that would be difficult to identify through trial-and-error experimentation.

The ability of AI to jointly optimise the natural and synthetic fibres or thermoplastic and thermoset matrices in a hybrid architecture can reduce material use and life-cycle emissions [97]. The pairing of generative design tools with surrogate models also enables the mass-reducing topology optimization of the composite components while maintaining structural performance and avoiding energy intensive mass production. The key implication is that AI-based eco-design promotes principles of circular economy. This can be achieved by introducing design-for-disassembly (DfD), recyclability constraints at an early stage. This happens during the design workflow as opposed to post-design stage. Nonetheless, the success of these techniques mostly depends on the availability of dependable sustainability data and well-defined environmental indicators, which remain fragmented across the automotive composites domain.

6.2 Life Cycle Assessment (LCA) and Carbon Footprint Optimization

LCA evaluates the environmental impact of hybrid automotive composites in the extraction of raw material, manufacturing, use, and end of life. Hybrid composites may produce lower emissions during use-phase due to vehicle lightweighting; however, their production stages can be energy-intensive, especially with the use of carbon or glass fibre [98]. AI-based approaches address this problem by allowing for the quick analysis of scenarios and optimization of carbon footprints over various design and process parameters [99].

The ML models based on LCA database can make predictions about the environmental impact without the high computational cost associated with traditional process-based LCA. This enables real-time feedback during material selection and structural optimization. These techniques let designers weigh trade-offs between savings in manufacturing energy, durability and operational emissions. Alongside this, AI-enhanced optimization has also been used to minimize carbon hotspots in composite manufacturing, such as during autoclave curing or resin infusion, through smart process control and energy-aware scheduling [100]. Carbon-footprint optimization is significantly hindered by uncertainties related to the LCA data of newer hybrid composites, especially those consisting of bio-based or recycled contents. Recognizing these uncertainties and addressing them through hybrid data-driven and physics-based LCA models is a priority research direction.

6.3 Recycling, Reuse, and EoL Challenges for Hybrid Composites

The most critical hurdle to the large-scale adoption of hybrid automotive composites is their recycling and EoL management. The inherent diversity of hybrid systems, which contain various fibres, matrices and interfaces, hampers conventional recycling routes, such as mechanical grinding or thermal recovery. The utilization of AI in the technologies associated with material identification and sorting is increasingly being implemented and investigated. New computer vision and spectroscopy-based techniques are developed for the automatic disassembly of composite parts and their waste segregation. AI-driven damage detection and remaining-life prediction models can support the reuse of composite parts for remanufacturing of components and secondary structural applications. It will also enable safe re-deployment of composite parts. Nonetheless, high-performance hybrid composites may exhibit degraded material properties upon recycling and which may limit their suitability for some automotive applications. The environmental and economic viability of chemical recycling and solvolysis for fibre recovery is still debated [101]. In the context of the circular economy, there is increasing emphasis on AI-supported design-for-recycling approaches to alleviate EoL issues. However, regulatory uncertainty and lack of standardized recycling infrastructure still constrain the implementation of circular hybrid composite systems in practice.

7 Advances and State-of-the-Art Developments

7.1 Recent Research Trends and Breakthroughs

Recent research in hybrid automotive composites is increasingly shifting towards multifunctional and data-driven material systems that combine structural performance with sustainability and smartness. Improvements in fibre hybridization techniques, such as carbon-basalt or natural fibre mixing, have shown enhanced damage tolerance and economic performance [102]. Thermoplastic-based hybrid composites have also attracted attention due to their recyclability and suitability for high-rate manufacturing processes [103]. Advances in AI and digital twin technologies have made it feasible to predict the behavior of composite materials at different scales, from microstructural damage evolution to the performance of components. These tools can reduce the burden of experimentation while speeding up material qualification cycles. The freedom of design has further increased with the introduction of AFP and AM. Furthermore, hybrid composites embedded with sensors can also monitor the health of structures, as the focus on intelligent and connected vehicles intensifies. The world is moving away from simple performance-driven composite design based primarily on conventional objectives to smarter integration of sustainable materials and digitally driven systems.

7.2 Case Studies from the Automotive Industries

7.2.2 Safety-Critical Structural Components: Bumper Beams and Crash Energy Management

Hybrid automotive composites have been widely explored for safety components in automotive structures, especially in impact energy absorption and in the design of bumper beams, where weight reduction should not compromise crashworthiness. In previous automotive research on the application of hybrid composite structures, the primary concept discussed is the ability to offer enhanced specific impact energy absorption and controlled deformation characteristics by laminating natural and synthetic fibres or metal layers [104]. Tests on the effects of jute and kenaf combined with glass fibre in a cost-effective configuration in the production of hybrid bumper beams [105] clearly indicated enhanced hardness, tensile strength, and flexibility than single-fibre structures at relatively cheaper costs, with maximum weight savings up to 33% in the optimized composite structure as opposed to conventional glass fibre-reinforced structures [106-108]. Numerical studies using finite element modelling and classical lamina theory confirmed the ability to control stiffness and impact absorption in optimized glass/carbon hybrid laminates and explored the general advantage and practicability of hybrid composites in the design and production of pedestrian-safe bumpers [104, 109].

7.2.3 Hybrid Composites for Brake and Friction Materials

Brake pads are one of the critical automotive subsystems where hybrid composites formulations have been investigated as alternatives to asbestos-based friction materials due to health and environmental hazards [110]. Previous automotive composite frameworks have pointed out that hybridization entails the synergistic balancing of reinforcement, binder, and filler contributions toward improved thermal stability in tribological applications and under wear conditions [104]. Experimental studies on natural fibre-reinforced hybrid friction composites, based on nettle, sisal, jute, and agricultural by-products embedded in a polymer matrix, demonstrated improved friction stability, reduced fade, and enhanced wear characteristics under SAE standardized testing conditions [111-113]. Full-scale dynamometer assessments further established the acceptability of eco-friendly hybrid brake pads in terms of brake effectiveness, recovery behavior, and thermal endurance for use in light motor vehicles and two-wheelers [1, 112].

7.2.4 Suspension and Chassis Systems: Anti-Roll Bars

Hybrid composites have further been identified for use in suspension parts like anti-roll bars, where resilience, durability, and load-bearing capability are critical. Automotive design work on composites suggests that hybrid composites made from natural and synthetic fibres could potentially replace metallic anti-roll bars if their design and material arrangement were optimized [104]. The design works conducted on kenaf and sugar palm hybrid composites using analytic hierarchy processes and life-cycle assessments showed a decrease in their carbon and energy footprints compared with their steel counterparts [114]. Design work further optimized using quality deployment and inventive problem-solving techniques made it clear that hybrid composites could successfully minimize stress concentration effects and support requirements while providing added emphasis on environmental and customer demands, thereby reaffirming their use in sustainable design applications related to chassis parts like anti-roll bars [115]. In extreme loading and turns, an anti-roll bar is capable of supporting about 30-40% of the collective weight of the suspension parts and thus plays a vital role in controlling roll and ride movements, which emphasizes material resilience, fatigue life, and efficient weight transfer as critical design requirements for their selection [116].

7.2.5 Interior and Exterior Automotive Applications

Market analysis indicates that one of the most common market applications of hybrid composites is for the interior and semi-structural parts of the car. This was attributed to the demand for clean processing, economy, and their ability to provide acoustic insulation. Automotive manufacturers, including Mercedes-Benz, Audi, BMW, Toyota, Ford, and Mitsubishi, have applied hybrid flax, sisal, kenaf, and bamboo. These manufacturers have also used agricultural-waste-reinforced composites in door panels, dashboards, seat backs, floor mats, and storage bins [117-119]. The assessment and evaluation of all the composites used in the automotive industry show hybridization of the

composites, emphasizing the improvement of the stiffness-to-weight ratio of the composites and the noticeable recyclability of the composites, especially the interior parts [104]. Further, the tests and experiments conducted have shown the mechanical requirements of the natural fibre hybrid composites for the interior parts of the car have been attained [120]. Moreover, the laminates made of hybrid glass-carbon and natural and synthetic fibres display an improvement of the flexural and compression strength of the exterior parts [121-123]. However, limitations include moisture and impact resistance [124-126].

7.2.6 Critical Insights and Industrial Relevance

When considered together, the different case studies demonstrate that hybrid composites offer a strong material solution for structural, safety-critical and non-structural automotive components through an integrated approach combining lightweighting, performance, and sustainability [1, 104]. The literature points out that impact robustness, moisture resistance, scalability and EoL recyclability issues remain, especially in natural fibre-dominated hybrids [104]. Addressing these limitations while maintaining the performance advantages of hybrid automotive composites requires integrated material design, advanced processing routes, and life-cycle-oriented optimization frameworks for wider uptake in future vehicle architectures [104].

7.3 Comparison with Conventional Optimization Approaches

Standard optimization strategies applied to hybrid automotive composites are often deterministic, rely on parametric studies or expert-based heuristics. These approaches can face difficulties in addressing complex high-dimensional designs. Methods of this type typically optimize a single objective, e.g., stiffness or weight, while treating sustainability and manufacturability as secondary constraints [127]. In comparison, optimization frameworks that utilize AI can take multiple objectives, which are often conflicting, into consideration at the same time. These objectives include mechanical performance, cost, carbon footprint, and recyclability.

Using ML surrogate models, computational speed can be improved significantly compared to finite-element based iterative optimization to quickly evaluate other hybrid designs. Moreover, as experimental and production-scale data become available, the adaptability of AI-based methods is established. Although AI-driven optimization methods work quite efficiently, there are certain issues associated with data quality, explainability, and generalizability with respect to material systems compared to traditional methods. Even though traditional methods may continue to be acceptable to the authorities for their early-stage validation, it is apparent that the trend is shifting towards hybrid optimization methodologies that blend a physics-informed model with AI capabilities that offers superior performance and sustainability along with design flexibility.

8 Challenges, Contradictions, and Research Gaps

8.1 Manufacturing Challenges and Process–Property Relationships

The production of hybrid automotive composites faces notable challenges due to the interaction of dissimilar fibres, matrices, and processing conditions [39-41]. Differences in the chemical characteristics of fibre interfaces can lead to non-uniform resin distribution during manufacturing and incomplete wetting of fibres which can cause material degradation and reduce strength of the composite [43-45]. Manufacturing defects can affect on mechanical properties, such as stiffness, strength, impact resistance, and fatigue performance, which are important for automotives [44, 46]. Process parameters such as temperature, pressure, resin viscosity, and consolidation time govern fibre orientation, voids formation, and the development of residual stress thereby establishing strong process–property relationships for hybrids [46-48]. Injection molding is a high-shear process that leads to fibre length degradation and greater anisotropy, while compression molding and RTM offer a greater fibre volume fraction and better surface quality [40, 46]. In addition, thermal gradients and differential shrinkage between the hybrid constituents can induce residual stresses that would compromise dimensional stability and long-term durability [44, 47]. Resolving all the aforementioned challenges would require integrated process design coupled with advanced monitoring and predictive modelling frameworks to reliably map the manufacturing parameters to automotive performance [48, 49].

8.2 Performance versus Recyclability Trade-offs

A key conflict concern in AI-aided optimization techniques for hybrid automotive composites is related to performance and recyclability. It has been observed that the majority of existing AI algorithms target the optimization of stiffness, strength, impact resistance, and durability while favoring hybrid topologies, fibre mixes, and thermoset-based materials that impede recyclability and the reuse of car components. Many AI models focus primarily on component performance, while explicit optimization of recyclability and sustainability remains comparatively limited and the use of single materials has not been fully pursued. A clear research gap remains regarding the optimization of recyclability and sustainability together with mechanical performance [15-17].

8.3 Data Scarcity and Lack of Standardized Datasets

Data scarcity and the lack of standardized datasets are among the critical challenges to robust deployment of AI in hybrid automotive composites. High-fidelity experimental datasets, such as X-ray micro-computed tomography-derived fibre orientation fields, process-structure-property relationships, and damage evolution data, are expensive, geometry-specific, and often proprietary. For these reasons, most AI models are based on simulation-generated data. This creates a high risk of overfitting and can limit generalization across materials, processes, and component scales. Meaningful comparison among studies and reproducibility is difficult because of the lack of openly available benchmark-quality datasets. Even though synthetic data generation and physics-informed surrogates alleviate this challenge to an extent, there is a strong need for shared data protocols, standardized testing frameworks, and collaborative data ecosystems that will enable transferable, data-efficient AI models, as reflected in the literature [15-17].

8.4 Model Interpretability and Reliability Issues

Despite reported gains in predictive accuracy, model interpretability and reliability are still concerns that remain unresolved, especially for safety-critical automotive components. Many deep neural networks and reinforcement learning models operate as black-box systems that provide limited physical insight into the governing mechanisms of fibre orientation evolution, defect formation, or failure initiation. This opacity can conflict with the traceability and explainability requirements associated with automotive certification, whose requirements place traceability, conservative design margins, and explainable decision pathways in focus. Moreover, a lack of robustness and industrial trust is brought about by the poor extrapolation shown by models trained within narrow parameter spaces under unseen processing conditions or at novel hybrid configurations. While XAI and physics-informed learning are highly recommended, their adoption has remained fragmented and lacks common validation metrics and reporting protocols suitable for regulatory acceptance [16, 17, 88].

8.5 Scalability and Industrial Implementation Barriers

Scalability and industrial implementation present additional challenges hampering translational readiness. Numerous AI-driven optimization frameworks have been validated at coupon or subcomponent levels but are not connected to full-scale automotive production settings. The challenges associated with their intensive computational requirements, complex sensor integration, latency of acquired data, and poor compatibility with existing Computer Aided Design – Computer Aided Engineering - Product Lifecycle Management infrastructures hinder their real-time or near-real-time deployment. Moreover, scaling up AI-optimized microstructural designs or architectural designs may prove impractical due to manufacturing constraints, quality variability, cost sensitivity, and robustness of the process. A substantial gap remains between the sophistication of current methods and their practical functionality in industrial environments. System-level integration and manufacturing-aware AI remain under-explored [15, 17, 88].

9 Future Directions and Research Opportunities

Future research in hybrid automotive composites is increasingly shaped by advances in AI, digitalization, and sustainability imperatives. In the near term, AI is foreseen to augment existing workflows in composite design and manufacturing by data-driven optimization, predictive analytics, and decision-support systems. In the longer term, on the other hand, point towards autonomous and self-adaptive composite systems capable to optimize performance over the full material life cycle. Critical research opportunities exist concerning the integration of digital twins with generative AI, autonomous materials discovery, and alignment of AI frameworks with policy, standards, and sustainability roadmaps. If AI is to mature to an industry-ready and certifiable technology for automotive composites, these dimensions need to be addressed holistically and not in isolation [16, 17, 88].

9.1 Integration of Digital Twins and Generative AI

In the near term, the integration of digital twins with generative AI expected to focus towards advanced process optimization and predictive analyses in hybrid auto composites. Digital twins, updated through AI, will enable adaptive process control, defect detection, and predictive repair. When implemented with generative intelligence, such as a variational auto-encoder or diffusion models, the technology would be able to test alternative textile architectures, fibre-matrix combinations, and process times, which would be impossible through traditional design methods [15, 17, 88]. Presently, the technology largely uses small data sets, along with simplifications of physics, that limit their use in critical auto applications.

In the long run, digital twins integrated with generative AI and LLMs will likely mature along the vision of holistic and lifecycle-conscious digital twins for hybrid composite systems. The digital twin would thus be capable of performing holistic optimization over the design, production, and operational cycles through the dynamic adjustment of material architectures with the aid of real-world performance and degradation data. The application challenges would lie in keeping pace with model fidelity, uncertainty quantification, and explainability with the increasing centrality of generative AI in design decision-making. The potential would lie in self-adaptive hybrid composite systems that would support optimal performance during prolonged service lives [15, 17, 88].

9.2 Autonomous Materials Discovery and Self-Optimizing Systems

In the short term, surrogate-based modelling along with evolutionary algorithms or reinforcement learning methods are expected to become important driver in autonomous material innovation for hybrid composites in the automotive sector. These AI-based methodologies are adept at handling large design spaces and can consider manufacturability and performance constraints. Closed-loop simulation infrastructures along with selective validation activities have already illustrated the potential to identify improved trade-offs between mechanical property requirements, mass, and cost and overcome the long-standing contradictions in the current composite designs [17, 88]. Nonetheless, human involvement will continue to be required owing to data unavailability and the absence of complete information regarding practical limitations.

The long-term roadmap would entail the use of fully autonomous and self-optimizing platforms where the AI agents could eventually support the automated suggestion, production, testing, and optimization of hybrid composite materials. The roadmap would ensure the conversion of the hypothesis-driven approach of materials development to a learning and AI-driven approach. The main research void would entail the integration of physics-driven constraints, lifecycle assessment, and recyclability aspects within the autonomous platforms that would avoid the search for materials with high performance but unsustainable and infeasible characteristics [15-17].

9.3 Policy, Standardization, and Industry–Academia Collaboration

In the short term, trust in AI-driven composite design tools will need to be established through standardized benchmarks, validation protocols, and reproducibility criteria. This includes measures required for regulatory acceptance of AI-enabled methodologies in the automotive sector. Collaboration between industry and academia can speed up technology transfer by comparing academic AI models to manufacturing realities, certification requirements, and industrial constraints [17, 88].

Long-term certification of AI-assisted composite design and manufacturing processes will require coordinated policy frameworks and international standards. This encompasses rules for XAI, standardized reporting of uncertainty, and strong validation protocols for automotive regulation-compliant digital twins. Sustained partnerships among industry, academia, and public innovation ecosystems will be essential to assure AI-enabled composite innovation pipelines embed sustainability, safety, and regulatory compliance by design [15, 16, 88].

9.4 Roadmap for AI-Enabled Sustainable Automotive Composites

In the short term, the roadmap for AI-enabled sustainable automotive composites should focus on multi-object optimization frameworks, that simultaneously consider various aspects of sustainability, including performance, costs, manufacturability, and recyclability. However, there is also evidence of many available short-term roadmaps regarding sustainability, treating it as an additional aspect, which may limit their effectiveness for long-term sustainability [16, 17].

In the long run, the developmental approach must be based on a systems level that encompasses lifecycle, circular economy, and EoL into AI-optimization methods. The amalgamation of digital twins, generative AI, and autonomous discovery platforms into an integrated system level approach could support scalable implementation and improvement. The developed AI-roadmaps shall shift the role of AI from marginal performance improvement towards a revolutionary tool for sustainable, intelligent, and resilient automotive composite design [15, 16, 88].

9.5 Explainable, Lifecycle-Aware, and Human-Centric AI Frameworks

Near term research should focus on the development of trustworthy AI approaches that are either explainable or human-centric to improve trust among engineering professionals for the design of hybrid composites. The combination of explainable approaches, sensitivity analysis, and input-level uncertainty estimation can be very effective in developing trustworthy AI approaches for adoption in a risk-sensitive automotive industry [15, 17].

In the long run, explainable and lifecycle-conscious AI and systematic worker upskilling could successfully reshape human-AI collaboration in composite engineering. Rather than replacing engineers, AI systems should augment expert knowledge by providing interpretable insights across design, manufacturing, and sustainability dimensions. This balance is essential for the successful application of hybrid automotive composites in future mobility applications through AI-integrated human-AI collaborations [16, 88].

9.6 Manufacturing-Aware and Sustainable AI Frameworks

Despite this progress, there is a key research gap: AI-based optimization remains largely decoupled from manufacturing realities and sustainability constraints. Process variability, defect tolerance, workforce readiness, and lifecycle issues have been largely ignored in the current literature. Future hybrid AI frameworks should integrate

physics-based constraints, uncertainty quantification, and real-time process feedback, where sustainability and recyclability objectives are explicitly embedded. Complementing this technical perspective, manufacturers will also need to overcome organizational hurdles associated with skill shortages, resistance to data-driven decision-making, and cybersecurity. Both technical and systemic gaps must be addressed as part of bridging the gap between laboratory demonstrators and certified large-scale automotive production [16, 88].

Conclusions

This review demonstrates that the field of hybrid automotive composites offers an integrated material strategy that can match diverse demands for lighter, high-performance, cost-effective and more sustainable automobiles. By merging different types of reinforcements and matrices, hybrid materials can provide tailored mechanical properties, crash resistance, and functional components that go beyond traditional materials. AI can play an enabling role in the design and optimization of such materials by providing efficient computational tools for exploring complex design spaces, accelerated optimization, precise prediction, and effective quality control for composites. However, the review identifies ongoing problems that include the trade-off between performance and recyclability, data scarcity, lack of standardized data sets, difficulties in interpreting models, and scaling problems. These problems currently inhibit the implementation of AI-based optimization from lab experiments to automotive application. Nonetheless, to move towards developing authentic, reliable, and green materials through AI technology-based optimization for automotive composites, transparent and informative AI-based models on digital twins and lifecycle assessments, as well as manufacturing-driven constraints, are crucial. The future of AI-enabled hybrid composite development lies in the ability of this technology to reshape the process of material development for vehicles in accordance with future mobility needs and regulations.

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