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The Convergence of AI and Composites - A Review Anchored in Patent Trends

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Abstract

The integration of artificial intelligence (AI) and machine learning (ML) techniques is revolutionizing the design, analysis, and optimization of polymer (PC/FRP), metal (MC), and ceramic matrix composites (CC). Techniques such as artificial neural networks (ANN), deep learning (DL), genetic algorithms (GA), and physics-informed machine learning (PIML) are employed to enhance property estimation, process optimization, and predictive modeling. These AI-driven frameworks enable virtual testing, application-specific material design, and real-time decision-making, while reducing computational and experimental burdens. Key applications span sectors such as aerospace, electronics, biomedicine, and advanced manufacturing. AI and ML approaches are being used to improve mechanical properties, including tensile strength, wear resistance, and thermal stability, as well as to optimize machining parameters and predict the fatigue life. The utilization of decision-making algorithms and advanced algorithms, such as convolutional neural networks (CNNs), allows for predictive maintenance, quality assurance, and real-time monitoring during fabrication. In parallel, global patent activity shows a steady rise, led by the United States, with increasing contributions from the emerging economies. Prominent IPC classes, such as G06F (electrical digital data processing), H01L (semiconductor devices), and G01N (investigating materials), reflect the growing innovations in computing, biotechnology, and material analysis. Together, these trends mark a paradigm shift towards intelligent, data-driven composite material development and innovation on a global scale, ushering in a new era of smart, efficient, and high-performance composites for advanced applications.

Keywords: Composite materials, Artificial intelligence, Machine learning, Neural networks, Patent landscape, Deep learning, Predictive modeling

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INTRODUCTION

By optimizing and predicting polymer composite properties using machine learning techniques, particularly artificial neural networks (ANN), support vector machines (SVM), and decision trees, noisy, high-dimensional data can be handled effectively. In the future, researchers should investigate the hybrid modelling of bio-composites and combine ML with sustainability assessments [1]. ML, specifically Ant Colony Optimization (ACO) for feature selection along with Support Vector Regression (SVR) in regression, provides excellent precision for forecasting the density of materials (R^2=0.90), but less so for energy efficiency (R^2=0.49). Research has shown that ML models are not always effective and recommends more data-driven approaches for material property forecasting [2]. Time and money can be saved by using ML techniques such as deep learning (DL), decision trees (DT), and regression to accurately predict the properties of natural fiber composites (NFCs). ML aids sustainable design by accelerating material optimization, although obstacles such as data scarcity and model interpretability exist [3]. By utilizing SVM, ANN, convolutional neural networks (CNN), decision trees, and other AI and ML approaches, it is possible to efficiently and accurately forecast the characteristics of composite materials, outperforming conventional approaches. Problems with data scarcity and the intelligibility of models persist, despite CNN's success of CNNs with image-based feature extraction along with SVR on tiny datasets [4]. Using LightGBM in addition to multi-time scale analysis, Yoshimori et al. achieved a reduction of over 90% in computation time and a significant improvement in root mean square error (RMSE) accuracy with their entropy-based deterioration estimation method for carbon fiber-reinforced polymers (CFRP) during fatigue. This method provides an economical substitute for conventional approaches by effectively predicting fatigue behavior, even in the absence of a loading history [5]. By reducing reliance on expensive experiments, the projected knowledge input-based active transfer learning (KIATL) technique achieves outstanding prediction accuracy with 50 percent less labelled data through information transfer and parameter adaptation. Considering the phase topology improves generalization while reducing overfitting and optimally modifies material characteristics [6]. By integrating micromechanical FE simulations, ANN, principal component analysis (PCA), and statistical RVE analysis, this study provides a high-accuracy projection framework for the long-term durability of CFRP under humid conditions. After optimization using Bayesian and cross-validation techniques, the model achieved greater precision and computational efficiency than previous methods [7]. Using 729 specimens from experiments and five input combinations, Milad et al. evaluated three heterogeneous ML models, namely, XGBoost, Multivariate Adaptive Regression Spline (MARS), and Random Forest (RF), to forecast the tensile behavior of fiber-reinforced polymers (FRP). The effectiveness of the RF model in modelling FRP composites under different conditions was demonstrated by its best efficiency ($R^2 \approx 0.99$, RMSE ≈ 0.15) [8]. Lee et al. demonstrated the efficacy of AI models in forecasting yield stress and other sheet metal properties from nondestructive magnetic testing data. Among these models, RF achieved the highest accuracy rate of 99.21%. The results showed that RF and XGB were the most effective of the five models evaluated, demonstrating the usefulness of AI in optimizing processes and improving product quality [9]. This study highlights the promise of ML techniques for rapid material design by reliably predicting CFRP mechanical properties. The tensile properties of RAFM steels employed in fusion reactors, such as yield strength and elongation, cannot be adequately predicted using conventional physical models [10]. By utilizing critical variables such as C, Cr, and annealing conditions, the tensile properties can be accurately predicted using machine learning and feature engineering. The results showed a high degree of accuracy in the predictions. This method is useful for predicting properties and designing steel, and SFRCs are popular because of their high performance and low cost [11]. To effectively anticipate the anisotropic elastoplastic behavior of short FRCs (SFRCs), considering variations in the volume fraction and fiber orientation, a multiscale framework is proposed that employs micromechanical modelling in conjunction with Hill's plasticity. This approach is useful for SFRC optimization and design because it lowers the computing cost without sacrificing the accuracy [12]. When it came to software quality forecasting, out of five ML methods tested on six datasets, ANN had the best accuracy along with AUC across the board, with SVM and Decision Trees (DT), and obtained good results in certain instances. The underperformance of Naive Bayes (NB) and k-nearest neighbor (kNN) underscores the significance of choosing features and dataset complexity for accurate defect forecasting [13]. Utilizing the volume fraction of the fibers as input, an ANN model built in LabVIEW accurately estimated the tensile strength of random glass fiber reinforced (GFR) composites with an error rate of less than 5% and a correlation coefficient of $R^2 > 0.99$. Although magnesium matrix composites encounter difficulties owing to their complicated and expensive manufacturing processes, this highlights the capacity of ANN for rapid and reliable property forecasting [14]. The most accurate ML model for forecasting the composite mechanical properties was XGBoost, which identified the particle form as the most influential factor ($R^2 = 0.94$, MAE = 8.19, RMSE = 10.42), according to Huang et al. The investigation verified that ML is a good tool for optimizing composites with a magnesium matrix, which helps solve the problem of complex behavior prediction [15]. To forecast material characteristics, Song et al. presented a multimodal fusion learning model that integrates microstructure features obtained by a CNN with component data analyzed using an MLP model. This method demonstrates how machine learning and artificial intelligence are changing the face of composite material studies by improving the analysis, optimization, and prediction in ways that were previously impossible [16]. According to recent studies, the prediction of mechanical properties and optimization of composite material performance are both improved by ML techniques, such as ANN, SVM, and deep learning. Simulation, fault detection, and the rate of material discovery are all enhanced through the integration of finite element analysis (FEA), digital twins, and non-destructive testing, which also reduces the experimental costs [17]. Among the ML models tested by Shirolkar et al. on 600 trials, RNN outperformed SVR, MLP, and GBRT in predicting carbon fibre manufacturing tensile strength and modulus ($R^3 = 0.85, 0.67$). Identifying process-property relationships and accelerating composite development with less experimental effort are two areas in which ML excels [18]. Marani et al. trained ML models to estimate the shear strength of FRP-reinforced concrete beams using tabular generative adversarial network (TGAN) -generated synthetic data, and Gradient Boosting Regression achieved $R^3 = 0.96$. The results demonstrated that Bayesian optimization, synthetic data, and ML outperformed conventional models for composite design in terms of precision and dependability [19]. Regarding ML techniques for environmental FRP degradation prediction, Machello et al. demonstrated that ANN, SVM, and GP models outperform more conventional approaches in collecting nonlinear durability patterns. This investigation highlights the importance of incorporating physics-based models and using more comprehensive datasets to enhance the ability of structural applications to forecast reliability in the long term [20]. Rayhan and Rahman predicted the elastic characteristics of unidirectional composites using Ansys Material Designer and demonstrated good agreement with analytical and experimental data, except for the prediction of G12 at high fiber volumes. To optimize composites efficiently and affordably, this study highlights the importance of computational homogenization, which lends credence to AI-driven material design [21]. Machello et al. (2024) employed DT and M5P with RF to predict the tensile strength retention of FRP. Among these models, Random Forest revealed that temperature and T_g were the most important factors, resulting in the most precise prediction ($R^2 = 0.97$). This research lends credence to data-driven innovation in structural design by demonstrating that ML outperforms more conventional models in predicting the longevity of FRP [22]. Supervised ML methods, such as ANN, SVM, RF, and XGBoost, have been widely employed in FRP-strengthened RC applications, particularly for beams and columns, according to a scientometric analysis of 96 studies (2016–2023). Thus, hybrid AI-physics models for sensor integration must be developed to address challenges related to data quality and model interpretability, even though ML improves predictive accuracy and decreases the need for experiments [23]. The thermal and mechanical characteristics of hybrid polymer composites were accurately predicted using the ANN model proposed by Mohit et al., which used the Levenberg-Marquardt algorithm. The model demonstrated superior performance when tested with dried leaves and Co fillers. This study highlights the importance of artificial intelligence in reducing costs and accelerating the creation of sustainable high-performance composites for use in advanced engineering [24]. According to Sorour et al. 's analysis of 278 studies on ML in composites, conventional, deep, and combination models were found to be successful in forecasting the modulus, strength, and crack conduct, among other properties. This investigation highlights the importance of combining AI, FEA, and sensors with hybrid frameworks to improve machining and create smart and effective composite materials [25]. Among the nine regression models tested for manufacturing fiber-reinforced and MMCs, SVR outperformed the more conventional approaches to improve the cutting parameters and offered the best predictive accuracy. The results showed that AI-driven regression is effective for enhancing machining productivity while decreasing trial costs in composite manufacturing, and the results were validated using statistical analyses [26]. To forecast the shear strength of FRP-reinforced beams devoid of stirrups, Yang et al. compared ML models with conventional codes. XGBoost demonstrated a 15 percent increase in R^2 and a 59 percent decrease in MAE. This study highlights the potential of ML to improve the prediction accuracy of structural composite engineering and to allow data-driven design [27]. The use of ML in progressive damage modelling was examined by Loh et al., who classified methods according to their focus on direct prediction, property assessment for FEA, and uncertainty quantification. By integrating experimental data with precise predictive models, they discovered that DL and hybrid AI-physics models improved the damage assessment [28]. To forecast and improve the properties of composite materials while reducing computational and experimental expenses, optimization strategies and advanced ML methods, such as DNNs, CGANs, XAI, and reinforcement learning, have been combined with FEA. Composite material development and construction engineering have been revolutionized by ML, as shown by the approaches that enhance layup design, attribute estimation, defect identification, and interpretability [29–37]. To genuinely want AI-driven predictions to be more reliable, we must compare them to classical micromechanical models. In the case of FRP composite elastic constant prediction, for example, studies have shown that ANN and RF models are compatible with the Mori-Tanaka and Halpin-Tsai models and that their outcomes are in agreement with the Voigt and Reuss limits. This research establishes that statistical correlations do not constitute the only limiting factor for AI predictions; physically plausible restrictions also play a role. Using hybrid physics-informed loss functions, the model forecasts are derived pursuant to anisotropy constraints and micromechanical notions, further reducing the risk of overfitting. Models powered by artificial intelligence complement rather than replace more conventional approaches to homogenization [38,39].

COMPOSITE CLASSIFICATION

Even though deep learning models including CNNs and DNNs by predicting multi-scale parameters and simulating damage in better way, their black-box nature makes them hard to employee in safety-critical fields like biomedical systems and aerospace. To solve this, XAI techniques like saliency mapping and feature identification, in addition to SHAP values, are being used on composite datasets. The results demonstrate that the models correctly identify physically significant parameters, including fiber direction, void percentage, and interfacial resilience. Additionally, by completely incorporating micromechanical parameters into training, PINNs enhance interpretability and legal compliance. These frameworks enable the adjustment of AI-powered models to meet certification standards without compromising their prediction capabilities [40-42]. Composite materials are classified into three types: polymer, metal, and ceramic matrix composites. The role of AI was analyzed in detail for each variant.

Polymer Matrix Composites

Polymer matrix composites (PC) are widely used because of their availability and flexibility in manufacturing. In addition, AI is a value-enhancing combination in which many parameters can be modified based on the specific application. Table 1 consolidates the PC and the role of AI.

Table 1 shows that PC and FRP have been modelled, characterized, and optimized using various AI and ML approaches [43-69]. Damage recognition in CFRP, tensile strength forecasting in hybrid natural-nanocomposites, and thermomechanical homogenization in FRPCs are some of the applications of techniques such as PIML, FIS, and XAI. Through the correlation of high-dimensional processing-structure-property relationships, AI-driven frameworks enable process optimization (e.g., machining parameters through RSM or drilling parameters via FIS), predict structural integrity, and improve properties. These models enable predictive modelling, virtual testing, and the design of application-specific materials, from aerospace components to flexible electronics, biomedical polymers, and feasible packaging, while limiting experimental overhead and computational cost. They also enable real-time decision-making and inverse design by integrating data-driven insights with the relevant domain knowledge.

Table 1. PC and its parameter optimisation for manufacturing and others using AI

S.N.	Material	Method	Description	Ref.
1	CFRP composite	Explainable artificial intelligence (XAI)	Damage recognition	43
2	Fiber -reinforced polymer (FRP)	AI and PIML	Refine manufacturing with quality and less cost	44
3	Plantain fiber (PF) with Multiwall Carbon Nanotube (MWCNT)	Artificial neural networks (ANN) and Box-Behnken Design	Estimate and optimize the tensile strength	45
4	Polylactic Acid (PLA) with Natural Fibre Polymer (NFP) composites	AI and ML	Manufacturing and characterization of material	46
5	Polymeric nano-composites	Response surface methodology (RSM) with AI and ML	Augmenting properties	47
6	PC	AI	Optimisation for food packing	48
7	PC	AI	Electrical resistivity prediction	49
8	Epoxy PC	AI	Classifying for aircraft structure	50
9	Green PC	AI	Improved efficacy for aviation components	51
10	FRP	AI	Augmenting fiber distribution	52
11	Glass fiber (GF) laminates	ANN	Bondage between cured laminates	53
12	Textile PC	ANN	Physical characterisation prediction	54
13	GFRP and SiC (silicon carbide)	ANN	Forecast the weight percentage inclusion of SiC for better strength	55
14	MWCNT, seashells with Nylon66 matrix (NSM)	Fuzzy inference system (FIS)	Drilling parameter optimisation	56
15	GFRP with nano-clay	ML	Parameters for machining are optimised	57
16	PC	DL	Study of engineering characteristics	58
17	PC	AI	To assess the impact of toughness owing to the include of solid particles	59
18	Functional PC	AI	For E-skin application	60
19	FRPC	AI	For hydrogen storage application	61
20	Particulate PC	AI	For stress field assessment	62
21	GF epoxy composite	AI	Enhancing the structures	63
22	FRPC	AI	For functional characterization	64
23	Shape memory polymer (SMP)	AI	For flexible materials for medical applications	65
24	CFRP	ML	Assessing the damage origination	66
25	FRPC	AI	For homogenization of thermochemical nature	67
26	FRP	DNN	Failure analysis	68
27	PC	ANN	Structural analysis	69

Metal Matrix Composite

Metal matrix composites (MC) are widely used because of their availability and flexibility in manufacturing. In addition, AI is a value-enhancing combination in which many parameters can be modified based on the specific application. Table 2 consolidates the MC and AI roles [70-96].

Table 2 shows the diverse ways in which hybrid computational techniques, ML, and AI have been integrated to improve the performance and characterization of different metal matrix composites (MCs). Mechanical characteristics, including tensile strength, toughness, wear resistance, machinability, porosity, and tribological behavior, have been improved through the strategic use of AI

Table 2. MC and its parameter optimisation for manufacturing and others using AI

S.N.	Material	Method	Description	Ref.
1	MC	ML	Improve the toughness	70
2	Titanium MC (TiMC) with graphene (Gr) and tungsten carbide (WC)	ML	To analysis the wear rate	71
3	Silicon carbide (SiC) particle (45 percent) with aluminium (Al)	Genetic modelling (AI)	Improving the machining ability	72
4	Al-SiC	GA	Improving the mechanical strength	73
5	MC	AI and ML	Improving the machining ability	74
6	Al with Boron Carbide (B_4C)	ML	To predict tensile strength	75
7	Al with tungsten carbide (WC) and graphite (C)	DL	For mechanical characterisation	76
8	Al MC	GA with NN	To improve the speed of Electrical Discharge Machining (EDM)	77
9	Al with B_4C and zirconium dioxide ZrO_2	ML and RSM	To assess tensile strength	78
10	Al MC	ML	Wear analysis	79
11	Ti alloy	ML	Tribological assessment	80
12	TiMC	RSM, ANN with GA	Optimising the porosity	81
13	Al alloy MC	AI	For brake application	82
14	Al MC	ML	Tool wear analysis	83
15	MC	CNN	In-situ monitoring during fabrication	84
16	Magnesium (Mg) – Al MC	ML	For nickel (Ni) coating	85
17	MC	ML	For aiding visual analysis of X-ray inspection	86
18	Al MC	ANN	Drilling parameter optimisation	87
19	Al alloy MC	ANN	To forecast the mechanical properties	88
20	Al-SiC	ANN	For roughness analysis	89
21	Al-SiC MC	Neurosymbolic AI (NSAI)	Wear analysis	90
22	Al with Gr	Supervised ML (SML)	Machinability	91
23	Al alloy MC	ML	To assess the slurry erosion nature	92
24	Al with Gr	ML	For better performance	93
25	MC	ML with decision making algorithm (DMA)	Wear prediction	94
26	Mg MC	ML	To forecast the mechanical properties	95
27	Al alloy with Zinc Oxide (ZnO)	ML and AI	Wear prediction	96

and ML approaches, such as DL, ANN, GA, RSM, and newer methods such as neurosymbolic AI (NSAI). Most applications involve Al-based composites. ML is useful for predicting tool wear, evaluating slurry erosion, and optimizing drilling parameters. Combinations with reinforcements such as SiC, B_4C, WC, and Gr improve the machining and strength of the composites. Wear rate analysis and coating performance are two areas that have been investigated in relation to titanium- and magnesium-based composites. The utilization of decision-making algorithms demonstrates the expanding function of intelligent systems in predictive maintenance and quality assurance, whereas the adoption of advanced algorithms such as CNNs permits real-time monitoring during fabrication. In general, the use of AI and ML techniques is causing a stir in the materials science community, changing the game when it comes to composite design, while simultaneously reducing the need for extensive experimentation.

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Table 3. CC and its parameter optimisation for manufacturing and others using AI.

S.N.	Material	Method	Description	Ref.
1	CC	ANN	Fatigue life estimation	97
2	CC with silicon oxy-carbide	ML	Forecasting the ablation	98
3	CC	GA	Failure anlaysis of Gas Turbine Engine	99
4	CC	ML	For higher precision in Mechanical and thermal properties	100
5	CC	ML	Quantifying the damage mechanism	101
6	SiC- SiC CC	DL	Damage analysis	102
7	CC	DNN	Analysis of tensile characteristics	103
8	SiC CC	DL	For microstructure analysis	104
9	Carbon fiber with SiC	AI	Oxidation effect analysis	105
10	SiC- SiC CC	AI	Crack detection	106

Ceramic Matrix Composite

Ceramic matrix composites (CC) are widely used because of their availability and flexibility in manufacturing. In addition, AI is a value-enhancing combination in which many parameters can be modified based on the specific application. Table 3 consolidates the CC and the role of AI [97-106].

Table 3 shows that CC, comprising more complex varieties such as SiC-SiC and SiC-reinforced systems, are modelled, analyzed, and optimized using various AI and ML approaches. To estimate the fatigue life of CC, ANN learns the complex relationships between fatigue performance and cyclic loading parameters, allowing predictions without conducting numerous experimental trials. Machine learning algorithms, which are trained on multivariate data, are used in high-temperature aerospace and defense applications to improve the predictive modelling of the ablation behavior of silicon oxy-carbide reinforced carbon–carbon (CC) and provide improved estimates of mechanical and thermal properties. In addition, using stress-strain responses and datasets collected from sensors, ML methods can quantify damage mechanisms and identify degradation pathways. By optimizing parameters such as stress intensity factors, crack growth rates, and thermal gradients, GA aid in the failure analysis of gas turbine engine components made of CCs. The goal is to predict when these components will fail. For damage analysis in SiC-SiC composites and microstructure interpretation in SiC CCs, DL models are used to help understand degradation at the microscale. These models are particularly well-suited for processing high-dimensional microstructural and imaging data. The tensile properties of CCs can be evaluated using a DNN that links the microstructural characteristics, loading conditions, and stress-strain responses. To analyze the oxidation effect in carbon fiber-SiC systems, which is important for both predicting the degradation of materials in oxidative environments and finding cracks in SiC-SiC composites, more generally using computer vision methods utilized for non-destructive evaluation (NDE) images, more comprehensive AI frameworks have been employed. Collectively, these methods usher in a new era of intelligent material design by eliminating the need for experimental verification of structural health, improving the accuracy of property predictions, and enhancing the performance optimization of ceramic composites.

ENVISAGING WITH PATENT LANDSCAPE

Further analysis was conducted using the patent landscape. This study aims to ensure the scope of composite-based manufacturing in the future. When attempting to predict the future of a certain field, it is helpful to consult the patent landscape, which is one of the most dynamic databases available [107 – 113]. Consequently, the World Intellectual Property Organization's patent scope database was used to search for specific keywords along with the international patent classification (IPC). The next part of the work is a detailed analysis of the role of composites with the aid of AI and prediction of the future scope of the field. The search was conducted in English for all the categories.

Table 4. Patent landscape analysis for "Polymer matrix composite" and "Artificial intelligence" [114]

S.N.	Countries	Count	IPC	Count	Year	Count
1	Patent Cooperation Treaty	15	C07K	6	2016	2
2	United States of America	11	G06F	4	2017	0
3	Canada	1	B33Y	3	2018	1
4	China	1	G06N	3	2019	1
5			A61F	2	2020	1
6			A61M	2	2021	1
7			A61N	2	2022	3
8			B21J	2	2023	4
9			B22F	2	2024	4
10			B29C	2	2025	7

Table 5. Patent landscape analysis for "Metal matrix composite" and "Artificial intelligence" [114]

S.N.	Countries	Count	IPC	Count	Year	Count
1	United States of America	85	H01L	55	2017	2
2	Patent Cooperation Treaty	21	G06N	16	2018	8
3	United Kingdom	7	F02C	13	2019	5
4	European Patent Office	3	G09G	13	2020	25
5	India	2	G06F	11	2021	17
6	Australia	1	G01N	10	2022	19
7	Brazil	1	G02F	8	2023	16
8	Italy	1	G11C	7	2024	17
9	Republic of Korea	1	H04N	7	2025	4
10			B33Y	6		

The keywords used were "Polymer matrix composite" and "Artificial intelligence" along with a few other options to narrow our search to just those terms, as well as to exclude any potential relatives. Both help reduce search results and eliminate duplicate patent filings in different countries. A total of 28 patents involving this term and its alternatives have been filed. The United States is the dominant country, with 11 patents.

Table 4 presents patent data organized by country, IPC codes, and years of filing, which shows interesting patterns in patent activities. With 15 patents, the Patent Cooperation Treaty (PCT) shows that there is a lot of international cooperation; the US comes in second with 11, and China and Canada do not contribute much. The classifications G06F (electrical digital data processing) and C07K (peptides) stand out among IPC, indicating advancements in computing and biotechnology. Recurring IPC codes, such as A61F, B29C, and B22F, indicate a rising trend in patent filings, which increases dramatically from 2016 (two patents) to 2025 (seven patents). This indicates a surge in technical progress and IP generation, particularly in the advanced manufacturing and biomedical industries.

The keywords used were "Metal matrix composite" and "Artificial intelligence" along with a few other options to narrow our search to just those terms, as well as to exclude any potential relatives. Both help reduce the search results and eliminate duplicate patent filings in different countries. A total of 122 patents involving this term and its alternatives have been filed. The United States is the dominant country, with 85 patents.

Table 5 shows that the United States has the most patents filed (85), especially in the category of semiconductor devices (H01L), and the most patents of any IPC class (55), indicating a high level of innovation in electronic devices. The most notable spike in patent activity occurred in 2020, with 25 patents, followed by a consistent rise until 2024. With 21 filings, the PCT route also shows a strong interest in preserving innovations across jurisdictions, which is significant on a global scale. India and Brazil, two rising powers in the global economy, are increasingly filing patents for technical innovations, particularly in the fields of computer science (G06F, G06N) and optical systems (G02F). The existence of advanced integrated product components (IPCs), such as B33Y for additive manufacturing and F02C for gas turbine engines, demonstrates a wide range of technical interests. The data show that patents for advanced electronics, computing, and production methods are on the rise worldwide, with the United States continuing to lead and other countries catching up to it.

The keywords used were "Ceramic matrix composite" and "Artificial intelligence" along with a few other options to narrow our search to just those terms, as well as to exclude any potential relatives. Both help reduce the search results and eliminate duplicate patent filings in different countries. Thus, 33 patents involving this term and its alternatives have been filed. The United States is the dominant country, with 13 patents.

Table 6 indicates that a wide focus on enhanced measurement, processing of materials, and manufacturing technologies is indicated by the global patent activity highlighted in the table, which spans countries, International Patent Classification (IPC) classifications, and years. Leading the pack in patent filings are the United States (13 patents) and the Patent Cooperation Treaty (14 patents), highlighting the shared interest in protecting innovations at the global and national levels. There seems to be a heavy focus on material characterization, as G01N (investigation or evaluation of materials) is the most common IPC code in this field. Powder metallurgy (IPC B22F), additive manufacturing (IPC B33Y), and measuring force (IPC G01L) are a few more prominent IPCs that demonstrate the increasing sophistication of manufacturing and metrology. The number of patent filings rose steadily from 2017 to 2024, reaching a peak of seven patents in a year, suggesting an upward trend in innovation. Regions with lower counts, such as Australia, China, and Singapore, highlight the global diversity in technological innovations owing to their focus on specialized fields.

When analyzed together, they show that patent activity is on the rise worldwide, with a noticeable increase in fields such as advanced electronics, computing, biomedical, and manufacturing industries. When it comes to filings, the US always comes out on top, especially in semiconductor devices and digital data processing fields. In contrast, the PCT route shows how strongly countries collaborate to protect innovations. Datasets with common IPC classes (e.g., G06F, H01L, G01N, B33Y, and C07K) highlight the increasing sophistication of computer science, biotechnology, additive manufacturing, and material analysis. From 2016 to 2024, patent filings show a clear upward trend with peaks in various years. This suggests that research and IP generation have intensified in recent years. Despite lower counts, countries, including China, India, Brazil, and Singapore, are showing signs of diversification and emerging innovation hotspots globally through their contributions in specialized domains such as optics, biomedical devices, and powder metallurgy.

Table 6. Patent landscape analysis for "Ceramic matrix composite" and "Artificial intelligence" [114]

S.N.	Countries	Count	IPC	Count	Year	Count
1	Patent Cooperation Treaty	14	G01N	13	2017	1
2	United States of America	13	G01R	4	2018	1
3	European Patent Office	3	G16C	4	2019	4
4	Australia	1	B22F	3	2020	5
5	China	1	B28C	3	2021	4
6	Singapore	1	B33Y	3	2022	2
7			C04B	3	2023	2
8			F01K	3	2024	7
9			G01B	3	2025	2
10			G01L	3		

IPC Class	Composite Property/Performance Linkage
B29C (Processing)	Manufacturing precision, defect minimization, scalability
G01N (Characterization)	Non-destructive testing, fatigue/damage monitoring
H01L (Semiconductors)	Thermal stability, integration with electronics
B22F (Powder Metallurgy)	Improved mechanical reliability, advanced fabrication
C04B (Ceramics)	High-temperature strength, fracture resistance
A61F/A61M (Biomedical)	Implants, biocompatibility, composite reliability

Figure 1. IPC patent class mapping to composite performance and property outcomes.

A systematic mapping of IPC classes to composite property outcomes as shown in Figure 1 gives useful information that goes beyond just counting patent activity. For example, IPC B29C (processing) inventions have been directly related to making polymer and metal composites more precise, reducing defects, and making them easier to scale up. In the same way, patents for G01N (investigating materials) are related to improvements in nondestructive inspection and tracking for fatigue and damage. Patents for H01L (semiconductors) show how composites regarding thermal stability requirements are being used in electronic applications. When these mappings are made, patent analysis goes from being a way to report on statistics to a way to prioritize R&D, showing which technical areas are making real improvements to composites. To show this connection, we are adding an interactive mapping framework that connects IPC classifications to thermal, mechanical, and environmental dependability effects.

CONCLUSION

Even though ANN, RF, and CNN have been used on polymer, metal, and ceramic composites, such classes are very different from each other in how they behave on a microstructural level, how they are processed, and how they fail. So, AI methods need to be altered instead of being employed everywhere. Transfer learning, for instance, lets models that were constructed on polymer composites regarding viscoelastic responses. For MMCs by retraining them with domain-specific features like fracture density or grain boundary impacts. In the same way, physics-informed priors over brittle fracture mechanics must be present when using AI on ceramic composites. Intelligent learning, hybrid AI-physics frameworks, and constraint embedding are a domain adaptation methods that keep cross-composite applications useful. These methods provide insights from making wrong generalizations and show how important it is to customize AI frameworks to fit the behaviors of different types of materials. Intelligent, data-driven material design and innovation are on the rise, as demonstrated by a review of artificial intelligence/machine learning (AI/ML) implications for polymer (PC/FRP), metal (MC), and ceramic composites (CC), as well as worldwide patent trends. ANN, DL, GA, PIML, and CNN are just a few examples of AI and ML methods that are transforming composite modelling. These methods allow virtual testing, process optimization, and real-time predictions, while reducing computational and experimental burdens. Aerospace, electronics, biomedical, and manufacturing sectors benefit from improved fatigue life, tensile strength, wear resistance, and thermal stability. The United States continues to lead the world in patent filings, especially in data processing and semiconductor technology, whereas countries such as Brazil, India, and China are making increasing contributions in more niche areas. This trend towards high-tech fields such as computing, biotechnology, and sophisticated manufacturing is further supported by common IPC codes such as G06F, H01L, G01N, B33Y, and C07K. In general, the use of AI in materials science is in line with the increasing amount of intellectual property (IP) activity worldwide, which indicates that innovation ecosystems are rapidly becoming smarter, more effective, and globally distributed.

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