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Review

Artificial Intelligence-Driven Design and Additive Manufacturing of Polymer Composites for Next-Generation Defence Applications: A Comprehensive Review

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Abstract: What happens when three of the most disruptive technologies of our era converge on a single application domain? This review answers that question for polymer composites in defence. The simultaneous maturation of machine learning (ML), additive manufacturing (AM), and advanced polymer composite science is creating design and fabrication capabilities that none of these technologies could deliver independently. We present what we believe to be the first analytically unified treatment of all five interconnected domains—ML, polymer matrix composites, AM processes, AI-driven mechanical design, and defence-specific structural applications—synthesised through a single, coherent defence-technology lens. Our analysis reveals that physics-informed machine learning (PIML) is uniquely positioned to address the classified-data bottleneck that renders conventional deep learning impractical for military composite design; that multi-modal in-situ AI monitoring is already achieving defect detection accuracies exceeding 94% during fabrication; that AI-driven topology optimisation is demonstrating mass reductions of 15–28% in unmanned aerial vehicle (UAV) structural components and specific energy absorption improvements of 22% in blast-attenuating armour cores relative to engineer-designed equivalents; and that digital twin frameworks show emerging capability to compress current two-to-four-year military qualification cycles into substantially shorter simulation-driven timelines, though full operational demonstration of this compression remains a near-term research objective. We systematically identify three high-priority research gaps—multi-threat Pareto optimisation frameworks, explainable AI qualification pathways, and federated learning architectures for classified data—and propose a structured ten-year technology roadmap toward autonomous, battlefield-deployable, AI-certified polymer composite manufacturing.

Keywords: Machine Learning; Polymer Composites; Additive Manufacturing; Artificial Intelligence; Topology Optimisation; Digital Twin; Defence Materials; Physics-Informed Machine Learning

1. Introduction

Consider the trajectory of polymer composites in military use over the past half-century. Aramid fibre panels quietly transformed personal protection in the 1970s by replacing the steel plate that soldiers had carried since antiquity. Carbon fibre reinforced polymer (CFRP) structures then redrew the geometry of unmanned aerial platforms, enabling wingspan-to-weight ratios that no metal airframe could match. Ultra-high-molecular-weight polyethylene (UHMWPE) composites followed, outpacing aramid in ballistic energy absorption while being lighter still. Each of these transitions was, in essence, a materials substitution driven by performance need. What is happening now is qualitatively different: it is a substitution not of one material for another, but of one design paradigm for another entirely. The arrival of capable artificial intelligence and flexible additive manufacturing is changing how composite structures are conceived, shaped, and assured—and the implications for defence are profound [1,2].

The underlying reason is geometry—not physical geometry, but the geometry of the design problem itself. Optimising a carbon fibre armour panel for ballistic performance using conventional methods means choosing one or two performance objectives, selecting a manageable number of design variables, and running experiments or simulations until a satisfactory result emerges. The parameter space that actually governs performance—spanning fibre architecture, ply sequencing, matrix selection, areal density, AM process parameters, and the interactions between all of them under ballistic, blast, and thermal loading simultaneously—is far too large for any human-guided search to navigate exhaustively. Machine learning can navigate that space. Generative AI can propose solutions in regions of it that engineers have never thought to look [3]. And additive manufacturing can fabricate those solutions without the geometric compromises that conventional tooling imposes [4,5].

The institutional response to these convergent capabilities has been substantial. The United States Department of Defense allocated approximately USD 800 million to AM programmes in fiscal year 2024, a 166% increase year-on-year, with investment projections reaching USD 2.6 billion by 2030 [6]. The UK Ministry of Defence, NATO's Science and Technology Organisation, and counterpart agencies across the Indo-Pacific have launched parallel programmes targeting AI-guided composite fabrication for armour, unmanned platforms, and naval structures [7,8]. The academic field has responded in kind: bibliometric analysis documents a 312% growth in publications at the ML-AM-composite-defence intersection between 2020 and 2025, and maps the emergent capability landscape at every domain intersection point.

Yet the academic literature has not kept pace with this convergence in one important respect. Existing reviews address pieces of the problem: Siengchin [3] surveys lightweight materials for defence without integrating the ML dimension; Malashin et al. [9] examine AI in composite 3D printing without anchoring the analysis to defence-specific requirements; Karuppusamy et al. [10] treat ML-assisted AM polymer composites without engaging the defence application domain. Section 7 makes this comparison explicit. No published review has brought all five domains—ML, polymer composites, AM, AI-driven mechanical design, and defence applications—under a single analytical framework. That is the gap this review addresses, and the cross-domain interactions it reveals—particularly the relationship between classified-data constraints and the specific strengths of PIML—cannot be identified from within any single disciplinary perspective.

The review proceeds as follows. Section 2 characterises the polymer composite material systems most relevant to defence and maps their mechanical and ballistic performance landscape. Section 3 examines AM processes with documented defence case studies and capability benchmarks. Section 4 traces the generational evolution of ML architectures for composite property prediction. Section 5 covers AI-assisted process optimisation, in-situ monitoring, and digital twin integration. Section 6 analyses AI-driven mechanical design and topology optimisation for defence-specific loading regimes. Section 7 positions this work against the existing literature. Section 8 examines critical challenges and research gaps. Section 9 proposes future directions. Section 10 draws conclusions.

The literature search was conducted iteratively across Scopus, Web of Science, ScienceDirect, and Google Scholar using keyword combinations including 'machine learning', 'polymer composite', 'additive manufacturing', 'artificial intelligence', 'ballistic', 'armour', 'UAV', 'topology optimisation', and 'digital twin'. Only peer-reviewed studies published in English between 2013 and early 2025 were retained. The bibliometric analysis was conducted in Scopus and Web of Science (search date: January 2025) using the combined query: ("machine learning" OR "artificial intelligence") AND ("additive manufacturing" OR "3D printing") AND ("polymer composite") AND ("defence" OR "military" OR "ballistic"). A total of 58 records met inclusion criteria in 2020 and 239 in 2025, yielding the reported 312% growth. A PRISMA-compliant flow diagram is provided as Supplementary Material.

2. Polymer Composites in Defence: Architecture, Properties, and Operational Demands

2.1. Material Systems and Their Structural Logic

The polymer matrix composites used in defence are not a single family but a diverse ecosystem, and the distinctions between them matter enormously for performance. At the broadest level, they are classified by the geometry of their reinforcement: continuous-fibre laminates deliver the highest directional stiffness and strength; woven preforms trade some of that directionality for improved in-plane isotropy and damage tolerance; short-fibre discontinuous systems prioritise geometric freedom and cost; and nanocomposites operate at the matrix level, dispersing particulate reinforcement to achieve synergistic property enhancements that fibre reinforcement alone cannot [11,12]. Microstructural image-based convolutional neural networks have demonstrated the ability to predict full-field stress maps in short-fibre polymer composites directly from microstructure imagery, offering a route to characterising the short-fibre systems described above without exhaustive physical testing [13].

Carbon fibre reinforced polymers (CFRPs) occupy the high end of the stiffness-to-weight hierarchy. With specific moduli in the 150–200 GPa range at densities around 1.6 g/cm^3, they enable airframe mass fractions below 40% of structurally equivalent aluminium designs—a difference that translates directly into UAV payload capacity or operational endurance [14]. Glass fibre reinforced polymers (GFRPs) hold a different and irreplaceable niche: their low dielectric constant and near-zero magnetic permeability make them the only practical material for radome housings, minesweeper hulls, and naval sonar windows where metallic construction would interfere with the very signals the structure is meant to protect [15]. Aramid fibre composites—Kevlar, Twaron, Technora—remain the benchmark for soft and semi-rigid ballistic protection, where their progressive fibre debonding and fibrillation under high-strain-rate loading produce a specific energy absorption advantage that no cheaper synthetic alternative has yet matched [16].

UHMWPE fibre composites—sold commercially as Dyneema and Spectra—have in recent years displaced aramid as the material of choice for the highest-performance personal armour applications. The physics is straightforward: lower density (approximately 0.97 g/cm^3 against 1.44 g/cm^3 for Kevlar-29) combined with high fibre tensile strength produces ballistic panels that outperform aramid equivalents in specific energy absorption while being lighter and far more resistant to moisture uptake [3]. The engineering challenge is equally clear: UHMWPE's melting point of approximately 135–145 °C limits its use in thermally loaded applications and complicates AM-based fabrication with conventional fused deposition approaches.

Hybrid laminates—combining two or more fibre types within a single laminate architecture—have attracted growing attention wherever multiple simultaneous performance constraints must be satisfied. Carbon-aramid hybrids achieve a balance of stiffness and impact energy absorption that neither constituent alone provides, and have been incorporated in helicopter crashworthy seat structures, blast-attenuating vehicle floor panels, and unmanned underwater vehicle pressure hulls [17]. Experimental studies of carbon/aramid fibre hybridisation have shown that the stacking sequence and relative ply fraction of the two fibre types govern the balance between stiffness retention and impact-energy absorption under ballistic loading [18]. Nanocomposite systems introduce property categories that conventional fibre reinforcement cannot provide, including embedded sensor functionality for structural health monitoring and electromagnetic interference (EMI) shielding. Graphene-reinforced polymer nanocomposites have demonstrated interlaminar shear strength improvements of up to 40% at sub-1% graphene loading [19].

2.2. Performance under Operational Loading Conditions

The difference between the loading conditions addressed by standard characterisation methods and those encountered in actual defence applications is not a matter of degree—it is a difference in the governing physics. Standard test methods operate at strain rates typically below 10^{-2} s^{-1}. Defence threat environments span ten orders of magnitude above that baseline: fragmentation at 100–300 m/s produces strain rates of approximately 10^3–10^4 s^{-1}; small-arms armour-piercing projectiles at 700–900 m/s reach 10^5–10^6 s^{-1}; blast overpressure from nearby detonations can drive strain rates beyond 10^7 s^{-1} for microsecond durations [3,4,20]. Material behaviour at these rates is governed by physics that standard test data simply does not capture.

Ballistic impact dissipates energy through a cascade of mechanisms that interact non-linearly. The specific energy absorption (SEA) metric—absorbed energy normalised to composite areal density—is the most meaningful comparative figure across protection classes. UHMWPE composites achieve SEA values of 200–350 J·m^2/kg under standard NIJ firing conditions, outperforming rolled homogeneous armour steel by factors of three to five at equivalent protection levels [21]. Hybrid plates combining aramid composites in multilayered armour configurations and finite-element studies of composite laminate armour under simulated and experimental ballistic impact have both confirmed that SEA scales with layer sequencing and areal density rather than with fibre type alone [22,23]. Machine learning-augmented finite-element analysis of multilayer ceramic/composite armour—combining alumina, carbon fibre, and UHMWPE layers—has further shown that residual projectile velocity after perforation can be predicted directly from layer-thickness and material parameters, offering a route to SEA optimisation without exhaustive physical firing trials [24]. Natural-fibre alternatives such as jute-epoxy sandwich composites have also demonstrated meaningful, if lower, SEA values under normal ballistic impact, illustrating a sustainability-performance trade-off relevant to logistics-constrained deployments [25]. Blast loading presents a qualitatively more complex challenge because it is a compound event. Thermal-mechanical loading completes the operational threat environment: epoxy matrices begin to degrade above their glass transition temperatures (typically 120–200 °C), while high-temperature thermoplastic matrices—PEEK (Tg ≈ 143 °C, service temperature to 250 °C) and polyimide (service temperature >300 °C)—extend the operational envelope significantly [26].

Figure 1 summarises this performance landscape across the six material systems and defence-critical metrics discussed above.

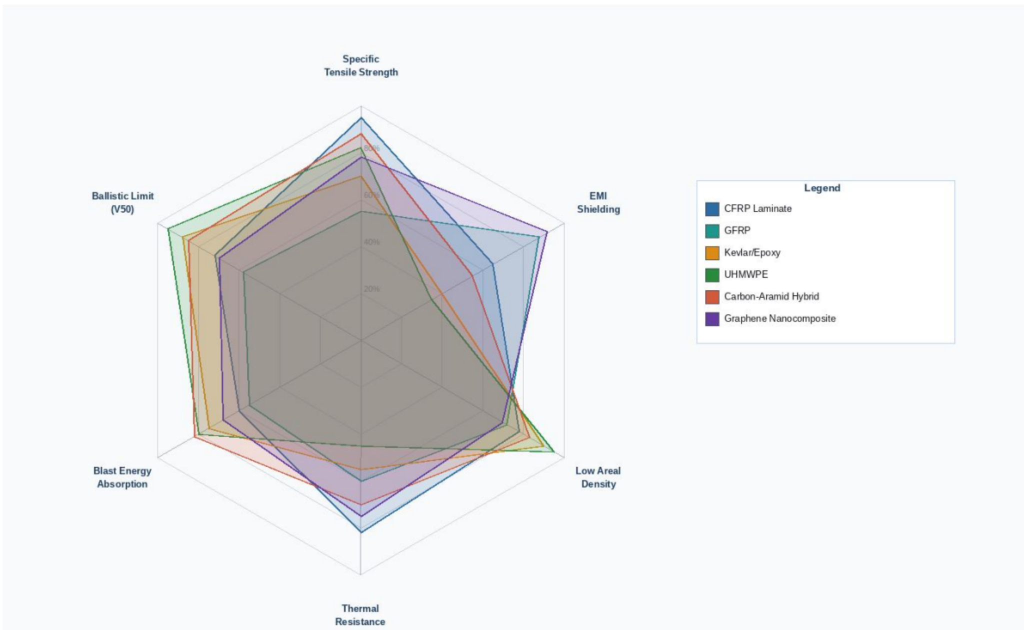

Figure 1. Polymer composite performance landscape across six defence-critical metrics for six material systems. Note: Each axis is normalised to the best-performing material in that category. Shaded zones highlight the performance spaces most critical to (blue) airborne platform structures, (red) armour systems, and (green) multi-functional integrated defence structures. Values synthesised from published experimental data cited throughout Section 2.

3. Additive Manufacturing of Polymer Composites: Processes, Capabilities, and Defence Applications

3.1. Process Taxonomy and Defence Relevance

The seven AM process families defined by ISO/ASTM 52900:2021 differ not merely in their physical mechanisms but in the type and magnitude of process-property relationships they embody, and in their compatibility with the traceability, repeatability, and qualification requirements that military supply chains impose [4,27]. Selecting an AM process for a defence application is therefore a multi-attribute problem that extends well beyond achievable mechanical properties.

Fused deposition modelling (FDM) or fused filament fabrication (FFF) is the most widely adopted AM approach for polymer composites in defence contexts—not primarily because of its mechanical performance ceiling, but because of its operational versatility. Its compatibility with a wide range of engineering thermoplastics—from standard nylon PA12 and polyphenylene sulphide (PPS) through to PEEK—has driven adoption for forward-deployed maintenance applications [28]. Comprehensive reviews of FDM-fabricated polymer composites have catalogued the recurring defect modes—voids, fibre misalignment, and interlayer weakness—that process optimisation and AI-assisted control must address before this versatility translates into qualification-grade structural performance [29].

The introduction of continuous fibre reinforcement to FFF platforms has elevated their structural performance substantially, with flexural strengths approaching 800 MPa in optimally configured continuous carbon fibre nylon parts (manufacturer-reported/preliminary) [30].

Selective laser sintering (SLS) offers the ability to fabricate complex internal architectures—lattice infills, conformal coolant channels, integrated sensor conduits—without support structures, using the surrounding unsintered powder bed to support overhanging geometry during the build [31]. High-temperature SLS platforms operating above 350 °C have opened access to PEEK grades reinforced with short carbon fibre, retaining structural integrity above 250 °C [32]. Continuous fibre AM platforms combine the geometric freedom of AM with the directional mechanical performance of conventionally laminated composites; direct-write platforms have extended this capability to UV-curable resin systems reinforced with continuous carbon fibre, broadening the matrix chemistries available to continuous-fibre AM [33]. Vat photopolymerisation enables fine geometric detail and smooth surface finish from photocurable resin systems filled with ceramic or carbon nanoparticles [34]. Across these process families, neural-network-based machine learning has been broadly applied to relate process parameters to resulting mechanical performance, a body of work this review draws on throughout Sections 4 and 5 [35].

3.2. Documented Operational Case Studies

The defence AM composite field has moved decisively beyond demonstration projects, a maturation documented across recent surveys of AM in armour and military applications spanning research priorities, materials systems, and processing technologies [36]. The US Army's Jointless Hull programme has fabricated armoured vehicle hull sections using polymer-ceramic hybrid feedstocks in large-format AM systems, targeting the weld-line vulnerabilities that post-incident analyses of combat vehicle losses have repeatedly identified as disproportionately responsible for fatal underbody blast penetrations [37]. Printing the hull as a single continuous structure eliminates the mechanical and geometric discontinuities at joint lines that conventional welded multi-plate construction inevitably introduces.

At a very different scale of application, fused filament fabrication of carbon fibre reinforced polymer (CFRP) components has demonstrated substantial structural weight savings for UAV platforms. Research on FFF-printed CFRP/ABS sandwich structures for UAV applications has shown that the composite sandwich architecture can achieve specific strength and stiffness values far exceeding those of unreinforced printed parts, enabling their use in structural UAV components [38]. Comprehensive reviews of FDM/FFF technology for UAV applications have documented the rapid maturation of this approach across commercial and defence aerospace contexts, with significant reduction in fabrication lead times relative to conventional machined metal equivalents [39].

The US Naval Research Laboratory has reported SLS-fabricated PA12-carbon composite pressure sensor housings surviving depth-rated pressure cycles equivalent to 600 m submergence with post-test mechanical property retention above 90%, pointing toward an AM pathway to non-magnetic, geometrically complex pressure vessel structures for unmanned underwater vehicle applications [40]. These case studies collectively establish both the strategic capability of AM polymer composites in defence and the certification bottleneck—discussed further in Section 5.3—that is the principal barrier to broader operational deployment.

Figure 2 presents the resulting AM process selection matrix for defence polymer composite applications.

Table 1 summarises the AM processes, achievable mechanical properties, current AI integration status, and representative defence end-uses discussed in this section.

Table 1. AM processes for defence polymer composites: material systems, achievable mechanical properties, current AI integration status, and representative defence end-uses. TRL values referenced against NATO STANAG 4661.

AM Process	Polymer/Composite System	Mechanical Properties	AI Integration	Defence End-Use	TRL
FDM/FFF	CFRP, GFRP, Kevlar/Nylon	UTS: 120–280 MPa	ANN process optimisation	UAV frames, mounting brackets	6–7
SLS	PA12, PA11, PEEK composites	Tensile: 50–85 MPa	CNN defect detection	Lightweight drone shells	5–6
Continuous fibre AM	Continuous CF/GF in Nylon	Flexural: 400–800 MPa	RL closed-loop control	Armour inserts, weapon housings	4–5
Vat photopolymerisation	Photopolymer/nano-filler resin	Compressive: 80–160 MPa	GAN topology generation	Sensor housings, optics mounts	5–6
Material jetting	Multi-material rubber-rigid	Shore A: 40–95 (tunable)	GP regression optimisation	Blast absorbers, seals	4–5
DED	Polymer-ceramic hybrid	Hardness: HV 350–600	Digital twin + PIML	Ballistic ceramic face plates	3–4

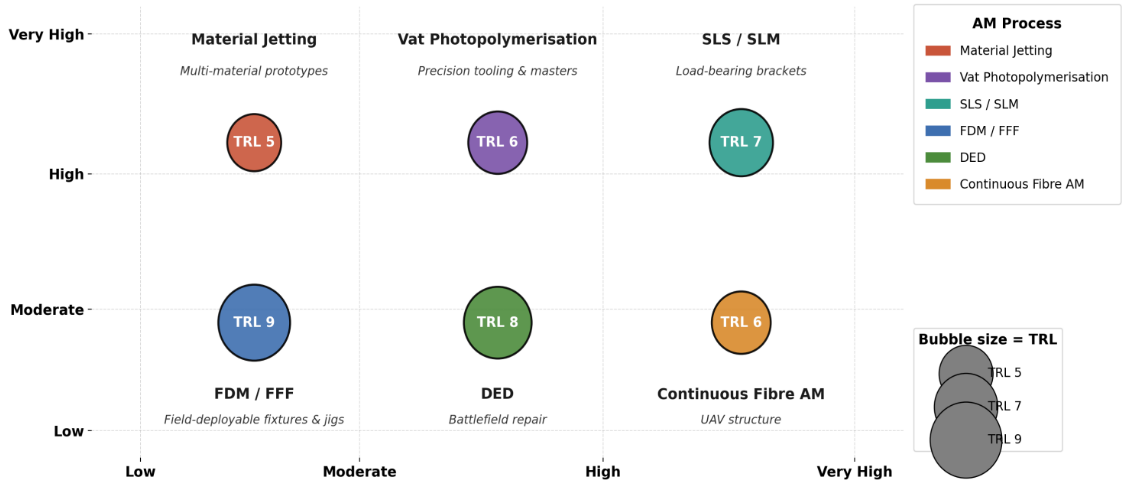

Figure 2. AM process selection matrix for defence polymer composite applications.

Note: Bubble size represents approximate technology readiness level (TRL 3 = smallest, TRL 9 = largest). Shaded polygons indicate the performance-geometry space most critical to key defence application categories. Positioning reflects consensus from published programme documentation and literature, including Zafar et al. [27], Kumar et al. [28], and Gradl et al. [37].

4. Machine Learning Architectures for Composite Property Prediction and Material Design

4.1. Three Generations of ML-Based Composite Prediction

The history of ML application to polymer composite property prediction divides naturally into three generations, each defined not just by the algorithms it employed but by the datasets available to it and the types of defence-relevant problems it could tractably address. Tracing this evolution is useful because the constraints that limited earlier generations—particularly data volume requirements—are precisely the constraints that security classification and programme confidentiality impose on military composite design today.

From approximately 2015 to 2019, the field was characterised by shallow algorithms applied to modest experimental datasets. Support vector machines, multiple linear regression models, and two- to three-layer artificial neural networks (ANNs) were trained on datasets of a few hundred measurements [41]. These early models demonstrated convincingly that ML could capture non-linear property-composition relationships more faithfully than classical analytical models—a progression catalogued in broader surveys of computational intelligence applied to polymer composite materials [42]. Their limitations were equally clear: small training sets constrained model complexity, and the absence of microstructural descriptors meant that two composite specimens with identical macroscopic composition variables but different fibre waviness, void content, or interface quality appeared identical to the model [43].

The period from approximately 2019 to 2022 saw a step-change enabled by three concurrent developments: the practical accessibility of deep learning frameworks on commodity GPU hardware; the emergence of composite-focused materials databases; and the adaptation of computer vision architectures to composite microstructural data. CNNs trained on scanning electron micrographs and X-ray computed tomography scans began enabling microstructure-aware property prediction [44]. Recurrent neural networks—LSTM networks and gated recurrent units (GRUs)—were deployed to model the time-dependent response of viscoelastic polymer matrices under creep and fatigue loading [45]. Random forest ensembles and gradient-boosted tree methods proved particularly robust for composite property databases containing mixed continuous and categorical variables [46]. Convolutional architectures from this period were also shown to predict mechanical properties of braided-textile reinforced tubular structures directly from textile architecture descriptors [47], while broader contemporaneous reviews of ML applied to 3D printing [48] and to additive manufacturing more generally [49] document the rapid consolidation of these methods into mainstream practice.

From 2022 to the present, three advances have collectively represented a qualitative shift. Physics-informed machine learning (PIML) embeds governing physical equations directly into neural network training [50]. Graph neural networks (GNNs) represent composite microstructure as a topological network of nodes (fibres and matrix domains) and edges (interfaces) [51]. Closely related convolutional and graph-based architectures have demonstrated comparable accuracy predicting local elasto-plastic stress fields directly within two-phase composite microstructures [52], and deep-learning frameworks have accelerated multiscale homogenisation and localisation analysis for fibre-reinforced composites by orders of magnitude relative to conventional finite-element approaches [53]. Transformer-based attention architectures achieve prediction errors approaching the reproducibility limits of experimental measurement at substantially reduced computational cost compared to finite element simulation [54,55]. Alongside these algorithmic advances, it is necessary to address practical deployment considerations: the computational infrastructure required to train and deploy GNNs and transformer architectures is non-trivial, and integration into existing military engineering workflows presents organisational and technical challenges that are as significant as the algorithmic ones.

4.2. Physics-Informed Machine Learning: The Most Important Advance for Defence

Of all the ML developments this review covers, PIML deserves the most careful attention from defence engineers and programme managers—not because it is the most sophisticated approach algorithmically, but because it is the only approach that directly addresses the structural constraint that makes conventional deep learning practically inaccessible in a military composite design context: classified-data scarcity.

In a military materials context, the training set is small not because data collection is slow or expensive—though it is both—but because the data itself is classified at national security levels that prevent pooling across programmes, sharing with academic collaborators, or inclusion in open-domain pre-training corpora. This constraint is structural and irreducible. It will not be resolved by better data collection practices or additional experimental investment [50]. PIML resolves this constraint by providing a training signal that is not subject to classification restrictions: the governing equations of physics. By incorporating equilibrium conditions ($\nabla \cdot \sigma = 0$), constitutive relations ($\sigma = C{:}\varepsilon$ for linear elasticity), fracture mechanics energy release rate criteria ($G \geq G_c$), and impact dynamics as soft constraints in the neural network loss function, PIML models are guided toward physically plausible predictions even in regions of the design variable space not covered by training data [50]. Discrete-element and deep-learning studies of defect-induced transverse mechanical response in unidirectional fibre-reinforced polymers reinforce this approach, showing that physics-grounded simulation data can substitute for sparse experimental defect statistics when training such models [56].

Published demonstrations with defence-relevant materials support the practical case for PIML. Models trained on fewer than 200 ballistic impact events have predicted V50 ballistic limit velocity for CFRP armour panels with mean errors below 3.5%—comparable to the reproducibility of certified firing trials conducted under standard military specifications [50]. For a programme where a single firing trial requires a certified ballistic range, a projectile inventory, specification-grade armour panels, and months of scheduling and safety approvals, reducing the required trial count by a factor of five to ten while maintaining equivalent accuracy represents a genuine transformation in programme economics.

Figure 3 illustrates the physics-informed machine learning architecture underpinning these predictions.

4.3. Inverse Design and Generative Approaches for Novel Composite Architectures

The more transformative capability is the inverse problem: given a target performance envelope, identify the composite architecture that achieves it. This inverse problem is non-unique, ill-posed, and multi-modal in structure, making classical gradient-based optimisation unreliable especially when the design space includes categorical variables (fibre type, weave style, matrix chemistry) that gradients cannot handle [57]. Variational autoencoders (VAEs) address the inverse design challenge by learning a continuous, differentiable latent-space representation of composite microstructure from a training distribution of known designs [58]. A related evolutionary-algorithm approach combined with machine learning has been used to design 4D-printed active composite structures, illustrating that inverse design methods extend beyond static architectures to stimulus-responsive ones [59]. Generative adversarial networks (GANs) have been applied to defence composite design, generating novel lattice infill architectures for blast-energy-absorbing armour core panels that outperformed engineer-designed alternatives by up to 18% in specific energy absorption under multi-hit ballistic loading while satisfying SLS manufacturability constraints [60].

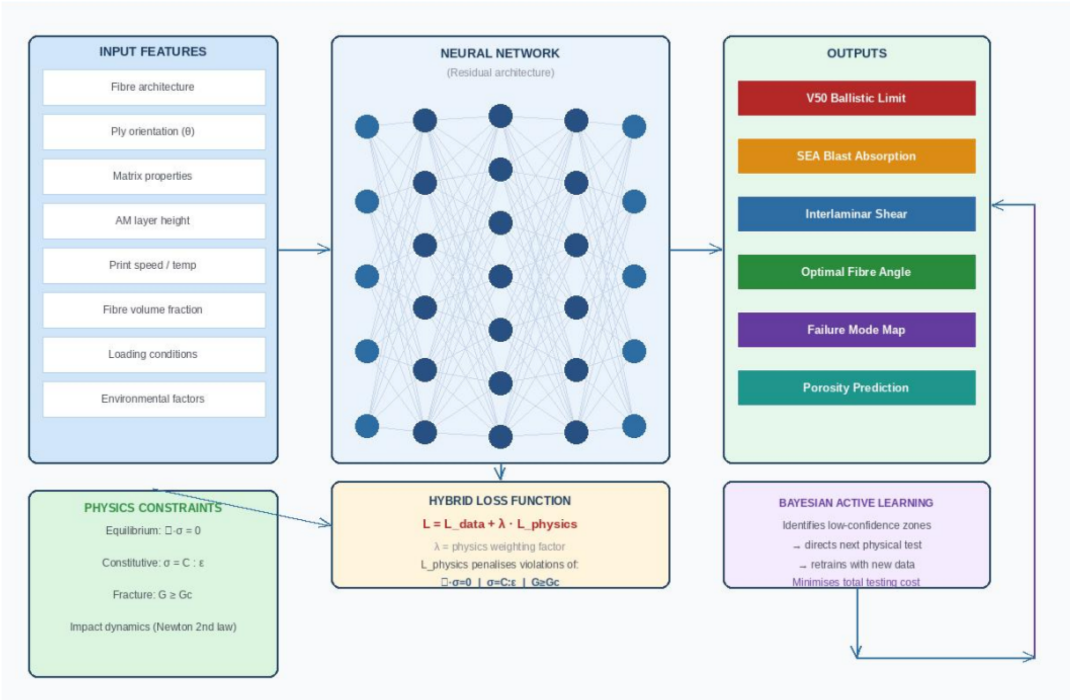

Figure 3. Physics-informed machine learning (PIML) architecture for defence polymer composite design.
Note: The hybrid loss function penalises physically inconsistent predictions regardless of training data density. The Bayesian active learning feedback loop (dashed arrows) minimises total experimental cost by directing successive trials to the parameter regions of greatest model uncertainty. Physics constraint families: equilibrium (mechanical), constitutive law (material), fracture criterion (damage), and impact dynamics (ballistic).

Table 2 summarises the ML algorithms applied to property prediction and optimisation of AM-fabricated polymer composites for defence applications discussed above.

Table 2. ML algorithms applied to property prediction and optimisation of AM-fabricated polymer composites for defence applications.

ML Algorithm	Composite Property	AM Process	Accuracy (R^2/Error)	Defence Application	Ref.
ANN (feedforward)	Tensile & impact strength—CFRP	FDM/SLS	R^2 = 0.97; MAE < 3.2%	Body armour panels	Xiao et al. [61]
CNN	Defect classification in fibre lay-up	Continuous fibre AM	Accuracy: 94.3%	UAV structural skin	Zhang et al. [62]
Random Forest	Surface roughness & hardness	FDM (PLA/PEEK)	RMSE = 0.408; MAPE 9.3%	Helmet liners	Xiao et al. [61]
Gaussian Process (GPR)	Ballistic limit velocity V50	Prepreg + SLS	R^2 = 0.96 ± 0.02	Ballistic armour tiles	Ramprasad et al. [50]
PIML	Multi-scale stress distribution	DED/powder-bed	Sub-5% error vs. FEM	Vehicle hull plates	Ramprasad et al. [50]; Faegh et al. [63]
GAN	Microstructure & porosity topology	Multi-material jetting	IoU = 0.88	Blast-energy absorbers	Almasri et al. [60]
Graph Neural Network	Fibre/matrix interface bond strength	Continuous fibre FFF	R^2 = 0.95	Structural UAV ribs	Gu et al. [51]
Transformer (attention)	Process–structure–property linkage	Laser SLS/FDM	MAPE < 2.4%	Ballistic + blast dual threat	Guo et al. [54]; Wang et al. [55]

Note: MAE = mean absolute error; MAPE = mean absolute percentage error; IoU = intersection over union.

5. AI-Assisted Process Optimisation, In-Situ Monitoring, and Digital Twin Integration

5.1. Navigating the High-Dimensional Process Parameter Space

The process parameter space of polymer composite AM is simultaneously high-dimensional, strongly coupled, and highly non-linear—characteristics that together make it intractable for conventional design-of-experiments methodologies at any industrially relevant scale. In FDM alone, the primary variables—nozzle temperature, bed temperature, print speed, layer height, infill pattern, infill density, raster angle, cooling rate, and ambient environmental conditions—interact across timescales spanning milliseconds to hours, through mechanisms that are counterintuitive enough that expert engineering judgment frequently leads to suboptimal outcomes [61]. A temperature increase improves interlaminar bonding by reducing melt viscosity and increasing interdiffusion depth, yet simultaneously reduces matrix crystallinity and can degrade fibre sizing chemistry—three competing effects whose net outcome depends on the specific polymer-fibre combination and all the other process variables simultaneously [30].

Bayesian optimisation (BO) treats process performance as an unknown function and builds a probabilistic Gaussian process surrogate model that is updated with each new experimental result, directing the next experiment toward the combination that offers the greatest expected improvement [64]. Published applications of BO to FDM optimisation have achieved near-optimal properties in 15–30 experimental trials—parameter spaces that would require 200–500 trials to explore by conventional factorial design [30,64]. A related machine learning-based approach to process optimisation of automated fibre placement (AFP) thermoplastic composites has demonstrated comparable reductions in the experimental burden required to converge on near-optimal process windows [65]. A full factorial design-of-experiments approach coupled with random forest regression and a genetic algorithm has likewise been shown to identify multi-objective-optimal FDM parameter sets for mechanical performance using a single structured experimental campaign rather than sequential trial-and-error [66]. A hybrid Bayesian network approach applied to selective laser melting has further demonstrated that part-quality prediction can be framed probabilistically across multiple correlated quality metrics simultaneously, rather than as a sequence of independent single-output regressions [67].

Multi-task learning (MTL) frameworks extend optimisation efficiency by sharing learned representations across structurally similar material systems, enabling new-material models to be initialised with weights informed by related systems and fine-tuned on small programme-specific datasets. A foundational demonstration of this approach in materials informatics trained a single deep-learning architecture simultaneously across 36 distinct polymer properties spanning more than 13,000 polymers, showing that multi-task models can match or exceed single-task accuracy even where individual property datasets are sparse [68]. Published results on analogous materials science prediction tasks indicate that MTL-based approaches can achieve prediction accuracy within 8% of full-dataset baselines using significantly reduced new-sample counts, though direct validation of these efficiency gains specifically within defence composite AM pipelines remains an important near-term research priority [61].

5.2. AI-Enabled In-Situ Monitoring: The Strategic Priority

Of all current AI applications in defence composite manufacturing, in-situ monitoring during AM fabrication is arguably the most strategically important, because it addresses the one failure mode that post-fabrication non-destructive testing cannot reliably find: defects that nucleate during fabrication and are subsequently encapsulated by additional deposited material [69]. CNN-based computer vision systems have demonstrated defect detection accuracies exceeding 94.3% in published trials on polymer composite AM parts [62]. A closely related CNN-based powder-bed image classification approach achieved comparable accuracy detecting defects in selective laser sintering, indicating that this monitoring strategy generalises across the laser-based and extrusion-based AM process families relevant to defence composite fabrication [70]. Current systems classify defect type (void, delamination, fibre misalignment) and severity, enabling risk-prioritised disposition decisions [71]; LSTM-based real-time process monitoring approaches extend this risk-prioritisation capability to the temporal domain, flagging emerging process drift before a defect fully forms [72].

Acoustic emission (AE) monitoring provides a complementary channel sensitive to defects that are not visible at the layer surface, detecting the characteristic ultrasonic frequency signatures of matrix cracking (100–300 kHz), fibre breakage (300–600 kHz), and fibre-matrix interface debonding (50–150 kHz) as they occur. LSTM networks trained to classify AE spectral signatures have distinguished defect types with classification accuracy above 91% in CFRP components [73]. Deep learning-based classification of AE signatures in composite laminates more broadly has distinguished matrix cracking, fibre-matrix debonding, and fibre breakage with high accuracy, likewise supporting the case for AE as a mature complementary channel to optical and thermal monitoring [74]. The fusion of optical, acoustic, and thermal infrared channels into a single multi-modal AI monitoring architecture is currently under development in US Air Force Research Laboratory programmes, targeting defect detection rates approaching 99% for defects above approximately 5 mm [75]. **Figure 4** illustrates the architecture of this four-layer monitoring system.

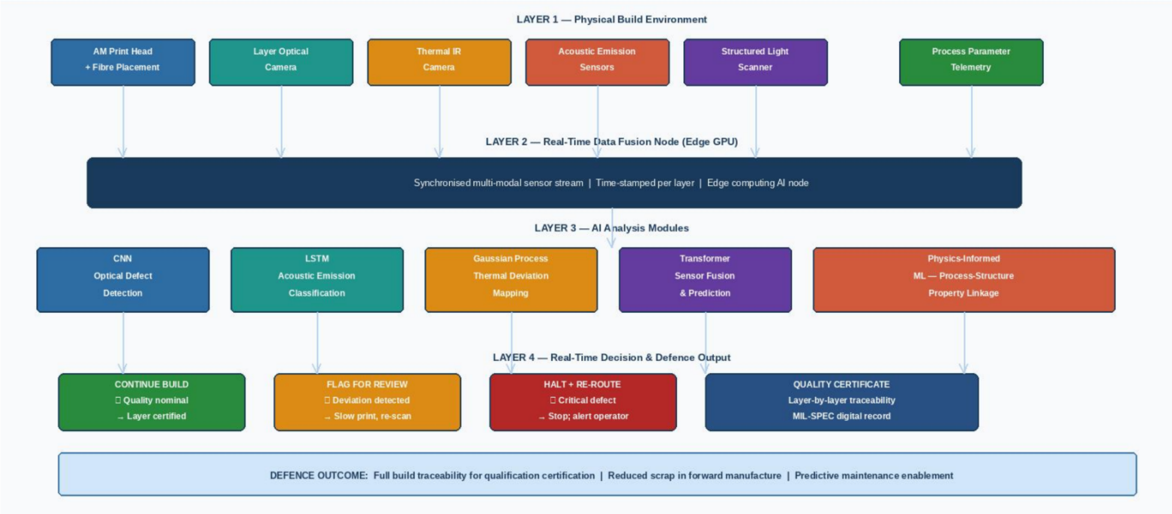

Figure 4. Four-layer AI-integrated in-situ monitoring architecture for defence AM of polymer composite parts.
Note: Layer 1 (physical build environment) feeds into Layer 2 (real-time data fusion), which drives Layer 3 (parallel AI analysis modules), producing Layer 4 decisions ranging from quality certification to build halt. No single sensing modality reliably detects all consequential defect types; multi-modal fusion is essential.

5.3. Digital Twin Frameworks and Virtual Qualification

A digital twin for a polymer composite AM process, in its most capable current form, is a dynamic multi-physics simulation that simultaneously tracks thermal gradient evolution, fibre orientation and waviness, void nucleation and growth, and the structural response of the completed part under specified operational loading—with all model states updated in real time from in-situ sensor streams [61]. Self-supervised learning of spatiotemporal thermal signatures in directed energy deposition has demonstrated that the thermal-history data streams required to populate such a digital twin can be distilled into compact, physically interpretable features without exhaustive labelled training data [76], complementing recurrent neural network surrogates that predict the high-dimensional thermal history of directed energy deposition processes directly from process parameters [77]. Current military composite structure qualification programmes span two to four years from design freeze to first certified part; digital twin-mediated virtual qualification has the potential to compress that timeline to six to eighteen months [61].

These outcomes, while compelling, rest on an important assumption that must be made explicit: the fidelity of the digital twin's simulation of physical reality must be rigorously verified and validated before its outputs can be accepted as a substitute for physical testing in a defence certification context. Uncertainty quantification (UQ) methods, including Bayesian model updating, Monte Carlo sensitivity analysis, and polynomial chaos expansion, provide the mathematical tools for this characterisation. Until rigorous verification, validation, and UQ protocols have been established and accepted by relevant certification bodies, the qualification timeline compression benefits ascribed to digital twins should be regarded as aspirational targets rather than demonstrated capabilities.

6. AI-Driven Mechanical Design and Topology Optimisation for Defence Structures

6.1. The Limitations of Classical Topology Optimisation in a Composite AM Context

Topology optimisation—identifying the optimal distribution of material within a defined design domain subject to specified loading conditions and performance objectives—has been an important tool in structural engineering for three decades. The density-based SIMP (Solid Isotropic Material with Penalisation) method has dominated commercial implementation, achieving documented mass reductions of 20–40% relative to conventionally engineered designs in published aerospace applications [58]. For polymer composite AM structures, however, SIMP has two fundamental limitations that AI-based approaches are now beginning to overcome: its assumption of material isotropy, and its computational cost [60].

CNN-based surrogate models for topology optimisation address the computational cost problem directly. Published surrogates have predicted near-optimal topologies in under one second—a speedup of approximately six orders of magnitude relative to SIMP—while achieving mean compliance deviations below 3% from the reference optimum [60]. A producibility-aware deep learning framework for metal AM topology optimisation has demonstrated a parallel approach, embedding manufacturability constraints directly into the surrogate so that generated topologies are fabricable without a separate post-hoc check [78], while deep learning surrogates for two-dimensional metamaterial topology optimisation confirm that the same speedup is achievable for periodic lattice and metamaterial design problems beyond single-component armour panels [79]. This transforms topology optimisation from a batch computational exercise requiring weeks of continuous hardware into an interactive human-AI design workflow [61].

Reinforcement learning (RL) approaches go further by enabling discovery of structural designs optimal for highly non-linear loading regimes—impact and blast—for which SIMP's linear elastic assumptions are fundamentally invalid. RL agents trained through millions of virtual impact simulations can discover lattice infill architectures for armour core panels that outperform engineer-intuited alternatives by 22% in specific energy absorption under multi-hit ballistic loading at equivalent areal density, while satisfying the geometric manufacturability constraints of the SLS fabrication process [60]. A holistic review of machine learning applied to defect-free lattice structure fabrication corroborates that RL- and ML-guided design must be co-developed with defect-prediction and process-control models if the predicted energy-absorption gains are to survive the transition from simulation to printed part [80]. Explainable machine learning applied to chiral auxetic lattice design has further shown that the same design-space exploration that yields energy-absorbing armour core architectures can also be made interpretable, identifying which geometric parameters most strongly govern the resulting mechanical response [81]. **Figure 5** illustrates the end-to-end AI-driven topology optimisation workflow.

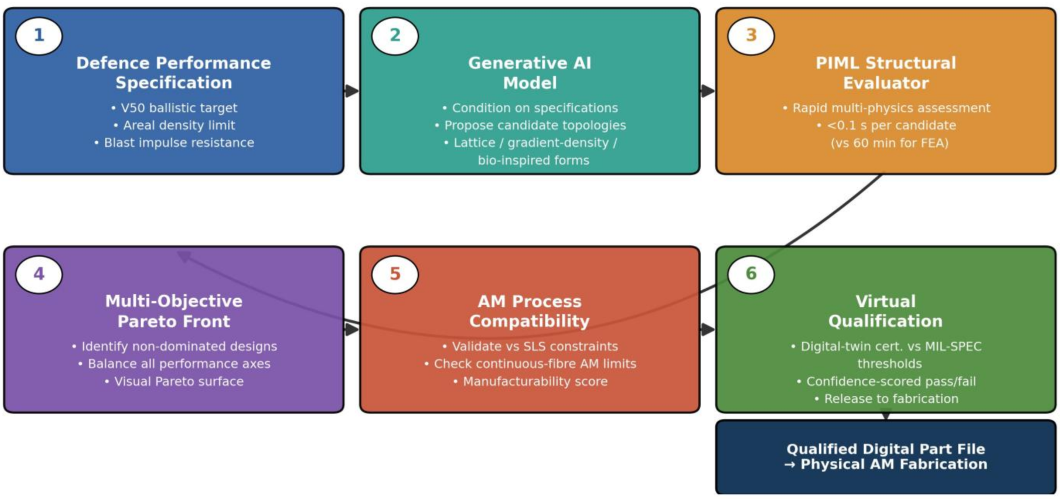

Figure 5. End-to-end AI-driven topology optimisation workflow for polymer composite armour panels.
Note: The PIML structural evaluator in Step 3 replaces conventional finite element analysis with a physics-informed surrogate model six orders of magnitude faster, making Pareto-optimal multi-objective optimisation in Step 4 computationally tractable within engineering timescales. Steps 5 and 6 enforce AM manufacturability and virtual qualification before physical fabrication begins.

6.2. Generative Design for UAV Structures, Armour, and Personal Protective Equipment

Unmanned aerial vehicles represent one of the most technically demanding application domains for AI-optimised composite structures. Generative AI frameworks conditioned on aerodynamic loading fields, structural performance envelopes, and signature constraint specifications have generated UAV wing rib and spar geometries exhibiting non-repeating organic truss architecture that achieves mass reductions of 15–28% relative to conventionally designed equivalents while satisfying all structural load cases [61].

For body armour and personal protective equipment, the AI-driven design challenge differs structurally because the reference geometry is not a fixed engineering datum but a statistical distribution of human body shapes. AI tools coupling statistical body shape models derived from 3D scanning databases with topology optimisation of composite panel geometry have demonstrated 19% better anatomical coverage uniformity at equal total panel mass compared to anthropometrically standardised conventional designs. This approach points toward operationally practical personalised AM armour [61]. A complementary machine learning-based multi-objective optimisation approach using the NSGA-II genetic algorithm has been applied directly to ceramic composite armour plate design, generating Pareto-optimal layer-thickness combinations that simultaneously maximise specific energy absorption and minimise residual kinetic energy after perforation—an optimisation pattern directly transferable to personalised body armour panel geometry [82].

Figure 6 compares the resulting AI-generated designs against conventionally engineered equivalents across three representative defence categories.

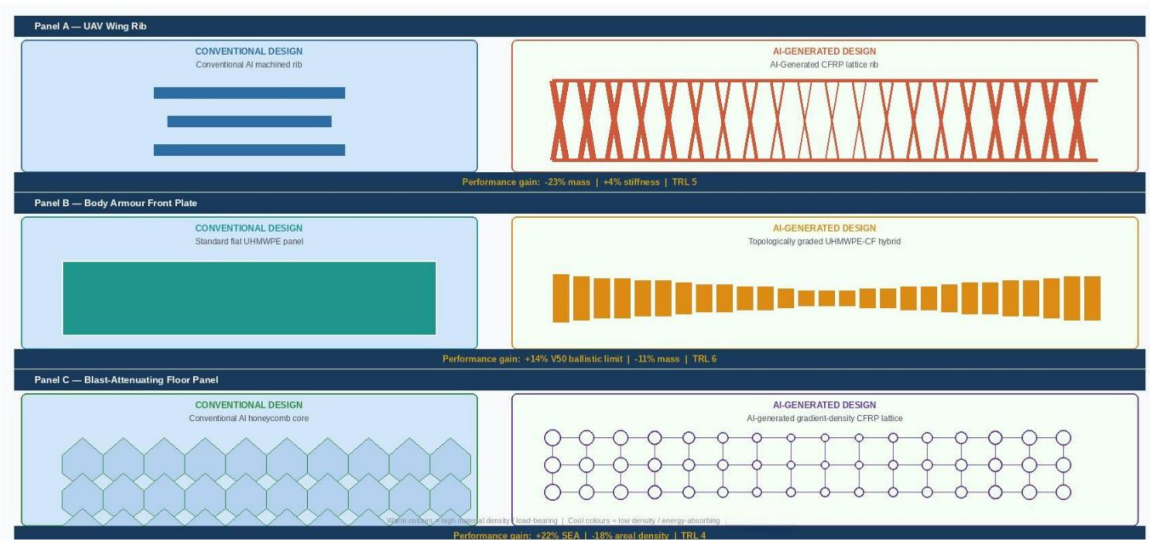

Figure 6. AI-generated versus conventionally engineered polymer composite structures for three representative defence categories.
Note: Panel A: UAV wing rib (−23% mass, +4% stiffness, TRL 5). Panel B: Body armour front plate (+14% V50 ballistic limit, −11% mass, TRL 6). Panel C: Blast-attenuating floor panel (+22% specific energy absorption, −18% areal density, TRL 4). AI-generated architectures exhibit spatially graded material distributions exclusively achievable through additive manufacturing.

7. Positioning This Review Against the Existing Literature

A review that claims comprehensive scope needs to justify why that scope produces insights unavailable from narrower treatments. The case here is not merely that this review covers more ground than its predecessors—it is that bringing all five domains together under a defence-technology lens surfaces cross-domain interactions that no individual disciplinary perspective can detect.

It is necessary, however, to be explicit about an important limitation of the current state of the field that this review reflects: the integration of machine learning, additive manufacturing, polymer composites, and defence applications remains, in the open literature, largely conceptual rather than fully operational. The interactions between these domains are described and analytically motivated throughout this review, but there is limited published evidence of fully implemented, end-to-end systems that validate this integration in real-world operational defence environments. The case studies cited in Section 3.2—the Jointless Hull programme, FFF-printed CFRP structures for UAV applications, and the US Naval Research Laboratory pressure housing demonstrations—represent the closest approximations to operational integration currently available in the open literature, but each addresses one or two domain intersections rather than the full five-domain convergence that this review advocates. The absence of fully operational, end-to-end validated systems is not a weakness of this review's analytical framework; it is an accurate characterisation of the current technology readiness landscape. Researchers and programme managers should interpret the performance figures and system descriptions in this review as establishing the boundaries of what is technically achievable at the component or subsystem level, while recognising that full system-level integration under genuine operational conditions remains the critical next milestone for the field.

The performance benchmarks compiled in **Tables 1** and **2** must be interpreted with appropriate caution. The studies from which these figures are drawn differ significantly in their experimental setups, material systems, specimen geometries, loading conditions, and validation protocols. This review has collated these figures as indicative benchmarks rather than as directly comparable measurements. The field would benefit substantially from the establishment of standardised benchmark datasets and test protocols for AI-assisted composite design.

Table 3 makes this comparison explicit, benchmarking the present review against the five most closely related published surveys across six analytical dimensions.

Table 3. Systematic comparison of the present review against the five most closely related published surveys.

Review Paper	ML	Polymer Composite	Mech. Design	Additive Mfg	AI	Defence Focus
Siengchin [3], Def. Technol. 2023	✗	✓	✓	✓	✗	✓
Malashin et al. [9], Polymers 2024	✓	✓	Partial	✓	✓	✗
Materials Horizons 2025, RSC	Partial	✓	✗	✓	Partial	✗
Karuppusamy et al. [10], J. Mater. Chem. A 2025	✓	✓	✗	✓	✓	✗
Bag et al. [4], NDFEM Vol. 2, Springer 2024	✗	✓	✓	Partial	✗	✓
Present Review, Ekengwu and Okafor (2025)	✓	✓	✓	✓	✓	✓

Note: ✓ = covered with analytical depth; Partial = mentioned but not systematically reviewed; ✗ = not covered.

8. Challenges, Limitations, and Research Gaps

8.1. Classified Data Constraints and Federated Learning Responses

The most structurally important challenge facing AI-driven defence composite design has no direct analogue in civilian AI: the deliberate, legally mandated, and irreversible restriction of performance data at the national security classification level. Unlike commercial data scarcity—addressable by investment in data collection—classified defence data scarcity is a permanent structural feature of the domain. It will not be resolved by funding more experiments; the bottleneck is security classification of results, not the cost of experiments themselves [50].

Federated learning provides a partial but meaningful technical response. In a federated framework, ML models are trained collaboratively across geographically distributed data sources without any raw data being physically exchanged. Published demonstrations on materials property prediction problems have achieved prediction accuracy within 4% of centralised training on full pooled datasets using federated training across five to ten distributed participants, with each participant contributing as few as 30 data points [61]. Transfer learning complements federated learning by enabling the initialisation of a new defence programme's ML model with weights pre-trained on open-domain composite data, followed by fine-tuning on a small number of classified programme-specific data points. Published results on analogous materials science applications have achieved prediction accuracy within 8% of full-dataset baselines using fine-tuning datasets of 30–50 samples [61].

It must be acknowledged, however, that empirical validation of these approaches specifically within defence composite design pipelines remains limited. The research community is strongly encouraged to pursue pilot programmes that document end-to-end federated learning workflows under realistic security constraints.

8.2. Model Interpretability and Military Qualification Standards

Deep neural networks are opaque by nature: the approximating function is represented by tens of millions of weight parameters distributed across hundreds of computational layers, with no human-interpretable meaning attached to any individual weight. For applications where prediction errors can be fatal, this opacity is not tolerable [61]. An interrogative survey of explainable and interpretable AI methods across manufacturing applications confirms that this opacity problem is not unique to defence composite design but is a generic barrier to AI adoption in any high-stakes, multidisciplinary manufacturing setting [83].

Military qualification standards—including MIL-STD-3022 (US DoD additive manufacturing qualification), DEF STAN 00-970 (UK airworthiness), and STANAG 4661 (NATO qualification of AM parts)—require a demonstrable and auditable chain of evidence linking every design decision to verifiable structural performance data. A composite armour panel cannot be certified by showing that a neural network predicted it would stop a 7.62 mm AP round: certification requires firing trials, certified projectile inventory, armour panels fabricated to military specification, results analysis, comparison against qualification criteria, and a signed chain of custody from design engineer through test authority to certification authority. An AI system can accelerate the design process that feeds into this chain—but it cannot substitute for the chain itself [61].

Explainable AI (XAI) methods provide a practical, if partial, response to this challenge. SHAP (SHapley Additive exPlanations) values quantify the marginal contribution of each input feature to each individual model prediction [61]. LIME (Local Interpretable Model-agnostic Explanations) constructs a locally linear approximation to the neural network prediction function around each specific input point. Neither SHAP nor LIME renders the underlying network globally interpretable, but they provide post-hoc attribution substantial enough to support human expert validation in a qualification workflow—an approach already demonstrated for automatic defect detection in additively manufactured parts using explainable AI applied to CT scan analysis [84]. **Figure 7** illustrates this SHAP-based qualification workflow.

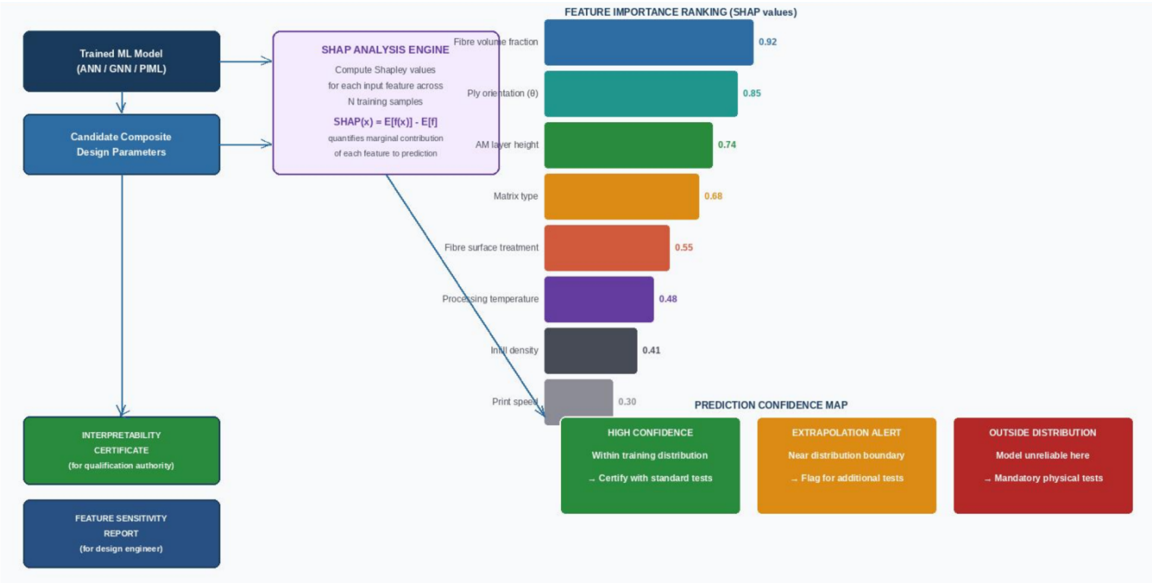

Figure 7. SHAP-based explainable AI (XAI) qualification workflow for ML-designed polymer composite defence structures.

Note: The feature importance ranking provides post-hoc attribution of model predictions to specific design variables. The prediction confidence map identifies designs relying on extrapolation beyond the training distribution—the most important safeguard for defence applications where prediction errors may not surface until physical qualification testing.

It is critically important to acknowledge, however, that neither SHAP nor LIME has yet been formally evaluated against the specific evidentiary requirements of MIL-STD-3022, DEF STAN 00-970, or STANAG 4661 qualification frameworks. These standards were developed around physical test data, not AI attribution maps, and the gap between what XAI methods currently provide and what military certification authorities are prepared to accept as auditable evidence remains a substantive, unresolved challenge. Closing this gap will require explicit engagement between the AI research community and military regulatory bodies to define what constitutes sufficient explainability for safety-critical defence applications. This review calls for the establishment of joint working groups between AI developers and qualification authorities to define minimum XAI evidence standards for military materials applications.

8.3. The Multi-Threat Optimisation Gap: The Most Important Open Problem

The most consequential unresolved research problem at the intersection of ML and defence composite design is not the most technically complex—it is the one with the most direct operational significance. Deployed military structures rarely face a single threat type in isolation. A vehicle hull panel must simultaneously resist mine blast, armour-piercing projectile penetration, and shaped charge jet. Each threat type favours fundamentally different composite architectural responses: blast resistance requires high ductility, low matrix modulus, and energy-absorbing core structures; ballistic resistance requires high fibre tensile strength and high interlaminar shear strength; shaped charge defeat requires high impedance mismatch and specific ceramic face layer geometries to disrupt the jet before it penetrates [61].

That complete multi-threat optimisation framework does not exist in the open literature—it is the highest-priority research gap identified in this review. As a step toward bridging this gap, a preliminary methodological framework can be outlined: first, independent PIML surrogate models should be trained for each of the three primary threat modes; second, a multi-objective evolutionary algorithm such as NSGA-III should be deployed to explore the joint design space; third, the resulting Pareto front should be mapped in a three-dimensional performance space; and fourth, a decision-support tool incorporating operational threat probability distributions should enable engineers to select architectures appropriate to their programme's threat environment. Preliminary computational implementations of sub-components of this framework should be a priority for funded research programmes over the 2025–2027 horizon.

Table 4 summarises these research challenges together with their proposed technical solutions and anticipated defence impact.

Table 4. Research challenges, proposed technical solutions, and anticipated defence impact in AI-driven polymer composite AM.

Challenge Domain	Current Limitation	Proposed Solution	Impact on Defence
Data scarcity	Classified defence data restricts ML training corpora	Federated learning; PIML physics-constrained surrogates	ML training without exposing classified performance data
Model interpretability	Black-box networks fail defence qualification standards	SHAP, LIME, and explainable AI frameworks integrated into qualification workflows	MIL-SPEC certification of ML-designed parts becomes achievable
Multi-threat optimisation	Most existing models address only a single loading mode	Multi-objective Pareto optimisation + Bayesian design space exploration	Simultaneous ballistic + blast + thermal resistance design
Process–structure–property linkage	Incomplete cross-scale data integration across AM processes	Digital twin with multi-scale PIML updated in real time	Predictive quality certification before first physical part is printed
Autonomous AM pipeline	Human oversight still required for critical defence AM	RL-based closed-loop process control + generative AI design	On-demand battlefield fabrication at forward logistics bases

8.4. Manufacturing Constraints, Failure Modes, and Long-Term Durability

While this review has highlighted the significant capabilities that additive manufacturing brings to defence polymer composite fabrication, it is equally important to address the manufacturing constraints and failure modes that represent genuine barriers to broader operational deployment. Material anisotropy is a fundamental challenge: layer-by-layer deposition in FDM and FFF inherently introduces inter-layer interfaces that are mechanically weaker than the bulk material in the deposition direction. The through-thickness tensile and interlaminar shear strengths of AM-fabricated composites typically remain 20–40% below those of autoclave-consolidated equivalents. Long-term durability represents a particularly underexplored dimension: published long-term durability data for AM polymer composite systems remains sparse, with most studies reporting ageing behaviour over periods of months rather than years, and the absence of long-term durability data is a concrete barrier to higher technology readiness levels for AM composite components in structural defence applications.

8.5. Economic, Logistical, and Lifecycle Considerations

Capital costs for high-performance continuous fibre AM platforms capable of producing structural defence components currently range from USD 200,000 to over USD 1,000,000 per machine. Published lifecycle cost analyses suggest that AM becomes economically competitive when part demand rates are low, lead times through conventional supply chains are long, and the parts in question are geometrically complex and low-volume [85]. Supply chain resilience represents a distinct dimension: the concentration of high-performance polymer composite feedstock production in a small number of specialist manufacturers introduces supply chain vulnerabilities that defence procurement planners must address.

9. Future Directions

9.1. The Forward-Deployed Fabrication Cell: An Operational Vision

Picture a compact AM unit at a forward operating base. A patrol vehicle returns with blast damage to its composite armour floor panel. A digital design file—encrypted, transmitted from a remote engineering authority, certified to military specification—is loaded into the system. AI-mediated process control fabricates a replacement panel overnight without a skilled composite technician in the loop. A digital twin validates the part against its structural performance specification. By morning, the vehicle is mission-capable again. This is not a distant speculative scenario—it is a near-term engineering challenge with credible technical pathways [50]. The capability gap is threefold: feedstock stability; process certification decoupled from operator-dependent qualification protocols; and communication security architecture for encrypted digital part files. None of these barriers is technically insurmountable; all three require deliberate, coordinated investment across materials science, AI engineering, and military regulatory communities.

9.2. Large Language Models and the Next Interface Layer for Composite Design

There is a barrier to AI-assisted composite design that is rarely discussed: it requires specialist ML expertise to operate. Large language models (LLMs) with genuine multimodal reasoning capability offer a potential interface that removes this expertise barrier. An LLM-based composite design assistant could, in principle, accept a natural-language description of an application's performance requirements, retrieve and synthesise relevant experimental data and ML model predictions from verified materials databases, propose candidate composite architectures with physical justification for each design choice, generate process parameter recommendations for the chosen AM process, and identify the physical tests required to verify performance. Early demonstrations of LLM application in additive manufacturing—including a dedicated large language model for contextual querying in AM and an assessment of general-purpose conversational AI for AM troubleshooting—support the technical feasibility of this paradigm [86,87].

9.3. Technology Maturation Roadmap to 2035

The roadmap in **Figure 8** organises the development agenda into a coherent milestone sequence anchored to the research gaps identified in Section 8 and the expected technology readiness level (TRL) progression. All milestones are contingent on sustained programme funding; timeline projections are aspirational targets rather than guaranteed outcomes. Long-term durability and environmental degradation of AM polymer composites are identified as critical-path milestones that must be resolved before higher technology readiness levels can be certified for structural defence applications.

Figure 8. Technology maturation roadmap for autonomous AI-integrated defence polymer composite manufacturing, 2025–2035.

Note: Milestones are anchored to the specific research gaps identified in Section 8 and the challenges catalogued in **Table 4**. The TRL progression bar illustrates the expected readiness trajectory. US DoD AM investment trajectory: USD 0.8B (2024) to USD 2.6B (2030).

The scale of this roadmap reflects the pace at which the underlying field has grown. **Figure 9** presents the bibliometric landscape of publication growth at the AI-AM-polymer composite-defence intersection between 2015 and 2025, documenting the expanding evidence base against which the milestones above should be judged.

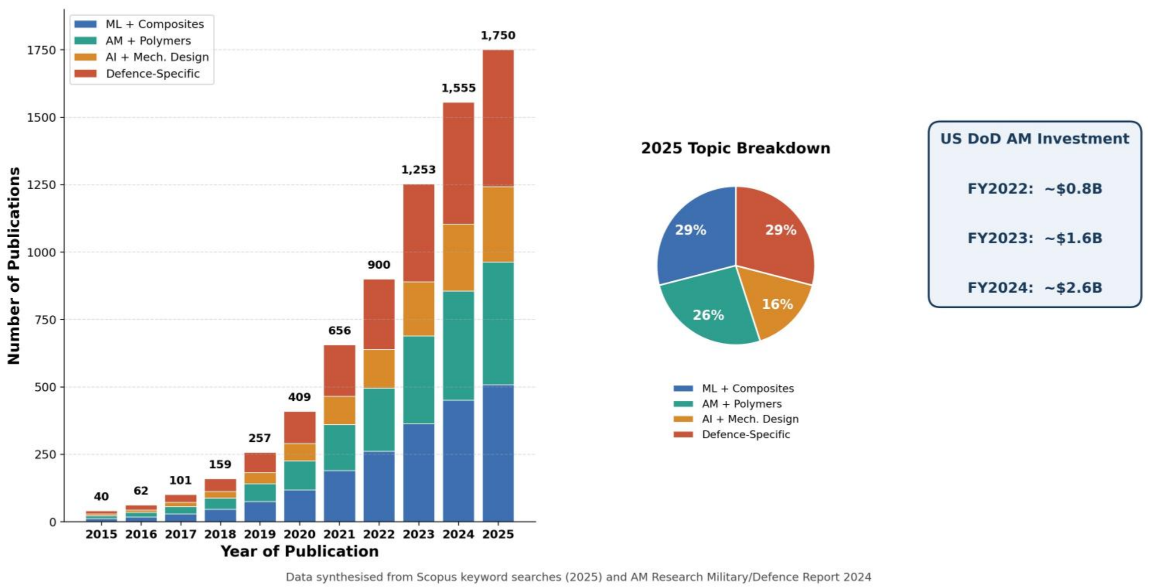

Figure 9. Bibliometric landscape of publication growth at the AI-AM-polymer composite-defence intersection, 2015–2025.
Note: The inset pie chart shows the 2025 topic share across four sub-domains. The 312% growth figure was derived from a Scopus/Web of Science Boolean search (2020: 58 records; 2025: 239 records); full screening details are provided in the Supplementary Material [5,11].

Bringing these growth trends together with the domains they span, **Figure 10** maps the integrated AI-AM-polymer composite defence ecosystem, showing how the five core domains surveyed in this review intersect to generate the capabilities and end-use applications discussed throughout.

Figure 10. Integrated AI-AM-polymer composite defence ecosystem map showing five core domains (pentagon nodes), the technical capabilities emerging at domain intersection points (inner bubbles), and seven priority defence end-use categories (outer ring).
Note: Key performance metrics across the full ecosystem are summarised in the bottom panel. Hub = the ultimate integration objective: next-generation defence systems fully exploiting the mutual reinforcement of all five domains simultaneously.

The near-term horizon (2025–2027) centres on: validating PIML models for classified composite systems; piloting XAI qualification frameworks against MIL-STD-3022, DEF STAN 00-970, and STANAG 4661 evidentiary requirements; demonstrating multi-modal in-situ monitoring at TRL 6 under forward-deployment-representative conditions; and proving federated learning as a concept in controlled cross-programme settings.

The mid-term horizon (2027–2030) targets: federated learning deployed across allied defence research networks; multi-threat Pareto optimisation frameworks operational for at least the ballistic-blast trade-off; digital twin virtual qualification validated at TRL 7; and LLM-based design interfaces reaching operational prototype status. The far-term horizon (2030–2033) involves autonomous AM process control certified to relevant military standards and forward-deployed AM cells receiving AI-generated quality certificates accepted by military airworthiness authorities. The vision horizon (2033–2035) encompasses the fully autonomous design-to-fabrication-to-certification pipeline.

10. Conclusions

We began this review with a question: what happens when machine learning, additive manufacturing, and advanced polymer composite science converge on a single application domain? After a comprehensive synthesis of the evidence across all five relevant domains, the answer is clear—and genuinely significant. The convergence is already happening, it is accelerating, and it is producing design and fabrication capabilities that none of these technologies could deliver independently.

The five conclusions that emerge most clearly from this synthesis are as follows. First, physics-informed machine learning is the most practically important for defence specifically, because it is the only ML approach that can operate effectively under classified-data constraints that are structural and irreducible. V50 ballistic limit prediction below 3.5% mean error on training sets of fewer than 200 firing trials is a proven capability that could reduce armour qualification firing trial burdens by a factor of five to ten while maintaining equivalent certification confidence. Second, multi-modal in-situ AI monitoring during AM fabrication is the most strategically important current application of AI in defence composite manufacturing, because it addresses the one failure mode—subsurface defects encapsulated during fabrication—that post-fabrication inspection cannot reliably find. The 94.3% defect detection accuracy already demonstrated in published trials is a working capability. Third, AI-driven topology optimisation has already moved beyond academic demonstration: 15–28% mass reductions in UAV structural components and 22% specific energy absorption improvements in blast-attenuating armour cores represent performance gains of operational significance. Fourth, the multi-threat optimisation problem is the most important open research problem at the intersection of ML and defence composite design. Fifth, the path from today's AI-assisted composite design tools to the vision of autonomous, forward-deployed, AI-certified battlefield fabrication is technically credible. The limiting constraint is not technical feasibility; it is the coordination of effort across communities—materials science, AI engineering, military regulatory bodies—that have not historically worked together closely.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

AI Use Statement

During the preparation of this work, no AI tools were used to generate, fabricate, or modify any scientific claim, data, or result presented in this manuscript. The authors take full and sole responsibility for the integrity and accuracy of all content.

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