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Artificial intelligence in additive and smart manufacturing: a critical review of design, process optimization, and quality control

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Highlights:

- AI accelerates design and reduces iterations in additive manufacturing.
- ML optimizes process parameters with high accuracy and fewer experiments.
- DL enables > 95% accurate real-time defect detection in AM systems.
- Digital twin and IIoT enhance smart manufacturing efficiency and control.
- AI improves sustainability via energy and material optimization.
- AI maturity assessment enables comparative evaluation of AM lifecycle adoption.

Abstract: The rapid adoption of artificial intelligence (AI) in the production sector has triggered a revolutionary change in the design, manufacturing, monitoring, and optimization. The paper is a critical analysis of AI-based additive manufacturing (AM) and smart manufacturing systems with an emphasis on design intelligence and process optimization, real-time quality control, and sustainable production. Based on recent literature, this paper considers the major AI methods, such as machine learning (ML), deep learning (DL), reinforcement learning (RL), and physics-informed neural networks (PINNs) throughout the manufacturing lifecycle. The results show that AI can greatly decrease the time spent on design iterations, increase the accuracy of predictions of process parameters, and allow *in-situ* defect detection with high accuracy. Moreover, AI helps to ensure predictive maintenance strategies, reduce the number of unforeseen failures and enhance operational efficiency. The interplay of AI and digital twin technology, Industrial Internet of Things (IIoT), edge computing, and big data analytics is cited as a pillar of Industry 4.0 and the future Industry 5.0 paradigm. Regardless of these developments, the issues of data sparsity, the applicability of the model, computational expense, and interpretability are the key obstacles to large-scale industrial adoption. The value of human-AI cooperation and the necessity to have explainable and reliable AI systems in critical safety areas are also emphasized in the study. Lastly, the review provides future research directions, which focus on multi-modal AI, large-scale manufacturing models, and sustainability-based optimization frameworks. In general, the article is a thorough synthesis of the recent developments and realistic directions of introducing AI-enabled smart manufacturing.

Keywords: artificial intelligence; additive manufacturing; machine learning; digital twin; smart manufacturing

1. Introduction

The convergence of artificial intelligence (AI), new materials science, and digital technologies is causing a paradigm shift in the global manufacturing industry. The manufacturing process hitherto operated under empirical rules and human skills is increasingly being substituted or supplemented with data-based intelligence systems which can make autonomous decisions, adapt in real-time and optimise continuously [1,2]. This shift, which can be summed up in a broad concept referred to as Industry 4.0 and, more often, Industry 5.0, is not just an enhanced version of the previous one, but a paradigm shift in the perception of manufacturing activities and how they should be carried out [3,4].

Additive manufacturing (AM) which also includes selective laser melting (SLM), fused deposition modelling (FDM), directed energy deposition (DED) and binder jetting has become one of the most radical technologies of production in the modern age [5,6]. Its inherent benefits of geometric freedom, material efficiency, and close to zero tooling overhead make it especially subject to optimization by AI. The process-structure-property relationships in AM are, however, too complex to be tackled by the conventional methods of analysis, which are not well suited to such large-scale analysis [7,8]. This is where AI stands to be a crucial opportunity.

Cyber-physically integrated, sensor-abundant, and networked intelligent manufacturing systems are creating new amounts of high dimensional process data such as never before. The computational tools that are needed to derive actionable knowledge out of this data deluge are AI methodologies, including classical machine learning (ML) algorithms, and advanced deep learning (DL) architectures and reinforcement learning (RL) frameworks [9,10]. Applied to AM, these tools can be utilized to synthesize intelligent designs, control adaptive processes, detect defects *in situ*, and optimize lifecycle processes with a level of performance and reliability that would not be possible without human expertise [11,12].

Although scholarly attention to AI in additive and smart manufacturing has grown rapidly, the literature remains fragmented along both disciplinary and topical lines, and several recent reviews have each addressed only a slice of this landscape. Mattera *et al.* [13] critically surveyed reinforcement-learning-based control specifically for robotic AM, concluding that most reported RL studies remain confined to simulation and rarely reach closed-loop control of melt-pool or bead geometry. Qin *et al.* [14] reviewed robot digital twin (RDT) architectures across manufacturing broadly, with AM treated as one of several application domains rather than as a focal technology. Chua *et al.* [15] catalogued process-monitoring and inspection hardware for metal AM but predate the deep-learning-dominated monitoring literature of the last five years. Mattera *et al.* [16] focused narrowly on wire-arc AM (WAAM), combining ML-based monitoring with bio-inspired parameter optimisation but excluding powder-bed and design-stage AI. Wang *et al.* [17] reviewed ML across the AM design-manufacturing-performance chain but did not extend into digital twins, Industrial Internet of Things (IIoT) infrastructure, or sustainability. None of these reviews spans the full AM value chain, from design through sustainable production, while also drawing an explicit boundary between AM-specific process intelligence and the broader smart-manufacturing enabling environment (IIoT, cloud/edge computing, big-data analytics) into which AM is increasingly embedded.

The present review addresses this gap directly: unlike the five prior reviews discussed above, it (i) traces AI applications across the complete AM-to-smart-manufacturing lifecycle within a single, consistently applied analytical framework; (ii) closes each thematic block with an explicit judgement of industrial maturity *versus* laboratory-stage status, rather than a purely descriptive inventory of methods; and (iii) treats AM as the central application domain while treating IIoT, digital twins, and big-data infrastructure explicitly as the enabling environment around it, a distinction that is frequently blurred in the existing literature.

1.1. Review methodology and scope

This is a critical, semi-systematic narrative review rather than a fully systematic review or meta-analysis. Candidate literature was identified through structured keyword searches of Scopus, Web of Science, and IEEE Xplore for the period January 2018 to March 2026, using combinations of the terms "machine learning," "deep learning," "reinforcement learning," "physics-informed neural network," "additive manufacturing," "digital twin," "Industrial Internet of Things," "smart manufacturing," and "Industry 4.0/5.0," together with process-specific qualifiers ("laser powder bed fusion," "LPBF," "directed energy deposition," "DED," "wire arc additive manufacturing," "WAAM"). Records were screened for relevance to the manufacturing-lifecycle stages defined in Sections 2 through 5; conference abstracts without peer review, non-English records, and studies reporting purely simulation-only results with no experimental or industrial validation context were excluded unless they represented a technique's earliest reported application. Priority was given to review and primary-research articles published between 2021 and 2026, supplemented by earlier foundational references where a method's original formulation is cited. Approximately 340 records were screened and 124 were retained in the reference list on the basis of topical relevance, methodological clarity, and citation influence within their respective sub-fields; this is therefore a purposively curated, critically synthesised sample rather than an exhaustive census of the field.

Consistent with this critical-review positioning, each major thematic block below (Sections 2 to 5) concludes with an explicit synthesis addressing four questions: which methods are mature enough for industrial deployment; which remain confined to laboratory or simulation settings; what the principal barriers to industrial adoption are; and which claims in the literature appear overstated relative to the evidence reported.

Scope boundary. This review treats AM as the central application domain and smart-manufacturing technologies, principally digital twins, IIoT infrastructure, and big-data analytics, as the enabling environment within which AM increasingly operates, rather than as parallel, equally weighted subjects. Sections 2 and 3 accordingly address AI applications that are specific to the AM process itself (design, process planning, *in-situ* monitoring, closed-loop control), while Section 4 addresses the broader data and connectivity infrastructure that is common to AM and conventional manufacturing alike, discussed here specifically insofar as it enables AM process intelligence. This distinction is intended to prevent the conflation, present in some of the literature discussed above, of AM-specific process physics with general smart-factory data-infrastructure concerns.

Figure 1 summarises this scope and the relationships between the four thematic blocks that structure the remainder of the review, distinguishing the AM-specific process core from the surrounding smart-manufacturing enabling environment.

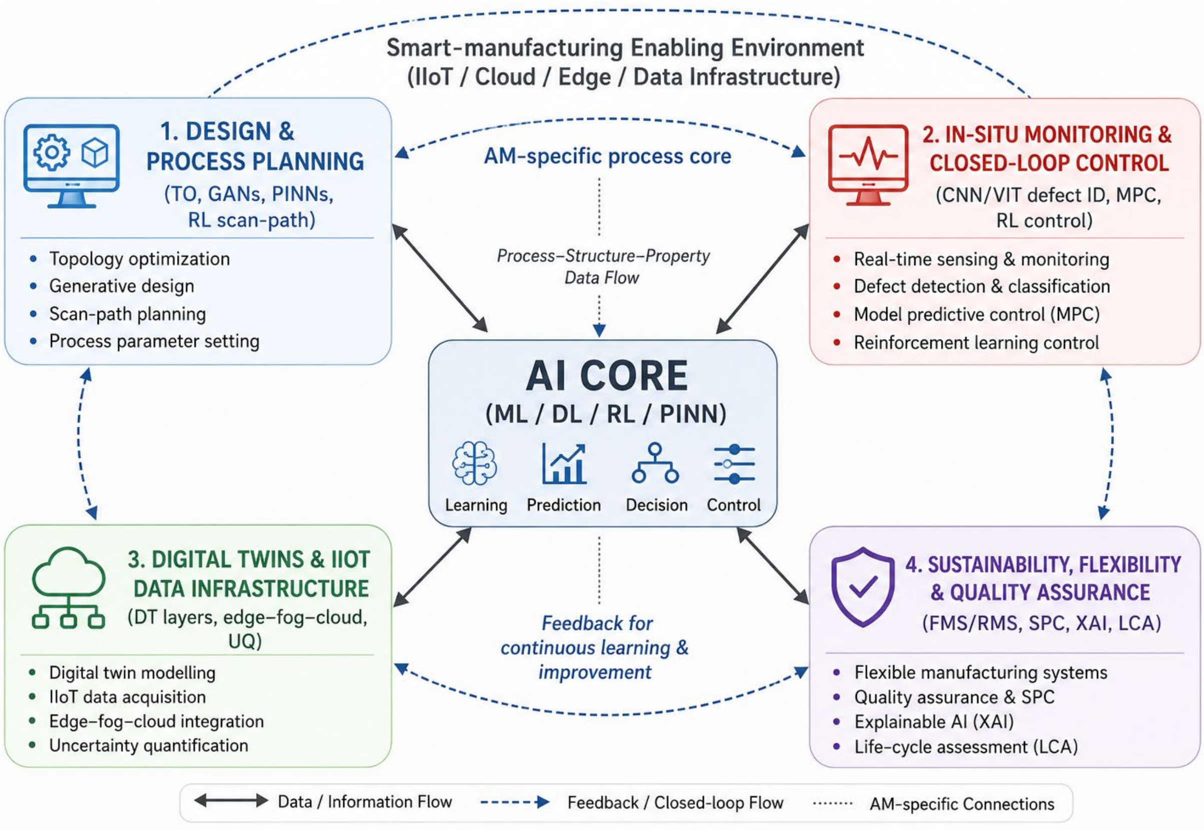

Figure 1. Conceptual map of AI-enabled additive and smart manufacturing, showing the AM-specific process core, the surrounding smart-manufacturing enabling environment, and the four thematic blocks structuring this review.

2. AI for design, process planning, and parameter optimization in additive manufacturing

Design, process planning, and process-parameter selection together determine whether an additively manufactured part is geometrically, mechanically, and economically viable before a single layer is deposited. Within this block, supervised machine learning for process-parameter-to-property prediction and Bayesian optimisation for process-window identification are, in the authors' assessment, the most industrially mature techniques discussed in this review: both have documented use in industrial process-qualification pipelines for LPBF and DED and require comparatively modest computational infrastructure. Generative design and topology-optimisation-by-deep-learning are emerging toward pilot-scale industrial use, principally in aerospace and medical-device design offices, but still require a human-in-the-loop validation step before fabrication. Physics-informed neural networks (PINNs), graph neural networks for microstructure-property linkage, and reinforcement-learning-based process planning remain, with few exceptions, at laboratory or simulation-only maturity: reported case studies are almost invariably validated on a single alloy-process combination and have not been demonstrated across the heterogeneous material-process space that industrial qualification requires. A recurring overclaim in this sub-field is the framing of generative and reinforcement-learning design tools as removing the need for engineering judgement; in the reviewed literature, every reported industrial deployment retains a human design-review step, and none reports closed-loop deployment from generative output directly to production without intermediate validation.

Downstream fabricability, performance and cost are all largely dependent on the design phase of any manufactured component. Classical computational design techniques such as finite element analysis (FEA), computational fluid dynamics (CFD), and rule-based computer-aided design (CAD) are limited by the need to rely on a predetermined design space and the computational cost of exploring the design space exhaustively by parametric means. The AI approach fundamentally provides a different approach: a generative, data-guided exploration that can explore high-dimensional design space and find non-intuitive optimal designs [18,19].

2.1. Generative design and topology optimization

Topology optimization (TO) is also an old tool that is used to get the overall optimal distribution of material in a given design space, with given constraints and boundary conditions as applied. Recent progress has paired TO frameworks with deep learning to radically reduce solution times with no, or even better, solution quality reduction. Convolutional Neural Networks (CNNs), trained on sizeable selections of FEA-solved design problems, have been demonstrated to predict nearly optimal topologies in a few milliseconds by contrast with the hours taken by traditional density-based models like Solid Isotropic Material with Penalization (SIMP) [20–22]. Generative adversarial networks (GANs) have been suggested as a complement to this, and are able to generate physically plausible 3D structures because of targets on mechanical properties through latent space representations. These types of models have found use in the design of lattice structures in lightweight aerospace parts, patient-specific orthopaedic implants, and high-performance heat exchangers. The key strength of GAN-based generative design is that it can explore the set of solutions in a stochastic manner, uncovering design ideas that a deterministic optimizer would never explore [23–25]. Another important development is PINNs, which explicitly fit governing physical equations, such as elasticity, heat conduction, and fluid mechanics, into the neural network loss function. This method allows training using much less labelled data than data-driven methods, and physical consistency of predictions. PINNs have been used to jointly optimize structural compliance and thermal performance of multi-material AM components, and generated designs that would not be feasible with sequential single-physics optimization [26–28].

Formally, a PINN loss combines a data-fidelity term with a physics-residual term: $L = L_{data} + \lambda \cdot L_{physics}$, where L_{data} penalises deviation from observed or FEA-generated training points and $L_{physics}$ penalises violation of the governing Partial Differential Equation (PDE) e.g. the heat-conduction or elasticity equation evaluated at collocation points, with λ balancing the two; this explicit physics penalty is what allows PINNs to train on markedly less labelled data than purely data-driven networks, at the cost of a harder-to-optimise loss landscape that the reviewed literature identifies as a continuing barrier to routine industrial use.

2.2. AI-assisted process planning and build preparation

In addition to geometry optimization, AI has been used in the intricate multi-objective AM process planning, which includes build orientation choice, support structure creation, selection of slicing strategy and optimization of scan path. Such strategies aid management of residual stress distributions, surface finish, dimensional accuracy, and post-processing requirements. Conventional methods are based on rules of thumb and engineering intuition which fail to serve geometrically difficult multi-material components. Reinforcement learning has become a popular form of sequential decision-making in process planning. Trained RL agents, using simulated AM process environments, learn policies that maximise multi-criterion goals, such as part quality, build time, and support volume, among others. Graph neural networks (GNNs) have been used to model and make decisions about complex geometric relationships in CAD models and allow context-sensitive feature detection and process-order planning. Hybrids of multi-objective evolutionary algorithms with surrogate ML have shown good performance in scan-strategy optimization of powder-bed-fusion processes, balancing thermal-gradient reduction with productivity [7,29,30].

Framed formally, an AM process-planning RL agent seeks a policy π that maximises the expected discounted return $E[\Sigma^t \gamma^t r^t]$, where the state s^t typically encodes current build-layer geometry and thermal history, the action a^t adjusts scan-path or support parameters, and the reward r^t penalises defects, build time, and material use jointly. In the authors' reading of the literature, the relative weighting assigned to these competing reward terms is rarely justified empirically and is a significant, under-acknowledged source of poor cross-study comparability in reported RL process-planning results.

2.3. Machine learning for process parameter optimization

Process parameters in AM-fabricated parts are very sensitive to the quality and mechanical performance of the parts. In SLM, for example, laser power, scan speed, hatch spacing, and layer thickness are combined to determine volumetric energy density, which subsequently determines microstructural properties, e.g. grain size, phase composition, porosity, and residual-stress state. The parameter space is enormous, the process-property interactions are non-linear and mutually dependent, and the characterization of experimental processes is time-consuming and material-intensive. Machine learning is a revolutionary approach to this complex optimization issue [29,31,32].

2.3.1. Supervised learning for property prediction

The effectiveness of supervised ML models in predicting AM part properties from process parameters has been demonstrated by a significant body of literature. It has been used to predict density, hardness, tensile strength, and surface roughness in metallic AM systems using Gaussian process regression (GPR), random forests, gradient boosting machines (GBM) and artificial neural networks (ANNs). Empirical research typically suggests that ensemble methods and neural networks are superior to classical regression models given adequate training data, but GPR still has benefits in low-data regimes owing to its intrinsic uncertainty quantification [33–35]. Transfer learning has been suggested as one approach to address the persistent issue of data shortage in AM. Fine-tuning of models trained on datasets of known alloy-process combinations can be done using a small amount of experimental data on novel materials, greatly decreasing the empirical cost of process qualification. This practice is part of a larger trend toward digital manufacturing certification, whereby simulation and data models replace or augment physical testing [36,37].

For Gaussian process regression, the most widely used probabilistic supervised model in this sub-field, the predictive distribution at a new process-parameter vector x^* is Gaussian with mean $\mu(x^*) = k^{*T}(K + \sigma_n^2 I)^{-1}y$ and variance $\sigma^2(x^*) = k(x^*,x^*) - k^{*T}(K + \sigma_n^2 I)^{-1}k^*$, where K is the training-data covariance matrix, k^* the covariance vector between x^* and the training inputs, and σ_n^2 the observation-noise variance. The explicit variance term is what gives GPR its native uncertainty quantification, distinguishing it from point-estimate models such as random forests or standard ANNs, and explains its continued preference in low-data industrial qualification settings even where ensemble methods report marginally higher point-prediction accuracy.

2.3.2. Bayesian optimization for efficient process qualification

Bayesian optimization (BO) has become the sequential experimental-design approach of choice for AM process-parameter optimization. BO intelligently chooses the next experiment to maximize expected improvement by maintaining a probabilistic surrogate model of the objective function, typically a Gaussian process, that trades off exploration of the uncertain parameter space against exploitation of promising regions. This has been shown to determine near-optimal SLM process windows for maximum density or desired microstructural targets using as few as 20–40 experiments, as opposed to the hundreds needed by traditional full-factorial or one-factor-at-a-time methods. Multi-objective variants of BO generalize this model to concurrently optimize conflicting goals, e.g. tensile strength *versus* ductility, surface roughness *versus* build rate. In conjunction with high-fidelity physics-based simulation models as virtual experiments, BO frameworks have significant potential to decrease the empirical workload of process development for new AM systems and materials, which has great industrial utility [38–41].

Formally, BO selects the next experiment x_{n+1} by maximising an acquisition function such as expected improvement, $EI(x) = E[\max(f(x) - f(x^+), 0)]$, where $f(x^+)$ is the best objective value observed so far and the expectation is taken with respect to the GP posterior at x. It is this explicit exploration-exploitation trade-off, rather than any particular surrogate architecture, that allows BO to locate near-optimal process windows within the 20–40 experiment budgets reported above.

2.3.3. Deep learning for microstructure-property linkages

Deriving quantitative relationships between microstructure and property has been a long-term goal in materials science with an immediate impact on AM qualification and certification. DL architectures, especially CNNs applied to electron backscatter diffraction (EBSD) maps, optical micrographs, and X-ray tomography reconstructions, have proved exceptionally powerful for feature classification of microstructural features and subsequent mechanical properties. U-Net models and variants have been used for grain segmentation of polycrystalline AM alloys, where automated statistical information on grain size distributions, texture and phase fractions at throughputs unreachable by human methods is obtained. Graph-based DL models representing microstructures as spatial graphs with grains (nodes) and grain boundaries (edges) have been suggested as a physically relevant way of predicting properties that explicitly learns crystallographic neighbourhood relations. These models have been found to have better predictive ability for fatigue-crack-initiation susceptibility than image-based CNNs that do not explicitly involve spatial relational reasoning [42–44].

Synthesis: Section 2

Data scarcity affects this thematic block unevenly across AM process families. LPBF benefits from comparatively large public and proprietary datasets, owing to its dominance in metal-AM research, so supervised property-prediction models for LPBF titanium and nickel alloys are the most data-rich sub-case reviewed here; DED datasets are smaller and more fragmented across laser- and arc-based process variants; and WAAM-specific parameter-optimisation datasets remain the sparsest of the three, which is reflected in Mattera *et al.*'s [16] observation that WAAM ML studies rely disproportionately on transfer learning and bio-inspired heuristics rather than data-hungry deep architectures. The principal barrier to industrial adoption in this block is therefore not primarily algorithmic but data-infrastructural: qualification bodies require traceable, alloy-specific validation data at a scale that few published studies provide, which is what currently separates the mature supervised-learning and Bayesian-optimisation techniques of Section 2.3 from the still-laboratory-stage generative and reinforcement-learning methods of Sections 2.1 and 2.2.

3. AI for *in-situ* monitoring, defect detection, and closed-loop process control

In-situ monitoring is the most industrially mature AI application area covered in this review: CNN- and, increasingly, vision-transformer-based defect classifiers are deployed commercially on several LPBF machine platforms, and the reported > 95% classification accuracies discussed in Section 3.1 are drawn from studies with industrial or near-industrial validation. Closed-loop control that acts on these detections in real time, however, is markedly less mature: the majority of reinforcement-learning-based melt-pool control studies reviewed here, consistent with Mattera *et al.*'s [13] finding for robotic AM control specifically, are validated only in simulation or on simplified single-track deposition rather than on multi-layer industrial builds. This gap between mature perception (detecting a defect) and immature action (correcting it in real time) is, in the authors' judgement, the single most consequential, and most frequently overstated, capability gap in the AM-AI literature: studies reporting a defect-detection accuracy figure are routinely cited as evidence for "AI-enabled process control" despite reporting no closed-loop control result at all.

Closed-loop quality assurance in manufacturing requires in-process monitoring. Complex sensing technologies, such as high-resolution machine vision, acoustic emission, optical coherence tomography (OCT), pyrometry, and structured light scanning, combined with AI-based signal interpretation, have established the basis for autonomous process control in both AM and traditional machining processes [45,46].

3.1. In-situ defect detection in additive manufacturing

The formation of defects in metal AM, encompassing porosity, lack of fusion, balling, delamination, and residual-stress-induced cracks, is critical in limiting part performance and is the major factor inhibiting adoption of the technology in safety-critical applications. Detecting these defects in real time during the build process, and then taking corrective action, opens a path toward zero-defect manufacturing. The most prevalent literature addresses AI-based image analysis of layer-wise photographs and thermal-camera data. CNN classifiers trained on both synthetic and experimental datasets of AM layer images have been able to detect defects with an overall accuracy of more than 95% when classifying defects such as porosity clusters, spattering, and geometric deviations [47–49]. Semantic segmentation networks allow pixel-wise defect mapping, which offers spatially resolved diagnostic data that can be used as input to adaptive process-control algorithms. Temporal sequences of thermal imaging data have been processed using recurrent neural networks (RNNs) and long short-term memory (LSTM) networks to detect process instabilities before they transform into critical defects, enabling proactive rather than reactive intervention. More recently, attention-based transformer architectures, initially trained on natural-language-processing tasks, have been applied to AM monitoring tasks [49,50]. Vision Transformers (ViTs) have shown competitive performance to CNNs along with better generalization to previously unseen process conditions owing to their global self-attention mechanism. Hybrid architectures that combine local CNN feature extraction with transformer-based global reasoning have been suggested as the next wave of AM monitoring intelligence [51,52].

In order to summarize the various artificial intelligence approaches applied across the phases of additive and smart manufacturing, a systematic comparison is made in Table 1. The table relates key AI methods to their areas of application, data needs, and output functions, and, in this revised version, adds an explicit industrial-maturity (TRL) judgement to support the critical, comparative assessment requested in review, rather than a purely descriptive inventory.

As based on Table 1, the issue of the artificial intelligence techniques is not limited to a particular stage but is spread throughout design, optimization of processes, monitoring, and quality control. Although machine learning and deep learning are the leading technologies in industrial applications because of their level of maturity and precision, new methods, including physics-informed models and hybrid ones, are gaining momentum to deal with data scarcity and enhance generalization in the complex manufacturing setting. The added Industrial TRL column makes explicit what the preceding text argues qualitatively: methods clustered at TRL 6–7 (supervised ML, CNN/ViT monitoring, Bayesian optimisation, computer-vision inspection) are industrially deployed today, whereas RL-based control, GNN-based microstructure modelling, and Explainable AI (XAI) remain at TRL 2–4 and should not be described as production-ready in the current literature.

Table 1. AI techniques and their role across the manufacturing lifecycle (revised: new Industrial TRL column added).

#	AI Technique	Manufacturing Stage	Input Data Type	Output/Decision	Key Advantages	Limitations	Industrial TRL (1–9)	Reference
1	Machine Learning	Process Optimization	Process parameters	Property prediction (strength, density)	Reduces experiments, high accuracy	Needs large datasets	7	[31,33,34]
2	Deep Learning (CNN, ViT)	Monitoring & Quality Control	Images, thermal data	Defect detection & classification	> 95% accuracy, automation	Black-box, data intensive	7	[47,49,50]
3	Reinforcement Learning	Adaptive Control & Scheduling	Real-time process states	Control policies	Dynamic optimization	Training instability	3	[53,54]
4	PINNs	Design & Simulation	Physics + data	Multi-physics prediction	Data-efficient, physically consistent	High computation	4	[26,27]
5	Generative Models (GANs)	Design Optimization	Design constraints	Novel geometries	Innovative designs	Validation challenges	5	[23,24]
6	Bayesian Optimization	Process Planning	Experimental/simulation data	Optimal parameters	Fewer experiments (20–40)	Slower in high dimensions	6	[38,39]
7	Graph Neural Networks	Materials Modeling	Microstructure data	Property prediction	Captures spatial relations	Complex implementation	3	[42,43]
8	Computer Vision (YOLO, R-CNN)	Inspection	Surface/XCT images	Defect localization	Real-time, non-destructive	Noise sensitivity	7	[55,56]
9	LSTM/TCN	Predictive Maintenance	Time-series signals	Remaining Useful Life	Early fault detection	Needs continuous data	6	[57,58]
10	XAI	Decision Support	Model outputs	Interpretability	Trust & certification	Limited depth	2	[59,60]
11	Hybrid AI (CNN + Transformer)	Monitoring & Control	Multi-modal data	Integrated prediction	Better generalization	High computation	4	[51,52]

3.2. Closed-loop adaptive control

Quality assurance requires detection of defects, but the ultimate goal is a completely closed-loop defect-prevention and defect-remedial control mechanism that responds to process parameters in real time. The use of ML-based control systems, in which a trained model predicts adjustments to process parameters to achieve desired melt-pool behavior, has been shown in laser powder bed fusion (LPBF) and DED processes [29,61]. Data-based thermal models of the AM process have been demonstrated for use in model predictive control (MPC) strategies that minimize inter-layer temperature variations leading to residual stress and dimensional distortion. Reinforcement learning is an especially promising model for adaptive AM control, as it does not assume an explicit forward model of the process and can learn control policies by interacting with the real or simulated process environment. RL agents developed to stabilize the melt pool during LPBF have demonstrated the ability to counteract intentional process perturbations such as powder-layer non-uniformity, laser-power changes, and inert-gas-flow perturbation, which are typical of real-world applications [53,54].

A representative MPC formulation for inter-layer temperature regulation solves, at each layer, $\min_u \sum_{k=0}^{N-1} \|\hat{T}(x,k) - T\_ref\|^2 + \lambda\|\Delta u_k\|^2$, subject to the thermal-process model $\hat{T}$ and actuator limits on laser power or scan speed u, re-solved in a receding-horizon fashion at each new layer. The computational cost of solving this optimisation within the sub-second layer time available in LPBF is the reason cited most often in the literature for the continued dominance of simplified linear thermal surrogates over full physics-based models in real-time deployments.

3.3. Predictive maintenance in smart manufacturing

One of the most expensive sources of discontinuity in discrete manufacturing is unexpected equipment failure, estimated to cost tens of billions of dollars every year across the automotive, aerospace, and electronics industries. The application of ML to vibration, current, temperature, and acoustic-emission signals has revolutionized predictive maintenance (PdM), a method of predicting an impending failure with enough lead time to plan an intervention [57,58,62]. Autoencoders, variational autoencoders (VAEs), isolation forests, and one-class SVMs are anomaly-detection models trained on large sets of nominal machine operating signatures, subsequently deployed to flag deviations indicative of degradation. Prognostic remaining-useful-life (RUL) estimation with LSTM and temporal convolutional networks (TCN) has been used for critical manufacturing equipment such as Convolutional Neural Networks (CNC) spindles, bearing assemblies, and hydraulic systems. To address the data-sovereignty issues that tend to hinder industrial PdM, federated-learning mechanisms that preserve data privacy while allowing collective model training across geographically distributed machine fleets have been suggested [63–65].

Synthesis: Section 3

Real-time inference latency requirements differ sharply by process. LPBF melt-pool control loops typically require sub-millisecond-to-millisecond response, given layer times on the order of tens of seconds and melt-pool dynamics on the microsecond-to-millisecond scale, whereas DED and WAAM, with substantially larger melt pools and slower thermal dynamics, tolerate control-loop latencies one to two orders of magnitude longer. This distinction is rarely made explicit in the literature reviewed, where latency claims are often generalised across AM process families without qualification. The dominant barrier to closed-loop deployment is therefore process-specific: for LPBF, it is the computational cost of physics-consistent real-time inference at the required layer rate; for WAAM, where thermal dynamics are slower, the barrier is less computational and more a lack of validated multi-layer closed-loop demonstrations, a gap explicitly identified in Mattera *et al.* [16]. On maturity, *in-situ* defect detection (Section 3.1) and predictive maintenance (Section 3.3) are industrially deployed today, whereas closed-loop RL-based control (Section 3.2) remains, with isolated exceptions, at simulation or single-track laboratory validation, and claims of "autonomous" AM process control should be read with this distinction in mind.

4. Digital twins, IIoT, and data-driven infrastructures for smart manufacturing

Digital twin (DT) and IIoT infrastructure sit, in the framing adopted in Section 1.1, in the enabling environment surrounding AM rather than within the AM process itself, and their industrial maturity should be judged accordingly. IIoT connectivity protocols (Open Platform Communications Unified

Architecture (OPC-UA), Message Queuing Telemetry Transport (MQTT) and cloud/edge computing architectures are industrially mature and widely deployed across discrete manufacturing generally, including AM. AM-specific process-structure-property (PSP) digital twins, by contrast, remain predominantly a research-stage capability: Qin *et al.* [14], reviewing robot digital twins across manufacturing broadly, note that AM-specific DT applications are among the least mature of the domains they survey, behind assembly and machining DTs, a finding consistent with the still-emerging status of the thermomechanical AM digital twins discussed in Section 4.2 below.

One of the most influential paradigms in contemporary manufacturing engineering is the DT, a constantly updated virtual image of a real manufacturing system or part. Digital twins are based on real-time sensor data streams, high-fidelity physics simulations, and ML-based surrogate models, which make it possible to monitor, analyze, predict and optimize manufacturing processes and products throughout their lifecycle without physical experimentation [66–68].

4.1. Digital twin architecture and integration

The manufacturing digital twin is realized by combining three fundamental layers: physical (sensors, actuators, manufacturing equipment), data (communication infrastructure, data preprocessing, storage), and virtual (simulation models, ML algorithms, optimization engines). Bidirectional data flow between physical and virtual layers, *i.e.*, physical states updating virtual models and virtual-model insights driving physical process changes, is the hallmark of a true digital twin and distinguishes it from traditional simulation or monitoring systems [69,70]. AI is critical in all three layers of the DT. At the data layer, signal processing, noise reduction, and anomaly detection are performed using ML to ensure that the virtual model is fed with quality, representative physical-state information. Physics-informed ML surrogate models can be used in the virtual layer to substitute computationally costly FEA and CFD simulations, providing real-time state estimation and optimization that would otherwise be infeasible with first-principles models alone. DTs incorporate uncertainty quantification (UQ) frameworks, such as Monte Carlo methods, polynomial chaos expansion, and Bayesian neural networks, which deliver confidence bounds on predictions, essential in safety-critical applications [71–73].

Formally, Bayesian-neural-network-based uncertainty quantification in a PSP digital twin approximates the posterior predictive distribution $p(y|x,D) = \int p(y|x,\theta)\cdot p(\theta|D)\cdot d\theta$ over model parameters θ given training data D, typically via Monte Carlo dropout or variational approximation. The resulting predictive variance is what allows a DT to flag process states for which its property prediction should not be trusted for qualification decisions, an increasingly explicit requirement in aerospace and medical-device certification pathways.

4.2. Digital twins for additive manufacturing

The special challenge of AM-specific digital twins is that the layer-by-layer material-deposition process requires modeling of the thermal history of each layer, which affects the microstructure and residual stress of all subsequent layers [69]. A thermomechanical DT model coupling thermal simulation with mechanical response has been developed to predict final part distortion and residual-stress fields prior to actual fabrication for LPBF and DED. Such models, accelerated with ML using data-based thermal-property models and surrogate mechanical solvers, have shown order-of-magnitude improvements in computational speed with accuracy within 5%–10% of full-fidelity finite-element solutions [74–76]. Particularly ambitious and scientifically influential are PSP digital twins that form quantitative correlations between AM process parameters, resulting microstructure, and end-of-process mechanical properties. Recent literature indicates such DTs have proved computationally tractable and can drive material-informed process optimization without large experimental campaigns, for titanium alloys (Ti-6Al-4V), nickel superalloys (IN718), and stainless steels (316L). Combining PSP DTs with closed-loop process control represents the current state of the art in AM intelligence, and multiple research teams have demonstrated microstructure-directed control of AM processes using this methodology [77–79].

4.3. IIoT infrastructure

IIoT platforms serve as the connectivity backbone of smart manufacturing, enabling standardized data acquisition, transmission, and storage from heterogeneous machines and sensors [80,81]. Communication protocols including OPC-UA, MQTT, and time-sensitive networking (TSN) have been widely adopted for deterministic, low-latency machine data exchange. At the device level, smart sensor nodes with embedded microcontrollers capable of local signal processing and ML inference have emerged as enablers of intelligent edge computing, reducing bandwidth requirements and latency compared to centralized cloud-processing architectures [82–84].

The integration of IIoT with AI creates a hierarchical intelligence architecture operating across multiple temporal and spatial scales. At the device edge, lightweight ML models perform real-time feature extraction and anomaly flagging. At the factory fog layer, more computationally intensive ML models perform inter-machine correlation analysis and production-scheduling optimization. In the cloud, large-scale AI platforms perform fleet-level analytics, model retraining, and enterprise integration. This distributed intelligence hierarchy, sometimes termed the “cloud-fog-edge” computing continuum, is increasingly recognized as the architectural standard for AI-enabled smart manufacturing [68,85,86].

4.4. Big data analytics for manufacturing intelligence

The canonical 4V dimensions of volume, velocity, variety, and veracity are used to describe manufacturing big data, with variability and value increasingly recognized as additional dimensions. Extracting actionable intelligence from such data requires a unified analytics pipeline spanning data acquisition, cleaning, integration, feature engineering, model training and validation, and deployment, each with its own technical challenges. Smart manufacturing has deployed stream-processing platforms such as Apache Kafka and Apache Spark Streaming to provide continuous real-time analytics on high-velocity machine data [87–89]. Continuous process-data streams are subjected to time-series analysis methods (dynamic time warping, spectral analysis, ML-based temporal pattern recognition) to identify changing process signatures indicative of quality deviations or equipment wear. Knowledge-graph methods have been suggested to combine heterogeneous manufacturing data sources, sensor data, maintenance logs, quality-inspection reports, and product specifications, into a single semantic representation supporting more advanced cross-domain reasoning than traditional relational-database methods [2,68,90].

Although single AI methods have local gains, the reconfiguration of manufacturing systems is led by their incorporation into a larger smart environment. To emphasize this system-level view, Table 2 presents the major elements of AI-based smart manufacturing along with their technological basis, functionalities, and challenges, and, in this revised version, an added industrial-maturity judgement for each system component.

Table 2 demonstrates that the real potential of AI in manufacturing lies in the seamless integration of design intelligence, real-time monitoring, digital twins, and data-driven decision-making frameworks. Nevertheless, the issues of interoperability, data quality, computational needs, and reliability still limit the scale of industrial usage, establishing the essential lines of further research and development. The Industrial TRL column makes explicit that the components clustered at TRL 6–7 (*in-situ* monitoring, IIoT infrastructure, quality-control systems) are where AI-enabled smart manufacturing is closest to mature deployment today, while adaptive control, digital twins, and human-AI collaboration, each central to the "autonomous factory" vision frequently invoked in the literature, remain at TRL 3–4.

Table 2. Integrated smart manufacturing framework (AI + Industry 4.0/5.0) (revised: new Industrial TRL column added).

#	System Component	Technologies Involved	Core Function	Key Benefits	Major Challenges	Industrial TRL (1–9)	Reference
1	Design Intelligence	AI, Generative Design, CAD	Optimal geometry & topology generation	Reduced design cycle, lightweight structures	High computational demand	5	[18,19]
2	Process Optimization	ML, Bayesian Optimization	Parameter tuning & process-window identification	Improved quality, reduced experimentation	Data scarcity, non-linearity	6	[38,39]
3	*In-situ* Monitoring	Sensors, DL, Vision Systems	Real-time defect detection	Enables zero-defect manufacturing	Sensor noise, calibration issues	7	[45,47]
4	Adaptive Control	RL, MPC	Real-time parameter adjustment	Process stability, defect prevention	Latency constraints, model reliability	3	[53,61]
5	Predictive Maintenance	ML, IoT, Edge AI	Failure prediction & RUL estimation	Reduced downtime, cost savings	Data privacy, model generalization	6	[57,63]
6	Digital Twin	Simulation + AI + IoT	Virtual replica & lifecycle optimization	Real-time monitoring & decision support	Integration complexity, high cost	4	[66,69]
7	IIoT Infrastructure	IoT, Cloud, Edge Computing	Data acquisition & communication	Real-time connectivity & scalability	Interoperability issues	7	[82,85]
8	Big Data Analytics	Data Mining, ML, Streaming Tools	Data-driven decision-making	Improved insights & optimization	Data heterogeneity, storage	6	[87,88]
9	Sustainable Manufacturing	AI, Energy Models, LCA	Energy & material optimization	Reduced carbon footprint, efficiency	Trade-offs in cost *vs.* sustainability	4	[91,92]
10	Flexible Manufacturing Systems (FMS)	AI Scheduling, Robotics	Dynamic production planning	High adaptability & responsiveness	System complexity	5	[93,94]
11	Human-AI Collaboration	Cobots, Vision AI	Assisted operations & safety	Improved productivity, ergonomics	Trust, safety concerns	4	[95,96]
12	Quality Control Systems	AI Vision, SPC, XAI	Inspection & validation	High accuracy, automation	Explainability limitations	7	[55,97]
13	Future AI Directions	Multi-modal AI, Foundation Models	Next-gen intelligent manufacturing	Scalability & innovation	Standardization gaps	1–2	[68,80]

Synthesis: Section 4

Synthesis. The principal barrier to industrial IIoT-DT integration for AM is interoperability rather than sensing or connectivity per se: heterogeneous machine vendors expose proprietary data formats, and the OPC-UA/MQTT standardisation discussed in Section 4.3, while mature as a protocol, is inconsistently implemented across AM machine platforms, which fragments the fleet-level data aggregation that PSP digital twins and predictive-maintenance models require.

Figure 2 consolidates the maturity assessments made throughout Sections 2 to 4 into a single comparative view across the AI techniques surveyed in this review, providing the structured comparative evaluation requested in review rather than a purely descriptive discussion.

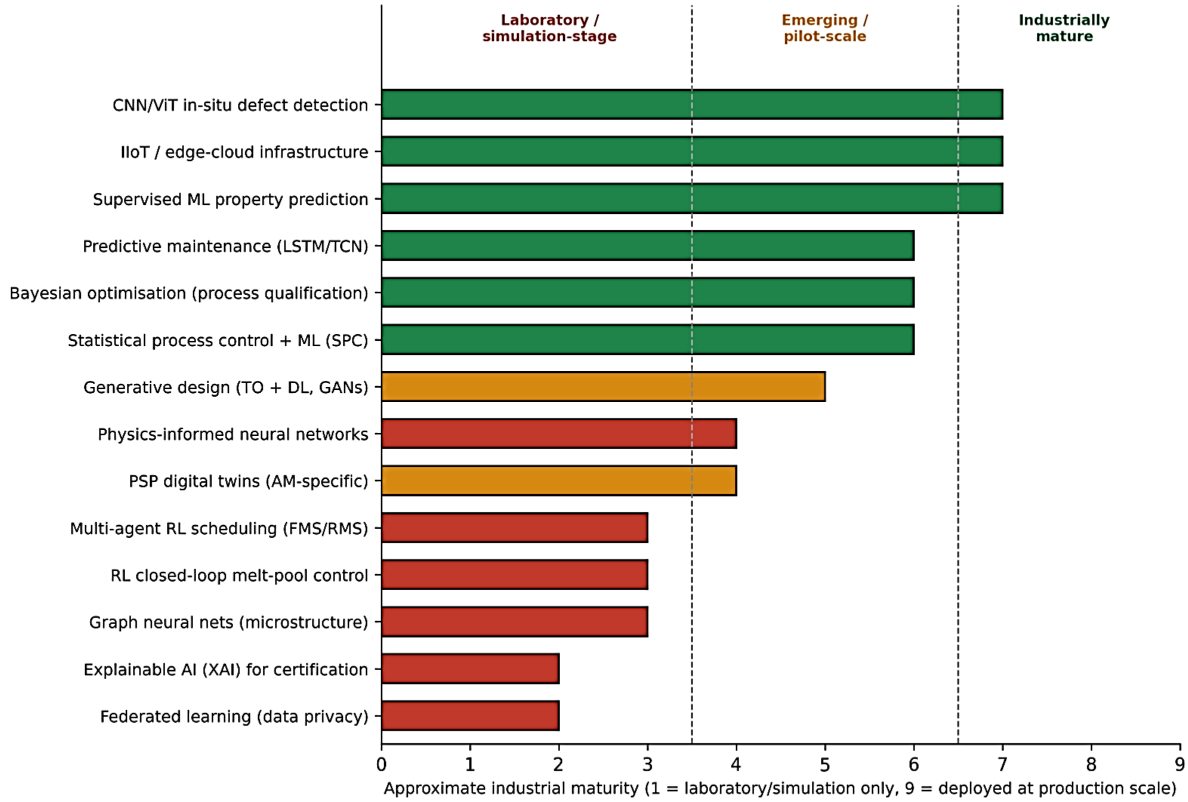

Figure 2. Author-assessed industrial maturity (approximate technology readiness level) of the AI techniques surveyed in Sections 2 to 4 of this review, synthesising the per-section critical assessments and Tables 1–2.

5. AI for sustainable, flexible, and quality-assured manufacturing

This block groups three application areas, energy/material sustainability, flexible and reconfigurable production scheduling, and final quality control, that are common to AM and conventional discrete manufacturing rather than AM-specific, consistent with the scope boundary set out in Section 1.1. AI-based statistical process control and computer-vision-based dimensional inspection are industrially mature and are, in several of the reviewed studies, already integrated into commercial AM quality-management software; XAI methods for certifying these decisions to auditors remain markedly less mature, with SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) reported almost exclusively in academic rather than qualification-pipeline settings.

5.1. AI for energy consumption optimization

The necessity of sustainable production, triggered by regulatory requirements, corporate social responsibility, and resource limitation, has placed AI as a central facilitator of the shift toward circular, energy-saving, low-carbon manufacturing systems. AI's ability to optimize the whole system, monitor energy in real time, and predict resource allocation directly addresses the main contributors to unsustainability in manufacturing: energy waste, material waste, and unplanned process losses [98,99]. Manufacturing accounts for a significant share of global energy consumption, with roughly a third of industrial energy estimated to be wasted. AI-based energy-management systems (EMS) use ML to continuously model the energy-consumption behaviour of individual manufacturing assets and entire factories, optimizing production scheduling in response to peak demand charges, relocating energy-intensive activities to low-tariff periods, and reducing idle-state consumption. Reinforcement learning applied to joint optimization of production scheduling and energy procurement in smart factories with on-site renewable generation has reported 15-30 percent reductions in energy cost and carbon intensity relative to traditional scheduling heuristics. DL-based energy-consumption prediction models for CNC machining and AM processes support proactive energy-budget planning and identify energy-excessive configurations at the design and planning stage, before physical production begins [91,100,101].

5.2. AI for material efficiency and circular manufacturing

A widespread inefficiency in traditional subtractive manufacturing is material waste, with buy-to-fly ratios for complex aerospace parts as high as 20:1. AM's near-net-shape capability substantially reduces this, and AI-based design optimization further minimizes material usage through topology optimization and lattice structure design [100]. Nevertheless, the effective recovery, characterization, and reuse of non-melted powder in metal AM processes, a considerable material cost, remains a challenge that AI-based quality evaluation and blending-optimization strategies can address [7,8]. Within the broader framework of circular manufacturing, AI-based models for material-degradation prediction, end-of-life disassembly planning, remanufacturing-process optimization, and remanufactured-component quality prediction are attracting increasing research interest. ML-augmented life-cycle-assessment (LCA) models have been suggested to deliver dynamic, data-driven sustainability indicators of manufacturing choices in real time, moving beyond static, product-average LCA models toward lot-level environmental-impact estimates [92,102,103].

5.3. AI-driven production planning, scheduling, and human-AI teaming

Modern markets are volatile and demand-oriented, requiring manufacturing systems that are fast and adaptable to changing product specifications, production volumes, and material inputs. FMS and reconfigurable manufacturing systems (RMS) employ modular machine structures, programmable automation, and flexible material handling to meet this need. AI is the intelligence layer that allows these systems to adapt not only through human reprogramming but through autonomous learning and decision-making [104,105]. FMS/RMS production scheduling is a combinatorially complex optimization problem, and in smart manufacturing, real-time disruptions such as machine failures, order changes, and material unavailability further complicate it. Traditional operations-research methods (linear programming, integer programming, metaheuristics) cannot produce quality schedules fast enough for the dynamic rescheduling that real-time events demand. DL-based scheduling policies, including RL and imitation learning, have been shown to produce near-optimal schedules in seconds for realistic job-shop problems with tens of machines and hundreds of jobs [93,94]. Multi-agent RL systems, in which individual machine agents learn cooperative scheduling policies through decentralized decision-making, have been suggested as a scalable and robust approach to dynamic scheduling in heterogeneous manufacturing systems. Transfer-learning methods allow scheduling models trained on past production data to adapt quickly to new product families and machine configurations, decreasing reconfiguration lead time [94,106,107]. The advent of collaborative robots (cobots) in flexible manufacturing cells has presented new opportunities and challenges for human-machine interaction. AI systems that perceive, model, and predict human-worker actions and intentions are essential for safe and efficient human-cobot collaboration. Pose-estimation and action-recognition DL models have been implemented as computer-vision systems to monitor worker posture, activity, and spatial position, allowing cobots to dynamically adjust motion trajectories for safety and complementarity. Imitation learning and inverse-RL methods have been used to transfer human-operator task experience to robots for assembly, inspection, and material-handling tasks. The resulting systems, merging human flexibility and tacit knowledge with robotic accuracy, endurance, and data-processing power, exemplify the human-centered AI philosophy central to the Industry 5.0 vision [68,95,96,108].

5.4. AI-driven quality control in additive and smart manufacturing

Quality assurance in manufacturing spans a continuum of processes: incoming-material checks, in-process quality control, and final-part certification. AI has significantly affected all these activities, increasing detection rates, inspection speed, and consistency relative to traditional manual or rule-based approaches [109–111]. Automated visual inspection (AVI) systems have been a mainstay of high-volume production for decades. DL, especially CNNs for defect classification and detection and semantic-segmentation networks for defect localization, has revolutionized AVI functionality, enabling detection of small-scale, complex defects not identifiable by traditional image-processing algorithms [55,112]. Object-detection models such as YOLO (You Only Look Once) and Faster R-CNN have been used to detect surface defects on rolled steel, castings, and AM components with mean-average-precision values exceeding 90 percent across various defect categories. Structured-light and photogrammetry-based 3D surface inspection, combined with X-ray computed tomography (XCT) and ML-based geometric-deviation analysis, delivers volumetric quality information beyond what 2D imaging systems provide. XCT-based internal-defect characterization, aided by DL-based segmentation and classification, has become the standard for non-destructive evaluation of complex metal AM components [49,56,113]. The computational burden of high-dimensional XCT data, potentially billions of voxels per scan, has motivated computationally efficient DL-based segmentation methods that match full-resolution accuracy while reducing processing time by an order of magnitude [114,115]. Conventional statistical process control (SPC) techniques, such as Shewhart control charts, CUSUM charts, and multivariate T^2 statistics, assume process stationarity and normally distributed data, assumptions often violated in complex manufacturing processes [114].

ML-based SPC alternatives, including support-vector-machine classifiers for out-of-control detection, random-forest-based process-parameter-importance ranking, and deep-learning-based anomaly detectors, offer higher sensitivity to small process changes without the distributional assumptions of classical methods [97,116,117]. XAI systems, such as SHAP, LIME, and attention visualisation, have been incorporated into AI-based quality-control systems to provide interpretable diagnostic information alongside anomaly warnings, a practical necessity in regulated manufacturing settings where quality verdicts must be justifiable to auditors and certification bodies. Naturally explainable ML architectures, including concept-based neural networks and prototype networks, are a current research direction seeking to eliminate the need for post-hoc explainability altogether [59,60,118].

Synthesis: Section 5

Energy- and material-efficiency gains reported for AI-optimised scheduling (15%–30%, Section 5.1) are consistently reported in the literature reviewed for discrete, non-AM manufacturing contexts; AM-specific energy-optimisation studies are comparatively scarce, and none of the AM-specific studies identified in this review reports plant-scale, as opposed to single-machine, validation, which the authors consider an overclaim risk when such figures are cited as general AM sustainability benefits. On maturity, computer-vision inspection and ML-based SPC (Section 5.4) are industrially mature and already embedded in commercial AM quality-management software; XAI certification methods, FMS/RMS multi-agent scheduling, and human-cobot collaboration (Section 5.3) remain at pilot or laboratory scale, with trust and safety validation identified across the reviewed literature as the principal, and not yet resolved, barrier to wider deployment.

6. Challenges, open questions, and future research directions

Although there are impressive advances, numerous obstacles continue to confront the incorporation of AI into additive and smart manufacturing that need to be resolved before the technology can fulfill its potential for complete transformation. These problems cut across technical, organizational, and sociotechnical levels and are briefly discussed below.

6.1. Data scarcity and quality

AI-system production is data-intensive in nature, yet quality, labelled training data for many manufacturing tasks is limited by the cost and time of physical testing, proprietary-data issues, and the scarcity of critical-failure incidents. Physics-informed data augmentation based on process simulations, transfer learning based on related domains, active learning to maximize information gain with limited experiments, and synthetic data generation based on generative models are strategies used to address this challenge. Federated learning, which allows joint model training across multiple manufacturing locations without raw-data exchange, provides an especially successful direction for overcoming data scarcity without violating industrial confidentiality [119–121].

Concretely, this manifests differently across AM process families: LPBF suffers primarily from a shortage of labelled defect data at the pixel/voxel level needed for segmentation-grade supervision, DED suffers from limited process-parameter coverage across the wider range of feedstock (wire and powder) and power sources used across DED variants, and WAAM suffers most acutely from a near-absence of standardised public datasets, a gap explicitly noted by Mattera *et al.* [16].

6.2. Model generalizability and domain shift

ML models trained on data from a particular machine, material, and process setup often suffer a severe performance drop when applied in new contexts, a phenomenon referred to as domain shift or covariate shift. This limits the applicability of AI models to heterogeneous manufacturing settings and restricts the payoff on model-development investment. Domain-adaptation techniques, such as adversarial domain adaptation, domain randomization, and physics-constrained domain-feature alignment, remain active areas of research toward more generalizable manufacturing AI. The creation of standard benchmark datasets and testing procedures for manufacturing AI, similar to ImageNet in computer vision, would significantly spur advances in the field [68,122–124].

For instance, an LPBF defect classifier trained on Ti-6Al-4V melt-pool imagery has been shown in the reviewed literature to degrade sharply when applied to IN718 without retraining, illustrating that domain shift in AM is often alloy-specific rather than only machine- or vendor-specific.

6.3. Interpretability, trust, and certification

The black-box quality of high-capacity DL models can be a major impediment to their use in safety-critical manufacturing processes, such as aerospace, medical-device, and nuclear-component fabrication, where process decision-making requires traceability and defensibility. Although regulatory frameworks for AI in manufacturing are evolving, they remain immature relative to the pace of technological advancement. This gap needs to be filled by XAI methods that provide meaningful and accurate explanations without compromising predictive performance. Hybrid modelling, incorporating ML into physics-based models such that physics-consistent predictions are achieved even in extrapolation regimes, offers a promising direction toward reliable manufacturing AI [125–127].

In safety-critical LPBF aerospace qualification specifically, traceability requirements extend to individual build layers, a granularity of explainability that current XAI methods, validated primarily on image-level classification tasks, do not yet natively provide.

6.4. Real-time inference and edge deployment

The latency requirements of closed-loop manufacturing process control, often in the millisecond range, impose severe constraints on the computational complexity of deployable AI models. State-of-the-art DL architectures that achieve the highest accuracy on manufacturing tasks are frequently too computationally intensive for edge deployment on embedded industrial hardware. Model-compression techniques, including pruning, quantization, knowledge distillation, and neural architecture search for hardware-efficient models, are critical enabling technologies for real-time manufacturing AI at the edge. The development of neuromorphic computing platforms and AI-optimized industrial chips (AI Application-Specific Integrated Circuit (ASICs)) promises to alleviate this constraint in the near future [128,129].

As noted in Section 3's synthesis, this constraint binds far more tightly for LPBF melt-pool control than for WAAM, where slower thermal dynamics afford correspondingly more computational headroom for on-line inference.

6.5. Future research directions

In accordance with the critical review made above, the research directions below can be considered as being of high priority in the development of AI in additive and smart manufacturing:

- Large-scale manufacturing models: Large-scale, pre-trained AI models, similar to GPT and BERT in natural language processing, conditioned on a wide range of manufacturing data, and trained on specific manufacturing tasks with limited labelled data, can be easily and efficiently fine-tuned.
- Multi-modal manufacturing AI: Multi-modal sensor modalities (visual, acoustic, thermal, spectroscopic) are combined in a single DL architecture trained to exploit cross-modal information complementarity for high-quality process monitoring and prediction.
- AI-materials co-design: Closed-loop systems that jointly optimize material composition, microstructure, and AM process parameters to achieve desired functional performance requirements, via active learning and physics-informed AI.
- Reliable and validated manufacturing AI: Creation of AI models with formal performance assurances, uncertainty quantification, and interpretable decision logic that can be qualified against aerospace (AS9100), medical-device (ISO 13485), and nuclear regulations.
- Human-centered AI in Industry 5.0: AI systems that augment rather than eliminate human labour, with ergonomic intelligence, cognitive-state monitoring of workers, and adaptive support to enhance productivity and worker wellbeing.
- Sustainability-aware AI optimization: AI frameworks that simultaneously optimize product quality, manufacturing productivity, and environmental footprint, considering lifecycle thinking and circular-economy principles.

7. Conclusions

This review set out, as stated in Section 1, to bridge the disciplinary fragmentation that has characterised the AI-in-manufacturing literature, by tracing AI applications across the complete additive-manufacturing lifecycle within a single analytical framework and by drawing an explicit boundary between AM-specific process intelligence and the broader smart-manufacturing enabling environment. Returning to that aim: the review has shown that this fragmentation is not merely presentational but reflects a genuine maturity gradient across the lifecycle. Supervised property prediction, Bayesian process optimisation, and CNN/ViT-based defect detection are industrially mature and increasingly interoperate in commercial qualification pipelines, whereas generative design, PSP digital twins, and reinforcement-learning-based closed-loop control remain predominantly laboratory- or simulation-stage, a distinction made explicit in the synthesis closing each of Sections 2 to 5 and consolidated in Figure 2.

The literature clearly shows that AI, including ML, DL, RL, PINNs, and generative models, is no longer a fringe technology in the manufacturing industry but an increasingly central enabling technology that broadens the capability of both AM and smart-manufacturing systems. AI-based design optimization is discovering component geometries not previously considered achievable; ML-based process-parameter models are shortening the time to material and process qualification; *in-situ* DL monitoring is bringing zero-defect AM within near-term reach; and digital-twin technology is providing lifecycle-scale process intelligence that seemed impossible a decade ago. Meanwhile, the problems of data scarcity, model generalizability, interpretability, real-time inference, and regulatory certification still limit the industrial use of manufacturing AI at a scale commensurate with the capabilities demonstrated in the literature reviewed here.

Positioned against the five recent reviews discussed in Section 1 [13–17], each of which addresses a slice of this landscape, robotic AM control, robot digital twins, metal-AM inspection hardware, WAAM-specific monitoring, and the AM design-manufacturing chain respectively, this review's contribution is the cross-lifecycle synthesis and the explicit maturity framework itself (Sections 2–5 syntheses and Figure 2), rather than any single new algorithmic finding. Overcoming the remaining challenges will require long-term, interdisciplinary research efforts spanning materials science, manufacturing engineering, computer science, and systems engineering communities, an integration this review has sought to synthesise rather than merely catalogue. Looking forward, the intersection of AM with smart manufacturing and foundation AI models, neuromorphic computing, human-centered AI design, and sustainability demands characterizes a research agenda of considerable scientific and industrial significance.

The persistent gap between detection and control identified in Section 3, and the interoperability barrier identified in Section 4, are, in the authors' assessment, the two most consequential open problems standing between the current state of the art and the zero-defect, fully closed-loop AM vision that much of the reviewed literature aspires to but has not yet demonstrated at industrial scale. AI in manufacturing is ultimately not only about automating existing processes but about opening entirely new manufacturing possibilities, in materials, forms, and processes, that redefine what is manufactured and how. Realising this vision, rather than merely asserting it, will be the technological measure of the coming decade of research in manufacturing.

Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors used generative AI tools only to improve language and readability. Specifically, the authors used ChatGPT on a limited basis for language polishing, grammatical correction, readability improvement, and minor rephrasing. AI was not used for idea, data generation, scientific analysis, interpretation, or conclusions. The research concept, methodology, experimental work, analysis, and conclusions are entirely the authors' original work; and the manuscript complies with academic integrity and publication ethics standards. All AI-assisted suggestions were reviewed and verified by the authors. The authors take full responsibility for the content of the manuscript.

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Authors' contribution

R.V.: conceptualization and supervision; S.A.: writing—original draft preparation and writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

Rajeev Verma holds the position of Guest Editor for *Advanced Manufacturing* and has not peer reviewed or made any editorial decisions for this paper. The authors declare no other competing interests.

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