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Roadmap on Artificial Intelligence-Augmented Additive Manufacturing

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Artificial intelligence-augmented additive manufacturing (AI2AM) represents a transformative frontier in digital fabrication, where artificial intelligence (AI) is embedded not as a peripheral tool, but as a central framework driving intelligent, adaptive, and autonomous additive manufacturing (AM) systems. The objective of this Roadmap is to present a comprehensive vision of the state-of-the-art developments in AI2AM while charting the future trajectory of this rapidly emerging field. As AM applications continue to expand across diverse sectors, conventional design and control strategies face growing limitations in scalability, quality assurance, and material complexity. AI uses tools like computer vision, generative design, and large language models to help solve problems in scalability, quality assurance, and material complexity, allowing for real-time defect detection, digital twin integration, and closed-loop process control. This roadmap brings together leading contributions from twenty internationally recognized research groups by uniting perspectives from materials science, computer science, robotics, and manufacturing. This work aims to create a cohesive framework for advancing AI2AM as a multidisciplinary science. The ultimate intent of this work is to establish a foundation for coordinated research and innovation in AI-powered AM and to serve as a strategic entry point for future breakthroughs in autonomous and sustainable production.

1. Introduction to Roadmap

Ali Zolfagharian, Mahdi Bodaghi

Additive manufacturing (AM) has rapidly transitioned from a prototyping tool to a disruptive platform for the fabrication of complex, customized, and high-performing components across several sectors, including aerospace and automotive,[1] health,[2] and construction.[3] The techniques—encompassing material extrusion,[4] vat photopolymerization,[5] powder bed fusion,[6] directed energy deposition,[7] and binder jetting[8]—provide distinct benefits in design flexibility, material efficiency, and functional integration. Recently, some or combinations of these processes have been progressively enhanced by artificial intelligence (AI),[9] facilitating more intelligent slicing algorithms, generative design, instantaneous fault detection, adaptive printing process control, and efficient post-processing techniques. The integration of AM and AI is establishing the groundwork

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for advanced, autonomous, and closed-loop manufacturing systems, thereby facilitating the artificial intelligence-augmented additive manufacturing (AI2AM) roadmap presented in this article.

The AI2AM represents a strategic evolution in the field of digital manufacturing, where AI is not merely a tool for automation, but an integral framework for enhancing every stage of the AM process.[10] As AM technologies continue to mature, the demands for greater complexity, material diversity, real-time quality assurance, and sustainability have outpaced traditional approaches. AI offers the computational power, adaptability, and predictive capability to overcome these bottlenecks—transforming AM into a more intelligent, autonomous, and responsive production ecosystem.

The growing adoption of AM across industries such as aerospace, biomedical, energy, and consumer products has exposed significant challenges: process variability, limited design flexibility, inconsistent mechanical properties, and lack of real-time control. AI2AM addresses these challenges by enabling intelligent design generation, data-driven process optimization, anomaly detection, digital twin (DT) integration,[11] and adaptive control systems. By leveraging machine learning (ML), computer vision (CV), generative design, and reinforcement learning (RL), researchers and practitioners are redefining how parts are designed, fabricated, and evaluated in real time.[12,13]

However, the integration of AI into AM is inherently complex and multidisciplinary. It draws on fields as diverse as materials science, computer science, robotics, manufacturing engineering, and data analytics. As different research groups and industries explore AI2AM through their own lenses—be it algorithm development, hardware innovation, or material characterization—there is a pressing need for a unifying framework to coordinate efforts, highlight synergies, and chart future directions. This roadmap is a direct response to that need. It brings together the collective insights of over ten internationally recognized research groups, each contributing to a distinct aspect of the AI2AM landscape. These include AI-guided design of complex structures and metamaterials, data-driven materials discovery, adaptive control of AM systems, generative AI in creative

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manufacturing, and the development of collaborative AI2AM platforms. The roadmap is a strategic call to action for researchers, developers, and industry stakeholders to shape the next generation of manufacturing innovation.

The contributions outlined in this roadmap provide a comprehensive and forward-looking vision for how AI can fundamentally enhance the flexibility, efficiency, and intelligence of AM strategies and products. They reflect a shared commitment to building a global, cross-disciplinary community that will drive innovation, establish standards, and unlock new opportunities for AI-powered design and fabrication. In the following section, we briefly introduce each of the roadmap topics under three themes, as listed in **Table 1**, and highlight the core focus of each contributing research group.

Theme I: Design and Strategies

The sections within "Theme I: Design and Strategies" collectively illustrate how AI is reshaping the front end of AM, moving from material-aware optimization to creativity-driven ideation and intelligent process planning. Section 2 shows how AI-augmented multimaterial design provides computational intelligence to manage voxel-level complexity that exceeds the capacity of traditional topology optimization. Section 3 builds on this foundation by demonstrating how generative AI expands design freedom by enabling early conceptual exploration of geometries and structures. Section 4 extends AI advances into the fabrication domain, where AI-driven multiaxis strategies reduce support dependency, align deposition paths with stress trajectories, and improve overall structural performance. Section 5 highlights the integration of AI into advanced material design and processing, showing how ML and hybrid modeling link microstructural evolution to macroscale performance, thereby tailoring functionality at multiple scales. Finally, Section 6 introduces synergies between generative AI and AM ontologies, which ensure that creative design outputs remain context-aware, manufacturable, and aligned with formalized engineering knowledge. Overall, these sections move progressively from material-level intelligence through generative creativity and multiaxis processing, culminating in a semantic framework that unifies creativity, manufacturability, and functionality under AI-enabled strategies in AM.

AI-Augmented Multimaterial Design in AM

The section on AI-augmented multimaterial design in AM explores how AI is transforming the design of components that incorporate two or more materials within a single print process.[11,14] From early dual-extrusion polymer systems to modern platforms capable of combining metals, ceramics, and functional polymers, multimaterial additive manufacturing (MMAM) has become essential for engineering spatially tailored properties in aerospace, biomedical, and soft robotic applications.[15–18] However, MMAM poses significant challenges beyond those encountered in single-material AM—such as managing intermaterial compatibility, addressing multiphysics behavior, and optimizing conflicting performance goals. Traditional design tools like topology optimization often fall short in this context due to their assumptions of continuous material distributions, while MMAM typically involves discrete, voxel-based design with complex thermal and mechanical interactions. This section

Table 1. The list of topics and authors in this roadmap.

Section No.	Title	Authors
1	Introduction to Roadmap	Ali Zolfagharian, Mahdi Bodaghi
Theme I: Design and Strategies		
2	AI-Augmented Multi-Material Design in Additive Manufacturing	Liuchao Jin, Qi Ge, Wei-Hsin Liao
3	Generative AI for supporting creativity and design for AM	Andrés Díaz Lantada, Francisco Franco Martínez
4	AI-Driven Multi-Axis Additive Manufacturing	Tianyu Zhang, Tao Liu, Charlie C.L. Wang
5	AI-Powered Strategies for Smart Design and Processing in Advanced Material Additive Manufacturing	Mohammad Hossein Mosallanejad, Reza Ghanavati, Abdollah Saboori
6	Synergies between Generative AIs and AM Ontologies	Alejandro De Blas-De Miguel, William Solórzano-Requejo
Theme II: Monitoring and Quality Control		
7	Digital Twin in Additive Manufacturing	Yi Cai, Xiangyang Dong, Huangyi Qu
8	AI for Online Monitoring and Defect Detection in AM	Najmeh Samadiani, Guangyan Huang
9	Real-time AI-driven Structural Validation for Additive Manufacturing	Austin Downey, Yanzhou Fu, Lang Yuan
10	Computer Vision-based AI in Additive Manufacturing	Tsz-Kwan (Glory) Lee, Arbind Agrahari Baniya, Eisha Waseem
11	AI-Controlled Closed-loop 3D/4D Printing	Abdul Rahman Sani, Abbas Z Kouzani, Ali Zolfagharian
Theme III: Product Developments		
12	AI for Soft Robotic Additive Manufacturing	Yijia Wu, Markus P. Nemitz
13	AI-driven Design of *Meta*-scaffolds	Masoud Shirzad, Dageon Oh, Seung Yun Nam
14	AI-Enhanced Development of 3D Bioprinting	Amedeo Franco Bonatti, Irene Chiesa, Gabriele Maria Fortunato, Giovanni Vozzi, Carmelo De Maria
15	Adaptive Metamaterials by AI and 4D Printing	Mahdi Bodaghi

highlights how AI-driven approaches—particularly hybrid models that blend physics-based simulation with ML—are enabling designers to navigate this complexity with greater efficiency.

Generative AI for Supporting Creativity and Design in AM

The generative AI is emerging as a powerful enabler of creativity in the design process, particularly in the early, conceptual stages of innovation for AM. Building on design for additive manufacturing (DfAM) principles,[19–22] which leverage AM's unique capabilities like complex geometries, multimaterial integration, and smart or living materials, generative AI tools now allow designers to create novel shapes and structures by simply providing textual prompts or images. This democratizes design exploration, enabling rapid generation of complex, bioinspired, and highly customized geometries that would be difficult or impossible to conceptualize through traditional CAD tools alone. Early experiments show promising applications in biomaterials design, artistic-technical integration, and accelerating cross-disciplinary discovery. Although challenges remain—particularly in achieving ready-to-print models that incorporate lattice structures, functional gradients, and optimized topologies directly from generative outputs—the trajectory points toward a future where design is seamlessly AI-generated, automatically validated, and materialized through AM, fundamentally reshaping the pace and scope of product innovation.

AI-Driven Multiaxis AM

The section on AI-driven multiaxis AM explores how the integration of AI is unlocking new possibilities in multiaxis 3D printing, overcoming the geometric and mechanical limitations of conventional layer-by-layer fabrication. Traditional AM systems, restricted by three-axis motion, struggle with surface roughness, inefficient support structures, and limited mechanical optimization due to fixed material deposition directions. AI-enhanced multiaxis printing introduces rotational and tilting motions, enabling near support-free fabrication and aligning material deposition along principal stress paths for superior mechanical performance.[23–25] Compared to traditional slicers, AI-powered solutions reduce reliance on high-quality meshes and enhance adaptability across diverse printing tasks. While challenges such as accurate anisotropic stress prediction, mesh resolution dependency, and collision detection persist, ongoing research points toward integrating anisotropic modeling, adaptive meshing, and reinforcement-learning-driven motion planning for safer, more robust, and high-performance multiaxis AM. These advancements position AI-driven multiaxis printing as a transformative capability for producing intricate components with reduced manufacturing waste.

AI-Powered Strategies for Smart Design and Processing in Advanced Material AM

AI-powered strategies are transforming the design and processing of advanced materials in AM, enabling the creation of complex, multimaterial components with tailored functionalities for demanding sectors such as aerospace, biomedical, and automotive.[26] Traditional techniques like welding and powder metallurgy often fall short when addressing intricate geometries and interface challenges, whereas AM combined with AI offers a powerful alternative by optimizing material combinations, predicting interface behavior, and enhancing process control. ML algorithms and multiscale physical models provide data-driven insights into how process parameters influence composition, microstructure, and performance, accelerating the development of functionally graded materials (FGMs) and site-specific property tuning. Emerging approaches such as computational alloying and digital metallurgy further enable real-time adaptation of processing conditions for each material zone.[12,13] Despite these advancements, challenges in material compatibility, interfacial bonding, and scalability persist, highlighting the need for continued innovation in ML frameworks and hybrid modeling. This convergence of AI and AM marks a critical leap toward intelligent manufacturing systems capable of producing next-generation smart components at scale.

Synergies between Generative AIs and AM Ontologies

The section on synergies between generative AI and AM ontologies highlights the powerful convergence of formal semantic structures and AI-driven creativity to enhance the design and manufacturing processes in AM, particularly for personalized medical devices. Ontologies provide a structured framework to integrate complex clinical, technical, and material data, ensuring quality and biocompatibility while identifying design flaws early.[27,28] When combined with generative AI, these ontologies guide AI systems to make context-aware decisions grounded in established knowledge bases. This synergy enables more intelligent design workflows where AI not only generates creative design variations but does so within defined material, geometric, and functional constraints, improving both efficiency and accuracy.[29–31] As this integration advances, it necessitates a shift in engineering practice, moving from traditional CAD operations to prompt-based interactions with AI systems. This evolution is crafting a new design formalism that blends natural language, symbolic precision, and taxonomical clarity, paving the way for more accessible, innovative, and high-performance AM across multiple industries.

Theme II: Monitoring and Quality Control

The sections under "Theme II: Monitoring and Quality Control" demonstrate how AI enables AM systems to evolve intelligent manufacturing pipelines. Section 7 introduces DTs as dynamic, data-driven replicas that bridge physical AM processes with their virtual counterparts, creating a foundation for defect detection and process optimization. Building on this, Section 8 focuses on AI for online monitoring and defect detection, where multimodal sensor data—acoustic, thermal, and visual—is processed by hybrid AI models to identify defects in real time, reducing waste and enhancing scalability. Section 9 advances this concept toward real-time AI-driven structural validation, enabling safety-critical parts to be evaluated during fabrication rather than post-production, a crucial step for aerospace and biomedical applications. Section 10 highlights the role of CV-based AI, which adds spatial and geometric context to AM, detecting surface inconsistencies while enhancing DT fidelity. Finally, Section 11 concludes in AI-controlled closed-loop 3D/4D printing, integrating sensing, analysis, and actuation into autonomous feedback loops that self-correct during manufacturing. Together, these sections present a coherent progression: from digital replicas and sensor-driven defect detection to structural validation, visual intelligence, and ultimately, autonomous closed-loop control—collectively redefining monitoring and quality assurance in AM.

DT in AM

DT technology is revolutionizing AM by enabling real-time, data-driven virtual replicas of physical printing systems and processes.[11] It provides a dynamic, bi-directional link between physical AM equipment and their digital counterparts, allowing continuous monitoring, simulation, and adaptive control. In AM, DTs facilitate predictive maintenance, process optimization, and defect detection through integration with sensor data and AI algorithms.[32] This empowers manufacturers to reduce downtime, enhance part quality, and improve scalability. With AI-enhanced DTs, AM systems gain the ability to autonomously interpret complex data, predict failures, and optimize print parameters in real-time. While challenges remain in data integration, standardization, and system interoperability, ongoing advances in AI, information technology (IT) infrastructure, and DT frameworks are rapidly advancing the field, positioning AI-driven DTs as key enablers of sustainable manufacturing.

AI for Online Monitoring and Defect Detection in AM

The section on AI for online monitoring and defect detection in AM highlights the critical role of AI in enabling real-time quality assurance across diverse AM processes. Defects such as porosity, surface inconsistencies, and delamination can significantly compromise part performance, making early detection essential.[10] AI-enhanced monitoring systems use sensor data—ranging from acoustic signals and thermal images to CV streams—to identify defects during the printing process. While no single method is universally applicable due to variations in materials, processes, and defect mechanisms, tailored AI models have demonstrated success in wire arc, laser-based, and extrusion-based AM.[33] Recent developments integrate ML with physics-informed neural networks (PINNs), large language models (LLMs), and generative AI for data augmentation and robust prediction.[34] These hybrid approaches address challenges like data scarcity, model generalization, and limited annotated datasets, while federated and adaptive learning strategies ensure scalable and privacy-preserving deployment. As the field progresses, comprehensive AI frameworks are being developed to unify detection, localization, and process feedback—paving the way for cost-effective, scalable, and real-time defect detection systems across industrial AM platforms.

Real-Time AI-Driven Structural Validation for AM

The section on real-time AI-driven structural validation for AM emphasizes the transformative potential of integrating AI into in situ validation processes, enabling printed components to be assessed for structural integrity in real time during fabrication. This advancement could shift AM from a prototyping tool to a reliable production method for safety-critical parts, especially in aerospace and automotive sectors. Traditional structural validation relies heavily on post-processing inspections and simulations, which are time-consuming and costly. AI2AM offers a solution by combining data-driven defect detection with physics-based modeling in a hybrid framework.[10,35,36] These innovations allow AI systems to make immediate decisions about part integrity during printing, drastically reducing downtime and material waste.

CV-Based AI in AM

The section on CV-based AI in AM highlights how the integration of CV into AM systems is revolutionizing the precision, adaptability, and intelligence of AM processes.[37] By providing spatial and geometric context, CV enables AM systems to detect surface inconsistencies, layer misalignments, and structural distortions in real time, thus directly improving product quality and process reliability. Evolving from early offline quality control using red, green, and blue (RGB) and thermal imaging to today's real-time, AI-enhanced visual analytics, CV has become a core sensing modality within DT frameworks for AM. This convergence of CV and AI empowers AM platforms to function as intelligent, self-adaptive systems capable of optimizing production workflows, reducing material waste, and supporting broader application across diverse industries.

AI-Controlled Closed-Loop 3D/4D Printing

AI-based closed-loop 3D/4D printing marks a pivotal advancement in AM by integrating real-time sensing, intelligent analysis, and autonomous process control into a unified system. Unlike traditional open-loop printing, which operates on pre-defined parameters, closed-loop systems employ sensors, such as acoustic, thermal, and vision-based devices, to continuously monitor print quality during fabrication.[10] These data streams are processed using AI algorithms capable of detecting anomalies like layer misalignment, nozzle blockage, or material flow inconsistencies. An intelligent feedback loop allows dynamic adjustments to critical parameters such as extrusion rate, temperature, and speed in response to detected deviations, thereby ensuring part integrity and reducing waste. In 4D printing applications, where time-dependent shape transformation adds another layer of complexity, AI-driven control is especially crucial for maintaining actuation performance and functional accuracy.[3,38] While current implementations are primarily experimental, ongoing advancements in AI model robustness and sensor fidelity are rapidly pushing this paradigm toward industrial deployment.

Theme III: Product Developments

The sections under "Theme III: Product Developments" highlight how AI is driving the transition of AM from a platform for prototyping to next-generation product innovation across multiple domains. Section 12 illustrates how AI is addressing fabrication challenges in soft robotic AM by detecting and correcting print defects in elastomeric materials, enabling cost-effective and reliable production of compliant robotic systems for applications ranging from healthcare to space exploration. Section 13 builds on this by focusing on AI-driven design of meta-scaffolds, where ML enables rapid optimization of biomimetic tissue-engineering architectures that balance mechanical integrity with biological function, paving the way for personalized regenerative medicine. Section 14 extends these insights into AI-enhanced development of 3D bioprinting, where AI streamlines bioink selection, optimizes printing parameters, and enforces automatic quality control across pre-, in-, and post-process stages to improve reproducibility and scalability toward clinical translation. Finally, Section 15 explores adaptive metamaterials enabled by AI and 4D printing, which combine stimuli-responsive materials with AI-driven modeling and real-time control to achieve programmable and multifunctional performance across diverse sectors. Collectively, these sections demonstrate a progression from soft robotic components and tissue-engineered scaffolds to biologically functional constructs and intelligent metamaterials, with AI serving as the unifying enabler.

AI for Soft Robotic AM

The section on AI for soft robotic AM explores how AI can address the unique fabrication challenges of soft robotics, a field that utilizes compliant, elastomeric materials to create robots capable of safe and adaptive interaction with dynamic environments. Unlike traditional rigid robots, soft robots are increasingly produced as monolithic systems via AM, aligning with the paradigm of physical intelligence, where the robot's form and material composition contribute to its behavior.[39] However, the soft, deformable nature of these materials makes them especially vulnerable to print defects that can compromise performance, such as leaks in pneumatic actuators.[38] AI offers transformative solutions by enabling automated detection and correction of such defects, optimizing slicer settings, geometry, and print parameters based on material behavior and functional requirements. AI-driven pipelines embedded into design and slicing software could proactively adapt fabrication strategies to printer capabilities and environmental conditions, ensuring repeatable and robust soft robotic systems. These advancements will be key to enabling cost-effective, high-performance soft robotics for applications in healthcare, agriculture, emergency response, and space exploration.

AI-Driven Design of Meta-Scaffolds

The section on AI-driven design of meta-scaffolds highlights how AI is transforming the development of architected tissue engineering scaffolds, known as *meta*-scaffolds, which are designed to replicate the complex mechanical and biological functions of human tissues.[40,41] These structures must simultaneously support cell adhesion, mechanical loading, and nutrient transport, requiring intricate internal architectures that conventional design methods struggle to generate efficiently.[42,43] AI and ML approaches offer a powerful solution by enabling rapid exploration and optimization of scaffold designs based on large datasets, bypassing the limitations of traditional simulation methods like finite element analysis (FEA). By learning from targeted properties and performance criteria, AI models can predict and generate scaffold architectures that are biomimetic, structurally robust, and biologically functional. Despite ongoing challenges, such as the need for large, high-quality datasets, limited biomaterial options, and fabrication resolution constraints, AI-driven strategies are paving the way for next-generation, patient-specific scaffolds in regenerative medicine.

AI-Enhanced Development of 3D Bioprinting

The integration of AI into 3D bioprinting is accelerating the development of tailored bioinks and processes that ensure both optimal biological compatibility and printability, addressing critical challenges in the fabrication of functional tissues and organ constructs.[44] Bioprinting technologies like extrusion-based bioprinting (EBB), inkjet bioprinting (IJB), and light-assisted bioprinting (LAB) have demonstrated potential across tissue engineering and in vitro modeling, yet they still face limitations in quality control and reproducibility. AI-driven approaches are transforming this landscape by enabling intelligent material screening, predictive process optimization, and real-time quality assurance.[45,46] Pre-process AI models streamline the selection of bioinks and fine-tune printing parameters, reducing the reliance on trial-and-error methods. During printing, AI-enhanced in-process monitoring systems utilize sensor data to detect anomalies and maintain print fidelity in real time. Post-process, AI models such as convolutional neural networks (CNNs) and generative adversarial networks (GANs) automatically assess the biological quality of printed constructs, analyzing cell viability, morphology, and proliferation patterns from microscopy images. These advancements collectively enhance the reliability, precision, and scalability of bioprinting, moving the field closer to clinical translation and opening new horizons for personalized regenerative medicine and tissue-engineered implants.

Adaptive Metamaterials by AI and 4D Printing

The section on adaptive metamaterials by AI and 4D printing captures how the fusion of AI with 4D printing is unlocking a new class of intelligent, programmable materials capable of complex, adaptive responses to external stimuli.[47,48] Mechanical metamaterials, designed with architected unit cells and responsive materials like shape memory polymers and liquid crystal elastomers, enable functionalities such as tunable stiffness, shape-shifting, and energy absorption across sectors like aerospace, robotics, and impact protection. However, the inherent complexity of multistimulus actuation, nonlinear behaviors, and intricate geometries presents significant design and process optimization challenges. As research advances, this convergence promises a new paradigm of adaptive, multifunctional metamaterials that can evolve with their use, paving the way for sustainable, high-performance solutions across industries from aerospace to healthcare.

2. AI-Augmented Multimaterial Design in AM

Liuchao Jin, Qi Ge*, Wei-Hsin Liao*

2.1. State of the Art

MMAM has evolved from early experiments with dual-extrusion polymers in the 2000s to present-day sophisticated systems capable of depositing metals, ceramics, and functional polymers within a single build.[4] This growth has been driven by rising demand for components with spatially engineered properties—aerospace turbines with gradient thermal barriers, biomedical implants with bone stiffness gradients, and soft robots with elastomer-metal hybrids for adaptive locomotion. However, the field was faced with a fundamental bottleneck: conventional trial-and-error design methods could not efficiently explore the vast and complex material-process-structure relationships inherent in MMAM.

Compared to single-material AM, MMAM introduces additional challenges due to the discrete nature of material placement, complex interactions between different materials, and the necessity of optimizing multiple competing objectives simultaneously. Traditional topology optimization (TO), which has been widely applied in single-material design, struggles with MMAM because it assumes a continuous distribution of materials. In contrast, multimaterial designs often involve discrete voxel-based arrangements and multiphysics considerations, such as thermal expansion mismatches, which further complicate the optimization process.

Recent advances in AI-driven design tools have been a game-changer[11,14] in enabling the exploration of combinations of materials, geometric architectures, and process variables to achieve functional coherence. ML-based approaches, such as evolutionary algorithms and neural networks, have started to bridge the gap by navigating the high-dimensional design space of MMAM, allowing for the automated discovery of optimal material layouts and fabrication parameters. The AI-driven multimaterial design in AM has led to the development of two approaches: parameter-based optimization and voxel-based optimization (**Figure 1**).

Parameter-based optimization aims at optimizing process and design variables (Figure 1), such as material ratios,[49] layer allocation,[50] and process parameters (e.g., laser power, print speed, and temperature).[51] Such methods generally utilize gradient-based optimization techniques and surrogate modeling to search high-dimensional design spaces for optimal performance at low computational cost.

Voxel-based optimization, however, investigates a smaller scale in that it optimizes at the voxel (3D pixel) level of the microstructure (e.g., the pixel hand of Figure 1). Nongradient-based optimization techniques like evolutionary algorithms and generative neural networks are usually employed for this method. Voxel-based techniques can both design and optimize FGMs or structures with specialized mechanical properties in different

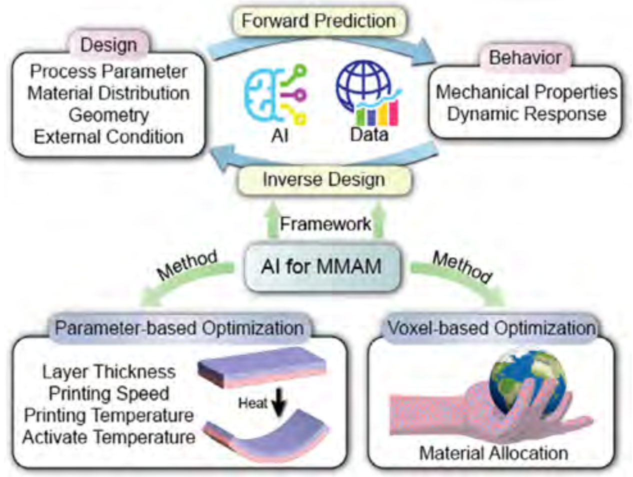


Figure 1. Schematic diagram illustrating the AI-augmented multimaterial design framework and methods in AM.

regions of the part. Assisted by AI algorithms, this method can potentially automate the design of multimaterial structures with optimized internal and external properties. These range from mechanical properties like modulus,[52] toughness (**Figure 2**a, b),[53–55] and stress–strain fields (Figure 2c)[56–58] to dynamic behaviors like 4D printing (Figure 2d,e),[15–18] deformed shape after loading,[59] soft robots with programmable actuation sequences.[15,60]

The intersection of these AI techniques is revolutionizing MMAM workflows. Further advancement of AI-based MMAM is hyped to radically enhance the efficiency of developing complex material systems. Through AI algorithms, the design can be automated, so as to enable the design of materials and components with target properties to achieve desired performance requirements. Such automation not only accelerates the development process but also allows one to explore a greater design space, coming to innovative solutions that would be impossible with traditional approaches.

2.2. Scientific Challenges and Technical Limitations

The integration of AI into MMAM design faces three main challenges: complex material interactions at interfaces, AI model inaccuracy, and computational scalability limitations.

The first challenge is the complicated interfacial behavior between dissimilar materials for the multimaterial system generated by AM. In AM processes, different materials—e.g., metal-polymer, ceramic-polymer, and even intra-system hybrids (e.g., soft-rigid polymer blends)—interact dynamically under spatially and temporally varied thermal, mechanical, and chemical conditions. These interactions produce localized phenomena, including residual stress accumulation, interfacial delamination, microcracking, and mechanical property degradation due to contamination, particularly at boundaries where thermally and mechanically mismatched properties (e.g., thermal expansion coefficients, elastic moduli) exist. Classical homogenized models, which average material properties across interfaces, fail to

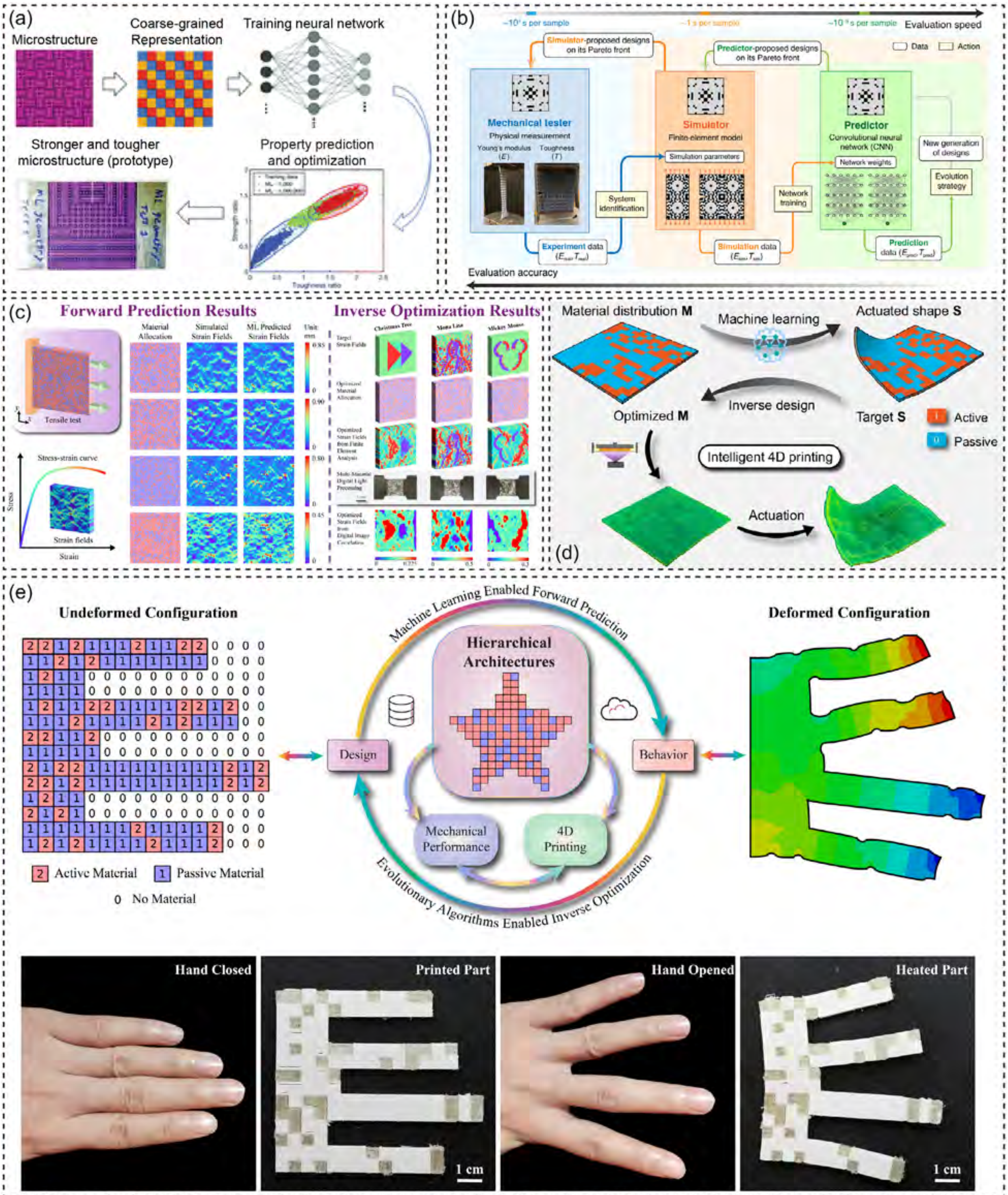


Figure 2. Overview of research in AI-enhanced multimaterial DfAM. a) Bioinspired, hierarchical composite developed by integrating ML with simulation and experimental AM. Reproduced with permission.[53] Copyright 2018, the Royal Society of Chemistry; b) A computational strategy for discovering microstructured composites that achieve an optimal balance between stiffness and toughness. Reproduced with permission.[55] Copyright 2024, The American Association for the Advancement of Science; c) A ML approach for inverse design of complex stress and strain distributions in hierarchical composite materials. Reproduced with permission.[56] Coyright 2025, Elsevier; d) An AI-enabled framework for forward prediction and inverse design in the design of active, 4D-printed plates. Reproduced with permission.[18] Copyright 2024, Springer Nature; and e) A ML-based method for forward prediction and inverse design applied to 4D-printed hierarchical architectures with arbitrary geometries. Reproduced with permission.[15] Copyright 2024, Elsevier.

resolve such complex localized effects. While data-driven AI approaches are promising, they exhibit limited generalizability due to sparse experimental datasets and the absence of integration with physical principles.

Additionally, another key challenge is the difficulty in reconciling AI-based predictions with real manufacturing outcomes due to insufficient training data, manufacturing uncertainties, and incomplete physics modeling. Although AI-driven tools excel at optimizing material distributions, topologies, and functional properties in silico, discrepancies persist between theoretical predictions and physical prints. One major limitation comes from the scarcity of high-quality, diverse datasets required to train AI models effectively. Given the vast design space and complex interactions in MMAM, existing datasets often fail to capture the full range of material behaviors, leading to suboptimal predictions when encountering new material combinations or processing conditions. Besides, the translation of AI-powered designs into physical parts is also hindered by process-induced uncertainties inherent to AM. These include instability of nozzle flow in multimaterial extrusion, powder bed inhomogeneity in laser-based systems, and thermal gradient-driven warping, all of which introduce deviations between computational predictions and as-printed outcomes. Furthermore, incomplete physics modeling remains a critical issue, as many AI-based approaches rely on approximations or surrogate models that do not fully account for multiscale interactions between materials, processing parameters, and environmental factors. Such discrepancies arise not only from fundamental errors in manufacturing the designs but also from the current limitations of AI models in fully capturing the complex, interdependent material-process-structure relationships. Moreover, this discrepancy will be magnified by the lack of rigorous validation of AI-enhanced MMAM designs under conditions more stringent than controlled laboratory settings. A majority of published advances[54,56] are developed through simplified bench-validated components (e.g., simplified geometries or uniaxial tensile bars) in replace of industrially relevant components with complex load, environmental variation, or prolonged durability issues. Absent stringent real-world verification in the form of, for instance, fatigue testing, environmental exposure (thermal cycling, humidity), and in situ monitoring in service environments, the usability of dominant methods remains uncertain.

Finally, the computational burden of high-resolution multimaterial design is also a challenge.[15–18] When designing FGMs or optimizing voxel-level material gradients, it is essential to perform microscale simulations that capture the fine compositional and structural heterogeneity intrinsic to these systems. Such detailed simulations require extensive computational resources—both in terms of memory and processing power—which can become prohibitively expensive. FEA of such systems becomes intractable for macroscale components, while AI-driven methods face scalability limitations when processing high-dimensional 3D voxel grids. These constraints compel reliance on reduced-order approximations, which trade resolution for computational feasibility.

2.3. Scientific Pathways and Technological Developments

Advances in science and technology to overcome the difficulties of AI-accelerated multimaterial design for AM are progressing in three complementary directions. First, hybrid physics–AI frameworks can be developed to integrate fundamental physical models with ML algorithms. These frameworks take advantage of the predictive power of classical mechanistic models and the data-driven adaptability of AI for more realistic simulations of interfacial phenomena and other localized effects neglected by conventional homogenized models. By incorporating physical constraints into deep learning (DL) architectures, the limitations posed by sparse experimental datasets and nonlinearity in material–process–structure relationships can be overcome.

Second, autonomous experimentation platforms are revolutionizing the design process by combining real-time manufacturing systems with high-throughput test systems.[20] These platforms enable iterative, closed-loop testing and optimization, and can dramatically reduce the time required for process parameter optimization. With autonomous feedback, AI systems are able to adjust experimental protocols in real time by optimizing material compositions and geometric designs to achieve target performance specifications with minimal human intervention.

Third, the development of DTs can bridge the gap between theoretical designs and practical manufacturability.[11,61] DTs create virtual replicas of the manufacturing process that are continuously updated with live production data. With this integration, real-time process monitoring and control of the AM process are facilitated to reproduce AI-designed geometries into physical parts independent of inherent process uncertainty such as thermal gradients and powder bed inhomogeneities.

In the future, these technological developments are expected to drive advancements that will not only enhance the efficiency of multimaterial system creation but also enable automatic material and component design. Future research is likely to give rise to autonomous material systems capable of self-adaptation, AI-accelerated design methods that dramatically reduce computational burdens, and global databases that consolidate MMAM data for enhanced AI model training. Together, they have the potential to redefine the research agenda of MMAM, enabling breakthrough discoveries and new design paradigms that reconcile complex material behaviors with simplified, automated fabrication.

2.4. Summary and Outlook

AI-driven multimaterial design is revolutionizing AM by enabling the systematic exploration of material, process, and structural relationships. Despite challenges such as complex interfacial interactions, manufacturing uncertainties, and computational scalability, advancements in hybrid physics-AI frameworks, autonomous experimentation, and DTs are paving the way for more efficient and adaptive design strategies. As these technologies continue to evolve, they promise to bridge the gap between theoretical optimization and real-world fabrication, accelerating the development of novel, high-performance multimaterial systems with unprecedented precision and functionality.

3. Generative AI for Supporting Creativity and Design for AM

Andrés Díaz Lantada*, Francisco Franco Martínez

3.1. State of the Art

DfAM has emerged as engineering design methodology aimed at making the best out of the possibilities provided by AM technologies for product innovation. DfAM strategies benefit from: 1) an in depth understanding the working principles and limits of different AM resources; 2) a capability for taking advantage of the vast portfolio of additively processable materials, which include "smart" or stimuli-responsive raw materials empowering 4D printing, as well as "living" bioprintable matter enabling biofabrication and engineered living materials; 3) design experiences focused on wisely employing the achievable shape complexity toward the customization of designs, the integration of functionalities and the attainment of unprecedented features and abilities in engineered products, often resorting to bioinspiration and biomimetics; and 4) a wide set of dedicated design tools for fostering creativity along the design lifecycle. Seminal references for modern AM contribute to outlining and applying DfAM strategies and principles for the engineering of advanced, customized, and intelligent products.[19–22] In this context, classical optimization methods based on different combinations of CAD modeling software and simulations tools have led to several examples of innovative structures optimized for their AM and application in several industrial sectors: finite-element modeling of components and processes followed by redesign operations, topology and topography optimization methods, generative design algorithms capable of autonomously transforming and assessing the impacts of geometrical changes on final performance, among others, define the current state-of-the-art.[62–66] Through these optimizations product innovation has been importantly fostered, but usually during the last stages of the innovation cycle, in connection with prototyping, testing, and reshaping.

However, the contemporary advent of generative AM is accelerating DfAM and may constitute a key driver of creativity in years to come, especially due to its potential impacts in the more conceptual phases of the innovation cycle, as further analyzed. These generative AI algorithms can create data, text, images, music, videos, design illustrations, and even CAD models following textual instructions or "prompts", following commands straightforwardly provided in a user-friendly environment for innovators. Besides, since the recent version of Chat GPT-4 and similar generative AIs, it is now possible to employ images and designs, as a complement or alternative to the textual prompts, for initiating the interaction with these AIs and driving the creative process with a higher degree of control and starting from self-developed content. Initial studies have already experimented with generative AI for: 1) biomaterials research-driven design, leading to impressive and futuristic furniture designs;[67] 2) the incorporation of AI-generated content into the design process, importantly fostering creativity;[68] and for accelerating scientific discovery in the boundaries between materials, biology, engineering, and art.[69] A detailed reading of such papers puts forward the shape-complexity intrinsic to many of the artificially generated design concepts, which directly bridges the gap with AM resources as key enabling technologies required for materializing shape complexity. Being the results of the prompt-guided generation process so random, a methodology for systematic creativity (and serendipity) promotion through constructive dialogues with artificial intelligences has been recently proposed.[70] Again, the conceptual illustrations generated clearly help to align the innovation cycle with the possibilities of AM from the very beginning of the concept screening phase.

3.2. Scientific Challenges and Technical Limitations

In short, the more relevant generative AIs, such as Chat GPT, are based on "generative pre-trained transformer" models. These models were introduced for natural language processing by Vaswani et al.[71] in 2017. The transformers employed two interconnected parts: the encoder and decoder, similarly to others AI models as the convolutional autoencoders. Specifically, ChatGPT only used the decoder.[72] The goal of this model is to minimize language loss. Therefore, during the "pre-trained" phase, these types of models treat to maximize the conditional probability. This probability is modeled using a neural network, and its parameters are optimized by using the stochastic gradient descent.[73] The GPT models apply the softmax layer to obtain the probabilities of each "token" generated.[71,73] Based on the probabilities obtained by the softmax layer, the transformer creates text by using probabilistic sampling techniques. Moreover, as mentioned in ref. [73] for the model GPT-2, these kinds of generalist models that can solve multiple tasks, should perform the conditional probability of the output considering both the input and the task. GPT-4 evolves from such models.

Indeed, to better understand the current possibilities and challenges of generative AI for DfAM, a set of case studies is prepared and presented following the aforementioned methodology based on constructive dialogues.[69] **Table 2** summarizes the conceptual design iterations for additively manufactured components performed. Briefly explaining, the CAD model of a spheric lattice typically oriented to AM is provided as image input to Copilot, the generative AI employed, together with a set of text prompts asking to illustrate the lattice employing different families of materials. The generated raw materials are employed as building blocks for the subsequent stages of the interaction with the generative AI, which is asked to illustrate possible AM technologies during the manufacturing of such geometries and to list down specific materials, as candidates within the different families, for creating the lattices. Finally, the generative AI is asked to propose a variety of industrial applications and to illustrate specific medical devices based on them. Some additional experiments are performed dealing with the illustration of more complex 4D-printed medical devices, with the functional integration of proposed ideas and with the support to stages closer to commercialization. The inspiring visual results of the generated concepts are shown in **Figure 3** and **4**.

In the current state, as illustrated in the experiences summarized in Table 2 and Figure 3 and 4, the interactions with generative AIs lead to conceptual designs and promote the screening of ideas, in connection with complex-shaped geometries requiring AM technologies for their physical materialization, from the beginning of the innovation cycle. Furthermore, the interaction with these AIs proves useful along the whole design cycle, helping to refine the concepts,[74] to approach 3D and 4D printing[75,76] and to plan their functional integration. Toward automated conceptual and geometrical generation of directly printable shapes, which

Table 2. Summary of inputs and outputs along a set of constructive dialogues with a generative AI linked to DfAM and to the finding and development of innovative applications. Related graphical results are included in Figures 3 and 4; thanks to the use of Microsoft Copilot as generative AI for creativity promotion.

First input and prompts	CAD model of a spheric lattice together with a textual description of the lattice, to be designed and manufactured additively employing different alloys, ceramics, polymers, and carbons			
First outputs: lattices/porous structures as raw materials families	Spheric lattice in anodized titanium with shades of orange and blue	Spheric lattice made of a high-performance ceramic	Elastomeric lattice represented in a bluish-white color	Pyrolytic carbon spheric lattice as scaffold
Second input and prompts	For the previous images, the generative AI is asked to illustrate possible AM technologies and to list down specific materials, as candidates within the different families, for creating the lattices			
Second outputs: proposed technologies for each raw material	Illustration of laser powder bed fusion creating a Ti lattice	Image of digital light processing building a ceramic lattice	Image of selective laser sintering building an elastomeric lattice	Image of pyrolyzed lattice (unable to provide a sequential process)
Second outputs: proposed candidates for each raw material	Anodized titanium as originally asked for	Alumina and zirconia	TPU	Pyrolytic carbon as originally asked for
Third input and prompts	For the different lattices, used as building blocks or raw materials, the generative AI is asked to propose a variety of industrial applications and to illustrate specific medical devices based on them			
Third outputs: proposals for application	Lightweight, high-strength components for spacecraft, panels or internal partitions for spacecraft, heat exchange or thermal management in satellite systems, applications where enhanced corrosion resistance and thermal stability may be needed (i.e., harsh environments), medical implants.	Fuel cell structures and backbones for solid oxide fuel cells, lightweight thermal barriers in spacecraft or aircraft, support structure for catalysts in reactors, heat-resistant filter for molten metals or high-temperature gases, bone scaffolds or dental implants, protective coatings for machinery and tools.	Impact absorbing layers, flexible seat ergonomic cushions, energy absorption systems and crash barriers, medical devices applied in prosthetics or orthotics to create lightweight, flexible components that adapt to the user's movements, flexible joints or grippers in soft robotics, soundproofing materials to dampen vibrations and noise	Lightweight structural elements in spacecraft or aircraft, battery electrodes or supercapacitors, catalyst supports or reactor components in high-temperature chemical processes, thermal shields, filtration systems, implants like: proximal interphalangeal joints implants and trapeziometacarpal joints implants
Third outputs: conceptual designs illustrations	Image of a futuristic Ti knee prosthesis	Bioinspired structure for reconstructing the sternum and some ribs	Visual representation of a soft robotics gripper	Tissue engineering carbon scaffold adapted to the tibia
Other possibilities for inputs and prompts	Please help me to illustrate the functionality of a 4D-printed medical device, give me a sequential scheme of a set of interconnected manufacturing processes, advise me about functional integration, give me relevant standards linked to my product, process or system, advise me about a commercialization route			
Output: help with process illustration	Support to illustrating 4D-printed concepts for medical devices, such as: 4D-printed stent deployment process; 4D-printed scaffold expansion in a broken meniscus defect, emphasizing hygroscopic behavior and moisture absorption; 4D-printed scaffold expansion in a broken tibial defect, emphasizing hygroscopic behavior and moisture absorption; multiscale and multimaterial tissue engineering scaffolds collection of interlocking geometries for critically sized bone defect reconstruction			
Output: support to CAD modeling	Innovative software resources are being developed (i.e., Meshy) for transforming -in a semi-automated way- the AI-generated illustrations into three-dimensional CAD models, for example as .stl files, ready to print			
Output: support to processing	As advanced, generative AIs and related software resources are focusing on the semi-automated generation of .stl files for printing and other contributions to supporting the processing of images and files, in connection with AM, can be highlighted: support to the automated correction of defects in the masks employed for additive photopolymerization processes, help with the generation and modification of G-codes guiding printing heads possibly linked to nonplanar printing processes, support with the finding of the ideal printing parameters for manufacturing with a specific technology and material, among other possibilities			
Output: support to functional integration	Among functional integration proposals in the performed constructive dialogues, through which the concepts of figures below have been obtained, some interesting suggestions and remarkable features have been provided or highlighted by the AI, including: the scaffold supports mechanical loads while gradually being replaced by natural bone tissue as it heals; the lattice-based structure provides flexibility and adaptability, allowing it to conform to various surfaces without causing damage; pneumatic or hydraulic actuators, or servo motors, would be required for the gripper depending on the required force and precision; the lattice would create an ideal environment for tissue growth, promoting cellular integration and vascularization; precise design, enabled by advanced fabrication techniques, tailors the lattice structure to mimic the native bone, encouraging a seamless fusion with the body, to cite a few			
Output: toward certification and commercialization	Furthermore, generative AI not only promote creativity by providing inspired illustrations for CAD modeling or by reformulating CAD models used as input for screening additional application concepts, but it also constitutes a very remarkable resource for finding application-related standards, standardized validation tests, and regulatory pathways to develop the specific applications and help users reach market			

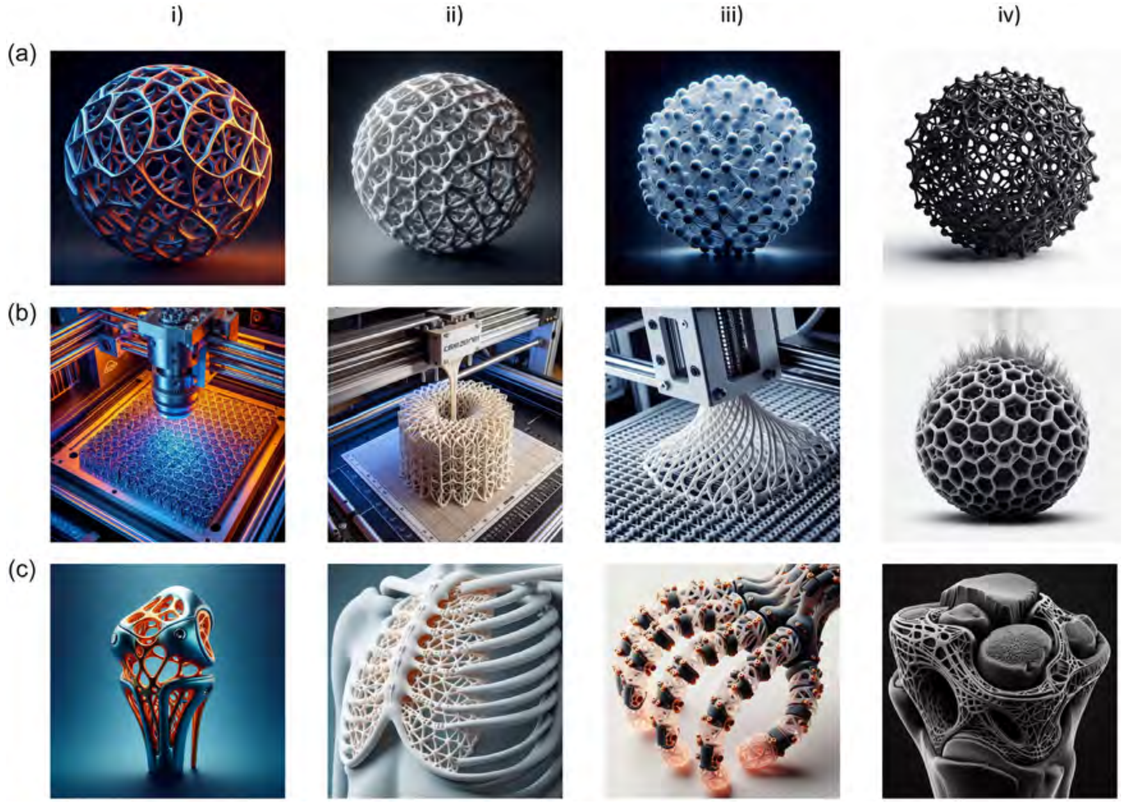


Figure 3. Generative AI applied to exploring geometries, methods, and applications in the field of biomedical AM for different materials: i) titanium alloys, ii) ceramics, iii) elastomers, and iv) pyrolytic carbon. a) Complex spheric lattices obtained in the first stage after providing a CAD model as input. b) Additive manufacturing technologies for the different lattices (from left to right: laser powder bed fusion, ceramic digital light processing, selective laser sintering, and pyrolysis of stereolithographic precursors. c) Medical application concepts for the different materials lattices: knee implant with lattice structure, sternum-rib scaffold implant, flexible gripper for soft robotics in TPU, and carbon scaffold adapted to the morphology of the upper part of the tibia with a PDMS cushion in the meniscal region.

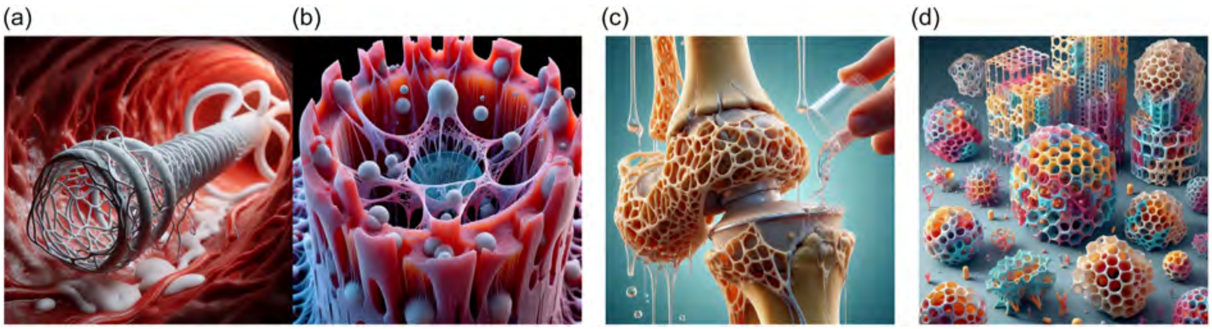


Figure 4. Generative AI applied to conceptually exploring biomedical applications for 4D-printed implants (conceptual images based on the following “prompts” or textual instructions): a) 4D-printed stent deployment; b) 4D-printed scaffold expansion in a broken meniscus defect, emphasizing hygroscopic behavior and moisture absorption; c) 4D-printed scaffold expansion in a broken tibial defect, emphasizing hygroscopic behavior and moisture absorption; and d) multiscale and multimaterial tissue engineering scaffolds collection of interlocking geometries for critically sized bone defect reconstruction.

would provide an additional turn of the screw to the pace of innovation, additional scientific-technological efforts are required.

Indeed, the presented designs are only illustrative concepts for innovative medical devices and creativity promotion tasks. The conceptual design process interacting with a generative AI starts from lattices acting as “raw materials”, which are transformed into the conceptual shapes of implants. In that way they connect with lightweight design strategies, such as those based on topology optimization and conformal lattice design, but in this case only as illustrative concepts. Among detected challenges in the use of generative AI for design tasks, starting the design with a textual description leads in too many cases to undesired thought-provoking shapes and to a lack of repeatability. In the illustrative examples presented, the generative AI-drive innovation process has been controlled toward enhanced repeatability by starting from simple CAD models of lattices, whose images are provided as input to the AI together with the textual description of the lattices as raw materials. Still, the final results are just illustrations, not printable designs. Besides, despite their appealing bioinspired geometries, as in the case of the bone-mimicking lattices for sternum and ribs implants, they are not truly mechanically optimized.

At present, the design process would continue taking inspiration on the generated illustrations, but a designer aiming at a personalized mechanically optimal implants would still need to process medical images, employ CAD modeling for creating the design boundaries and the basic scaffolds or lattices, and finally perform a conformal lattice design or a topology optimization to reach mechanically sounded and printable devices. In fact, the current "holy grail" in generative AI for AM is the autonomous creation of reliable and printable designs (materialized as ready-to-print.stl files) directly from the textual prompts and supporting image inputs provided to the generative AI at the beginning of the constructive dialogue. Interesting resources, such as Meshy (AI 3D model generator), are already helping 3D artists, game developers, hobbyists, and makers to turn text and images into high-quality 3D models. Nevertheless, the intricate geometries of lightweight DfAM objects, including lattices, porous structures, functional gradients of density, topology and topography optimizations, to cite a few, are still extremely challenging to design from textual prompts or 2D images, and innovative strategies should be explored to leverage gen-AI for AM.

Some of the possible approaches to overcome these limitations and facilitate mechanically sounded designs, geometric fidelity, direct manufacturing, and decision making from conceptualization to printing and postprocessing, are discussed in the following subsection.

3.3. Scientific Pathways and Technological Developments

Regarding scientific pathways and further technological developments for fostering creativity while leveraging generative AI-based DfAM, it is important to highlight relevant supporting or complementary strategies showcasing pioneering studies on de novo designing architected materials designs using transformer neural networks;[77] and the generation of 3D architectured nature-inspired materials and granular media using diffusion models based on language cues.[69]

In the first case,[77] Contrastive Language-Image Pre-Training (CLIP) and VQGAN neural networks are employed in an iterative process to generate images that reflect text prompt driven materials designs. Subsequently, the resulting images are used to generate three-dimensional models that can be realized using AM. Importantly, the mechanical evaluations of printed objects are analyzed by supporting finite element methods, which would enable optimization and validation from the design stage. These validations will prove fundamental for the spread of generative AI for design purposes, especially in industrially relevant and demanding areas like healthcare, space and aeronautics, transport, and energy.

In the second case,[69] a trained stable diffusion model and consider it as an experimental system, examining its capacity to generate novel material designs especially in the context of 3D material architectures. A series of methods to translate 2D representations into 3D data, including movements through noise spaces via mixtures of text prompts, and image conditioning, are provided. In addition, physical samples using AM are obtained, and material properties of materials designed via a coarse-grained particle simulation approach are evaluated, hence also contributing to illustrate how the required mechanical evaluation of materials and devices generated by AI can be performed, especially in connection with demanding applications and mechanical responsibility.

More recently, graph-native methods are already complementing (even outperforming) the more classical LLMs in a desire to facilitate and accelerate scientific discoveries and promote creativity.[78] For instance, graph-native reasoning models trained with RL can embed explicit graph reasoning and recursive reflection into LLMs, which is expected to generate verifiable models beyond pattern matching but incorporating structured reasoning with agentic methods to achieve in situ verification.[78,79]

3.4. Summary and Outlook

Toward the future, as the direct fabrication of complex printable geometries -based on lightweight lattices or porous biomaterials- advances to the point of enabling text- or image-driven generative designs for patient-specific medical devices, it will become essential to implement standardized and widely accepted benchmarking methods in parallel. These methods should evaluate generative AI-derived solutions against current gold-standard approaches. One possible procedure for quantitatively assessing the capability of AI-based 3D model generators to produce dimensionally and geometrically accurate complex shapes could involve the following steps: 1) a collection of standardized complex-shaped scaffolding structures or lattices is designed; 2) from these CAD models, images (isometric views, frontal, upper and lateral projections...) as input for the AI 3D model generators are obtained; 3) the generative tool is asked to recreate.stl files from the provided images; and 4) the generated files are compared with those from the CAD models library, in terms of volume, dimensions, and shapes, for quantification purposes.

In addition to these geometric evaluations, robust and standardized methods must be developed for autonomously verifying the alignment between designed implants and patient anatomy, in the case of healthcare, or to benchmark a product's design against the design requirements or constraints. This will require accurate processing of medical imaging data, the use of medical images as input to generative AI tools capable of automated design and .stl file creation, and systematic comparison with the AI-generated designs. For upscaling and transforming truly transforming engineering design, for instance for medical practice, research, and development of software and hardware resources for the execution of generative AI and language models with increased speed and energy efficiently (i.e., Groq with LPU for NPL as an alternative or complement to GPU) is also fundamental.

Concluding, the future shapes of additively manufactured creations are bound to be artificially generated, automatically validated, and additively obtained, although for the time being additional research is needed.

4. AI-Driven Multiaxis AM

Tianyu Zhang, Tao Liu, Charlie C.L. Wang*

4.1. State of the Art

Advancements in AM technology, driven by AI, have led to significant progress in geometric design, process planning, and quality inspection. AI-enhanced AM technologies demonstrate outstanding performance, especially in improving manufacturing efficiency, optimizing process parameters, and enhancing product quality.[80]

AI-driven methods, especially DL and GANs, have advanced topology optimization by enabling efficient design of complex, lightweight structures. Conditional GANs (cGANs) reduce volume while preserving strength, optimizing support, and minimizing overhangs.[81] CNNs predict geometric deviations with high accuracy, as shown in x/y/z-axis error detection for PBF prints.[82] In process planning, ML models effectively optimize parameters and monitor quality. CNN-LSTM networks in two-photon lithography enable 95.1% accuracy in real-time monitoring,[83] while CNNs in laser polishing achieve 97%–100% classification accuracy.

Multiaxis 3D printing represents an innovative breakthrough that overcomes the limitations of traditional AM technologies. Conventional AM systems mainly rely on three-axis motion and 2.5D tool paths, which, while convenient, exhibit notable weaknesses in force direction matching and mechanical performance.[84] The inherent staircase effect of layered manufacturing results in poor surface roughness, failing to meet high-precision requirements.[85] To address the issue of overhanging structures, traditional methods often rely on substantial support structures, leading to material waste and increased post-processing costs.[86]

By introducing rotating and tilting degrees of freedom, multiaxis 3D printing surpasses planar printing limitations, achieving support-less or even zero-support material accumulation, effectively avoiding the drawbacks associated with support structures.[23–25] Moreover, adjusting printing paths and material deposition directions allows fibers to align with the principal stress direction, maximizing mechanical performance.[87,88]

4.2. Scientific Challenges and Technical Limitations

Despite the advantages of multiaxis 3D printing in enabling support-free structures, improved mechanics, and surface quality, current methods remain limited by specific optimization strategies and scope. Most focus on single objectives, making it difficult to meet multiple manufacturing goals simultaneously. Dai et al.[89] introduced a curved layer decomposition using local optimization, reducing support use but lacking global consistency for complex geometries. Etienne et al.[90] proposed a slightly curved layer method for three-axis machines to reduce staircase effects, but its limited degrees of freedom constrain path flexibility. Fang et al.[91] optimized fiber orientation in fused filament fabrication (FFF) to enhance strength, yet their method is tied to single-material, single-path setups, without addressing multiple objectives like support minimization or surface refinement.

Although multiaxis 3D printing has made significant progress in recent years, existing multiaxis slicing techniques, especially non-neural network slicers based on traditional geometry, continue to face considerable challenges in practical application and performance optimization. S^3-Slicer,[92] as one of the most advanced non-neural network slicing frameworks, employs nonlinear optimization to deform tetrahedral meshes through rotational driving, mapping the height values back to the input model to generate curved layers meeting multiple manufacturing objectives. However, S^3-Slicer still faces the following three key challenges: 1) bottlenecks in complex mesh generation: S^3-Slicer relies on generating high-quality tetrahedral meshes. However, when applied to models with high geometric and topological complexity, the meshes often become overly dense, leading to massive computational overhead and potential mesh distortion or geometric inaccuracies. This stringent requirement for mesh quality severely limits its application to complex structures and large-scale model printing. 2) Limitations of indirect optimization objectives: the optimization objective of S^3-Slicer is indirectly achieved through rotational element deformation rather than direct optimization on the curved layer itself. While this method can partially meet path planning needs, the mismatch between deformation space and model space can result in deviations from manufacturing requirements. Particularly in tasks involving complex geometries or stringent mechanical performance demands, this indirect approach may lead to geometric inaccuracies and insufficient mechanical performance. 3) High dependency on initial posture: the nonlinear optimization process of S^3-Slicer is highly dependent on the initial posture of the input model. If the initial posture is suboptimal, the optimization process may easily fall into local optima, resulting in subpar path planning or inadequate mechanical performance. This dependency necessitates extensive manual adjustments and iterative trials, reducing operational efficiency and reproducibility.

4.3. Advantages of Neural Network-Based Slicers

In contrast to geometry-driven slicing frameworks, neural network–based slicers leverage modern optimization and powerful shape/field representation capabilities to overcome many of the limitations. First, neural implicit representations bypass the reliance on dense tetrahedral meshes, enabling efficient and flexible curved layer generation even for geometrically complex models.[93] Second, DL methods allow multiobjective optimization within a unified framework, simultaneously considering support minimization, surface quality, and mechanical performance, which traditional optimization approaches often handle separately.[94] Third, by learning global geometric and stress patterns from data, neural approaches exhibit strong generalization ability and robustness, reducing sensitivity to initial posture and manual tuning.[95,96] These advantages make neural network slicers a promising direction for practical multiaxis AM.

4.4. Scientific Pathways and Technological Developments

As multiaxis 3D printing technology continues to evolve rapidly, traditional non-neural network slicing methods face numerous challenges in performance optimization and handling complex geometries. For instance, nonlinear optimization frameworks like S^3-Slicer, while achieving multiobjective path planning to some extent, are constrained by their dependence on high-quality tetrahedral meshes and initial posture optimization. This limitation often results in inadequate performance when dealing with complex geometric forms and topological structures. The introduction of neural network technology brings new breakthroughs and developmental directions for multiaxis 3D printing (**Figure 5**).

The problem of curved layer generation in multiaxis 3D printing can be formalized as a scalar field optimization task. For any given input model M, an implicit function $H(x)$ is evaluated, where $H(x) < 0$ indicates that point x is inside the model, and $H(x) \geq 0$ indicates that x is outside. The zero-level set of this function approximates the model boundary surface. By computing a mapping function x, a curved layer scalar field $G(x)$ is generated, where x represents a continuous deformation mapping to meet the multiobjective requirements of multiaxis printing. 1) Flexible function expression capability: unlike traditional methods relying on piecewise functions for tetrahedral element deformation, neural networks (*NN*) possess highly nonlinear expression capabilities, capturing more complex deformation scenarios. By constructing a differentiable neural network pipeline, complex geometry and multiobjective optimization tasks can be efficiently addressed.[93,94] 2) Direct loss function definition: the neural slicer directly defines the loss function on the scalar field $G(x)$ and its gradient $\nabla G(x)$, allowing local print direction to be evaluated at any point within the computational domain. This directly optimized mechanism avoids deformation mismatch issues caused by rotation-driven methods. 3) Enhanced robustness and adaptability: by employing modern stochastic optimization methods within the neural network solver, rapid convergence and adaptive adjustment under various initial states are achieved. Since all slicing parameters are represented within a differentiable network, quick adaptation to geometric changes and manufacturing requirements is possible.

The slicing algorithm of the neural network slicer consists of three major stages: preprocessing, mapping optimization, and post-processing: 1) Preprocessing stage: construct the implicit function representation $H(x)$ of the input model M using voxel FEA to calculate internal stress fields, generating a tetrahedral mesh C as a discrete representation of space Ω. 2) Mapping optimization stage: initialize neural network parameters θ_q and θ_s to compute local rotational quaternions and scaling ratios. Apply As-Rigid-As-Possible (ARAP) deformation to generate deformed mesh C_d and use backpropagation to adjust network weights to minimize the loss function. 3) Post-processing stage: extract curved layer isosurfaces from deformed mesh C_d and trim them using implicit function boundary constraints, ensuring that the final curved layers meet support-free (SF) and strength reinforcement (SR) requirements.

Experimental results demonstrate that the neural slicer generates high-quality curved layers in complex geometries and high-genus structures. For example, in a bridge model, the curved layers produced by the slicer improved fracture strength by 101.9% during three-point bending tests, while in a BunnyHead model, specimens enhanced with SR optimization showed a 30.6% increase in fracture strength. Compared to S^3-Slicer, the maximum strain reduction reached 40.5%, validating significant mechanical performance improvements. Furthermore, physical experiments demonstrated that curved layers generated by the neural slicer exhibited strong robustness to initial posture and flexible path planning on complex models (e.g., spiral fish model), reducing overhang area by 94.2% and significantly decreasing support material requirements.

To overcome these challenges, we propose a neural network-based slicer (Neural Slicer) in ref. [95] that directly defines

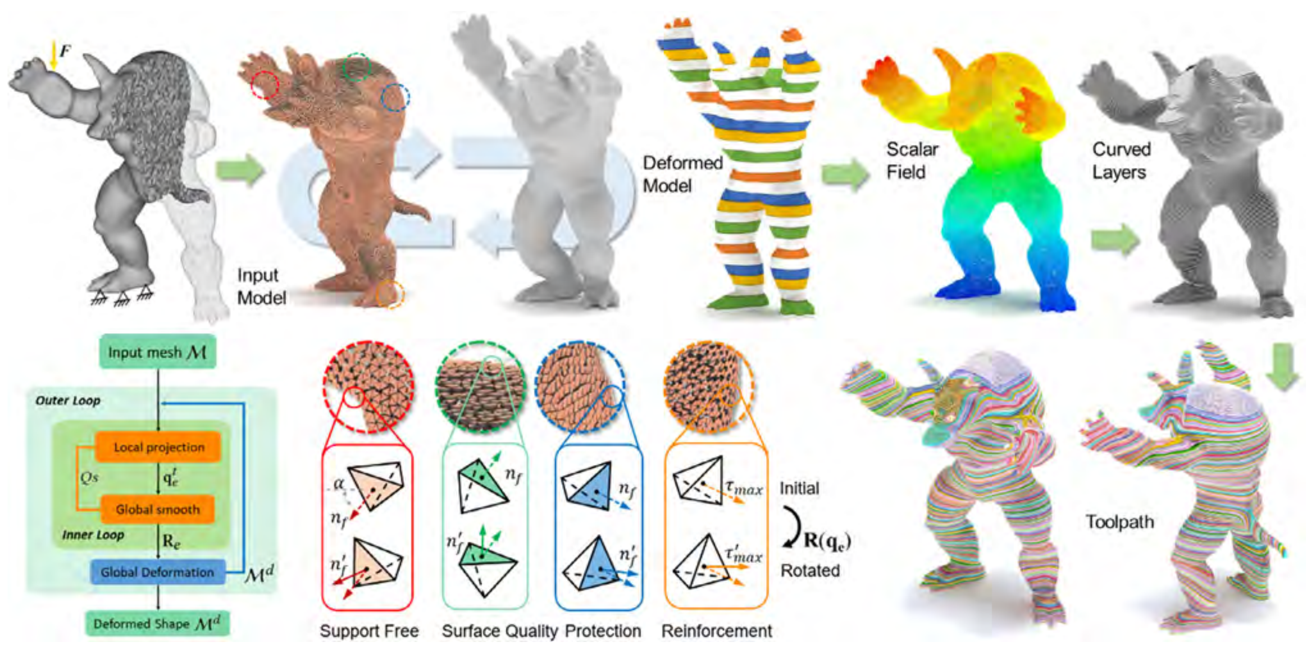


Figure 5. Pipeline of S^3-Slicer for multiaxis 3D printing. Reproduced with permission.[93] Copyright 2022, Association for Computing Machinery.

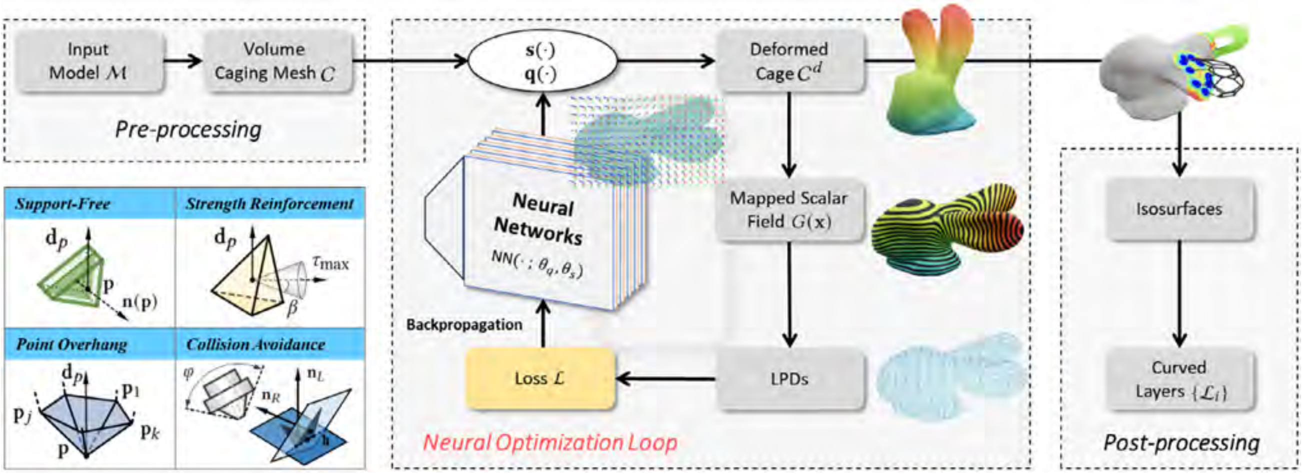


Figure 6. Pipeline of neural slicer for multiaxis 3D printing. Reproduced with permission.[95] Copyright 2024, Association for Computing Machinery.

continuous functions $q(x)$ and $s(x)$ to represent local rotational quaternions and scaling ratios, generating the mapping $q(x)$, $s(x)$ (**Figure 6**). This innovative approach offers the following advantages:

4.5. Summary and Outlook

The neural network-based multiaxis 3D printing slicer has made significant advancements in support freedom, mechanical enhancement, and surface quality optimization. Compared to traditional non-neural network slicers such as S^3-Slicer, the neural slicer directly optimizes the curved layer scalar field, avoiding the indirect optimization of rotational elements and the dependency on high-quality tetrahedral meshes. All these advantages are due to the implicit neural field-based representation of deformation fields that can be effectively solved by advanced stochastic gradient solvers for neural network-based self-learning. This greatly improves printing efficiency and path accuracy in complex geometric structures and multiobjective manufacturing tasks. In practical applications, the neural network slicer exhibits high flexibility and adaptability, facilitating high-quality printing of complex structures and mechanical performance enhancement.

Despite their promise, neural network slicers in multiaxis 3D printing still face key challenges. First, they often assume isotropic material behavior, overlooking anisotropy from curved layer deposition, which leads to inaccurate stress predictions. While anisotropic FEA can improve accuracy, it adds significant computational overhead, limiting its integration in optimization loops. Second, mapping relies on intermediate caging meshes; although convergence is generally consistent across resolutions, complex geometries can still cause variation in layer quality and speed, affecting robustness. Lastly, collision detection remains difficult-flattening layer paths with harmonic weights helps, but in complex setups, it may default to planar layers, undercutting the advantages of curved printing.

Future work should focus on embedding anisotropic stress modeling into neural frameworks to improve mechanical performance prediction. Adaptive mesh generation could help reduce resolution-related variability in curved layer optimization. Integrating real-time collision prediction with motion planning for toolpaths represented as diverse graphs would enhance path robustness and safety when reinforcement-learning-based planner is conducted.[97]

5. AI-Powered Strategies for Smart Design and Processing in Advanced Material AM

Mohammad Hossein Mosallanejad, Reza Ghanavati, Abdollah Saboori*

5.1. State of the Art

Components designed with tailored combinations of materials achieve specific functionalities within a single part in demanding applications. This approach is beneficial for sectors such as aerospace, biomedical, and automotive, enabling the development of innovative structures.[26] Although traditional manufacturing techniques like powder metallurgy and welding can produce metal-based advanced material systems, including multimaterial components, they often face challenges when dealing with complex geometries and structural integrity.[98] AM methods have shown significant potential in producing components with novel material designs. These methods allow for the precise deposition of different materials within a single build process, enabling the creation of complex geometries and customized components with tailored properties. Research has demonstrated that AM is a viable option for producing advanced material systems. However, challenges such as material compatibility, interface bonding, and process optimization still need to be addressed.[99,100]

Incorporating AI in advanced material design for AM offers significant advantages. AI can optimize the design process by capturing the complexity of interactions in AM and predicting effective material combinations and configurations. ML algorithms analyze extensive datasets, revealing patterns that may elude human designers and enhancing efficiency and innovation.[101] Additionally, AI improves process control and monitoring, ensuring the quality and performance of components comprising advanced materials.[102] Due to the complex nature of processing advanced materials by AM methods, multiscale physical models combined with ML may offer insights into how process variables relate to part geometry, composition, microstructure, mechanical properties, and defects.[101,103] For instance, computational alloying with real-time monitoring systems using ML techniques such as digital metallurgy can expedite alloy design procedures to conceptualize functionally graded parts and manufacturing with optimal processing conditions for every compositional region.[12,13]

5.2. Scientific Challenges and Technical Limitations

Selecting the appropriate materials for particular applications and their subsequent processing via AM presents many challenges, necessitating a comprehensive understanding of metallurgy[103] and other related disciplines, such as fluid dynamics, heat transportation, and chemistry. There are several designs commonly used for advanced materials by AM, including MMAM, such as bimetal, FGMs, and hybrid materials (**Figure 7**a).[100] Material compatibility is essential for selecting a design that ensures the successful integration and performance of diverse materials. The thermodynamics calculation of phase diagram (CALPHAD) method can provide an informed design, as Figure 7b depicts infeasible compositions (pink nodes) and the transition path (red arrows) through feasible compositions (green nodes) between terminals (purple nodes) on a quaternary compositional diagram.[104] Nevertheless, some local phenomena during the (post-)processing stage, such as micro-segregations and liquation (Figure 7c) and the dilution effect (Figure 7 d), could result in a significant deviation from its primary prediction and fall into an infeasible region with high cracking susceptibility.[105,106] In addition, the mismatch in thermophysical properties should be considered to mitigate other types of defects like internal porosity (Figure 7e) and residual stress (Figure 7f) within multimaterial structures.[107,108] Furthermore, addressing scalability is vital for transitioning from prototypes to large-scale production while maintaining efficiency. Lastly, cost-effectively achieving these advancements is critical for the widespread adoption and sustainability of these technologies. Consequently, as AI progresses, converting 3D layouts into high-quality products using advanced materials systems will necessitate (i) the creation of innovative mechanisms, such as mechanistic modeling and ML methodologies, that determine the correct pathways based on the aforementioned considerations. Additionally, (ii) real-time data extraction equipment enables precise monitoring and control of the AM process, ensuring consistent quality.

The present issues identified represent critical challenges to the adoption of AI-aided multimaterial development within the context of AM:1) Product design: the lack of specialized software that can define and optimize the topology and material placement throughout the multimaterial structure, particularly in relation to its application, hinders product efficiency. 2) Material compatibility: ensuring strong bonds between terminal materials and addressing issues such as deleterious phases and cracking susceptibility in multicomponent systems, considering the entire thermal history and the viability and performance of the transition path in AM machines. 3) Printability database: development of processing windows for each material combination and AM processes with minimum risk of various defects, including poor mixing, unmelted particles, porosity, residual stress, delamination, *etc*. 4) Post-processing treatments: planning essential bulk/surface post-treatments and adjusting their variables with respect to site-specific characteristics of multimaterial parts. 5) Scalability and cost: the scalability of multimaterial AM processes and the associated costs remain significant barriers to widespread adoption. 6) Data management: handling the vast amounts of data generated during the multimaterial AM process, ensuring its security against cyber-intrusions while offering DTs to utilize AI models poses challenges to its adaptation. 7) Standardization: lack of standardized methods for characterizing and certifying multimaterial composites, especially for safety-critical applications. The lack of standardization and the need for consistent quality control are significant barriers to the widespread adoption of AI-augmented AM. However, AI can assist in developing standardized processes and improving quality control measures.

5.3. Scientific Pathways and Technological Developments

5.3.1. Advanced ML Algorithms

Advanced ML algorithms can be developed for post-process inspection, real-time in situ monitoring, and defect detection.[109] Meanwhile, a notable development is the use of physics-informed ML, where mechanistic models based on process physics—such as heat transfer, solidification kinetics, and melt pool dynamics, are embedded within data-driven ML frameworks.[103,110] Such algorithms should be refined to manage advanced materials systems by AI-augmented metal AM processes and to process multimaterial systems, where varying thermal and physical behaviors across materials demand broader generalization in predictive models.[100] Moreover, multiobjective optimization algorithms can help in balancing trade-offs between different material properties and performance metrics.[111]

5.3.2. AM-Specific Materials Featurization Packages

The challenge of multimaterial systems stems from their varied behaviors, which are influenced by specific material combinations and operating conditions. To address this issue, while adopting data-driven approaches in metal AM processes, it is necessary to provide feature sets that accurately account for energy absorption, melting, possible mixing, and solidification of multimaterials. Specifically, features that govern atomic-scale interactions, electron behavior, and optical and thermal characteristics should be identified and optimized.[112] These features are critical for predicting and tailoring the performance and compatibility of materials in AM processes.[113] Automated feature learning through DL techniques, like convolutional and graph neural networks (GNNs), enhances the identification of significant features from raw data. Additionally, scalable cloud-based architectures enable efficient processing of large datasets during production, improving the understanding of advanced material systems.

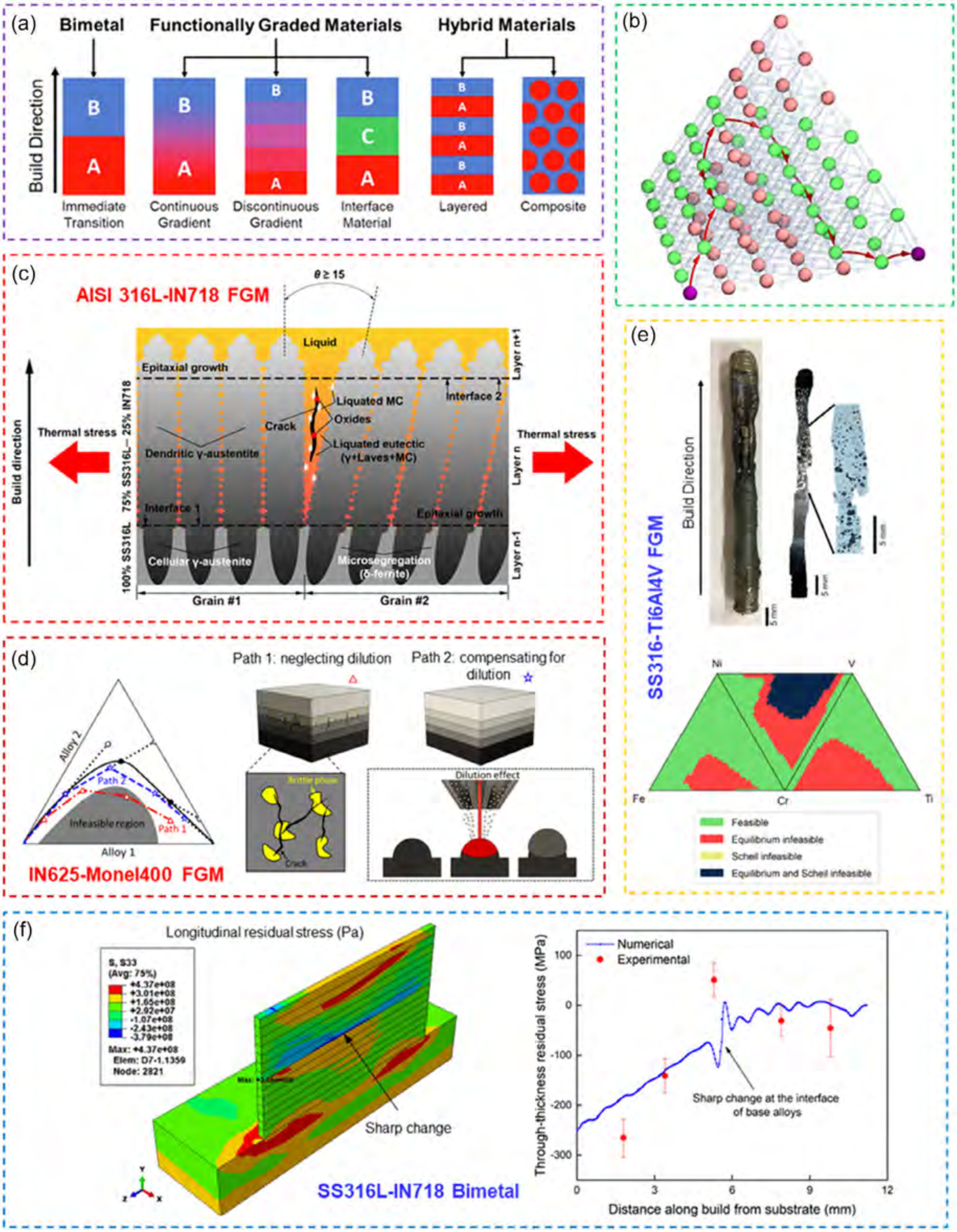


Figure 7. a) Common designs used for MMAM; Reproduced with permission.[100] Copyright 2021, Elsevier; b) A quaternary compositional diagram with discrete compositions (purple: terminal, green: feasible, pink: infeasible) and possible paths. Reproduced with permission under Open Access.[104] Copyright 2025, IOP Publishing; c) Mechanism of liquation crack formation in AISI 316 L-IN718 FGM. Reproduced with permission under Open Access.[105] Copyright 2025, Elsevier; d) Dilution effect in the deviation from a feasible region. Reproduced with permission.[106] Copyright 2025, Elsevier; e) High volume fraction of porosity in a feasible pathway between SS316-Ti6Al4V FGM. Reproduced with permission.[107] Copyright 2022, Elsevier; and f) Sharp change in residual stresses at the interface of SS316L-IN718 bimetal. Reproduced with permission.[108] Copyright 2023, Elsevier.

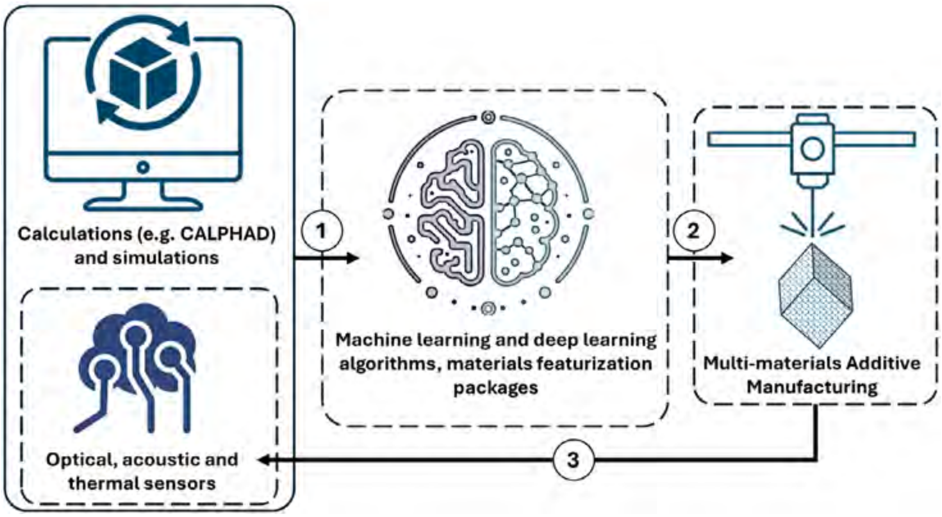


Figure 8. Real-time data extraction equipment coupled with computation and AI cores make DTs to process multimaterials by AM.

Furthermore, machine-learning workflows enable passing information from atomistic to continuum scales by training models on molecular dynamics data and embedding defect/failure classifiers into macroscale simulations,[114] while multiagent AI systems that couple LLM reasoning with physics-aware agents accelerate materials discovery for multimaterial metal AM.[114,115]

5.3.3. Real-Time Data Extraction Equipment, DTs, and the Internet of Things (IoT)

Advanced materials systems in AM involve dynamic, multiscale interactions—from atomic-scale bonding and phase transformations to meso- and macro-scale properties like thermal gradients and compositional variations. The process also generates extensive data streams from sensors such as optical imaging systems, laser profilometers, acoustic detectors, spectroscopic devices, and thermal cameras, each capturing distinct aspects of the AM process for advanced materials. As schematically illustrated in **Figure 8**, ML and DL techniques should be integrated with sensor data to dynamically optimize process parameters. Combining advanced ML models with in situ monitoring sensors creates AI models that adhere to fundamental physical laws. These models utilize extensive sensor data to optimize process parameters based on local composition and to predict defects such as porosity, layer delamination, or spatter formation. In advanced materials systems, interfaces often arise where composition and microstructure change rapidly due to mixing, diffusion, and thermal gradients. Synchronized DTs and IoT facilitate real-time monitoring, improve predictive modeling, and optimize control. This integration combines sensing-driven, computation-driven, and data-driven cores into a unified framework tailored for processing novel chemistries or advanced materials (Figure 8).

5.3.4. LLMs

To enable AI-augmented AM for processing advanced materials systems, advanced LLMs should integrate comprehensive datasets encompassing compositions, structures, and properties specific to multimaterial systems, including gradient and interfacial phenomena.[116] Developing comprehensive knowledge graphs integrating data on material properties, process parameters, and performance outcomes is crucial.[69,79,117] LLMs can utilize these graphs to deliver accurate recommendations for the process. Advancements in real-time data processing and ML will enable LLMs to adapt to dynamic conditions during AM, facilitating adjustments to process parameters and material selections based on real-time feedback, thereby enhancing efficiency and quality in multimaterial manufacturing.

5.4. Summary and Outlook

In conclusion, integrating AI into AM of the advanced materials systems represents a significant advancement in addressing the challenges posed by traditional manufacturing techniques. By leveraging ML and multiscale physical models, the field can optimize material selection, enhance process control, and drive the development of innovative components with tailored properties for demanding applications. However, addressing issues such as material compatibility, interface bonding, and scalability remains crucial for the successful transition from prototypes to large-scale production. These challenges can be resolved by utilizing advanced ML, DL algorithms, and feature engineering packages.

6. Synergies between Generative AIs and AM Ontologies

Alejandro De Blas-De Miguel, William Solórzano-Requejo*

6.1. State of the Art

AM has revolutionized personalized medicine by enabling the creation of medical devices tailored to the anatomical and functional needs of each patient. Efficient management of clinical and technical data is crucial to ensure the quality, biocompatibility, and performance of these personalized implants.[29,30] Ontologies, as formal semantic structures based on descriptive logic, are increasingly used to integrate diverse information from clinical databases, patents, scientific articles, medical images, AM processes, and material specifications.[29,30,118] Notable initiatives in AM ontologies include the Additive Manufacturing Ontology,[30] the PBF-AMP-Onto for powder bed fusion processes,[119] and the Digital Manufacturability Analysis Ontology, which helps select technologies compatible with specific CAD designs.[120] These ontologies also help to identify design flaws early in the AM process by systematizing key geometric and material criteria.[27,28] In the medical field, ontologies such as the 3D Modeling Ontology are used to semantically index anatomical models to improve the retrieval of 3D medical data.[118] These ontologies are increasingly being integrated with generative AI, enhancing the design process by facilitating creativity and iterative refinement.

Thus, ontologies support knowledge integration and provide the foundation for combining them with advanced computational approaches such as generative artificial intelligence (AI), which enhances design processes by fostering creativity, iterative refinement, and improved decision-making through constructive dialogue with AI systems. The process begins by providing the AI with a conceptual design image and context. The AI then interacts with the designer, refining the initial concept into a more robust product through a series of iterative steps.[70] This interaction enables continuous design improvement, helping to identify optimizations and adapt the design for better performance. When combined with ontologies, generative AI benefits from structured semantic knowledge, which guides the AI system in understanding material constraints, functional requirements, and geometric parameters, thereby improving the reliability of the generated solutions.[121,122]

In 4D printing, recent developments have led to the creation of an ontology that describes the entire lifecycle of a product, including dimensional changes, triggering stimuli, materials, and AM processes.[121] This ontology serves as a language for interacting with AI, guiding material selection and manufacturing decisions, and providing a visual representation of the final design. Such advances illustrate how ontologies and generative AI are progressively converging in AM, bridging structured knowledge with creative design. Moreover, this type of ontology can be combined with biomedical ontologies to provide a richer clinical and anatomical context, further assisting the personalized design of medical devices.

6.2. Scientific Challenges and Technical Limitations

Despite significant progress, the practical application of ontologies in biomedical AM faces several challenges, mainly due to the inherent complexity of semantic modeling. Developing and maintaining these ontologies demands highly specialized expertise, which often limits their widespread adoption in clinical and production environments.[29,123] A key challenge is the effective integration of highly heterogeneous data, as interoperability and re-use of information requires rigorous, widely accepted semantic normalization, which is especially critical in medical contexts.[29–31] In this regard, FAIR (Findable, Accessible, Interoperable, Reusable) frameworks play a crucial role in enhancing the management of clinical, experimental, and computational data.[124] Their emphasis on interoperability and reusability aligns directly with the objectives of biomedical AM ontologies, as both approaches seek to reduce information fragmentation and promote knowledge transfer across research, clinical, and industrial stakeholders.

Closely related to this is the integration of ontologies with AI-based digital CAD platforms, a development of particular relevance for biomedical AM. This convergence enables automated manufacturability analysis, optimal machine and material selection, and the early detection of problematic geometries that could compromise the printing process.[27,120] Yet, its implementation remains challenging due to the complexity of both the ontological structures and the advanced AI technologies involved. Moreover, the design of a medical device generally requires a three-dimensional reconstruction of the patient's anatomy to produce a personalized implant.[125] While this process usually results from the synergistic collaboration between physicians and engineers, it would be highly valuable if AI could interpret such anatomical data and propose design models consistent with predefined clinical and engineering requirements.[27,120]

In addition, current ontologies still struggle to automate the recognition of critical features in CAD models. These tasks are often still performed manually by experts, limiting the potential for increased efficiency in the design and manufacturing process.[27,28] As AM technologies continue to evolve, the need for more sophisticated ontological frameworks to manage the increasing complexity of designs and processes becomes more apparent.

Finally, there is a lack of consensus on terminology within biomedical publications related to 3D printing. This lack of standardized terminology is a significant barrier to semantic interoperability, limiting the clarity and reproducibility of research and making it difficult to compare studies and build on previous work.[126,127]

6.3. Scientific Pathways and Technological Developments

In response to the challenges, generative AI has emerged as a critical tool for supporting the development, maintenance, and use of ontologies. For example, LLMs such as GPT-4o greatly facilitate the dynamic construction and updating of ontologies, enabling rapid adaptation to technological advances and emerging needs within the sector.[128]

As a proof of concept, the methodology and ontology developed in ref. [88] were used, modifying the prompts to assess whether an ontology for the design of 4D-printed material systems and structures could support the design of medical devices using ChatGPT-4o. The first two prompts follow the steps outlined in the previous work, while the third prompt allows the ontology to be adapted for the design of the specific 3D or 4D medical device. The fourth prompt requires an initial CAD image of the medical device, along with its corresponding code, and asks for instructions regarding geometric modifications and material selection. These selections are made from a pre-defined family of materials tailored to the selected manufacturing process. The fifth prompt then requests further geometric modifications, focusing on optimizing the DfAM, with the AI providing guidance, including how the implant should be oriented on the printing platform.

The sixth and seventh prompts provide a visual representation of the new implant, taking into account the information from the previous prompts, with ChatGPT connecting to DALL-E to generate the visual output. The process is outlined in **Figure 9**, and the results of each prompt are shown in **Table 3**. For example, a short stem hip prosthesis was selected for the 3D device, while a coronary stent was selected for the 4D device.

In addition, based on the visual output generated by DALL-E, the STL file can be obtained via the Meshy platform, which allows the generation of a mesh from an image. The AI generates four options, from which the designer chooses the most suitable one, thus finalizing the model for printing.

Although this is proof of concept, the methodology shows how an ontology can be reused for more specific purposes,

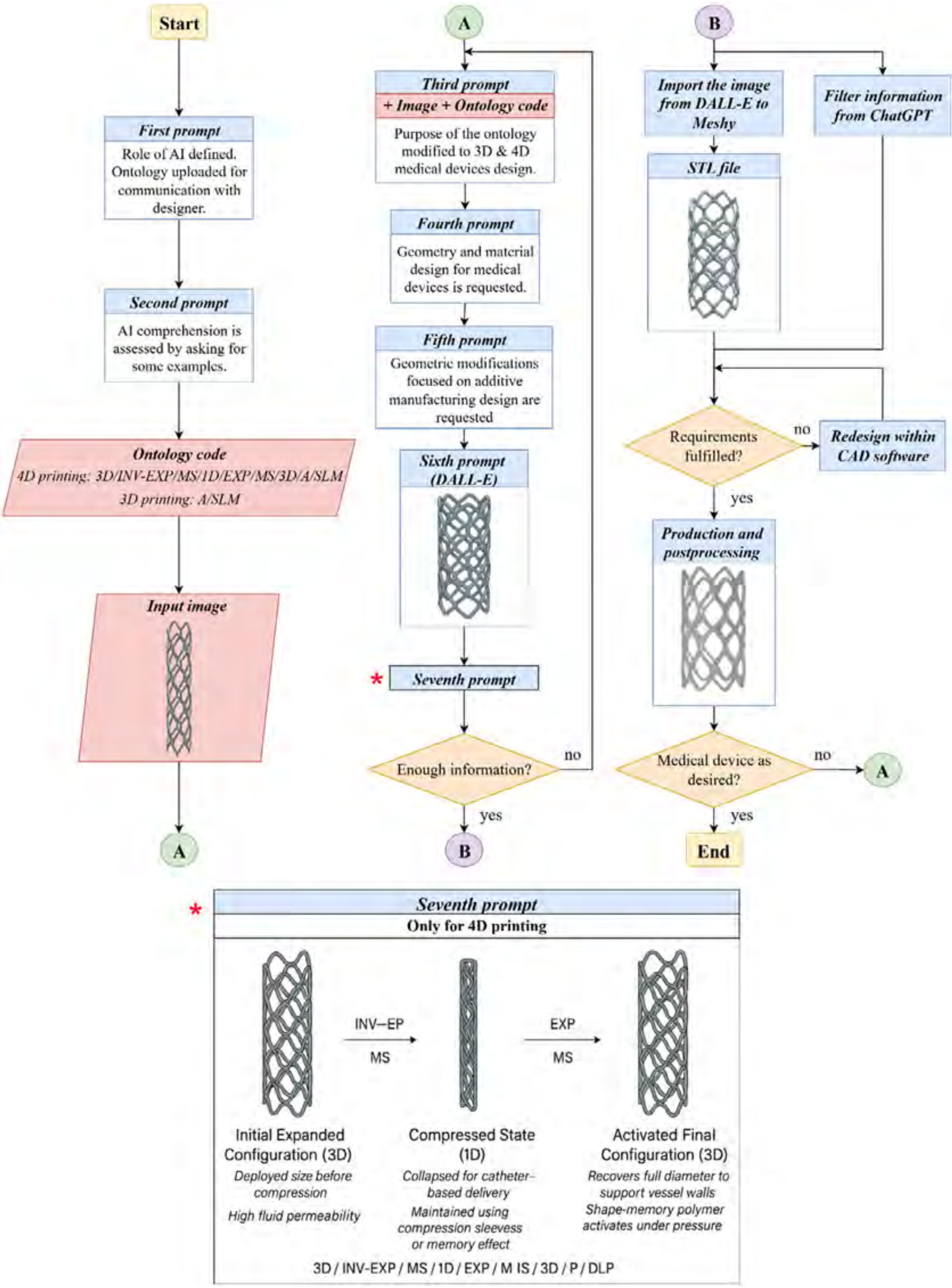


Figure 9. Workflow for 3D and 4D medical device design employing generative AI and semantic ontology.

Table 3. Outcomes of ChatGPT-4 prompts in the development of 3D and 4D medical device designs.

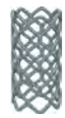
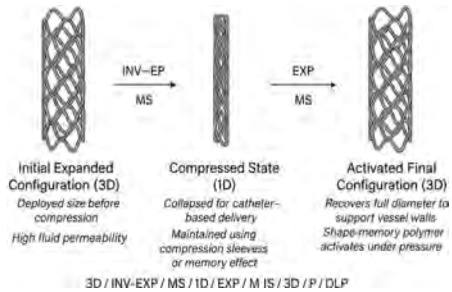
Prompt	Outcomes for 3D-printed medical devices	Outcomes for 4D-printed medical devices
Input: image		
Input: code	A/SLM	3D/INV-EXP/MS/1D/EXP/MS/3D/P/DLP
Third prompt: Thank you very much. As a 4D printing engineer, you are the best. I want to make a modification to the ontology to design custom medical devices using parts of the existing coding. 1) Accordingly, I will provide you with an image of the initial medical device followed by a code line that introduces the material and additive technology to be used. Do you think you are able to adapt to this new requirement? 2) To do this, I'll provide an image of the initial medical device, followed by a line of code excluding shape details. Do you think you'd be able to adapt to this new requirement?		
Fourth prompt: Could you provide me with descriptions of how to design the attached medical device with the following coding, including geometric and material aspects based on the selected AM technology?	Visual analysis: • It resembles a femoral stem. • It has tapered, curved base body for intramedullary insertion. • Neck which likely interfaces with the joint mechanism. Material consideration: • Select titanium alloys (e.g., Ti-6Al-4 V) for: high biocompatibility, excellence osseointegration, corrosion resistance, and load-bearing strength. • Include microporosity or lattices structures to enhance bone in-growth. • Surface texturing or coating may be done post-print. Design guidelines for SLM: • For optimal quality, maintain a minimum wall thickness of 0.3–0.5 mm for critical features, provide support for overhangs below 45°, orient the build vertically (stem upright) to reduce support needs at key joint interfaces, and use post-processing methods like polishing (for the neck) or grit-blasting (for the stem) to achieve the desired surface finish.	Description based on image and code: • The structure is a 3D cylindrical tube with a repeating, wavy mesh lattice. Based on Table A.1, this best fits the T (Tube) category in both its initial and final states, although the compressed intermediate state could resemble a 1D bar (B) or thin cylinder (CY). • The code uses 1D to describe the compact configuration, implying a collapsed or rolled-up stent. Shape-morphing transformations: • This implies a shape-memory mechanical mechanism—the stent temporarily holds a small diameter (to travel through vessels) and then expands in place. Material selection: • You should use a photocurable, biocompatible polymer suitable for DLP, such as: PEGDA, PCL-based resin, medical-grade acrylates or methacrylates, smart polymers with moderate shape recovery capability under mechanical stress. • The material should offer elasticity, biocompatibility, and mechanical resilience to radial stress. Design guideline: • DLP allows high-resolution printing of small, intricate geometries, consequently, it is perfect for cardiovascular structures like stents. Use isotropic resolution settings in DLP to ensure strength uniformity in both radial and axial directions.
Fifth prompt: Using the principles of DfAM, can you please consider the geometric modifications required given the design provided and the AM technology selected?	Use a 3–5 mm fillet at the neck junction to minimize stress and reduce support needs, make the stem core hollow with a 1 mm wall thickness for lighter weight and improved heat dissipation, embed a lattice structure in the proximal region to encourage osseointegration, apply a smooth gradient in the transition zone to avoid stress concentrations, and keep the distal tip solid for effective load transfer and stable insertion. Additionally, maintain a rough finish on the stem (enhancing bone integration) with a polished neck for proper mechanical fit, and incorporate recessed ID markings to ensure traceability without compromising the implant's integrity.	Use a minimum lattice thickness of 200 µm for durability and printability, with at least 300 µm spacing to prevent fusing. Smooth out sharp curves to support elastic deformation, and include drainage paths (open lattice ends or microchannels) to allow resin outflow. Incorporate thinner wall zones for shape- memory functionality and compensate radial dimensions slightly to account for resin shrinkage. Maintain smooth transitions, avoid enclosed voids to meet biocompatibility standards, and facilitate sterilization. For compression and expansion, a radial auxetic pattern (e.g., rotating units or reentrant hexagons) can replace wavy meshes, enabling more reversible expansion and improved load-bearing capability.
Sixth prompt: Could you provide a visual representation of the medical device based on the coding provided above and your recommendations? *Each right image comes from DALL-E and each left, Meshy (STL file).*	 	 

Table 3. Continued.

Prompt	Outcomes for 3D-printed medical devices	Outcomes for 4D-printed medical devices
Seventh prompt: Could you please create a labeled 2D diagram showing the shape transformation of the designed medical device?	Not applicable in the case of the hip prosthesis.	

demonstrating its versatility. Future developments may involve algorithms that can read and modify STL files directly according to the selected material and AM process. This will likely require a combination of artificial life algorithms, such as AI, genetic algorithms, and cellular automata.

Beyond these initial explorations, novel frameworks such as Graph-PRefLexOR broaden the scope of AI in ontology-driven design. Graph-PRefLexOR is a framework that extends LLMs with in situ graph construction, symbolic abstraction, and recursive refinement. This is different from models such as ChatGPT, which generate responses sequentially without building explicit reasoning structures. Graph-PRefLexOR offers the advantage of integrating graph-based symbolic representations.[78] This enables greater transparency, interpretability, and generalization to domains not present in the training data. This architecture produces textual output by first organizing knowledge into graphs of concepts and relationships, identifying abstract patterns that allow reasoning processes to be more closely aligned with scientific methods. When combined with biomedical or engineering ontologies, this approach can enrich the graph with standardized, semantically consistent vocabularies, thereby enhancing interoperability, reducing ambiguity, and facilitating the integration of clinical, experimental, and industrial data. Thus, the synergy between Graph-PRefLexOR and ontologies could lead to systems capable of proposing testable hypotheses, detecting inconsistencies, and generating personalized designs with a level of rigor and traceability that goes beyond what conventional LLMs can offer.

In parallel, field-driven design methodology is being employed to generate topologically optimized structures while significantly reducing computational costs. Software such as Ntop integrates this approach, whereby any physical parameter - including geometry, patient anatomy, simulation results, experimental data, manufacturing toolpaths, and more - can be defined as a field.[125] The optimization process then involves integrating these fields. Building on this concept, Effective Field Neural Networks (EFNNs), which are inspired by field theory, provide a powerful computational framework that can automatically refine and capture complex, multibody interactions through recursive field–quasi-particle representations.[129] By combining EFNNs with generative AI and ontologies, diverse biomedical and engineering data can be represented as interoperable fields and optimized in a physics-informed manner, enabling the automated generation of personalized medical devices tailored to patient anatomy, designed for AM with appropriate materials, and ensuring the required mechanical and biological properties.

6.4. Summary and Outlook

Generative AI opens up new possibilities in design and can further improve the performance of AM, transforming multiple industrial sectors. However, incorporating it as a design resource requires new methodologies and training for designers to transition from traditional CAD modeling and simulations based on mouse-clicking commands to textual and image-based instructions provided as "prompts". Consequently, a new design language is emerging that combines the expressive power of natural language for describing context and details with the precision and efficiency of taxonomies, ontologies, and related codifications. The examples reviewed in this work demonstrate the potential of combining generative AI and AM ontologies, showcasing pioneering studies in this area.

Looking ahead, several research directions stand out. First, the development of standardized biomedical AM ontologies is crucial for ensuring semantic interoperability across disciplines. Secondly, integrating graph reasoning frameworks and field-driven neural networks with generative AI could lead to hybrid platforms combining creativity with rigorous physical constraints. Thirdly, establishing robust evaluation metrics and error estimation methods will be crucial for validating the reliability and reproducibility of AI-driven design pipelines in clinical and industrial contexts.

Taking together, these advances demonstrate that the synergy between generative AI and AM ontologies is feasible and highly promising for accelerating innovation. By embedding reasoning, physics-informed optimization, and semantic clarity into the design cycle, the next generation of medical devices could achieve levels of personalization, reliability, and clinical impact that are currently unattainable.

7. DT in AM

Yi Cai*, Xiangyang Dong, Huangyi Qu

7.1. State of the Art

DT was first conceptualized by Michael Grieves in 2002 and later defined by NASA as a multiphysics, multiscale computational simulation that mirrors the lifecycle of a physical entity or system.[11] When integrated with AM, DTs enable the creation of adaptive, real-time digital replicas of AM processes and machinery,[130] facilitating advanced functionalities such as live process monitoring, anomaly detection, iterative optimization, and predictive maintenance strategies.[131] A DT framework in AM is structured around five core elements: the physical object, its virtual twin model, data-driven services, dynamically updated twin data, and their bidirectional interactions.[132]

DT technology is transforming AM by enhancing hardware capabilities and process efficiency, as illustrated in **Figure 10**. For 3D printers, DTs serve as high-fidelity virtual counterparts that dynamically simulate printer behavior across diverse operational scenarios.[32] Through continuous sensor data streams, they empower predictive maintenance by proactively identifying abnormal patterns before failures. This enables manufacturers to minimize unplanned downtime, prolong equipment longevity, reduce lifecycle costs, and maintain product quality. In process optimization, multiphysics DTs model intricate phenomena such as thermal gradients, energy distribution dynamics, and material flow during fabrication.[133] These insights allow precision calibration of critical parameters—including laser power intensity, scan velocity, and layer resolution—to achieve optimal print outcomes. Emerging research is also expanding DT-based analytics into end-to-end AM workflows, spanning from design and production to post-processing and recycling.[134]

The integration of AI has further advanced DT capabilities. At the design stage, AI-powered DTs generate optimized AM geometries tailored for AM constraints, such as weight minimization, stress distribution optimization, and material usage reduction.[135] These generated designs undergo virtual validation within DT environments prior to production, significantly mitigating manufacturability risks and eliminating costly trial-and-error iterations. During production, cutting-edge AI architectures, notably deep RL,[136] create self-learning DTs.[137] Such adaptive twins continuously refine their predictive models by synthesizing real-time sensor inputs with historical process data, enabling them to anticipate complex thermo-mechanical behaviors, recalibrate parameters, and evolve decision-making protocols iteratively. This closed-loop intelligence drives precision gains while fostering resilient, self-correcting manufacturing ecosystems. Post-production phases also benefit from AI-augmented DTs. Machine vision-enhanced simulations forecast outcomes of treatments like thermal annealing or abrasive surface polishing, allowing operators to preempt defects and calibrate post-processing variables virtually.[138] These advancements highlight the transformative potential of AI-enhanced DTs in driving innovation, improving sustainability, and reshaping the future of AM.

7.2. Scientific Challenges and Technical Limitations

Although various DTs for AM have been developed and demonstrated, this endeavor is still in its infancy and facing numerous

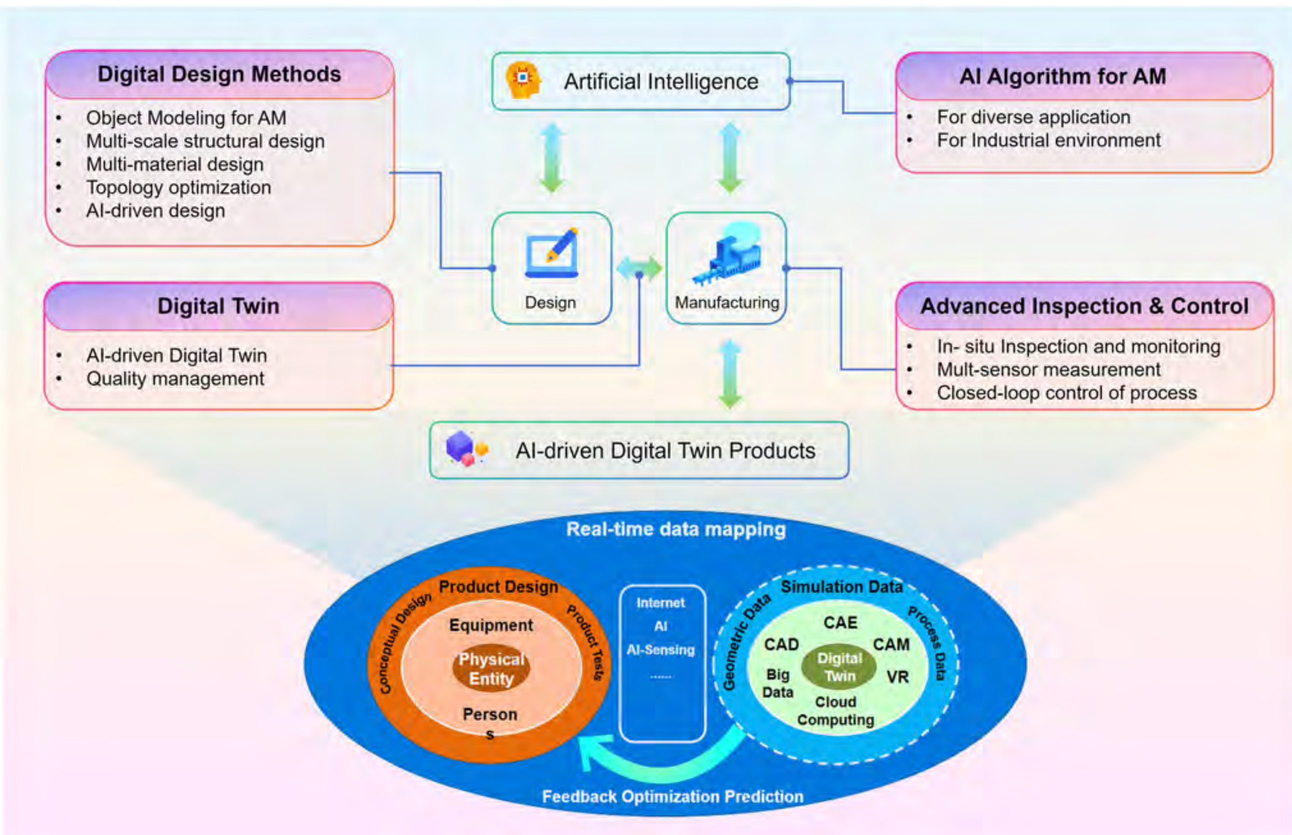


Figure 10. Research framework for AI-driven DT of AM.

challenges. Immature hardware components, segmented software ecosystems, and cross-domain collaboration barriers collectively restrict the realization of complete DT functionality. Below are key challenges based on the fundamental components of DTs in AM:

7.2.1. Physical Object

Sensor Integration: High-fidelity sensors are essential for capturing real-time process parameters in AM. Poor sensor placement or insufficient sampling rates can result in incomplete datasets, reducing the accuracy of twin models.

7.2.2. Virtual Model

Model Fidelity and Scalability: Virtual models should accurately replicate the physical system but achieving high fidelity in AM is complex due to nonlinear material behavior, process variability, and multiscale modeling requirements. Scaling DTs for large-scale AM production also presents challenges, including high computational costs, system complexity, and interoperability issues.

7.2.3. Twin Data

Data Integration: AM generates vast amounts of data from sensors, CAD models, simulation tools, and post-processing systems. The complexity of integrating these diverse data streams, coupled with risks such as "garbage in, garbage out" (GIGO) from noisy or incomplete data, threatens the reliability of DTs.

Security and Privacy: The reliance on IoT and cloud platforms opens the door to intellectual property theft, reverse engineering, and industrial sabotage. Sensitive design blueprints are at risk of cyberattacks, while malicious commands could disrupt production lines.

7.2.4. Services

In Situ Monitoring and Analysis: AM processes require in situ monitoring to ensure precision and quality. These processes generate vast amounts of data from diverse sources, which is often heterogeneous, ranging from temperature profiles to material stress readings, and must be analyzed in real-time to detect issues like overheating, porosity, or material inconsistencies. However, the large volume and variety of data, combined with the dynamic nature of AM processes, make analysis challenging.

Real-Time Processes Control and Optimization: Achieving precise control over key parameters requires millisecond-level adjustments based on real-time feedback from sensors. However, the integration of diverse, high-volume data streams introduces latency and synchronization issues, and many controllers are currently unable to make real-time adjustments based on actual conditions. Additionally, the nonlinear interdependencies between parameters make optimization computationally intensive and time-consuming

7.2.5. Twin Interaction

Interoperability: The lack of open-source framework and standardization across AM systems leads to "ecosystem silos," where proprietary protocols and fragmented toolchains isolate data. This prevents seamless integration with systems like Enterprise Resource Planning (ERP), breaking global optimization chains and limiting DT functionality.

7.3. Scientific Pathways and Technological Developments

Despite the challenges above, advancements in DT theory, AI tools, IT technologies, and standardization offer promising solutions to unlock the full potential of DTs, as shown in **Figure 11**.

Advancements in DT theory, such as Parallel Systems theory and the "ACP" framework, play a critical role.[139] This framework

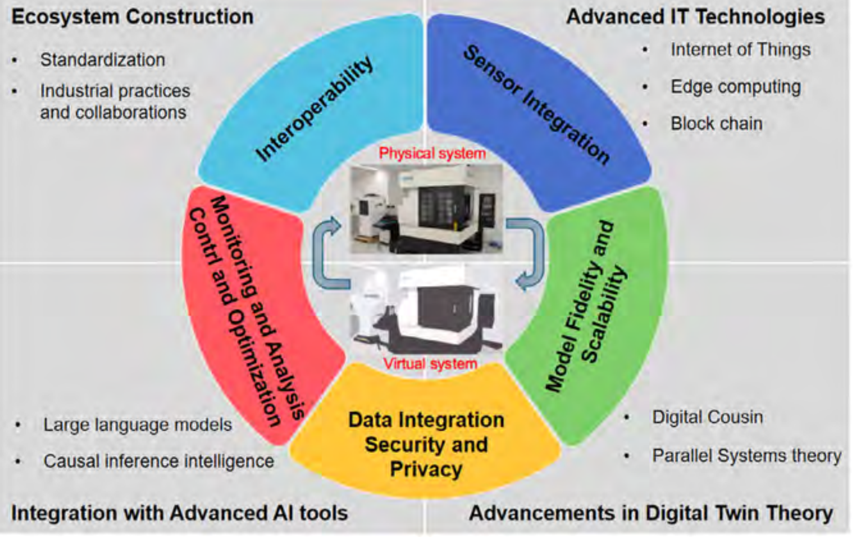


Figure 11. Challenges and potential solutions in DTs for AM.

consists of Artificial Systems (A), which create virtual models replicating physical systems; Computational Experiments (C), which simulate and test scenarios using these models; and Parallel Execution (P), ensuring continuous interaction between physical and virtual systems.[140] This real-time interaction enables monitoring, analysis, prediction, and optimization of AM processes. Additionally, the concept of Digital Cousins, abstracted models applicable to multiple systems, reduces the need for build high-fidelity models of physical systems, significantly reducing computational costs while delivering valuable insights for diverse manufacturing needs.[141]

The integration of advanced AI technologies, such as LLMs and causal inference intelligence, is transforming DT capabilities. LLMs process and analyze large volumes of unstructured manufacturing data, enabling accurate predictions and automated decision-making.[142] For instance, they can identify complex patterns in sensor data to detect anomalies or recommend process parameters optimizations. Causal reasoning enhances DTs by uncovering cause-and-effect relationships within complex systems,[143] enabling root-cause analysis and proactive real-time problem-solving. These advancements evolve DTs from reactive tools into intelligent, adaptable systems for improving manufacturing outcomes.

Advanced IT technologies, such as IoT and edge computing, further enhance DT capabilities by enabling real-time data collection, processing, and feedback.[144] High-precision sensors monitor key parameters, while edge computing reduces latency by processing data locally, allowing faster decision-making and adjustments. Blockchain technology further strengthens DT systems by ensuring data integrity, providing transparent audit trails, and mitigating cyberattack risks through decentralized and immutable ledgers.[145]

In terms of ecosystem construction, standardization efforts are vital in breaking down barriers between systems. Standardization fosters interoperability and scalability by establishing common data formats (e.g., STL, AMF) and communication protocols (e.g., OPC UA). These standards ensure compatibility across various tools and systems, enabling seamless integration of DTs with platforms like ERP and supply chain management.[146] As a result, standardization reduces complexity, lowers costs, and creates a unified ecosystem that supports the widespread adoption of DTs in AM. Moreover, increased industrial practices and collaborations[147] can help accelerate the development and acceptance of these standards, ensuring they meet the diverse needs of real-world applications and drive faster progress in standardization efforts.

7.4. Summary and Outlook

AM plays a vital role in future manufacturing industries, enabling design freedom of complex geometries, customization, and material efficiency. However, it currently suffers from major shortcomings in part quality, process reliability, and production scalability. DT technology tackles these issues by creating dynamic virtual replicas of physical processes and equipment, enabling in situ monitoring, defect detection, process optimization, and predictive maintenance. The integration of AI further amplifies DT's capabilities in AM, as advanced AI technologies empower DTs to analyze vast datasets, identify root causes of deviations, predict defects, and optimize parameters, ensuring adaptive and intelligent process control. These AI-driven DTs not only enhance precision, efficiency, and adaptability but also accelerate innovation, unlocking the full potential of AM. Although challenges remain including real-time monitoring of the agent in action, data integration, and interoperability across a large landscape of potentially relevant properties, significant efforts and progress have been made in advancements of DT theory, development of novel AI tools, implementation of powerful IT technologies, and establishment of standardization. By systematically addressing current barriers and fostering a synergistic collaboration ecosystem, AI-driven DTs are poised to revolutionize AM toward smarter, more efficient, and sustainable manufacturing processes, bringing extensive and far-reaching changes to the whole manufacturing industry.

8. AI for Online Monitoring and Defect Detection in AM

Najmeh Samadiani*, Guangyan Huang.

8.1. State of the Art

Real-time defect detection and automated quality control are essential for ensuring the reliability of AM components, as defects such as porosity, cracks, surface irregularities, and spreading faults can significantly compromise mechanical performance. Early identification is, therefore, critical to minimizing waste and ensuring consistency.

Substantial progress has been made in AI-driven online monitoring, underpinned by in situ sensors that capture diverse phenomena during fabrication (**Figure 12**). Camera-based vision systems, including visible-light, high-speed, and near-infrared imaging, are the most widely deployed, offering detailed views of melt pool dynamics and surface evolution.[148] Thermal and pyrometer imaging complement these by detecting heat-flow anomalies linked to porosity, while acoustic and vibration sensing capture spreading faults and process instabilities. No single monitoring architecture addresses all AM variants, however, defect types and sensor requirements vary by material and technique. Consequently, domain-specific systems have been reported for wire arc welding,[9,149] laser-based AM,[150] polymer extrusion-based AM,[151] and material extrusion.[152]

From a modeling perspective, early AI2AM studies relied on single-modality deep models. For instance, Lu et al.[153] evaluated Recurrent Convolutional Neural Network (R-CNN), Single Shot Multi-Box (SSD), and You Only Look Once v4 (YOLOv4)—to detect misalignment and abrasion in real-time videos of Carbon Fiber Reinforced Polymer (CFRP) composites. While such approaches demonstrate the feasibility of automated defect recognition, their generalization across machines, geometries, and materials remains limited. To move beyond passive detection, RL has been adopted for process adaptation: Chung et al.[154] demonstrated that RL can dynamically optimize FFF parameters and reduce defect rates via real-time mitigation.

The influence of AI-based real-time defect detection extends beyond AM. In the construction sector, researchers[155] have

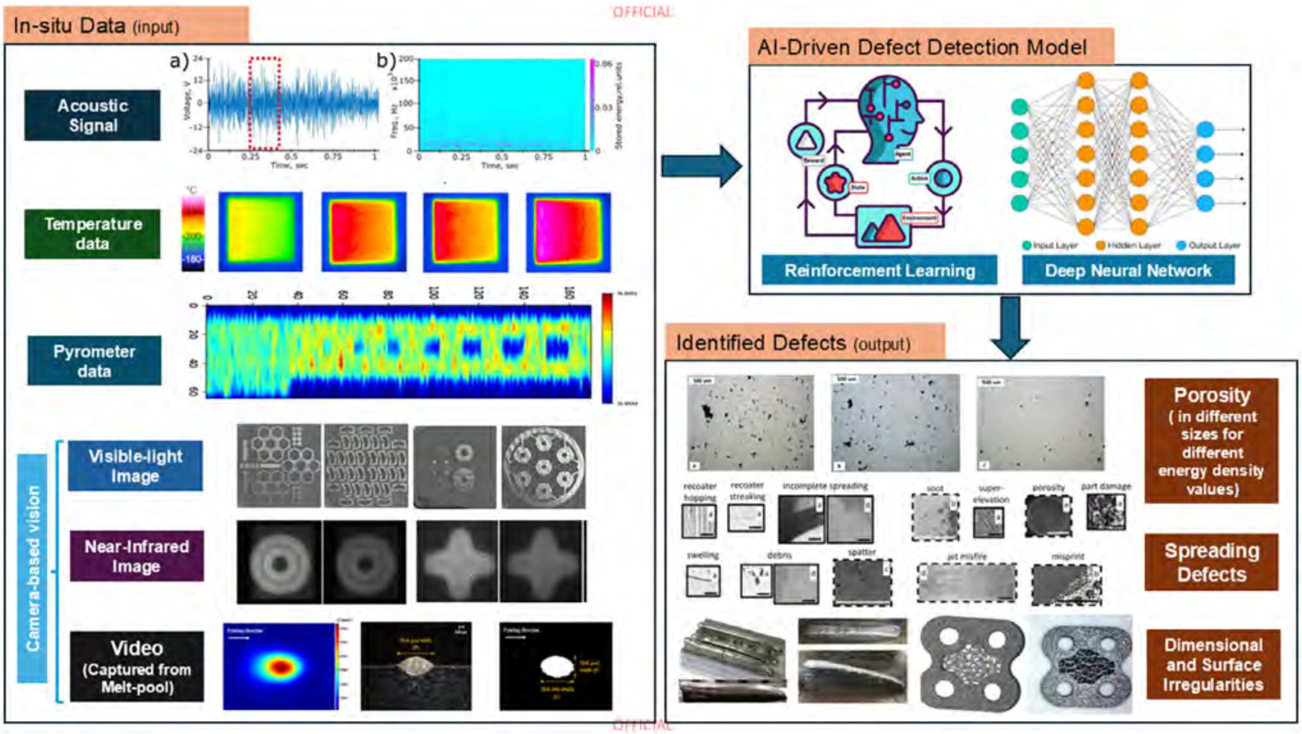


Figure 12. A simple scheme of an AI-driven defect detection system involves capturing various real-time data streams from sensors during the AM process. These data streams are then processed through an AI model, which analyzes the information to identify different defect types.

utilized ensembles of deep networks and a StyleGAN3 architecture to detect breakpoints during 3D concrete printing (3DCP), whereas in biomedicine, online monitoring has facilitated flaw-free, industrial-scale bioprinting of tissue constructs.[156] These cross-sector successes reinforce the potential of AI for adaptive quality assurance across diverse manufacturing contexts.

Building on these foundations, recent work is beginning to extend AI2AM from feasibility studies toward frameworks with broader industrial relevance. Current developments integrate multimodal sensing, hybrid modeling, and emerging agent-based orchestration,[157,158] approaches that enhance robustness under varying conditions while helping to mitigate the challenges discussed in the following section. Collectively, these trends suggest that AI-driven defect detection is evolving from isolated, single-modality models into more cohesive and distributed ecosystems capable of adaptive, real-time quality assurance.

8.2. Scientific Challenges and Technical Limitations

Despite rapid advancements in AI-driven defect detection for AM, several challenges hinder its widespread adoption: 1) Data scarcity and lack of benchmarks: high-performing AI models require large, diverse, and well-annotated datasets,[159] but generating AM data is costly and time-consuming. Many AM systems demand expensive fabrication steps, making it impractical to collect vast amounts of real-world data. As a result, most available datasets are restricted to simplified geometries (e.g., cylinders or cubes in metal AM),[159] which limits the ability of models to generalize effectively across complex shapes, materials, and process parameters. The absence of standardized, high-quality public benchmarks further restricts reproducibility, method comparison, and collaborative progress across the community. 2) Costly, time-intensive annotation: reliable ground truth often requires destructive or high-cost nondestructive inspection (NDI) techniques such as micro-CT scanning. These methods are not always accessible, and because most annotations are generated post-build, models trained on such data cannot support real-time adaptation. This delay reduces the ability of AI models to intervene during the build to prevent defect propagation. 3) Defect heterogeneity, process variability, and hidden flaws: differences in material properties, such as thermal conductivity and melt pool dynamics, cause defects to manifest inconsistently even within the same AM technique. This variability, combined with the inherently multiscale and multiphysics nature of AM, makes it difficult for AI models to generalize across different machines, materials, and geometries, as accurate prediction requires capturing coupled thermal, mechanical, and material interactions.[160] A further complication is the prevalence of internal defects, such as pores or cracks buried within components, which cannot be detected by surface sensors alone. Detecting these flaws in real time is especially challenging, as conventional NDI methods (e.g., CT, ultrasound) are too slow and costly for inline monitoring. 4) Real-time constraints and closed-loop integration: achieving millisecond-level latency for on-the-fly defect mitigation requires efficient deployment of models at the machine (edge). However, high-speed data streams and large networks create bandwidth and computational bottlenecks, while cloud-based inference introduces delays.

At the same time, most AM platforms lack native closed-loop interfaces, limiting the integration of AI-driven monitoring with real-time process control. 5) Human factors and explainability: current AI systems for defect detection rarely provide clear, interpretable outputs, making it difficult for operators to understand or act on predictions. This lack of transparency undermines confidence and poses a barrier to industry adoption.

8.3. Scientific Pathways and Technological Developments

Although challenges remain in online monitoring and defect detection in AM, recent advancements in AI methods and IT infrastructures provide promising solutions to address these difficulties:

8.3.1. Data Augmentation, Knowledge Transfer, and Multimodal Fusion

Data scarcity and the lack of benchmarks can be mitigated with synthetic data generation (GANs, diffusion, domain randomization) and knowledge transfer from pretrained vision–language models (VLMs), while federated learning enables cross-site improvement without sharing proprietary data.[161] Beyond single-sensor inputs, multimodal fusion increasingly adopts voxel-based analytical models as a common substrate for heterogeneous streams; for example, camera images, laser light-section data, and ex situ CT can be co-registered into a consistent voxel representation that combines nominal and sensor-derived information.[162] Such unified substrates support holistic QA and can improve generalization across machines, materials, and geometries.

8.3.2. Unsupervised Annotation and Adaptive Learning

To reduce the cost and delay of annotation, unsupervised, semi-supervised, and active learning approaches are being developed to exploit unlabeled data and prioritize limited micro-CT validation. LLMs[163,164] with retrieval-augmented generation (RAG) can further integrate expert knowledge and prior reports to support annotation and harmonize label protocols. Beyond labelling, adaptive learning enables continuous refinement from real-time sensor feedback, while large-concept models,[165] combining vision, RL, and multimodal fusion, exemplify adaptable systems that adjust dynamically to evolving AM conditions.

8.3.3. Physics-Informed and Hybrid Modeling

To improve defect prediction accuracy and reduce reliance on purely data-driven models, PINNs[166] incorporate fundamental material behavior and process physics. Hybrid AI approaches, which merge ML with FEA, provide a robust framework for defect modeling by combining empirical data with engineering simulations. This enhances both real-time defect detection and process optimization, making AI2AM systems more interpretable and reliable.

8.3.4. IoT-Enabled Real-Time Systems and Multiagent Control

Real-time monitoring in AM can be achieved by integrating IoT-enabled sensor networks with edge–cloud computing. Edge devices provide low-latency inference at the machine, while cloud platforms support large-scale retraining and fleet-level monitoring. Multiagent systems,[165,167–169] particularly when coupled with DTs, distribute tasks such as sensing, detection, and control, enabling closed-loop defect mitigation through RL or model predictive control.

8.3.5. Explainability and Human–AI Collaboration

Transparent decision-making is essential for adoption. Explainable AI methods (saliency maps, counterfactuals, calibrated uncertainty) provide insight into defect alarms, while LLM- and RAG-based copilots translate predictions into actionable instructions. New forms of interaction are also emerging: the integration of augmented reality (AR) and VLMs has been shown to improve operator training, and similar methods could be adapted for automatic defect detection. By combining real-time data streams with AR overlays, systems could highlight inconsistencies, misalignments, or process anomalies as they occur, offering both automated detection and human-readable explanations.[170]

8.4. Summary and Outlook

AI-driven real-time defect detection is transforming AM by improving quality control, reducing material waste, and optimizing processes. However, widespread adoption remains constraint by several challenges: data scarcity and the absence of benchmarks, annotation complexity, defect heterogeneity and process variability (including hidden flaws), real-time constraints with limited closed-loop integration, and human factors related to explainability and trust. Addressing these barriers requires an integrated framework that combines advanced AI methods with physics-informed modeling and modern system architectures. Generative AI, diffusion models, and voxel-based multimodal fusion can mitigate data scarcity, while LLMs with RAG, active learning, and adaptive learning reduce annotation costs by integrating expert knowledge and unlabeled sensor streams. PINNs and hybrid models coupling ML with FEA embed physical constraints, improving interpretability and enabling better generalization across materials and processes. IoT-enabled sensor networks with edge–cloud infrastructures, supported by multiagent systems and DTs, provide the real-time foundation for scalable, closed-loop monitoring and corrective action. Finally, explainable AI, uncertainty calibration, and AR/VLM-based operator interfaces are essential for building trust and ensuring industrial usability. Future efforts should focus on expanding high-quality datasets, deploying adaptive multimodal and multiagent pipelines, and strengthening explainability to deliver cost-effective, reliable, and industrial-scale AI-driven defect detection across diverse AM technologies.

9. Real-Time AI-Driven Structural Validation for AM

Austin Downey*, Yanzhou Fu, Lang Yuan.

9.1. State of the Art

Validation in AM refers to a staged demonstration that a defined process consistently produces parts meeting functional and structural requirements under realistic manufacturing variability. In situ structural validation, enabled by AI2AM, is poised to transform AM from primarily prototyping-focused to viable production of structurally critical components. As shown in **Figure 13**, effective AI2AM-based in situ structural validation would allow printed components to be taken from the print bed and placed into the next natural manufacturing step or directly into service, dramatically reducing production time, inspection demands, and overall costs. Moreover, adopting AI2AM techniques would streamline quality assurance processes, particularly benefiting industries, such as aerospace and automotive, where component performance is safety-critical. However, ensuring structural performance in situ and in real-time remains challenging due to the computational complexity of model-based methods and the extensive data requirements of data-driven approaches. Accordingly, validation should be reported with deployment-oriented metrics, including per-layer calibrated strength or pass/fail accuracy with confidence intervals, defect-detection sensitivity and specificity, and cross-setup robustness across machines and operators.

Model-based validation methods, typically involving FEA, provide accurate physics-based predictions of structural behavior but are computationally expensive and typically infeasible for online assessment. For instance, Garg and Bhattacharya showed that FEA effectively models the elastoplastic behavior of FDM components, highlighting the influence of layer thickness and raster orientation on failure.[171] However, its computational complexity limits its use in real-time applications. Scapin and Peroni developed efficient FEA models that integrate real infill geometries and transversely isotropic material behavior, yet these simulations remain computationally intensive for real-time monitoring.[172]

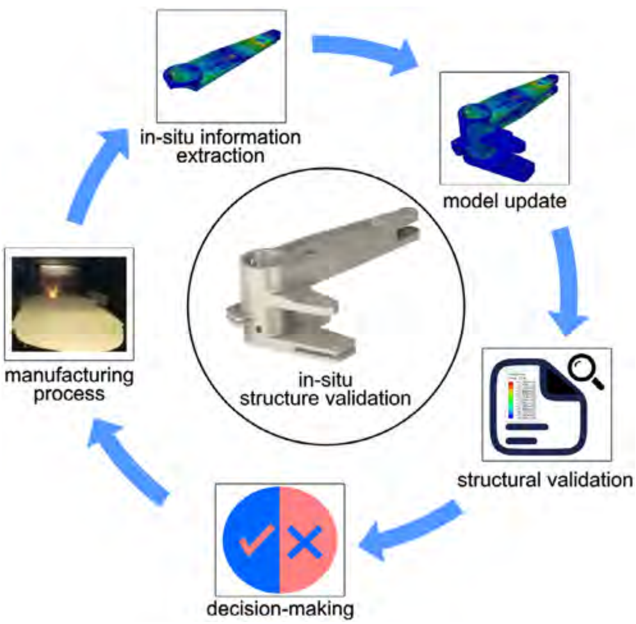


Figure 13. The overview of in situ structural validation to ensure the printed component quality.

Purely data-driven methods excel at rapid defect detection but struggle to generalize across diverse defect types and print conditions. For instance, Avro et al. achieved over 97% accuracy in detecting under-extrusion defects with a CNN-YOLO (Convolutional Neural Network-You Only Look Once) framework but stressed the need for extensive labeled data.[173] Similarly, Jin et al. demonstrated real-time anomaly localization using YOLO and DeepLabv3 networks, though their system required controlled imaging setups.[174]

The model-based and physics-driven paradigms are not mutually exclusive; typically, data-driven processes are used for processing sensor data.[175] Our recent work highlights a combination of these approaches. For a data-driven decision-maker, an accumulation-threshold-based approach leveraging CNN rapidly identifies defects during printing, enabling immediate decisions on structural integrity with over 90% accuracy.[176] In parallel, we developed a physics-based simulation-in-the-loop framework that integrates U-Net image segmentation with real-time updated FEA models.[177] This hybrid approach incorporates defect data into structural models during printing, achieving predictive accuracy within 5% of validated tensile strengths. By leveraging model-based methods, initial DT models can evolve throughout the product's lifecycle, incorporating real-time sensor data and inspections to enhance long-term structural assessment and predictive maintenance.[35,36]

Recent work on agentic and multiagent systems offers a complementary route to reduce reliance on large labelled datasets and to incorporate physics constraints.[178–180] In these frameworks, coordinated agents plan experiments, curate or synthesize data, invoke physics-based solvers and property models as tools, and adapt decisions based on in situ observations. Studies across science and engineering report coordinated hypothesis generation, design workflows, and physics-informed simulation scheduling, with improvements in sample efficiency and robustness under distribution shift. Within AI2AM, such layers are best viewed as a future integration path: agents can propose targeted parameter sweeps and defect-injection plans, enforce process and design constraints through tool calls, and prioritize prints that maximize expected information gain under domain randomization.

9.2. Scientific Challenges and Technical Limitations

While AI2AM-based in situ structural validation shows significant promise, several fundamental challenges limit broader adoption: 1) Computational complexity of real-time physics-based methods: physics-based validation methods, particularly real-time FEA, require substantial computational resources. Advances could be measured by achieving reliable structural assessments within seconds per layer, even for complex geometries. 2) Scalable and robust sensing systems: current sensor technologies for defect detection often rely on high-cost, high-resolution imaging or delicate instrumentation, limiting industrial scalability. Progress can be quantified by reducing sensor costs below 5% of total system acquisition cost and achieving operational reliability above 95% across diverse manufacturing environments. 3) Generalization capabilities of data-driven methods: data-driven approaches typically demand extensive training data and struggle to generalize to new or unforeseen defect scenarios. Improvements would be demonstrated by achieving defect detection accuracy exceeding 95% for defect types or conditions not explicitly represented in the training dataset, significantly reducing the need for retraining. 4) Integration and establishment of AI2AM industry standards: integrating AI2AM techniques into existing manufacturing processes and quality assurance frameworks faces substantial logistical and regulatory barriers. Success would involve developing widely recognized and adopted international standards (e.g., ASTM, ISO) that facilitate compatibility and interoperability across different industries and manufacturing environments. 5) Cybersecurity-assured reliability, certification, and industry acceptance: demonstrating the reliability of AI-based validation under stringent cybersecurity measures, particularly for critical structural components in aerospace and automotive industries, is paramount. Successful outcomes would include regulatory approval by relevant certification bodies (such as the FAA for aerospace or NHTSA for automotive components) and adoption by major industry stakeholders.

9.3. Scientific Pathways and Technological Developments

Meeting the identified challenges in AI2AM-based in situ structural validation will require significant advances in science, technology, and standardization frameworks. Key areas of advancement include: 1) Computational efficiency and physics-informed AI: advancements in physics-informed ML, including methods like PINNs,[178,179] will enable accurate, real-time structural assessments with significantly reduced computational demand. By merging physics-based FEA models with AI approaches, these techniques promise rapid, layer-by-layer validation without compromising prediction accuracy. 2) Edge Computing for Sensor Data Processing: To minimize data transfer and dependency on centralized computing infrastructure, advances in edge computing[180] and embedded AI processors (ASICs, FPGAs)[181] are critical. Developing robust, self-contained edge devices capable of performing in situ data processing and providing immediate, reliable "go/no-go" validation decisions directly at the manufacturing station, as shown in **Figure 14**, will ensure manufacturing continuity, enhance system redundancy, and significantly reduce infrastructure costs and maintenance complexity. 3) Integration and Industry Standardization: Establishing unified, widely accepted standards, testing procedures, and interoperability frameworks is essential for seamlessly integrating AI2AM technologies into existing manufacturing ecosystems.[182,183] Collaborative efforts between academia, industry leaders, and regulatory agencies will be vital to defining clear guidelines, protocols, and best practices, fostering industrial confidence, regulatory alignment, and streamlined adoption of AI-driven structural validation processes. 4) Cybersecurity Best Practices for AI2AM Systems: System designers and manufacturers must adopt robust cybersecurity protocols at the sensor, controller, and cloud-management levels to safeguard AI2AM systems. Implementing secure communication standards, routine vulnerability assessments, and intrusion detection measures is critical for industry stakeholders. While edge computing inherently reduces some cybersecurity risks by limiting central points of vulnerability, rigorous attention to security practices remains essential.

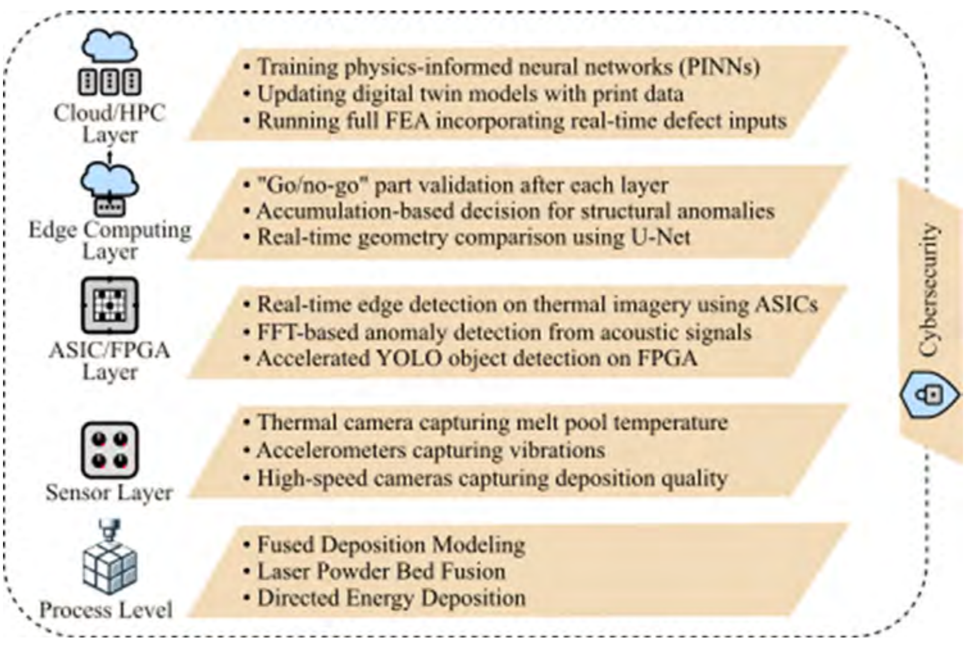


Figure 14. Layered system combining sensing and edge computing for real-time, low-cost in situ structural validation.

9.4. Summary and Outlook

AI2AM-based in situ structural validation holds significant potential for transitioning AM into the mainstream production of safety-critical components. Future research efforts should prioritize three key directions: improving computational efficiency through physics-informed AI approaches, advancing edge computing capabilities to enable robust on-site data processing, and developing standardized, production-ready protocols that extend beyond controlled laboratory settings to enable seamless integration into industry practice. Establishing clear, quantifiable metrics will be essential for measuring progress and ensuring tangible outcomes. Successfully addressing these areas will result in substantial reductions in production time, inspection efforts, and costs, facilitating broader industrial acceptance and enabling safer, more sustainable manufacturing practices.

10. CV-Based AI in AM

Tsz-Kwan (Glory) Lee*, Arbind Agrahari Baniya, and Eisha Waseem.

10.1. State of the Art

CV is a key enabler of AI2AM, transforming traditional DTs into smarter systems with visual perception and adaptive intelligence.[37] In AM workflows where challenges like surface inconsistency, layer misalignment, and structural distortion compromise structural integrity, product quality, and performance,[184] integrating CV provides spatial and geometric context to support more informed process-aware decisions.[185]

Figure 15 illustrates five key stages that shaped the evolution of AI2AM. The development originated from the concept of DT in the 1960s during NASA's Apollo program, where physical spacecraft replicas were used alongside digital simulations to telemetrically monitor and analyze missions.[186,187] This progression builds upon imaging advancements since the 1990s, when RGB images and thermal cameras enabled offline quality control. Although initially disconnected from control loops, these early systems laid the groundwork for CV-based automation. From the 2020s, enabled by IoT, edge computing, and advanced sensors, AM platforms began integrating live camera feeds into control loops, allowing dynamic correction based on visual input, marking the Industry 4.0 era.[188] More recently, this has led to AI vision analytics for DTs AM systems, where DL interprets visual data to support adaptive decision-making and 3D reconstruction of print states using high-dimensional sensor data.[186]

Recent breakthroughs in AI2AM include: 1) Advanced sensors and data acquisition: in situ monitoring systems via camera imaging, acoustics, multimodal data acquisition using coaxial monitoring, X-ray computed tomography, and spectroscopic sensors, combined with edge computing and IoT networks, enable precise data capturing.[189] 2) Sophisticated simulation models: high-fidelity multiphysics solvers, digital thread integrations, and immersive Augmented Reality (AR)/Virtual Reality (VR) simulate printing behaviors and test alternative designs to prevent defects.[190,191] 3) Integration of AI-driven optimization and control: Physics-informed ML, generative AI-powered design and process parameter tuning, anomaly detection, predictive maintenance, neural networks, edge AI, and federated learning to analyze vision data, classify defects, improve decision-making, and enable adaptive control under uncertainty.[189]

The convergence of CV and AI has resulted in a new generation of CV–AI solutions in AM. CV is becoming a core sensing strategy, enabling DTs to act as intelligent agents capable of learning and adapting. It offers a data-driven approach to analyze patterns and make real-time predictions, improving process accuracy and efficiency, reducing material waste, and enhancing final product quality, broadening AM's applicability across domains.[192]

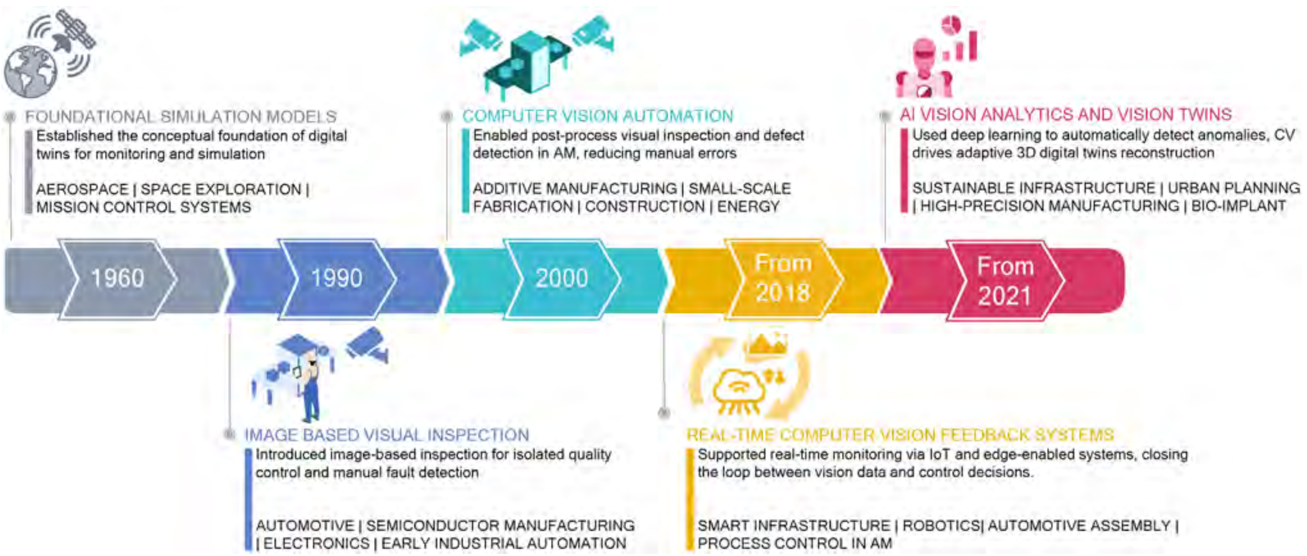


Figure 15. Evolution of CV enabler in AM, highlighting key technological milestones, functional advancements, and industrial applications from early simulation models to adaptive AI-enabled vision twins in smart AM systems.

10.2. Scientific Challenges and Technical Limitations

The growing adoption of AI2AM brings exciting opportunities but also key challenges that must be addressed for broader implementation and societal benefits. These challenges can be grouped into technical, economic, and ethical dimensions.

Technical challenges include: 1) *Data acquisition and processing:* managing large volumes of sensor data in real-time requires efficient acquisition systems and robust storage and processing infrastructure.[193] 2) *3D modeling and reconstruction:* accurate stereo imaging registration and 3D reconstruction remain complex, especially when comparing predicted models to true geometries.[194] 3) *Model accuracy and validation:* reliable simulation outcomes depend on high-fidelity models, validated material properties, and rigorous testing.[195] 4) *Real-time performance:* high computational demands, especially with complex geometries, require optimized algorithms and capable hardware.[195] 5) *System integration and interoperability:* integrating DTs into existing AM workflows is limited by platform compatibility.[196] 6) *Cybersecurity:* As AI2AM systems become more interconnected and reliant on data exchange, securing data and protecting intellectual property are critical.[197]

Economic challenges focus on the cost of implementation, especially for small and medium-sized enterprises (SMEs).[198] High investment requirements for sensors, computing infrastructure, and skilled expertise limit accessibility, especially in early-stage, nonstandardized environments. This hinders advancements due to SMEs' limited capacity for R&D required to realize AI2AM's potential.

Ethical challenges involve bias and fairness. AI models trained on imbalanced or incomplete data can lead to inaccurate or discriminatory outcomes, raising concerns around trust and accountability. Ensuring fairness and addressing bias are crucial for the responsible use of AI2AM.[199]

10.2.1. An AI2AM Case Study

While the pipeline in **Figure 16** showcases an example of CV-based AI2AM application, it also reflects the multifaceted challenges, include 1) Technical challenges: AI2AM systems require precise depth estimation, segmentation, and calibration, yet these remain difficult under varying lighting, surface textures, or complex geometries. Robust algorithm design and extensive validation with diverse datasets are essential but still evolving. 2) Economic challenges: the cost of developing and maintaining ML-driven inspection systems is high. Investments in computing infrastructure, data storage, and skilled personnel can be prohibitive, especially for manufacturers without a clear short-term return on investment. 3) Ethical challenges: biases in training data can cause misclassification of defective parts. Without transparency in how decisions are made, these errors complicate certification and reduce trust in AI2AM technologies.

10.3. Scientific Pathways and Technological Developments

10.3.1. Scientific and Technical Progress

While challenges continue to limit the widespread adoption of CV–AI DTs in AI2AM, they also drive significant innovation and research. Complexities in data acquisition, 3D reconstruction, and real-time responsiveness are driving the development of multimodal sensing, edge computing, and high-frequency data processing technologies. Simultaneously, new modeling methods, such as implicit surface representations, neural

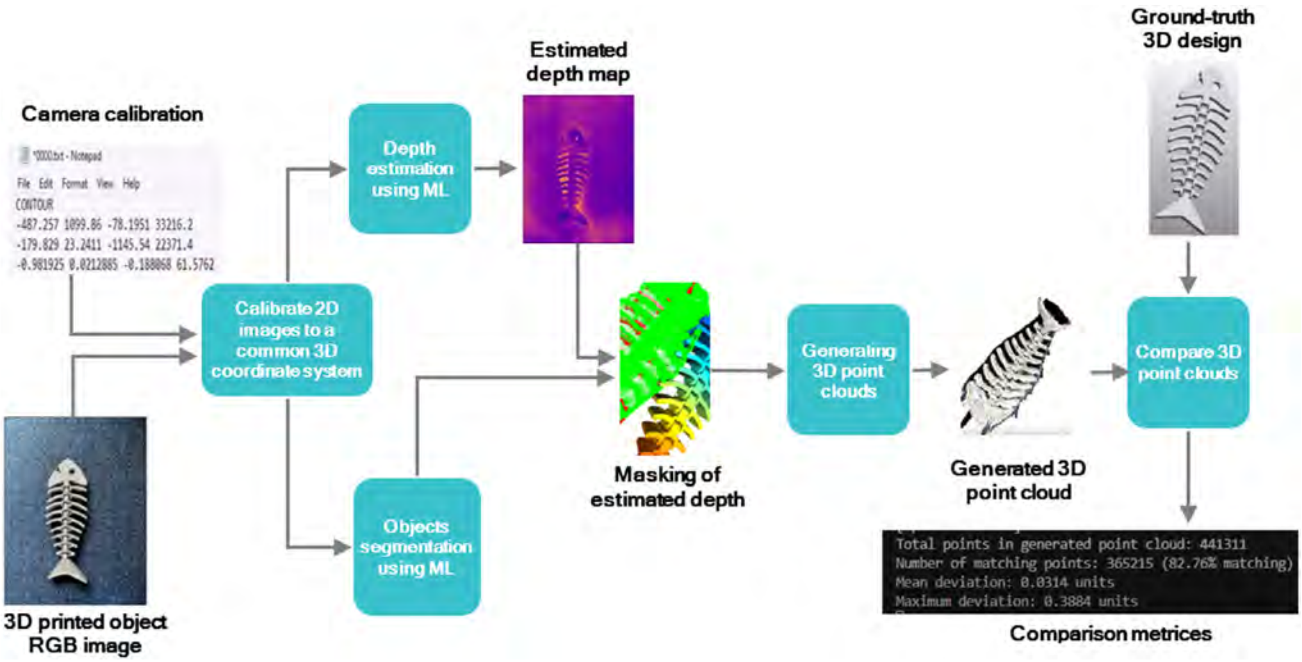


Figure 16. A case study of a ML pipeline for assessing the geometric accuracy of a 3D-printed object via RGB image-based reconstruction and point cloud comparison to the CAD model.

radiance fields (NeRFs), and differentiable simulations, are enabling higher fidelity and responsiveness in DT systems.

Emerging research is focused on self-adaptive DTs capable of online learning and autonomous control. Integrating RL and continual learning into AM workflows offers pathways to closed-loop optimization. Furthermore, hybrid approaches bridging the gap between data-driven and physics-based modeling with ML are also proving effective in addressing model accuracy, scalability, and interpretability.

10.3.2. Industry, Economic, and Societal Impact

The industrial impact of CV-based AI2AM is projected to be transformative across sectors, including aerospace, biomedical, automotive, and advanced manufacturing, where precision, quality assurance, and traceability are critical. AI2AM enables predictive defect detection, in situ process correction, and part customization, particularly valuable for high-performance and safety-critical applications. In smart manufacturing environments, AI2AM also contributes to digital supply chain integration, real-time validation, and achieving zero-defect manufacturing goals.

From an economic perspective, while upfront costs remain high, cloud-based deployment and CV-based AI2AM-as-a-service models are lowering entry barriers for SMEs. These approaches enable scalable, on-demand access to advanced AI2AM capabilities without requiring substantial capital investment. Societally, AI2AM supports sustainability by reducing waste, optimizing energy use, and enabling circular manufacturing practices. It also stimulates new skills development at the intersection of AI, simulation, and manufacturing engineering.

Ethical and regulatory considerations are increasingly relevant. Bias in AI models, often stemming from skewed or incomplete training data, poses risks for decision-making. As a result, research is shifting toward fairness-aware modeling and explainable AI frameworks specifically designed for industrial applications. Concurrently, regulatory bodies are advancing standards for DT validation, cybersecurity, and AI transparency to support safe and trustworthy deployment.

10.3.3. Future Directions

In the coming decade, CV-based AI2AM will drive autonomous, self-improving manufacturing by combining real-time learning, visual reasoning, and adaptive control. Advancements in continual learning and vision AI will support closed-loop AM, accelerating production and enhancing quality. Widespread adoption will depend on collaboration, ethical AI governance, and standardized validation to ensure trustworthy, sustainable systems.

10.4. Summary and Outlook

The integration of CV into DTs for AM represents a transformative synergy toward addressing critical challenges in quality, efficiency, and reliability. CV–AI technologies are reshaping AM by linking physical processes with intelligent models capable of learning and adaptation. This evolution moves beyond workflow automation toward self-adaptive manufacturing systems that optimize production in real time, supporting gains in precision, sustainability, and customization. Despite notable advancements, challenges remain in achieving real-time performance, integrating with legacy infrastructure, and addressing ethical concerns such as bias and data transparency. However, ongoing research in areas such as RL, hybrid modeling, and decentralized AI is addressing these limitations, suggesting that these hurdles are transitional rather than permanent.

Looking forward, AI2AM is positioned as a key enabler in the digital transformation of manufacturing. As regulatory frameworks mature and access to cloud-based platforms increases, broader adoption will become viable even for resource-limited industries. Realizing the full potential of CV–AI in AM will require sustained innovation, ethical design, workforce training, and strong collaboration across academia, industry, and government. Together, these efforts will help establish a new era of intelligent, responsible, and resilient manufacturing systems.

11. AI-Controlled Closed-Loop 3D/4D Printing

Abdul Rahman Sani, Abbas Z Kouzani, Ali Zolfagharian*.

11.1. State of the Art

The adoption of AI has significantly advanced AM, particularly through the implementation of closed-loop control systems for 3D and 4D printing. Traditional AM approaches frequently employed open-loop strategies, where predetermined process parameters remained constant throughout fabrication. These static methods were limited in their ability to manage process variations, resulting in inconsistencies in print quality, geometry, and material performance. In contrast, AI-powered closed-loop frameworks enable real-time sensing, decision-making, and control adjustment, providing a dynamic and adaptive printing process.[200,201]

Closed-loop AI control systems utilize data from thermal cameras, acoustic sensors, visual feedback, and other in situ monitoring tools. ML techniques, including RL, DTs, and predictive neural models, leverage this data to autonomously address anomalies in real-time.[202,203] In the context of 4D printing, where time-dependent material transformations are essential, AI plays a pivotal role in forecasting actuation behaviors and aligning stimuli-responsive outputs with design objectives.[38,171,204]

A prominent example of this integration is the recent framework proposed by Sani et al., which combines AI-powered vision systems with multilayer process monitoring for adaptive control during 3D/4D printing.[10,172] Similarly, Pugliese et al. demonstrated an AI-enabled pathway for biomedical 4D-printed structures using real-time optimization of smart polymers.[201] Other recent developments include closed-loop Q-learning frameworks for personalized drug-delivery structures[205] and predictive control for thermally responsive composite printing.[206] Beyond academic innovation, industrial interest in AI-based feedback control is growing in applications such as robotic AM, hybrid subtractive–additive systems, and medical microdevices. DT technologies now complement these setups, creating virtual replicas of physical processes to enable proactive decision-making and predictive simulation.[202,203]

Traditional open-loop systems rely on pre-set parameters, making them vulnerable to process disturbances such as material inconsistency or environmental changes. Recent advances are increasingly focusing on embedding sensors directly into 3D printers—most notably, acoustic sensors and CV systems. These sensors continuously capture real-time data on printing dynamics, such as nozzle vibration, flow anomalies, or layer defects. However, the transformative potential arises when this data is processed through AI algorithms within a closed-loop control system. **Figure 17** illustrates this intelligent feedback loop, wherein real-time monitoring, defect detection, and AI-driven process control converge to dynamically adjust printing parameters such as temperature, speed, and extrusion rate for optimal results. This paradigm shift enables in situ error correction, reducing reliance on post-processing inspection, minimizing waste, and opening pathways for defect-free, high-precision manufacturing.

11.2. Scientific Challenges and Technical Limitations

Despite significant advancements, the implementation of AI-based closed-loop systems in 3D and 4D printing faces several technical and practical challenges. One of the foremost issues is the integration and synchronization of real-time sensor data with AI decision-making modules. Achieving low-latency data processing from multimodal sources, such as thermal imaging, optical cameras, and acoustic sensors is essential but remains computationally demanding and sensitive to environmental noise.[202,207]

A second major hurdle is the development of robust, generalizable AI models. Most RL frameworks are currently trained in simulation environments or narrowly defined material/process settings. This limits their ability to new materials, geometries, or printer platforms without extensive retraining.[200,205] In 4D printing, where materials exhibit time-dependent or stimulus-responsive behaviors, model complexity increases further, often requiring hybrid physics-informed learning strategies that are not yet standardized.

Data scarcity and quality also impede closed-loop optimization. Unlike traditional manufacturing datasets, AM processes often lack consistent, labeled data across diverse printers, materials, and environmental conditions. This leads to overfitting and suboptimal performance in real-world deployments.[203] Additionally, collecting high-resolution, in-process defect data with reliable ground truth remains a bottleneck, particularly in high-throughput environments.

In addition to sensor-driven feedback, two complementary optimization paradigms are emerging in AI-augmented AM: tool or instruction-based and voxel-based approaches. Tool or instruction-based methods operate at the G-code or process-parameter level, directly modifying extrusion rate, nozzle temperature, or print speed in response to detected defects.[208] These methods are computationally efficient and readily implementable on existing printers, but they may overlook localized microstructural variations. In contrast, voxel-based optimization represents the build volume as a 3D grid of discrete elements, enabling fine-grained control of material deposition at the voxel level.[209] While voxel approaches achieve higher resolution in defect localization and correction, they require intensive computation and significant memory overhead, making real-time deployment on embedded systems challenging. Recent work is exploring hybrid strategies, where voxel-level anomaly detection is paired with instruction-level corrective actions, balancing precision with practical feasibility.[208]

From an industrial perspective, scalability and system interoperability are significant challenges. Closed-loop systems must be hardware-agnostic to support wide adoption across different printer architectures. However, most current systems are tightly coupled with specific machines or materials, limiting flexibility and commercialization.[33,210,211]

Cost and complexity also pose barriers to mainstream adoption. Integrating smart sensors, edge computing modules, and

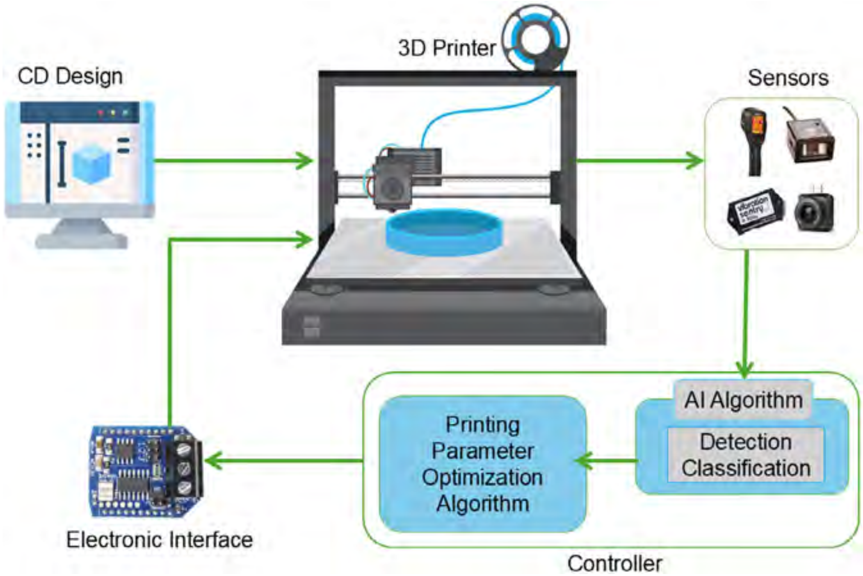


Figure 17. An illustration of the closed-loop feedback loop 3D printing. Reproduced with permission under Open Access.[10] Copyright 2024, Wiley.

adaptive controllers into AM platforms increases capital and operational expenditure. Furthermore, lack of regulatory frameworks and standardization for AI-enabled adaptive printing systems presents challenges in certification, especially in safety-critical applications like medical or aerospace devices.[212] In the long term, cybersecurity and real-time system validation will become critical as autonomous systems are connected to cloud-based infrastructures and DTs. Ensuring trustworthy, tamper-proof AI decisions in a closed-loop pipeline will require explainable AI (XAI), secure communication protocols, and robust fault-detection strategies.

11.3. Scientific Pathways and Technological Developments

To overcome the current limitations in AI-based closed-loop 3D/4D printing, recent research has made significant strides in algorithmic development, hardware integration, and real-time computational frameworks, as illustrated in **Figure 18**. A variety of ML methods, including DTs, RL, and SVM can be employed for this purpose. One of the most promising areas is the use of RL and DT to simulate and optimize printing outcomes before and during fabrication. DTs enable real-time feedback by creating virtual replicas of the physical printing process, allowing predictive model updates and adaptive decision-making during print runs.[33,210]

Multimodal sensor fusion frameworks have emerged to enhance data quality and process visibility. These systems integrate thermal cameras, machine vision, acoustic emission detectors, and layer-by-layer optical imaging, and feed this data into DL models for accurate anomaly detection and process correction. Recent advances allow this entire loop to be executed at the edge using lightweight AI models, reducing the latency associated with cloud-based inference.[201]

Another major scientific development is the integration of PINNs and hybrid models that combine first-principles physics with data-driven learning. These models significantly improve the generalization of AI in unfamiliar material environments or with previously unseen geometries.[207] For 4D printing, where materials respond dynamically to environmental stimuli, ML models are now being trained not only on shape or structural fidelity but also on temporal actuation behavior, enabling better prediction and control of stimuli-induced transformations.[3]

In addition to PINNs and hybrid models, agentic and multiagent approaches have recently been introduced as promising alternatives. Unlike conventional ML or PINNs, which require extensive, high-quality datasets and are limited outside their

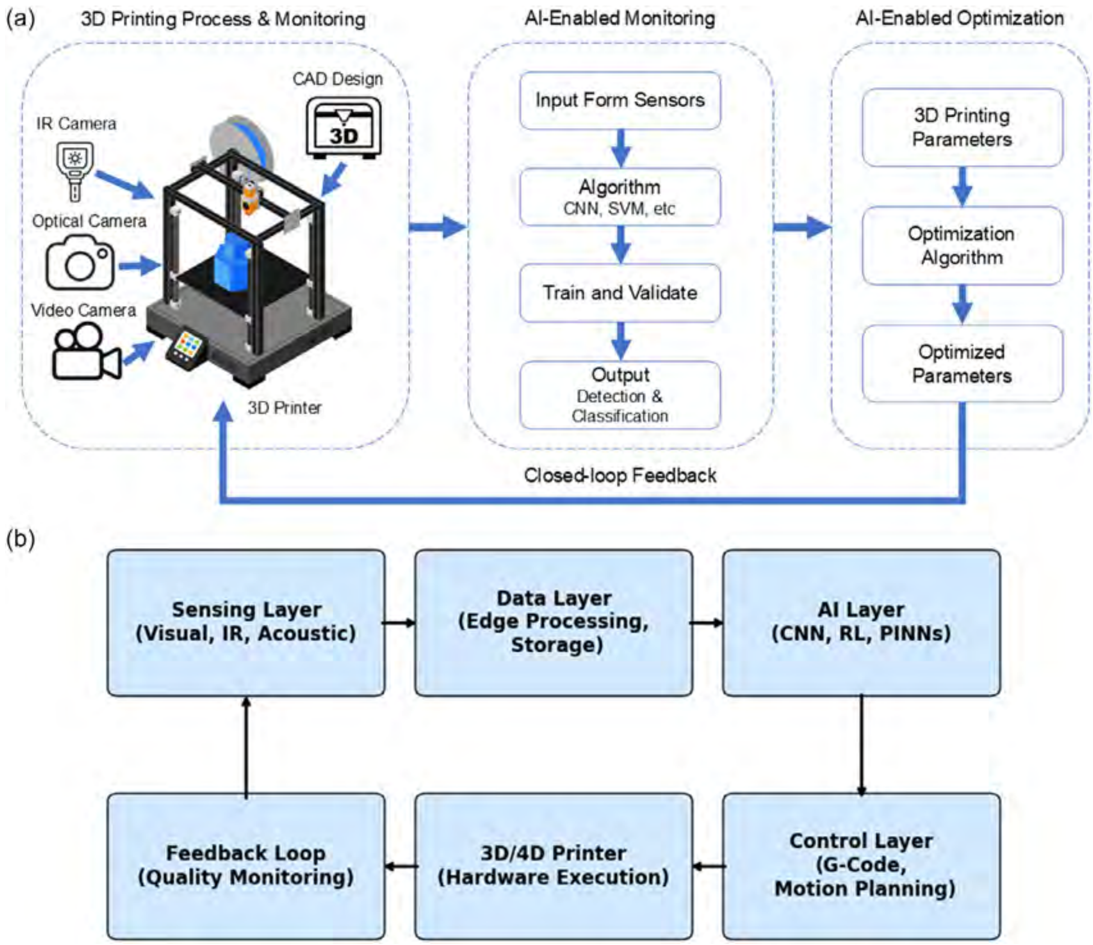


Figure 18. a) AI-enabled closed-loop system integrating sensor feedback and optimization framework for adaptive 3D printing. Reproduced with permission under Open Access.[10] Copyright 2024, Wiley. b) AI-driven technology stack for closed-loop 3D/4D printing.

training distribution, agentic models demonstrate self-learning and reasoning abilities by simulating their own experimental data and operating under physics-based constraints. Early demonstrations, such as "Agentic AI for Scientific Discovery",[157,213] multiagent frameworks for data-driven discovery,[214] adaptive self-learning systems,[34] and Mech Agents for engineering applications,[158] highlight their potential to enable robust defect reasoning, adaptive control, and generalization across materials and geometries in closed-loop 3D/4D printing.

Moreover, the closed-loop 3D/4D printing can also be viewed as a true multiscale materiomic problem, where atomic and molecular-level interactions influence mesoscopic process dynamics and macroscopic performance. Physics-informed AI can be enhanced by coupling atomistic simulations such as molecular dynamics or density functional theory with continuum-scale models to bridge structure-property relationships across scales. Recent work such as *Structure-aware Graph Neural Network based Deep Transfer Learning Framework* by Gupta et al.[215] demonstrates that transfer learning with GNNs across diverse datasets improves predictions even in out-of-domain settings. Another example is the Materials Graph Library (MatGL) by Ko et al.,[216] an open source graph DL library for materials science which supports invariant and equivariant graph architectures and scales to large atomic data. These materiomic strategies show promise for capturing multiscale behaviors, though they bring significant computational complexity. Ensuring real-time implementation remains challenging; lightweight graph models, edge-AI accelerators, and reduced-order physics models will be essential enablers for practical closed-loop 3D/4D printing.

Interoperability and platform-agnostic architectures are also being actively explored. Researchers have begun developing AI middleware that can be integrated with different slicers, control boards, and printer firmware, allowing easier translation of AI models across machines.[170] Additionally, standardized data pipelines and open-source datasets are under development to support more consistent training and benchmarking.

From an industrial and societal perspective, these technologies are driving innovation in precision bioprinting, adaptive medical implants, autonomous soft robotics, and aerospace structures. The incorporation of secure communication protocols and blockchain-based traceability ensures data integrity and verifiability in mission-critical applications.[217]

Looking ahead, we anticipate a growing emphasis on explainable AI (XAI) and AI auditing mechanisms that make closed-loop decisions interpretable, fostering trust and regulatory acceptance. These advances will facilitate closer collaboration between industry, academia, and policymakers, supporting standardization and wide-scale deployment of AI-augmented AM systems.

11.4. Summary and Outlook

AI-based closed-loop 3D and 4D printing technologies are redefining the boundaries of intelligent manufacturing. By embedding ML, real-time sensing, and adaptive control into additive processes, these systems move beyond traditional trial-and-error fabrication toward self-correcting, data-driven manufacturing. By harnessing real-time data from acoustic, thermal, and visual sensors, and leveraging AI to process this data dynamically, manufacturers can adjust designs and processing conditions on-the-fly to mitigate defects and optimize performance. This closed-loop system seamlessly integrates intelligent monitoring with autonomous process control, paving the way for fully adaptive manufacturing environments. While current deployments are primarily research-focused, advances in sensor technology, AI algorithms, and computational infrastructure are rapidly accelerating industrial adoption. Future research will likely focus on expanding cross-platform applicability, improving model explainability, and embedding predictive maintenance capabilities into AM systems. Ultimately, this evolution will not only enhance part quality and production efficiency but will also enable the realization of truly autonomous, intelligent factories.

12. AI for Soft Robotic AM

Yijia Wu, Markus P. Nemitz*

12.1. State of the Art

Soft robotics leverages compliant elastomeric materials to design robots capable of safely and adaptively interacting with delicate and unstructured environments, tasks that remain challenging for conventional rigid robots. Unlike traditional robots constructed by assembling discrete mechanical components, soft robots are increasingly designed as integrated, monolithic material systems, enabled through advances in AM. This shift from assembled structures to fully integrated systems aligns closely with the concept of physical intelligence, wherein the morphology and material properties of a robot directly contribute to its intelligent behavior,[218] representing a fundamental departure from conventional silicon-based computational approaches. Recent developments have further advanced this vision through techniques such as the direct 3D printing of fluidic circuits that serve as embedded controllers,[219,220] paving the way toward fully autonomous robotic materials.[181] Advances in AM have expanded the range of compatible materials and improved the scalability of soft robot fabrication.[218] These innovations enable soft robots for applications in rehabilitation, minimally invasive surgery, wearable devices, precision food handling, search and rescue, and space exploration, among others.

However, soft lithography remains the most commonly used manual fabrication technique in soft robotics.[221] Despite widespread use, soft lithography is expert-driven, labor-intensive, and challenging to reproduce, particularly due to the curing properties and air-bubble-induced defects common with additive-curing elastomers. These challenges drive a significant demand for transitioning manual fabrication techniques to reliable AM methods for soft robots, promising reproducibility and consistency in soft robot production.[222] Unfortunately, current digital fabrication approaches, FFF in particular, cannot yet reliably produce defect-free prints. Even small printing errors often lead to leaks, severely compromising soft robotic performance.[39] Closed-loop printing plays a fundamental role in this transition by incorporating real-time defect detection and dynamic correction capabilities, employing custom printer software and sensors, such as cameras, lasers, infrared sensors,[175] to identify and rectify

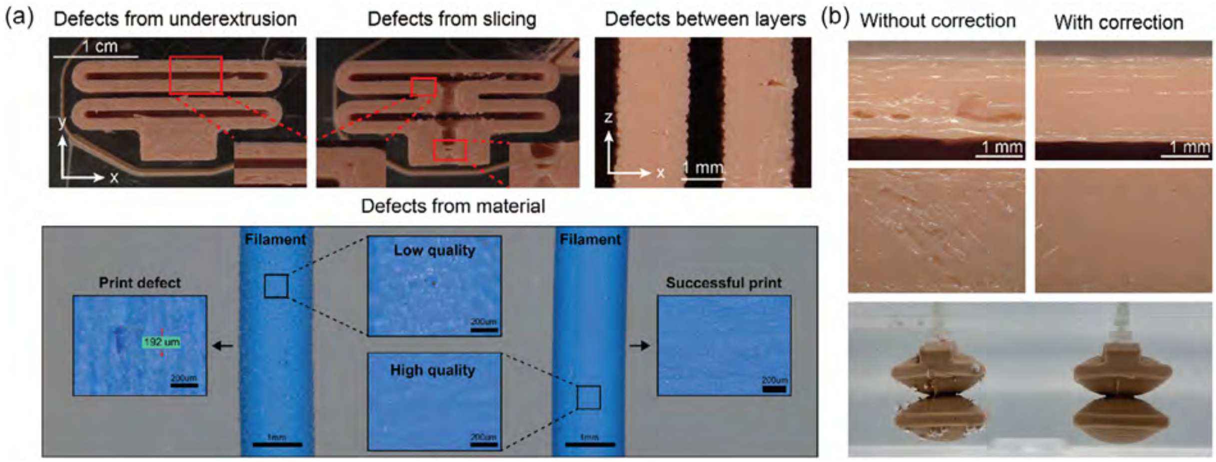


Figure 19. Examples of print defects and their impact on soft robotic components using FDM printing. a) Examples of common defects in the AM of soft robots. Macroscopic and microscopic views show print defects from various sources, often caused by material quality issues or suboptimal print parameters and b) Microscopic view of the influence of correction on the soft actuator and leakage test comparing actuators fabricated with and without defects.

defects through localized adjustments of print parameters or targeted reheating (**Figure 19**).

Digital fabrication of soft robots holds significant promise but faces substantial technical challenges. The compliant nature of soft materials causes fabrication defects to be amplified during structural deformation, such as during actuator inflation, ultimately compromising robotic performance. As a result, effective AM of soft robotic systems demands highly reliable and reproducible processes capable of ensuring impermeability and robust multimaterial integration. Current AM techniques frequently encounter material-specific challenges, particularly with thermoplastic polyurethane (TPU). TPU filaments exhibit buckling under extrusion forces, especially in Bowden-style extruder configurations. Variations in filament quality, stemming from inconsistencies in material composition, inaccurate spooling, and sensitivity to ambient humidity, further degrade print reliability. Since optimal printing parameters must be meticulously tuned for each filament batch and individual printer, achieving scalable, repeatable production remains challenging with hardware solutions only. To address these challenges, integrating AI to close the control loop, rather than relying solely on expert human intervention, offers a promising strategy to substantially improve both the reliability and scalability of AM processes for soft robotics.

12.2. Scientific Challenges and Technical Limitations

Although substantial research has addressed defect detection for AM, these studies predominantly target conventional rigid polymers such as PLA and ABS, while closed-loop AM for elastomers, especially relevant for soft robotics, remains underexplored.[39] This gap stems from the interdisciplinary expertise required across robotics, materials science, AM, and AI-supported detection. Existing detection methods typically emphasize surface defects that are visually apparent, but soft robotic applications demand precise detection of internal micro-defects, such as voids, which can lead to air leakages and functional failure. Establishing clear correlations between internal defects and robot performance is essential yet challenging, particularly when attempting to connect localized leaks to specific internal anomalies. Advanced techniques like micro-computed tomography, high-resolution sensing, and sensor fusion from multiple sensor arrays show promise for accurate defect identification, but these methods are often expensive and computationally intensive.[223,224] Processing large volumes of sensor data in real time for reliable detection remains an open challenge.[225] Correction methods specifically adapted for soft elastomeric materials present unique complexities that fundamentally differentiate them from traditional rigid-material printing approaches. The deformable nature of elastomers leads to nozzle-induced deformation during extrusion, pronounced material oozing due to their low viscosity, and necessitates inherently slow print speeds to achieve void-free, leak-proof layers. The key parameters and strategies for reliable real-time correction and effective defect prevention in soft-material AM remain largely unknown. Advancing closed-loop printing for soft robots requires systematic approaches that go beyond reactive correction to proactively mitigate errors before they occur. This entails more precise control over print parameters, enhanced detection and decision-making frameworks, and the development of comprehensive models that accurately capture the complex interactions between soft materials and print process dynamics (**Figure 20**).

12.3. Scientific Pathways and Technological Developments

Addressing the unique challenges of closed-loop AM for soft robotics requires targeted advances in defect detection, correction, and prevention. A promising direction for improving defect detection involves initially deploying high-accuracy, high-cost sensors to collect precise measurements, establishing a reliable ground-truth dataset of critical defects. These detailed measurements can subsequently be leveraged to augment lower-cost sensing systems, potentially through DL knowledge distillation, so that inexpensive sensors can achieve comparable accuracy without continuous reliance on expensive hardware.[224,226] Sensor fusion, where multiple low-cost sensors are integrated using learning-based algorithms, offers another pathway to

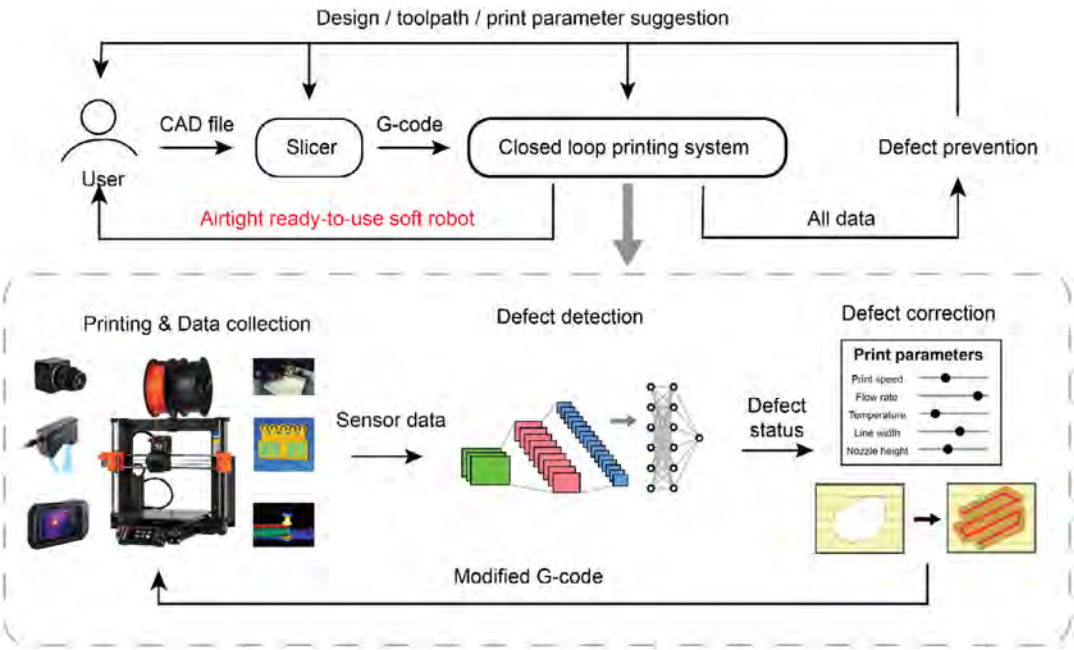


Figure 20. Conceptual overview of an AI-enabled closed-loop AM system for soft robots. The system integrates multimodal sensing, neural network-based defect detection, and adaptive control to optimize print parameters in real time, enabling the direct fabrication of airtight, ready-to-use soft robotic systems.

improve detection accuracy while maintaining system affordability. While learning-based methods have already outperformed traditional CV techniques in detecting irregular anomalies,[227] there remains a lack of high-quality datasets specifically focused on defects relevant to soft robot printing. Automating data collection pipelines and incorporating state-of-the-art DL methods will be critical in achieving high accuracy and real-time defect detection capabilities.[228] For defect correction, it is crucial to establish robust correlations between print parameters and the emergence of specific defects, enabling precise, targeted interventions.[174] RL and predictive modeling could help develop adaptive correction strategies that optimize print parameters based on live feedback.[229] Comprehensive studies evaluating the impact of different correction strategies on final robot performance are currently lacking and must be expanded. Importantly, closed-loop systems should extend beyond reactive symptom correction and facilitate root cause analysis to systematically eliminate defect origins. Regarding defect prevention, research efforts should prioritize holistic optimization encompassing geometry design, slicer configurations, and a comprehensive set of print parameters, overcoming the narrow parameter adjustments typically examined in existing work. Techniques such as Bayesian optimization,[230] topology optimization,[64] and generative design[231] could help explore broader design and process spaces.

To ensure widespread adoption, future systems should adopt modular architectures, standardized interfaces, and cloud-based infrastructures to enable integration across different hardware and software platforms. Collaboration with industry, through co-development, shared benchmarks, and DTs, will be crucial to validating these technologies in real-world environments. Open-source datasets and frameworks will further support community-driven innovation and accelerate progress in scalable, intelligent AM systems for soft robotics.

12.4. Summary and Outlook

Future research directions in AI2AM present substantial opportunities for transformative advancements across academia, industry, and society. Although defect detection has received considerable attention, future developments must prioritize reliable yet inexpensive detection solutions, leveraging sensor fusion techniques to lower costs and facilitate widespread adoption. Broader deployment of these accessible systems will generate extensive, shareable datasets essential for training robust DL algorithms. Error prevention and correction remain significantly under-researched, particularly given the unique challenges posed by soft materials. Near-term research efforts are thus expected to make substantial progress in these areas, particularly by establishing clear correlations between internal print defects and functional failures such as leakage, and by developing strategies that optimize geometry, slicer configurations, and print parameters proactively. The ultimate goal is to establish fully automated design-to-fabrication pipelines, where AI-driven recommendations embedded directly into CAD and slicing software intelligently guide adjustments to the design, print orientation, and print parameters. These recommendations will comprehensively account for specific material properties, intended functionality such as the pneumatic characteristics of a soft actuator, and integrate critical factors like the printer model and laboratory environment, including humidity levels, to ensure reliable and consistent print quality prior to initiating the fabrication process. Such advancements will significantly enhance industrial adoption, enabling reliable and cost-effective manufacturing crucial for sectors including healthcare (custom prosthetics, surgical tools), agriculture (precision food handling), consumer products (customizable wearable devices), emergency response (low-cost, mass-manufacturable robotic systems), and space exploration (customizable, made-to-order solutions tailored to emerging mission requirements).

13. AI-Driven Design of Meta-Scaffolds

Masoud Shirzad, Dageon Oh, Seung Yun Nam*

13.1. State of the Art

In today's rapidly evolving world, conventional engineering approaches often fall short in addressing complex challenges. Interdisciplinary strategies, particularly in intricate fields such as biomedical engineering and life sciences, offer a promising pathway for developing effective engineering solutions for multifaceted problems.[232] One such innovative solution is the creation of tissue engineering scaffolds with complex and predefined structures, which hold great potential in addressing the challenges of repairing damaged organs. These scaffolds must not only provide an appropriate environment for proper cell interaction and adhesion but also support external loads and ensure the diffusion of nutrients to the implanted site.[233]

To address the requirements, meta-scaffolds with diverse internal architectures have been developed.[234] Owing to their architectural structures, meta-scaffolds exhibit adaptable physical and mechanical properties.[40,41] This adaptability enables the biomimicry of human tissues, a feat unattainable with conventional design approaches. Furthermore, *meta*-scaffolds with tailored internal structures enhance the longevity of scaffolds under various static and dynamic loading conditions.[235] However, the processes of designing, biomimicking, and optimizing *meta*-scaffolds are highly time-intensive and require substantial effort. While some studies have utilized the finite element method (FEM) to evaluate the physicomechanical properties of scaffolds, this approach is constrained by its time-consuming nature and the limited number of variables it can accommodate.[236]

To tackle these challenges, AI-based strategies based on ML algorithms have been explored to accelerate the design and evaluation of meta-structures. These algorithms operate within a framework that uses a training dataset, allowing the model to learn targeted properties and make comprehensive predictions to achieve the desired objectives.[237] An overview of using AI algorithms for designing meta-scaffolds is displayed in **Figure 21**.

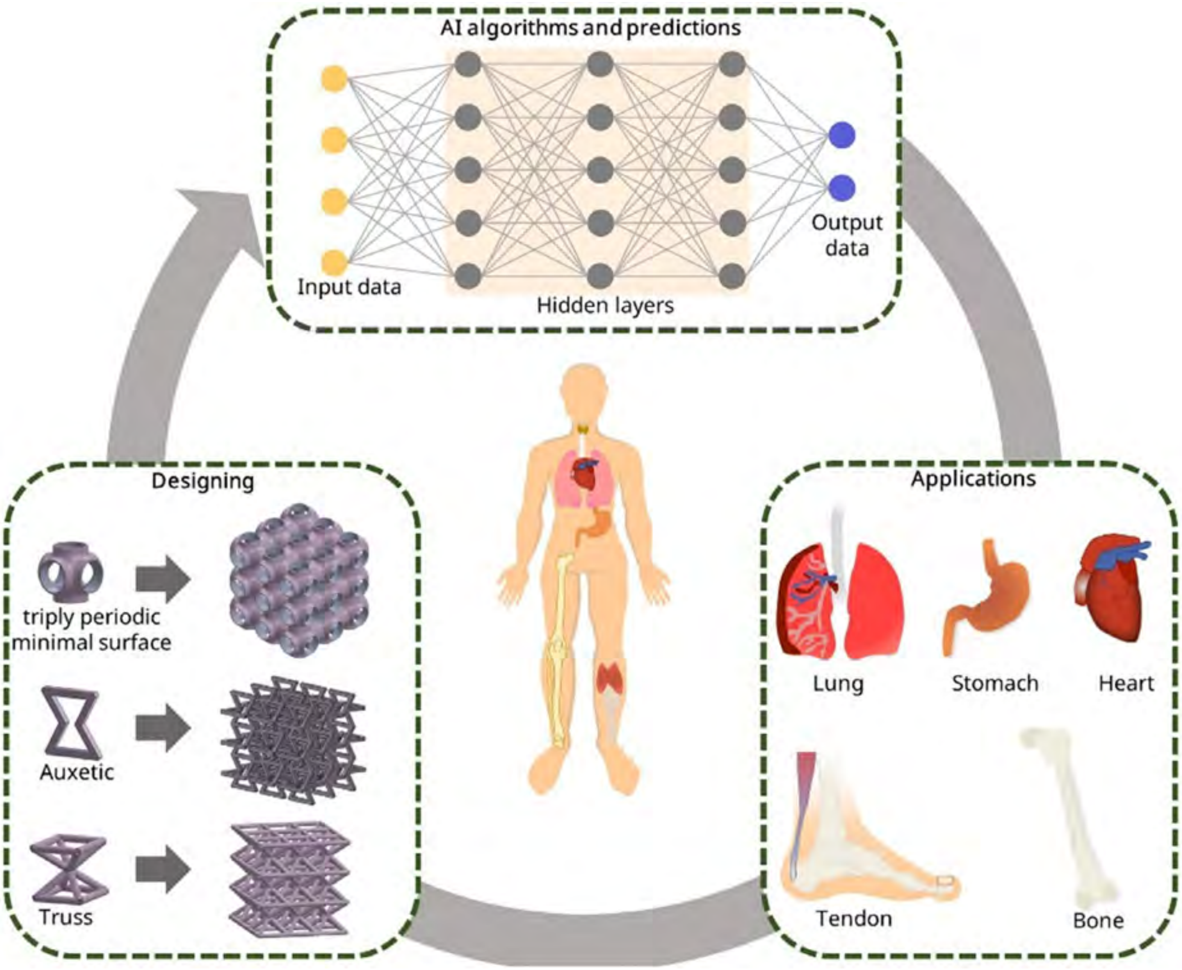


Figure 21. Overview of using AI algorithms for designing meta-scaffolds.

13.2. Scientific Challenges and Technical Limitations

The integration of AI and ML in the design of meta-scaffolds offers significant potential for fabricating highly precise structures with optimized physicomechanical properties. However, limited fabrication resolution and the low printability of complex meta-structures remain critical challenges, restricting their widespread applications in tissue engineering, particularly in achieving the appropriate pore size and shape. These fabrication issues stem from inherent limitations in manufacturing techniques. For instance, while EBB offers advantages such as material versatility and ease of use, it still faces challenges in achieving the high resolution required for intricate meta-structures. Moreover, challenges related to biomaterials and the difficulty of identifying effective methods for incorporating newly developed materials into scaffold fabrication pose additional obstacles in the manufacturing of meta-scaffolds.[42,43]

Additionally, the aforementioned challenges further complicate the biomimicry of the physical and mechanical properties of native tissue, which often exhibit gradient or hierarchical structures. Failure to accurately replicate these physicomechanical properties can lead to significant issues, such as stress shielding or reduced durability. Although AI has shown promise in predicting scaffold performance, its effectiveness depends on large, high-quality datasets, and the implementation of multiobjective optimization frameworks capable of balancing competing conditions and requirements.[238,239] For instance, *meta*-scaffolds must not only demonstrate appropriate physicomechanical behavior but also exhibit controlled degradation rates and support critical biological functions, including cell adhesion, formation, and proliferation. Optimizing all these parameters simultaneously is computationally intensive, often requiring extensive datasets and prolonged processing time.[240] In addition to the complexity of multiobjective optimization in the fabrication of meta-scaffolds, most advanced ML algorithms rely on greedy strategies to predict predefined outputs.[237,241] It is important to note that many meta-structures are designed using repetitive 2D or 3D unit patterns. However, in interface problems involving various meta-structures, the demand for extensive input datasets can become even more challenging, further complicating the optimization process.

13.3. Advances in Science and Technology to Meet the Challenges

The implementation of ML across various fields presents significant challenges, particularly due to the data-intensive requirements of advanced ML algorithms. Additionally, the design and fabrication of meta-scaffolds using suitable materials and structural configurations introduce further complexities.[242] Consequently, addressing both challenges simultaneously poses a substantial burden for researchers, often discouraging engagement with such multiobjective optimization problems. However, several strategies have been proposed to facilitate the use of AI-based approaches in the design and fabrication of biocompatible meta-scaffolds.

Bioinspired strategies often provide optimal approaches to various biomedical problems. Mimicking natural tissues not only enhances the physiomechanical properties of scaffolds but also improves their biological performance. However, the fabrication of such bioinspired structures requires high-resolution manufacturing techniques. In this regard, photo- or laser-based fabrication methods offer a promising solution, enabling the precise construction of complex 3D structures with high resolution.[243] Advancing these fabrication techniques necessitates close collaboration between academia and industry to establish a highly precise, efficient, and scalable manufacturing process.

It is worth noting that the selection of biocompatible materials for tissue engineering scaffold fabrication remains limited for use in the precise manufacturing process. Consequently, one of the most critical challenges in this field is the development of novel composite materials. For instance, enhancing the biocompatibility of conventionally available resins presents a promising strategy. Additionally, the development of new printable materials offers another viable approach for advancing the fabrication of *meta*-scaffolds with tunable physicomechanical properties.[244,245]

Beyond advancements in fabrication methods, several strategies can facilitate the integration of ML approaches in the development of meta-scaffolds. The FEM is a widely utilized and reliable technique for evaluating the mechanical and physical properties of scaffolds. This method can significantly accelerate the generation of sufficient input data for advanced ML models. Additionally, hybrid ML approaches have gained considerable attention across various fields. These methods can substantially reduce errors in ML predictions while mitigating the dependency on large input datasets.[241] Furthermore, ML methods such as the attention-based diffusion model enable both property prediction and inverse design of hierarchical structures—common in natural tissues—within a single framework, thereby reducing data requirements by exploiting structural patterns and physics-informed behavior. Likewise, a variational autoencoder–long short-term memory (VAE–LSTM) approach compresses complex designs into low-dimensional latent spaces, facilitating the generation and optimization of new structures beyond the initial dataset. These methods illustrate how generative and representation-learning strategies can lower data barriers in scaffold research, advancing intelligent design and rapid prototyping. **Figure 22** illustrates potential solutions for reducing the complexity of AI-driven challenges in meta-scaffold fabrication.[246,247]

13.4. Summary and Outlook

In conclusion, meta-scaffolds represent a promising and innovative approach for the fabrication of reliable tissue engineering scaffolds with desirable physicomechanical behavior. AI-based approaches can extensively accelerate the advancement of this concept within the field of biomedical engineering. However, there are still challenges such as large input datasets, the limited availability of suitable biomaterials, and the resolution constraints of current fabrication techniques, which can hinder the development of meta-scaffolds with AI-based methods. However, emerging technologies and the development of advanced strategies hold the potential to overcome these limitations and enable the fabrication of applicable meta-scaffolds with tailored mechanical, physical, and biological characteristics.

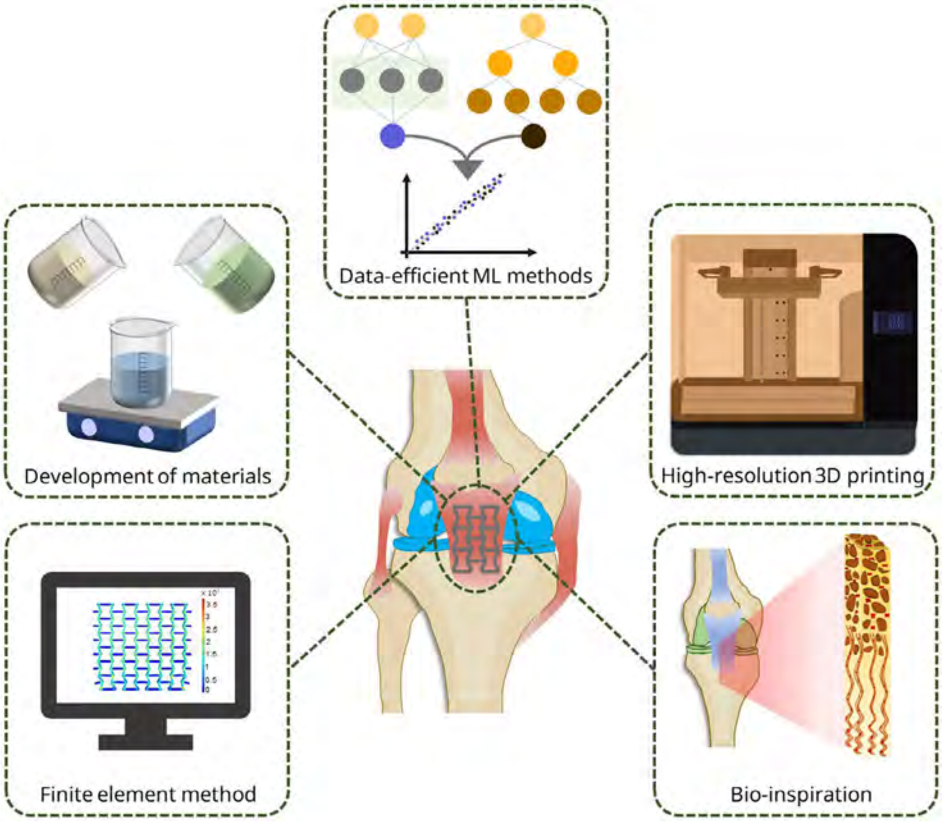


Figure 22. Future solutions to facilitate the applications of ML in the fabrication of meta-scaffolds.

14. AI-Enhanced Development of 3D Bioprinting

Amedeo Franco Bonatti, Irene Chiesa, Gabriele Maria Fortunato, Giovanni Vozzi, Carmelo De Maria*

14.1. State of the Art

The possibility of exploiting AM to (bio)print tissues and even whole organs has recently gained traction both at academic and industrial level. A plethora of papers and patents are being published every year on the topic of bioprinting (defined as the use of AM to print biomaterials, cells, and biomolecules into biologically active constructs),[248] while several companies currently operate in the market, mainly selling bioprinters and materials.[44] From a technological standpoint, there has been a trend to use standard AM techniques tailored to the constraints of processing more delicate biomaterials. Among these techniques, the most used include EBB, IJB, and LAB. EBB, currently the most prevalent method in bioprinting, operates by extruding materials from a syringe-like reservoir through a needle, using mechanical, pneumatic, or screw-driven forces, and deposits them onto a printing plate. Its popularity stems from the versatility and ease of use, as it can process hydrogels and pastes with a wide window of viscosities. IJB encompasses methods that jet droplets of liquid inks onto a substrate. Different modes of jetting actuation are currently being used, including thermal, piezoelectric, and valve-based approaches. In the laser-induced forward transfer (LIFT) technology, droplets of bioink are propelled onto a collector by laser energy.[249] Finally, LAB techniques use light to enable material processing, including vat photopolymerization, which solidifies photosensitive resins layer-by-layer.

14.2. Scientific Challenges and Technical Limitations

Bioprinted constructs have successfully replicated various tissues, including bone, cartilage, and skin, and have find applications in in vitro modeling of physiological or pathological tissues, drug screening, and even cosmetics.[44] However, the use of these constructs for transplantation purposes still remains a major challenge, with only a few clinical trials currently active in the world and only at the recruiting stage.[250] The lack of quality control procedures to manufacture high quality products with low batch-to-batch variability represents one of the major hurdles limiting the clinical translation of these promising results.

In the current era of pervasive AI, where these models are embedded in almost every aspect of our lives, bioprinting serves as no exception. Although the field is relatively young, frontier examples of its application to bioprinting have already been set out and promise to accelerate the pathway to clinical translation by improving material screening and automatizing quality control procedures.[45,46]

14.3. Scientific Pathways and Technological Developments

Examples on the application of AI to bioprinting for quality control can be grouped in three main categories (as summarized in **Figure 23**): i) pre-process optimization, where AI is used to optimize the process before the production of the final construct, effectively reducing the trial-and-error typical in the preliminary phases of bioprinting; ii) in-process monitoring, by embedding sensors (e.g., cameras, temperature, pressure) in the printer and using AI models to understand from these data if the printing process is going well or not in real-time; iii) post-process quality assessment, to evaluate after printing the quality of the construct based on some relevant quality features (e.g., overall shape fidelity, biological performance).

In the context of pre-process quality control, AI can build predictive models able to elucidate the complex interrelations between operating parameters/material properties and: i) shape fidelity quality features, including pore size and line width in EBB,[251] ii) construct properties like compressive modulus,[252] and iii) biological performance, like cell viability.[253] For example, Dai et al. proved that the successive use of design-of-experiments (DoE) and ML algorithms could speed up the development of new materials for EBB. In their work, DoE was used to narrow down the number of possible combinations to test poly(ethylene glycol)diacrylate (PEGDA)-based composite inks, while an ML regression model (namely, a multilayer perceptron) was effectively used to predict the pore size starting from the input air pressure, printing speed, and the component concentration ratio of the inks (as selected by the DoE procedure).[254] Interestingly, Nadernezhad and Groll showed how ML could be used to predict printability based on more complex rheological data in EBB. Different hyaluronic acid-based inks were characterized rheologically (i.e., flow curve, amplitude sweep) and through printing tests (i.e., printing of rectangular meshes with varying line spacing and needle diameters), effectively building an extensive dataset correlating rheology to printability results. The dataset was then used to train and test a random forest classifier algorithm which resulted in F1-scores > 90%.[96] Although successful, these approaches require extensive and curated dataset which are time consuming to produce. Interestingly, a more comprehensive dataset of material and construct properties have been recently compiled by Rafieyan et al. The authors mined data

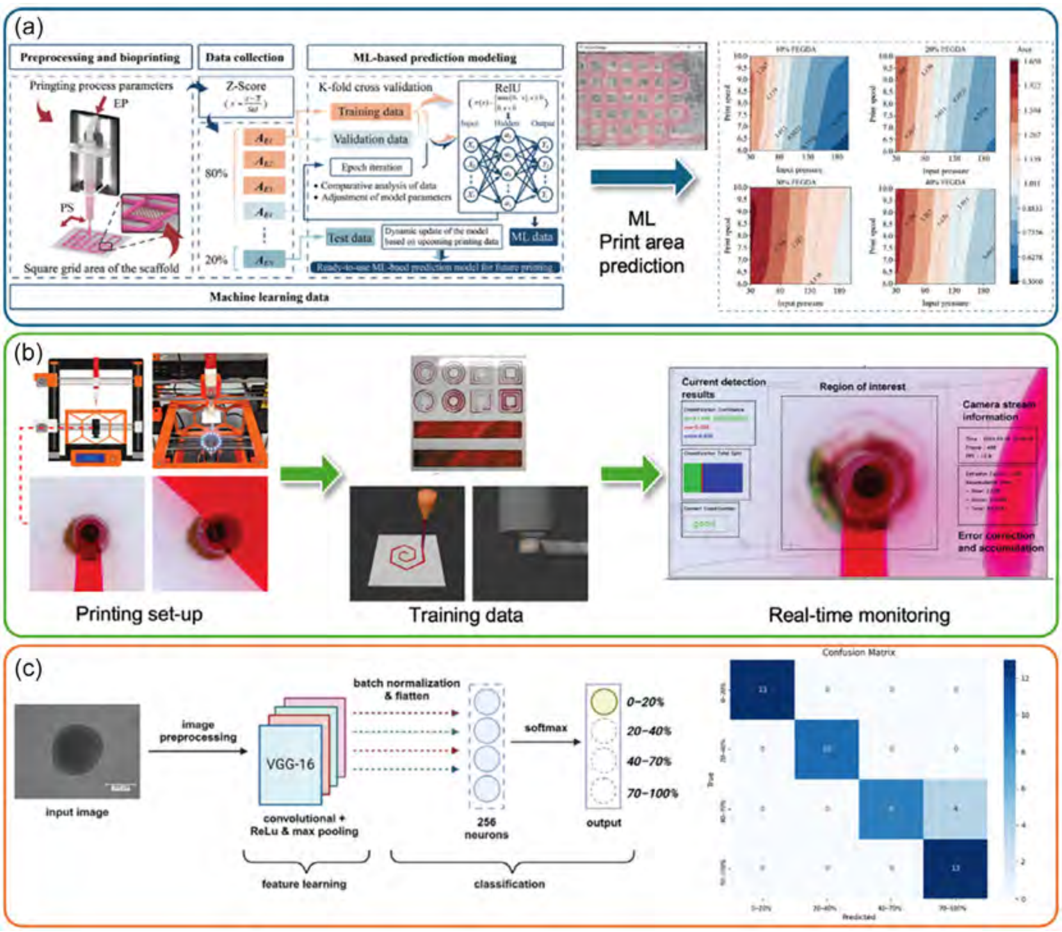


Figure 23. Summary of the examples for quality control in bioprinting. In a), an example of building predictive ML models for pre-process ink composition and printing parameters optimization. Reproduced with permissions.[254] Copyright 2024, Wiley-VCH GmbH; In b), an example of using a CNN model for real-time monitoring of the EBB process. Reproduced with permissions.[257] Copyright 2025, Wiley-VCH GmbH; In c), an example of using the ML to predict the vitality of organoids after extrusion printing. Adapted with permissions.[259] Copyright 2025, MDPI.

related to EBB constructs from literature, building a dataset of more than 1000 constructs with 60 biomaterials and 49 different cell lines. Both supervised and unsupervised models were then trained on these data to draw insights on the correlation between printing parameters and cell viability after printing.[255]

More complex ML models based on DL techniques have shown promising results for the in-process monitoring application. In this regard, image/video data represent the most common data source for training and testing these models, as cameras can be easily mounted in different locations inside the bioprinter, and the data acquisition process is straightforward. For example, Jin et al. used a pneumatic extrusion bioprinter to fabricate two-layer constructs with varying infill patterns (i.e., grid, rectilinear, gyroid, honeycomb). Each pattern was printed with a different extrusion speed, imaged from a top-looking view, and the resulting images were manually labelled depending on their quality. This dataset was subsequently used to train and evaluate several ML models for classification, including a DL CNN model.[256] In another recent example, Kelly et al. customized an extrusion printer by adding a camera below the printing plate. The collected images of the printed lines were labelled based on the quality (i.e., good, under- or over-extruded) and the resulting data merged with synthetic data coming from Blender simulations. A CNN model was then trained and implemented in a closed-loop extrusion control system able to vary the flowrate in real-time, thus correcting possible printing errors during printing.[257] A major limitation of these works lies in the use of simple, almost two-dimensional patterns which are not representative of the final three-dimensional construct shape. To this end, Bonatti et al. developed a comprehensive video dataset by recording the printing process from a front view. Each video corresponded to a print with a different combination of parameters, including layer height, flow, bioprinter configuration (pneumatic versus piston-actuated extrusion), ink color. Two main errors were introduced resulting from a nonoptimal printing parameters combination, including under- and over-extrusion. A CNN model was then trained and tested on the dataset, with the aim of monitoring the printing process online to stop the print if an error occurred before completion, to save time and reduce material waste.[258]

Finally, AI can automatize the post-print quality assessment by analyzing the biological performance of bioprinted constructs. Image data of printed cells can provide insights on the cell viability, like in the recent example from Sheikh et al. The authors printed organoids (i.e., 3D multicellular aggregates of one or more cell types) with EBB and imaged them at a phase-contrast microscope after three days of culture. The images were fed to a CNN model which was tasked to infer the cell viability.[259] Furthermore, segmentation algorithms are particularly useful to automatically extract quality features related to cells and then use these data for other downstream tasks. For example, Yao et al. used GANs for the automatic segmentation of cell nuclei in 3D scaffolds. They printed multilayer PCL constructs, seeded them post-printing, and used the resulting image dataset to train the network. The model performance was compared with other segmentation tools (e.g., CellProfiler), showing a comparable performance across multiple cell types. Finally, the authors showed how quantitative data related to adhesion and proliferation could be extracted from the segmented images to infer construct-cell interaction.[260]

14.4. Summary and Outlook

In conclusion, AI represents an enabling technology to implement automatic quality control procedures throughout the whole bioprinting process, potentially accelerating the translation of the technology to the clinics, lifting researchers from time- and material-consuming optimization work and allowing them to focus on the actual application instead of the manufacturing process. Even though the results are promising, the adoption of AI in bioprinting is still at an early research stage, with applications mainly limited to controlled laboratory settings. Indeed, the combination of these two technologies is at an early development stage, taking traction in the literature only in recent years.[45] To stimulate the adoption in the bioprinting workflow and fully to unlock the transformative potential of bioprinting for the patient health, future endeavors should focus on i) AI tools testing on other technologies apart from EBB, and on their combination, ii) focusing more on the post-process evaluation, which is currently understudied, and iii) creating curated, open-source and large-scale datasets, which can be used to benchmark different AI tools.

15. Adaptive Metamaterials by AI and 4D Printing

Mahdi Bodaghi*

15.1. State of the Art

Mechanical metamaterials fabricated via 4D printing are emerging as transformative platforms for adaptive, multifunctional systems. These architected materials, often composed of periodic or hierarchical unit cells, exhibit unconventional behaviors such as negative Poisson's ratio, tunable stiffness, and shape memory. **Figure 24** illustrates their functional behavior, structural topology, stimulus types, and applications across sectors. Enabled by stimuli-responsive materials such as shape memory polymers (SMPs) and liquid crystal elastomers (LCEs), 4D-printed metamaterials can undergo programmable mechanical transformations when exposed to external stimuli like temperature, magnetic fields, or humidity, enabling applications in soft robotics, aerospace actuators, and impact-mitigating systems.[261,262] However, the complexity of nonlinear thermo-mechanical behaviors, geometric intricacy, and multistimulus actuation makes design optimization computationally expensive and experimentally intensive. Brute-force FEM simulations struggle to resolve large design spaces spanning time-dependent, path-dependent responses. In response, AI is enabling transformative advances in the modeling, inverse design, and process control of such systems.

Forward ML models, including CNNs, gradient boosting regressors, and GNNs, can predict stress–strain curves, activation responses, or energy dissipation across a spectrum of geometries and materials. Inverse design is advancing via VAEs and conditional GANs, generating microstructures that satisfy predefined metrics such as high recovery ratios or broadband damping.[232,261,262] Emerging data-driven surrogates are extending beyond elasticity to model complex thermo-viscoelastic behaviors, often trained on FEM data. However, phase-transition-aware, elasto-plastic, and fatigue-calibrated models

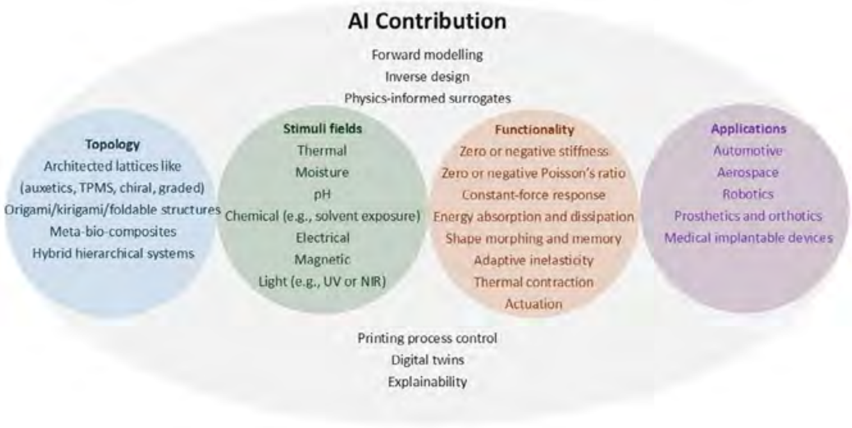


Figure 24. Multidimensional classification of AI-driven 4D-printed mechanical metamaterials based on functional performance, structural topology, actuation stimuli, and target applications.

for smart metamaterials remain an open research frontier.[47] Multiphysics-informed surrogates are expected to play a critical role in validating AI-generated geometries for manufacturability, actuation reliability, and cyclic durability. AI's impact also extends to process optimization. RL is applied to path planning, extrusion control, and multiphysics actuation sequencing, particularly under heat-induced or magnetic stimuli.[61] High-fidelity datasets are being constructed using molecular dynamics (MD), DTs, and coupled thermomechanical simulations.

The convergence of AI and 4D printing heralds a new generation of intelligent metamaterials, systems adaptive in both function and design evolution. As open-source databases expand and explainable AI gains traction, the synergy will unlock programmable, sustainable material platforms for next-generation engineering.

15.2. Scientific Challenges and Technical Limitations

Despite major strides, integrating AI into 4D printing of mechanical metamaterials presents persistent scientific, computational, and practical challenges.

15.2.1. Realistic Modeling of Smart Materials

Stimuli-responsive materials like SMPs exhibit nonlinear, time-, strain-, and temperature-dependent behaviors, including elasto-plasticity, visco-elasticity, and dissipating hysteresis.[263] Most AI models rely on elasticity-based assumptions or simplified FEM solvers, which fail to capture coupled nonlinear multiphysics response or phase transition mechanics. Without physics-aware surrogates, AI-generated designs often fail to suggest a right programming protocol, and to predict shape recovery, actuation, shape-memory fatigue, and time-dependent responses.[47]

15.2.2. Lack of Integrated Co-Optimization Frameworks

Most studies isolate structure, material, programming, or printing process during design. Co-optimizing (Figure 24) across all levels, geometry, smart materials, programming, and actuation profiles, and print parameters, is rare.[261] A practical design must consider fabrication path, stimuli placement, and topology[247] simultaneously, yet no framework currently enables this at scale.[47]

15.2.3. Limitations of Generative Models

Generative models such as GANs, VAEs,[246] and generative inverse design networks (GIDNs) have enabled the creation of novel metamaterial topologies. However, physical feasibility and printability remain significant challenges.[264] For example, Voronoi-based conditional GANs (CGANs) and PatchGANs can produce geometries that violate mechanical or manufacturing constraints, often requiring separate solvers to verify stiffness, Poisson's ratio, or printability.[261,264] While GIDNs improve performance through active learning and backpropagation-based optimization, they still require extensive retraining for new material systems, stimulus types, or boundary conditions.[264]

15.2.4. Dataset Scarcity and Standardization

Current materials databases such as AFLOW, Materials Project (MP), and NOMAD primarily provide static properties like elastic constants and band structures, lacking the dynamic, multistimuli, time-resolved data essential for 4D-printed metamaterials.[261,262] Datasets incorporating cyclic actuation, fatigue, and programming-response history remain rare and nonstandardized. This limits the generalization ability of AI models trained on such data and hinders reproducibility. High-throughput pipelines integrating FEM, MD, and experimental data are needed to close this gap.

15.2.5. Lifecycle Durability and Multistimuli Actuation

4D-printed metamaterials often experience a drop in thermomechanical properties under repeated thermo-mechanical cycling.[265] SMP-based devices face reduced recovery ratios, drift, or failure modes that are poorly predicted by current AI models. Long-term fatigue, creep, and shape recovery/fixity loss are rarely included in inverse design loops.

15.2.6. Explainability and Industrial Trust

Most AI models in 4D printing are black boxes, limiting adoption in regulated fields. PINNs and ontology-based models aim to embed physical laws and design logic for interpretability DIMA.[121,266,267] Ontologies help formalize programming logic, while PINNs offer consistent predictions under multiphysics stimuli. Yet, both approaches require further validation for time-dependent, multistimulus applications.

15.3. Scientific Pathways and Technological Developments

Addressing the current limitations of AI-driven 4D printing of mechanical metamaterials requires coordinated progress across model architectures, data infrastructure, real-time control, and interpretability.

15.3.1. Physics-Informed AI for Reliable Design

To enhance physical consistency and generalizability, researchers are adopting PINNs. These can embed governing laws (e.g., elasto-plasticity, shape memory effects) into neural frameworks, enabling accurate modeling of nonlinear, stimulus-coupled behaviors in shape memory-based metamaterials. Recent applications have demonstrated PINNs' ability to predict deformation and stress distribution with far fewer samples than black-box networks. For instance, PINNs could recently model nonlinear heat transfer with noisy boundaries and complex geometries, showing promise for inverse mechanics in SMPs.[268]

15.3.2. Multistimuli Datasets and DT Integration

The development of large-scale, multitopology, multistimuli datasets could enable better AI training and validation. Coupled with physics-based DTs,[134] and infrastructure-level cloud collaboration platforms,[269] these datasets could capture multistimuli actuation, and thermo-mechanical and shape-memory fatigue. A cloud-connected DT pipeline could generate smart metamaterials coupled with feedback-based optimization.

15.3.3. RL for Adaptive Process Control

RL is now being applied to dynamically control extrusion paths, thermal cycles, and actuation timing in 4D printing. For instance, RL enhanced adaptive control in multimaterial printing with feedback loops.[270] This allows optimization in real-time, particularly for soft robots and SMP lattice generation.

15.3.4. Explainable and Neuro-Symbolic AI

Explainability remains a major hurdle for AI adoption in safety-critical 4D printing applications. Neuro-symbolic AI frameworks, combining neural networks with symbolic reasoning and design ontologies, are gaining traction for interpretable, rule-based decision making. Researchers[271] recently demonstrated their utility in automating 4D printing workflows while preserving traceability and logic-based constraints. These hybrid systems improve trust and transparency, particularly when embedded with geometric rules and stimulus-response logic, and represent a promising direction for bridging data-driven and physics-informed paradigms.

15.3.5. Applications and Impact

AI-driven 4D printing has near-term industrial potential in aerospace (morphing wings, shock dampers), biomedicine (self-deploying scaffolds), and automotive energy absorbers. Societal benefits include customizable prosthetics, soft robotic implants, and lightweight disaster-resilient structures.[47] Commercialization is expected to accelerate with maturing digital threads and certification frameworks for smart metamaterials.

15.4. Summary and Outlook

AI is transforming the design and deployment of 4D-printed mechanical metamaterials by enabling data-driven modeling, inverse design, and adaptive process control. This chapter has outlined how stimuli-responsive materials, such as shape memory polymers and LCEs, pose complex, nonlinear challenges that demand new AI frameworks trained on multiscale, multiphysics data. Current methods are limited by elasticity-based assumptions, black-box models, and fragmented workflows that overlook cyclic durability, co-programming, and actuation constraints. Through critical analysis of the field's current barriers, the need for physics-informed surrogates, RL for real-time optimization, and structured DT-integrated datasets was highlighted. The promise of interpretable and neuro-symbolic AI offers a path to trusted, certifiable solutions, especially in safety-critical applications. This chapter contributes to the AI2AM roadmap by identifying the essential advances needed to fully leverage AI in the 4D printing of intelligent metamaterials. It proposes actionable directions across modeling, fabrication, and validation, while emphasizing the importance of reproducibility, explainability, and domain-integrated knowledge. As this subfield evolves, it will enable programmable, multifunctional, and sustainable material systems tailored to the demands of aerospace, automotive, healthcare, robotics, and beyond.

Discussions and Future Directions

Within the AI2AM framework, developments in Design and Strategies collectively mark a transition from isolated design innovations to an integrated design ecosystem where AI actively mediates between creativity, physics-based rigor, and manufacturing feasibility. By embedding hybrid physics–AI models, generative design tools, neural slicers, and ontology-guided workflows into AM pipelines, AI2AM can help overcome persistent challenges such as interfacial incompatibility, anisotropic stress prediction, and the gap between conceptual design and printable models. The result is a more adaptive, creative, and calculated design process that not only accelerates the discovery of new material–process–geometry combinations but also ensures their robustness through validated integration to AM. This positions AI2AM as a driver of a new design paradigm in AM—one where automated ideation, real-time optimization, and knowledge-based constraints converge to deliver high-performance and manufacturable components. In doing so, AI2AM empowers engineers and designers to move beyond trial-and-error methods toward an AI-mediated strategy for AM design.

AI2AM's role in Monitoring and Quality Control framework also is highlighted via a transformative pathway toward intelligent, adaptive, and autonomous AM systems. AI-enhanced DTs and multimodal monitoring provide unprecedented visibility into the printing process, while real-time defect detection and structural validation ensure quality assurance without the need for extensive post-processing. CV and hybrid AI approaches bridge the gap between raw sensor data and actionable input, ensuring that deviations are not only detected but contextualized within physics-informed frameworks. The integration of these elements into AI-controlled closed-loop systems transforms AM from a static, parameter-defined process into a dynamic, self-correcting platform capable of learning from each build. This positions AI2AM as a critical enabler of industrial scalability, end-user friendliness, safety-critical adoption, and sustainable manufacturing. By integrating sensing, simulation, validation, and control, AI2AM advances monitoring and quality control from merely quality checks to a unified, autonomous intelligence layer—laying the groundwork for robust product development pipelines.

In the context of Product Developments, the AI2AM advances showcase how AI can transform product development in AM by providing intelligence at every stage of the innovation cycle—from design and material discovery to fabrication and functional deployment. By embedding AI-driven design and adaptive manufacturing process control into soft robotics, AI2AM ensures reliable, application-ready devices for medicine, agriculture, and emergency response. In tissue engineering, AI2AM accelerates the design and optimization of meta-scaffolds and bioprinted constructs, making personalized implants and regenerative therapies more attainable by addressing quality assurance challenges. Meanwhile, in advanced engineering domains, it enables the creation of adaptive metamaterials that evolve under real-world conditions, meeting the rigorous demands of aerospace, automotive, and defense applications. Overall, these contributions position AI2AM as the critical catalyst for moving AM beyond experimental prototypes to high-performance, certifiable, and scalable products. By unifying predictive design, adaptive control, and functional validation under one framework, AI2AM empowers AM industry to deliver informed, application-specific solutions that are not only manufacturable but also dynamically adaptable to changing requirements, thereby reshaping the landscape of product innovation.

Despite the clear promise of AI2AM, many solutions remain at early stages, with limitations that constrain their immediate industrial deployment. Challenges arise not only from technical readiness but also from economic and infrastructural barriers that hinder widespread adoption. High computational costs, the need for specialized hardware and sensors, and the lack of standardized datasets or interoperable frameworks increase entry barriers for industry, particularly for small- and medium-sized enterprises. AI-driven defect detection often suffers from data scarcity, lack of standardized benchmarks, and limited generalizability across different AM processes. Real-time structural validation and closed-loop control face challenges in computational efficiency and integration with legacy hardware. AI-enhanced generative design tools, while powerful for creativity, often struggle to output manufacturable, ready-to-print geometries. Nonetheless, notable progress has been made toward practical adoption. Commercial platforms such as EOS already employ AI-driven monitoring systems integrated with in situ sensors to improve defect detection and part qualification, while companies like HP leverage data-driven closed-loop calibration in their Multi Jet Fusion systems to optimize consistency and throughput. In design, Autodesk's Fusion 360 and nTopology incorporate AI-augmented generative approaches that are being used in aerospace and automotive industries for lightweighting and lattice optimization. Bioprinting companies such as CELLINK and Organovo are exploring AI-assisted print parameter optimization to enhance cell viability and reproducibility in biomedical applications. Despite these advances, widespread industrialization is still limited by economic barriers such as the high cost of AI infrastructure, proprietary restrictions on data sharing, and the need for workforce reskilling. Encouragingly, collaborative initiatives—such as the development of open-source datasets, cloud-based AI integration to reduce hardware costs, and industry–academia pilot programs—are emerging to address these bottlenecks. As these pathways mature, they are expected to lower adoption costs, improve trust in AI-driven workflows, and accelerate the translation of AI2AM from experimental demonstrations into sustainable industrial practice over the coming years.

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Conflict of Interest

The authors declare no conflict of interest.

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3D printing, additive manufacturing, Ai2AM, artificial intelligence

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[1] Y. Qiu, Q. Li, K. Yang, F. Jin, J. Fan, J. Liang, Y. Zhou, X. Sun, J. Li, "Thermal Shock Resistant 3D Printed Ceramics Reinforced with $MgAl_2O_4$ Shell Structure," *J. Mater. Sci.Technol.* **2024**, *178*, 100.

[2] T. Majumdar, N. Eisenstein, J. E. Frith, S. C. Cox, N. Birbilis, "Additive Manufacturing of Titanium Alloys for Orthopedic Applications: A Materials Science Viewpoint," *Adv. Eng. Mater.* **2018**, *20*, 1800172.

[3] M. Sayah Irani, S. Ranjbar, M. Lakhi, A. Zolfagharian, "Enhancing Damage Tolerance of Structures Using 3D/4D Printing Technologies," *Adv. Mater. Technol.* **2025**, *10*, e00535.

[4] J. Cheng, R. Wang, Z. Sun, Q. Liu, X. He, H. Li, H. Ye, X. Yang, X. Wei, Z. Li, B. Jian, W. Deng, Q. Ge, "Centrifugal Multimaterial 3D Printing of Multifunctional Heterogeneous Objects," *Nat. Commun.* **2022**, *13*, 7931.

[5] K. Foroutani, S. Khademi, S. Sharafkhani, A. Enayati-Gerdroodbar, N. Afsarimanesh, A. Zolfagharian, M. Salami-Kalajahi, B. Pourabbas, "Conducting Polymer-Based Coatings and Thin Films: A Review on Film Processing and Deposition Techniques," *Polym. Rev.* **2025**, *65*, 1057.

[6] M. R. Khosravani, P. Frohn-Sörensen, B. Engel, T. Reinicke, "Improvement of strength in single-lap adhesive joints of AlSi10Mg alloys fabricated by laser powder bed fusion," *Eur. J. Mech. A. Solids* **2025**, *109*, 105458.

[7] L. Chen, S. K. Moon, "In-Situ Defect Detection in Laser-Directed Energy Deposition with Machine Learning and Multi-Sensor Fusion," *J. Mech. Sci. Technol.* **2024**, *38*, 4477.

[8] R. Onler, A. S. Koca, B. Kirim, E. Soylemez, "Multi-Objective Optimization of Binder Jet Additive Manufacturing of Co-Cr-Mo using Machine Learning," *Int. J. Adv. Manuf. Technol.* **2022**, *119*, 1091.

[9] G. Mattera, L. Nele, D. Paolella, "Monitoring and Control the Wire Arc Additive Manufacturing Process using Artificial Intelligence Techniques: A Review," *J. Intell. Manuf.* **2024**, *35*, 467.

[10] A. R. Sani, A. Zolfagharian, A. Z. Kouzani, "Artificial Intelligence-Augmented Additive Manufacturing: Insights on Closed-Loop 3D Printing," *Adv. Intell. Syst.* **2024**, *6*, 2400102.

[11] L. Jin, X. Zhai, K. Wang, K. Zhang, D. Wu, A. Nazir, J. Jiang, W. H. Liao, "Big Data, Machine Learning, and Digital Twin Assisted Additive Manufacturing: A Review," *Mater. Des.* **2024**, *244*, 113086.

[12] M. H. Mosallanejad, R. Ghanavati, A. Behjat, M. Taghian, A. Saboori, L. Iuliano, "Untapped Opportunities in Additive Manufacturing with Metals: From New and Graded Materials to Post-Processing," *Metals* **2024**, *14*, 425.

[13] S. Ali, M. J. Prajapati, C. Bhat, C.-P. Jiang, J.-Y. Jeng, "Additive Manufactured Enabled Digital Metallurgy Processes, Challenges and Future Prospects," *Appl. Mater. Today* **2025**, *42*, 102580.

[14] S. Zhou, K. Zhang, L. Jin, Q. Gao, W. H. Liao, "Efficient Data Driven Optimization Framework for Designing B-Spline Honeycombs with Excellent Energy Absorption," *Thin-Walled Struct.* **2025**, *209*, 112941.

[15] L. Jin, S. Yu, J. Cheng, H. Ye, X. Zhai, J. Jiang, K. Zhang, B. Jian, M. Bodaghi, Q. Ge, "Machine Learning Driven Forward Prediction and Inverse Design for 4D Printed Hierarchical Architecture with Arbitrary Shapes," *Appl. Mater. Today* **2024**, *40*, 102373.

[16] L. Jin, X. Zhai, J. Jiang, K. Zhang, W.-H. Liao, *Proc. SPIE 12949, Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems*, Vol. *129491D*, SPIE, Bellingham, WA **2024**.

[17] X. Sun, L. Yue, L. Yu, H. Shao, X. Peng, K. Zhou, F. Demoly, R. Zhao, H. J. Qi, "Machine Learning-Evolutionary Algorithm Enabled Design for 4D-Printed Active Composite Structures," *Adv. Funct. Mater.* **2022**, *32*, 2109805.

[18] X. Sun, L. Yue, L. Yu, C. T. Forte, C. D. Armstrong, K. Zhou, F. Demoly, R. R. Zhao, H. J. Qi, "Machine Learning-Enabled Forward Prediction and Inverse Design of 4D-Printed Active Plates," *Nat. Commun.* **2024**, *15*, 5509.

[19] I. Gibson, D. Rosen, B. Stucker, M. Khorasani, *Design for Additive Manufacturing*, Springer International Publishing, NewYork **2021**, pp. 555–607.

[20] P. F. Egan, "Design for Additive Manufacturing: Recent Innovations and Future Directions," *Designs* **2023**, *7*, 83.

[21] F. Demoly, M. L. Dunn, K. L. Wood, H. J. Qi, J. C. André, "The Status, Barriers, Challenges, and Future in Design for 4D Printing," *Mater. Des.* **2021**, *212*, 110193.

[22] D. Athinarayanarao, R. Prodhon, D. Chamoret, H. J. Qi, M. Bodaghi, J. C. André, F. Demoly, "Computational Design for 4D Printing of Topology Optimized Multi-material Active Composites," *NPJ Comput. Mater.* **2023**, *9*, 1.

[23] X. Huang, Y. Xie, "Evolutionary Topology Optimization of Continuum Structures Including Design-Dependent Self-Weight Loads," *Finite Elem. Anal. Des.* **2011**, *47*, 942.
[24] I. Mitropoulou, M. Bernhard, B. Dillenburger, in *Proc. of the 5th Annual ACM Symposium on Computational Fabrication* **2020**.
[25] J. Wu, N. Aage, R. Westermann, O. Sigmund, "Infill Optimization for Additive Manufacturing—Approaching Bone-Like Porous Structures," *IEEE Trans. Visual Comput. Graphics* **2017**, *24*, 1127.
[26] M. H. Mosallanejad, B. Niroumand, A. Aversa, A. Saboori, "In-Situ Alloying in Laser-based Additive Manufacturing Processes: A Critical Review," *J. Alloys Compd.* **2021**, *872*, 159567.
[27] M. Dinar, D. W. Rosen, "A Design for Additive Manufacturing Ontology," *J. Comput. Inf. Sci. Eng.* **2017**, *17*, 021013.
[28] G. Formentini, C. Favi, M. Mandolini, M. Germani, "A Framework to Collect and Reuse Engineering Knowledge in the Context of Design for Additive Manufacturing," *Proc. Des. Soc.* **2022**, *2*, 1371.
[29] T. Bjarsch, K. Drechsler, J. Schilp, "Ontologies for FAIR Data in Additive Manufacturing: A Use Case-Based Evaluation," *Adv. Eng. Mater.* **2025**, *27*, 2401528.
[30] M. M. Ali, R. Rai, J. N. Otte, B. Smith, "A Product Life Cycle Ontology for Additive Manufacturing," *Comput. Ind.* **2019**, *105*, 191.
[31] N. Hasan, M. H. Rahman, A. Wessman, T. Smith, M. Shafae, "Process Defects Knowledge Modeling in Laser Powder Bed Fusion Additive Manufacturing: An Ontological Framework," *Manuf. Lett.* **2023**, *35*, 822.
[32] A. Gaikwad, R. Yavari, M. Montazeri, K. Cole, L. Bian, P. Rao, "Toward the Digital Twin of Additive Manufacturing: Integrating Thermal Simulations, Sensing, and Analytics to Detect Process Faults," *IISE Trans.* **2020**, *52*, 1204.
[33] A. R. Sani, A. Zolfagharian, A. Z. Kouzani, "Automated Defects Detection in Extrusion 3D Printing using YOLO Models," *J. Intell. Manuf.* **2024**, 1.
[34] A. Ghafarollahi, M. J. Buehler, Sparks: Multi-agent artificial intelligence model discovers protein design principles. arXiv preprint arXiv:2504.19017 **2025**.
[35] B. D. Bevans, A. Carrington, A. Riensche, A. Tenequer, C. Barrett, H. S. Halliday, R. Srinivasan, K. D. Cole, P. Rao, "Digital Twins for Rapid In-Situ Qualification of Part Quality in Laser Powder Bed Fusion Additive Manufacturing," *Addit. Manuf.* **2024**, *93*, 104415.
[36] F. Corradini, M. Silvestri, "Design and Testing of a Digital Twin for Monitoring and Quality Assessment of Material Extrusion Process," *Addit. Manuf.* **2022**, *51*, 102633.
[37] H. Hao, Y. Wang, "Smart Curb Digital Twin: Inventorying Curb Environments using Computer Vision and Street Imagery," *IEEE J. Radio Freq. Identif.* **2022**, *7*, 168.
[38] A. Zolfagharian, L. Durran, S. Gharaie, B. Rolfe, A. Kaynak, M. Bodaghi, "4D Printing Soft Robots Guided by Machine Learning and Finite Element Models," *Sens. Actuators, A* **2021**, *328*, 112774.
[39] Y. Wu, Z. Dai, H. Liu, L. Wang, M. P. Nemitz, in *2024 IEEE 7th Int. Conf. on Soft Robotics (RoboSoft), San Diego, CA*, IEEE, Piscataway, NJ, **2024**.
[40] B. Peng, Y. Wei, Y. Qin, J. Dai, Y. Li, A. Liu, Y. Tian, L. Han, Y. Zheng, P. Wen, "Machine Learning-Enabled Constrained Multi-Objective Design of Architected Materials," *Nat. Commun.* **2023**, *14*, 6630.
[41] H. Pahlavani, K. Tsifoutis-Kazolis, M. C. Saldivar, P. Mody, J. Zhou, M. J. Mirzaali, A. A. Zadpoor, "Deep Learning for Size-Agnostic Inverse Design of Random-Network 3D Printed Mechanical Metamaterials," *Adv. Mater.* **2024**, *36*, 2303481.
[42] S. Naghieh, X. Chen, "Printability–A key Issue in Extrusion-based Bioprinting," *J. Pharm. Anal.* **2021**, *11*, 564.
[43] P. X. Lan, P. T. M. Nguyen, T. T. H. Nguyen, L. Bang, T. K. Nguyen, "Effect of Additive Biomaterials on the Printability and Characterization of PCL-based Composite Scaffolds Fabricated by Screw Extrusion 3D Printing," *Mater. Res. Express* **2025**, *12*, 015401.
[44] S. Santoni, S. G. Gugliandolo, M. Sponchioni, D. Moscatelli, B. M. Colosimo, "3D Bioprinting: Current Status and Trends—a Guide to the Literature and Industrial Practice," *Bio-Des. Manuf.* **2022**, *5*, 14.
[45] A. F. Bonatti, G. Vozzi, C. De Maria, "Enhancing Quality Control in Bioprinting through Machine Learning," *Biofabrication* **2024**, *16*, 022001.
[46] Z. Zhang, X. Zhou, Y. Fang, Z. Xiong, T. Zhang, "AI-Driven 3D Bioprinting for Regenerative Medicine: From Bench to Bedside," *Bioact. Mater.* **2025**, *45*, 201.
[47] M. Bodaghi, L. Wang, F. Zhang, Y. Liu, J. Leng, R. Xing, M. D. Dickey, S. Vanaei, M. Elahinia, S. V. Hoa, "4D Printing Roadmap," *Smart Mater. Struct.* **2024**, *33*, 113501.
[48] A. Zolfagharian, A. Kaynak, A. Kouzani, "Closed-Loop 4D-Printed Soft Robots," *Mater. Des.* **2020**, *188*, 108411.
[49] A. Zolfagharian, H. R. Jarrah, M. S. Xavier, B. Rolfe, M. Bodaghi, "Multimaterial 4D Printing with a Tunable Bending Model," *Smart Mater. Struct.* **2023**, *32*, 065001.
[50] G. D. Goh, S. L. Sing, Y. F. Lim, J. L. J. Thong, Z. K. Peh, S. R. Mogali, W. Y. Yeong, "Machine Learning for 3D Printed Multi-Materials Tissue-Mimicking Anatomical Models," *Mater. Des.* **2021**, *211*, 110125.
[51] B. Rankouhi, S. Jahani, F. E. Pfefferkorn, D. J. Thoma, "Compositional Grading of a 316L-Cu Multi-Material Part using Machine Learning for the Determination of Selective Laser Melting Process Parameters," *Addit. Manuf.* **2021**, *38*, 101836.
[52] F. Sui, R. Guo, Z. Zhang, G. X. Gu, L. Lin, "Deep Reinforcement Learning for Digital Materials Design," *ACS Mater. Lett.* **2021**, *3*, 1433.
[53] G. X. Gu, C.-T. Chen, D. J. Richmond, M. J. Buehler, "Bioinspired Hierarchical Composite Design using Machine Learning: Simulation, Additive Manufacturing, and Experiment," *Mater. Horiz.* **2018**, *5*, 939.
[54] C. T. Chen, G. X. Gu, "Generative Deep Neural Networks for Inverse Materials Design using Backpropagation and Active Learning," *Adv. Sci.* **2020**, *7*, 1902607.
[55] B. Li, B. Deng, W. Shou, T.-H. Oh, Y. Hu, Y. Luo, L. Shi, W. Matusik, "Computational Discovery of Microstructured Composites with Optimal Stiffness-Toughness Trade-Offs," *Sci. Adv.* **2024**, *10*, eadk4284.
[56] L. Jin, S. Yu, J. Cheng, Z. Liu, K. Zhang, S. Zhou, X. He, G. Xie, M. Bodaghi, Q. Ge, "Machine Learning Powered Inverse Design for Strain Fields of Hierarchical Architectures," *Composites, Part B* **2025**, *299*, 112372.
[57] Z. Yang, C.-H. Yu, M. J. Buehler, "Deep Learning Model to Predict Complex Stress and Strain Fields in Hierarchical Composites," *Sci. Adv.* **2021**, *7*, eabd7416.
[58] C. Yang, Y. Kim, S. Ryu, G. X. Gu, "Prediction of Composite Microstructure Stress-Strain Curves using Convolutional Neural Networks," *Mater. Des.* **2020**, *189*, 108509.
[59] B. Zhao, M. Zhang, L. Dong, D. Wang, "Design of Grayscale Digital Light Processing 3D Printing Block by Machine Learning and Evolutionary Algorithm," *Compos. Commun.* **2022**, *36*, 101395.
[60] M. Zhang, X. Fan, L. Dong, C. Jiang, O. Weeger, K. Zhou, D. Wang, "Voxel Design of Grayscale DLP 3D-Printed Soft Robots," *Adv. Sci.* **2024**, *11*, 2309932.
[61] L. Jin, X. Zhai, W. Xue, K. Zhang, J. Jiang, M. Bodaghi, W.-H. Liao, "Finite Element Analysis, Machine Learning, and Digital Twins for Soft Robots: State-of-Arts and Perspectives," *Smart Mater. Struct.* **2025**, *34*, 033002.
[62] N. A. Sbrugnera Sotomayor, F. Caiazzo, V. Alfieri, "Enhancing Design for Additive Manufacturing Workflow: Optimization, Design and Simulation Tools.," *Appl. Sci.* **2021**, *11*, 6628.

[63] T. Zegard, G. H. Paulino, "Bridging Topology Optimization and Additive Manufacturing," *Struct. Multidiscip. Optim.* **2016**, *53*, 175.
[64] Z. Jihong, Z. Han, W. Chuang, Z. Lu, Y. Shangqin, "A Review of Topology Optimization for Additive Manufacturing: Status and Challenges," *Chin. J. Aeronaut.* **2021**, *34*, 91.
[65] L. Meng, W. Zhang, D. Quan, G. Shi, L. Tang, Y. Hou, P. Breitkopf, J. Zhu, T. Gao, "From Topology Optimization Design to Additive Manufacturing: Today's Success and Tomorrow's Roadmap," *Arch. Comput. Methods Eng.* **2020**, *27*, 805.
[66] T. Briard, F. Segonds, N. Zamariola, "G-DfAM: A Methodological Proposal of Generative Design for Additive Manufacturing in the Automotive Industry," *Int. J. Interact. Des. Manuf. IJIDeM* **2020**, *14*, 875.
[67] Y. K. Abdallah, A. T. Estévez, "Biomaterials Research-Driven Design Visualized by AI Text-Prompt-Generated Images," *Designs* **2023**, *7*, 48.
[68] H. Yin, Z. Zhang, Y. Liu, "The Exploration of Integrating the Midjourney Artificial Intelligence Generated Content Tool into Design Systems to Direct Designers towards Future-Oriented Innovation," *Systems* **2023**, *11*, 566.
[69] M. J. Buehler, "Accelerating Scientific Discovery with Generative Knowledge Extraction, Graph-based Representation, and Multimodal Intelligent Graph Reasoning," *Mach. Learn.: Sci. Technol.* **2024**, *5*, 035083.
[70] W. S. Requejo, F. F. Martinez, C. A. Vega, R. Z. Martinez, A. M. Cendrero, A. Díaz-Lantada, "Fostering Creativity in Engineering Design through Constructive Dialogues with Generative Artificial Intelligence," *Cell Rep. Phys. Sci.* **2024**, *5*, 102157.
[71] V. Ashish, "Attention is All You Need," *Adv. Neural Inf. Process. Syst.* **2017**, *30*, https://dl.acm.org/doi/10.5555/3295222.3295349.
[72] A. Radford, K. Narasimhan, T. Salimans, I. Sutskever, Improving language understanding by generative pre-training, **2018**.
[73] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, I. Sutskever, "Language Models are Unsupervised Multitask Learners," *OpenAI blog* **2019**, *1*, 9.
[74] A. Sriwastwa, P. Ravi, A. Emmert, S. Chokshi, S. Kondor, K. Dhal, P. Patel, L. L. Chepelev, F. J. Rybicki, R. Gupta, "Generative AI for Medical 3D Printing: A Comparison of ChatGPT Outputs to Reference Standard Education," *3D Printing in Medicine* **2023**, *9*, 21.
[75] F. Faruqi, A. Katary, T. Hasic, A. Abdel-Rahman, N. Rahman, L. Tejedor, M. Leake, M. Hofmann, S. Mueller, in *Proc. of the 36th Annual ACM Symp. on User Interface Software and Technology* **2023**.
[76] M. Nafea, "4D Printing of Generative AI-Assisted Designs," *Smart Mater. Struct.* **2025**, *34*, 025029.
[77] Z. Yang, M. J. Buehler, "Words to Matter: De Novo Architected Materials Design using Transformer Neural Networks," *Front. Mater.* **2021**, *8*, 740754.
[78] M. J. Buehler, "In Situ Graph Reasoning and Knowledge Expansion using Graph-PRefLexOR," *Adv. Intell. Discovery* **2025**, 202500006, https://doi.org/10.1002/aidi.202500006.
[79] M. J. Buehler, "Generative Retrieval-Augmented Ontologic Graph and Multiagent Strategies for Interpretive Large Language Model-based Materials Design," *ACS Eng. Au* **2024**, *4*, 241.
[80] F. Ciccone, A. Bacciaglia, A. Ceruti, "Optimization with Artificial Intelligence in Additive Manufacturing: A Systematic Review," *J. Braz. Soc. Mech. Sci. Eng.* **2023**, *45*, 303.
[81] N. Hertlein, P. R. Buskohl, A. Gillman, K. Vemaganti, S. Anand, "Generative Adversarial Network for Early-Stage Design Flexibility in Topology Optimization for Additive Manufacturing," *J. Manuf. Syst.* **2021**, *59*, 675.
[82] J. Liu, N. Zhu, L. Chen, X. Liu, "Structural Multi-Objective Topology Optimization in the Design and Additive Manufacturing of Spatial Structure Joints," *Int. J. Steel Struct.* **2022**, *22*, 649.
[83] N. Hu, L. Ding, L. Men, W. Zhou, W. Zhang, R. Yin, "Dual Visual Inspection for Automated Quality Detection and Printing Optimization of Two-Photon Polymerization based on Deep Learning," *J. Intell. Manuf.* **2024**, *36*, 4025.
[84] S. H. Ahn, M. Montero, D. Odell, S. Roundy, P. K. Wright, "Anisotropic Material Properties of Fused Deposition Modeling ABS," *Rapid Prototyping J.* **2002**, *8*, 248.
[85] D. Chakraborty, B. A. Reddy, A. R. Choudhury, "Extruder Path Generation for Curved Layer Fused Deposition Modeling," *Comput.-Aided Des.* **2008**, *40*, 235.
[86] Y. Zhang, A. Bernard, R. K. Gupta, R. Harik, "Evaluating the Design for Additive Manufacturing: A Process Planning Perspective," *Procedia Cirp* **2014**, *21*, 144.
[87] G. Fang, T. Zhang, Y. Huang, Z. Zhang, K. Masania, C. C. Wang, "Exceptional Mechanical Performance by Spatial Printing with Continuous Fiber: Curved Slicing, Toolpath Generation and Physical Verification," *Addit. Manuf.* **2024**, *82*, 104048.
[88] K.-M. M. Tam, C. T. Mueller, "Additive Manufacturing Along Principal Stress Lines," *3D Print. Addit. Manuf.* **2017**, *4*, 63.
[89] C. Dai, C. C. Wang, C. Wu, S. Lefebvre, G. Fang, Y.-J. Liu, "Support-Free Volume Printing by Multi-Axis Motion," *ACM Trans. Graphics TOG* **2018**, *37*, 134.
[90] J. Etienne, N. Ray, D. Panozzo, S. Hornus, C. C. Wang, J. Martínez, S. McMains, M. Alexa, B. Wyvill, S. Lefebvre, "CurviSlicer: Slightly Curved Slicing for 3-Axis Printers," *ACM Trans. Graphics TOG* **2019**, *38*, 1.
[91] G. Fang, T. Zhang, S. Zhong, X. Chen, Z. Zhong, C. C. Wang, "Reinforced FDM: Multi-Axis Filament Alignment with Controlled Anisotropic Strength," *ACM Trans. Graphics TOG* **2020**, *39*, 1.
[92] T. Zhang, G. Fang, Y. Huang, N. Dutta, S. Lefebvre, Z. M. Kilic, C. C. Wang, "S3-Slicer: A General Slicing Framework for Multi-Axis 3D Printing," *ACM Trans. Graphics TOG* **2022**, *41*, 277.
[93] V. Sitzmann, J. Martel, A. Bergman, D. Lindell, G. Wetzstein, "Implicit Neural Representations with Periodic Activation Functions," *Adv. Neural Inf. Process. Syst.* **2020**, *33*, 7462.
[94] J. J. Park, P. Florence, J. Straub, R. Newcombe, S. Lovegrove, in *Proc. of the IEEE/CVF Conf. on Computer Vision and Pattern Recognition* **2019**.
[95] T. Liu, T. Zhang, Y. Chen, Y. Huang, C. C. Wang, "Neural Slicer for Multi-Axis 3D Printing," *ACM Trans. Graphics TOG* **2024**, *43*, 85.
[96] A. Nadernezhad, J. Groll, "Machine Learning Reveals a General Understanding of Printability in Formulations based on Rheology Additives," *Adv. Sci.* **2022**, *9*, 2202638.
[97] Y. Huang, Y. Guo, R. Su, X. Han, J. Ding, T. Zhang, T. Liu, W. Wang, G. Fang, X. Song, "Learning based Toolpath Planner on Diverse Graphs for 3D Printing," *ACM Trans. Graphics TOG* **2024**, *43*, 229.
[98] M. Naebe, K. Shirvanimoghaddam, "Functionally Graded Materials: A Review of Fabrication and Properties," *Appl. Mater. Today* **2016**, *5*, 223.
[99] R. Ghanavati, H. Naffakh-Moosavy, "Additive Manufacturing of Functionally Graded Metallic Materials: A Review of Experimental and Numerical Studies," *J. Mater. Res. Technol.* **2021**, *13*, 1628.
[100] D. Feenstra, R. Banerjee, H. Fraser, A. Huang, A. Molotnikov, N. Birbilis, "Critical Review of the State of the Art in Multi-Material Fabrication via Directed Energy Deposition," *Curr. Opin. Solid State Mater. Sci.* **2021**, *25*, 100924.
[101] O. Eliseeva, T. Kirk, P. Samimi, R. Malak, R. Arróyave, A. Elwany, I. Karaman, "Functionally Graded Materials through Robotics-Inspired Path Planning," *Mater. Des.* **2019**, *182*, 107975.
[102] A. Moradi, S. Tajalli, M. H. Mosallanejad, A. Saboori, "A Review on Machine Learning for Process Optimization and Property prediction," *Int. J. Adv. Manuf. Technol.* **2025**, *136*, 527.
[103] T. DebRoy, T. Mukherjee, H. Wei, J. Elmer, J. Milewski, "Metallurgy, Mechanistic Models and Machine Learning in Metal Printing," *Nat. Rev. Mater.* **2021**, *6*, 48.

[104] A. Richter, A. M. Krajewski, Z. Yang, A. M. Beese, Z.-K. Liu, "AMMap Tool for Additive Manufacturing Design, Alloy Discovery, and Path Planning," *J. Phys.: Mater.* **2025**, *8*, 035008.
[105] R. Ghanavati, H. Naffakh-Moosavy, M. Moradi, F. Mazzucato, A. Valente, S. Bagherifard, A. Saboori, "Design Optimization for Defect-Free AISI 316 L/IN718 Functionally Graded Materials Produced by Laser Additive Manufacturing," *Mater. Charact.* **2025**, *220*, 114697.
[106] Z. Yang, C. D. Jamieson, Z.-K. Liu, A. M. Beese, "Effect of Dilution on Fabricated Functionally Graded Materials Compositions: Modelling and Mitigation Strategies Validated using the Ni-, Fe-, Cu-Alloy System," *Addit. Manuf.* **2025**, *102*, 104730.
[107] L. D. Bobbio, B. Bocklund, E. Simsek, R. T. Ott, M. J. Kramer, Z.-K. Liu, A. M. Beese, "Design of an Additively Manufactured Functionally Graded Material of 316 Stainless Steel and Ti-6Al-4V with Ni-20Cr, Cr, and V Intermediate Compositions," *Addit. Manuf.* **2022**, *51*, 102649.
[108] R. Ghanavati, H. Naffakh-Moosavy, M. Moradi, E. Gadalińska, A. Saboori, "Residual Stresses and Distortion in Additively-Manufactured SS316L-IN718 Multi-Material by Laser-Directed Energy Deposition: A Validated Numerical-Statistical Approach," *J. Manuf. Processes* **2023**, *108*, 292.
[109] V. Pandiyan, R. Wróbel, C. Leinenbach, S. Shevchik, "Optimizing In-Situ Monitoring for Laser Powder Bed Fusion Process," *J. Mater. Process. Technol.* **2023**, *321*, 118144.
[110] D. Liu, Y. Lu, Y. Wang, in *Machine Learning for Powder-Based Metal Additive Manufacturing*, Elsevier, NewYork **2025**, pp. 77–106.
[111] T. Erps, M. Foshey, M. K. Luković, W. Shou, H. H. Goetzke, H. Dietsch, K. Stoll, B. von Vacano, W. Matusik, "Accelerated Discovery of 3D Printing Materials using Data-Driven Multiobjective Optimization," *Sci. Adv.* **2021**, *7*, eabf7435.
[112] H. Gashmard, H. Shakeripour, M. Alaei, "Predicting Superconducting Transition Temperature through Advanced Machine Learning and Innovative Feature Engineering," *Sci. Rep.* **2024**, *14*, 3965.
[113] M. H. Mosallanejad, H. Gashmard, M. Javanbakht, B. Niroumand, A. Saboori, "A Novel Feature Engineering Approach for Predicting Melt Pool Depth During LPBF by Machine Learning Models," *Addit. Manuf. Lett.* **2024**, *10*, 100214.
[114] A. Ghafarollahi, M. J. Buehler, "Automating Alloy Design and Discovery with Physics-Aware Multimodal Multiagent," *Proc. Natl. Acad. Sci.* **2025**, *122*, e2414074122.
[115] S. Xiao, R. Hu, Z. Li, S. Attarian, K.-M. Björk, A. Lendasse, "A Machine-Learning-Enhanced Hierarchical Multiscale Method for Bridging from Molecular Dynamics to Continua," *Neural Comput. Appl.* **2020**, *32*, 14359.
[116] B. Ni, B. Glaser, S. M. Taheri-Mousavi, "End-to-End Prediction and Design of Additively Manufacturable Alloys using a Generative AlloyGPT Model," *npj Comput. Mater.* **2025**, *11*, 294.
[117] S. Miret, N. A. Krishnan, "Enabling Large Language Models for Real-World Materials Discovery," *Nat. Mach. Intell.* **2025**, *7*, 991.
[118] L. F. Sikos, "A Novel Ontology for 3D Semantics: Ontology-based 3D Model Indexing and Content-based Video Retrieval Applied to the Medical Domain," *Int. J. Metadata Semant. Ontol.* **2017**, *12*, 59.
[119] M. Abd Nikooie Pour, P. Tarafder, A. Wiberg, H. Li, J. Moverare, P. Lambrix, in *First International Workshop on Semantic Materials Science: Harnessing the Power of Semantic Web Technologies in Materials Science*, Amsterdam, The Netherlands September 17, 2024. **2024**, CEUR Workshop Proceedings.
[120] J. Han, D. Schaefer, "An Ontology for Supporting Digital Manufacturability Analysis," *Procedia CIRP* **2019**, *81*, 850.
[121] W. Solórzano-Requejo, C. A. Vega, R. Z. Martínez, M. Bodaghi, A. D. Lantada, "Ontology for Smart 4D Printed Material Systems and Structures Synergically Applied with Generative Artificial Intelligence for Creativity Promotion," *Smart Mater. Struct.* **2025**, *34*, 015045.
[122] O. Perera, J. Liu, "Exploring Large Language Models for Ontology Learning," *Issues Inf. Syst.* **2024**, *25*, 299.
[123] M. Verdonck, F. Gailly, S. de Cesare, "Comprehending 3D and 4D Ontology-Driven Conceptual Models: An Empirical Study," *Inf. Syst.* **2020**, *93*, 101568.
[124] M. Almada, L. Midao, D. Portela, I. Dias, F. Núñez-Benjumea, C. L. Parra-Calderón, E. Costa, in *Acta Médica Portuguesa*, Vol. *33*, Ordem dos Médicos, Lisbon, Portugal **2020**, pp. 828–834.
[125] W. Solórzano-Requejo, A. Martinez Cendrero, A. A. Altun, S. Nohut, C. Ojeda, J. Garcia Molleja, J. Molina-Aldareguia, M. Schwentenwein, A. Diaz Lantada, "Topology Optimisation and Lithography-based Ceramic Manufacturing of Short-Stem Hip Prostheses with Enhanced Biomechanical and Mechanobiological Performance," *Virtual Phys. Prototyping* **2024**, *19*, e2387280.
[126] A. E. Alexander, N. Wake, L. Chepelev, P. Brantner, J. Ryan, K. C. Wang, "A Guideline for 3D Printing Terminology in Biomedical Research Utilizing ISO/ASTM Standards," *3D Print. Med.* **2021**, *7*, 8.
[127] L. Chepelev, A. Giannopoulos, A. Tang, D. Mitsouras, F. J. Rybicki, "Medical 3D Printing: Methods to Standardize Terminology and Report Trends. 3D Printing in Medicine," *3D Print. Med.* **2017**, *3*, 4.
[128] M. P. Joachimiak, M. A. Miller, J. H. Caufield, R. Ly, N. L. Harris, A. Tritt, C. J. Mungall, K. E. Bouchard, "The Artificial Intelligence Ontology: LLM-assisted construction of AI concept hierarchies," *Appl.Ontol.* **2024**, *19*, 408.
[129] Y. Z. Xi Liu, Chun Yu Wan, Yang Zhang, Junwei Liu, Effective Field Neural Network. ArXiv preprint arXiv:2412.08821, **2025** (arXiv:2502.17665).
[130] Y. Cai, Y. Wang, M. Burnett, "Using Augmented Reality to Build Digital Twin for Reconfigurable Additive Manufacturing System," *J. Manuf. Syst.* **2020**, *56*, 598.
[131] L. Zhang, X. Chen, W. Zhou, T. Cheng, L. Chen, Z. Guo, B. Han, L. Lu, "Digital Twins for Additive Manufacturing: A State-of-the-Art Review," *Appl. Sci.* **2020**, *10*, 8350.
[132] F. Tao, H. Zhang, C. Zhang, "Advancements and Challenges of Digital Twins in Industry," *Nat. Comput. Sci.* **2024**, *4*, 169.
[133] V. Karkaria, A. Goeckner, R. Zha, J. Chen, J. Zhang, Q. Zhu, J. Cao, R. X. Gao, W. Chen, "Towards a Digital Twin Framework in Additive Manufacturing: Machine Learning and Bayesian Optimization for Time Series Process Optimization," *J. Manuf. Syst.* **2024**, *75*, 322.
[134] T. Shen, B. Li, "Digital Twins in Additive Manufacturing: a State-of-the-Art Review.," *Int. J. Adv. Manuf. Technol.* **2024**, *131*, 63.
[135] E. Bendoly, A. Chandrasekaran, M. D. R. F. Lima, R. Handfield, S. H. Khajavi, S. Roscoe, "The Role of Generative Design and Additive Manufacturing Capabilities in Developing Human–AI Symbiosis: Evidence from Multiple Case Studies," *Decis. Sci.* **2024**, *55*, 325.
[136] K. Xia, C. Sacco, M. Kirkpatrick, C. Saidy, L. Nguyen, A. Kircaliali, R. Harik, "A Digital Twin to Train Deep Reinforcement Learning Agent for Smart Manufacturing Plants: Environment, Interfaces and Intelligence," *J. Manuf. Syst.* **2021**, *58*, 210.
[137] M. Groshev, C. Guimaraes, J. Martín-Pérez, A. de la Oliva, "Toward Intelligent Cyber-Physical Systems: Digital Twin Meets Artificial Intelligence," *IEEE Commun. Mag.* **2021**, *59*, 14.
[138] P. Stavropoulos, A. Papacharalampoloulos, K. Tzimanis, "Design and Implementation of a Digital Twin Platform for AM Processes," *Procedia CIRP* **2021**, *104*, 1722.
[139] Y. Lin-Yao, C. Si-Yuan, W. Xiao, Z. Jun, W. Cheng-Hong, "Digital Twins and Parallel Systems: State of the Art, Comparisons and Prospect," *Acta Autom. Sin.* **2019**, *45*, 2001.

[140] Z. Shen, X. Dong, Q. Fang, G. Xiong, C.-C. Ge, F.-Y. Wang, "Parallel Additive Manufacturing Systems," *IEEE J. Radio Freq. Identif.* **2022**, *6*, 758.
[141] S. Datta, *Digital Twins: Digital Twin Meets Digital Cousin* **2022**.
[142] Y. Wang, T. Fu, Y. Xu, Z. Ma, H. Xu, B. Du, Y. Lu, H. Gao, J. Wu, J. Chen, "TWIN-GPT: Digital Twins for Clinical Trials via Large Language Model," *ACM Trans. Multimedia Comput., Commun. Appl.* **2024**, https://dl.acm.org/doi/10.1145/3674838.
[143] M. Z. Naser, "Causality and Causal Inference for Engineers: Beyond Correlation, Regression, Prediction and Artificial Intelligence," *Wiley Interdiscip. Rev.: Data Min. Knowl. Discovery* **2024**, *14*, e1533.
[144] A. Phua, C. Davies, G. W. Delaney, "A Digital Twin Hierarchy for Metal Additive Manufacturing," *Comput. Ind.* **2022**, *140*, 103667.
[145] S. M. H. Bamakan, S. B. Far, "Distributed and Trustworthy Digital Twin Platform based on Blockchain and Web3 Technologies," *Cyber Secur. Appl.* **2025**, *3*, 100064.
[146] K. Wang, Y. Wang, Y. Li, X. Fan, S. Xiao, L. Hu, "A Review of the Technology Standards for Enabling Digital Twin: [version 2; peer review: 2 approved]," *Digital Twin* **2024**, *1*, 4.
[147] K. Mondal, "Advanced Manufacturing and Digital Twin Technology for Nuclear Energy," *Front. Energy Res.* **2024**, *12*, 1339836.
[148] Y. Zhang, S. Shen, H. Li, Y. Hu, "Review of In Situ and Real-Time Monitoring of Metal Additive Manufacturing based on Image Processing," *Int. J. Adv. Manuf. Technol.* **2022**, *123*, 1.
[149] Y. Guo, Y. Zhang, Z. Pan, W. Zhou, "Recent Progress of Sensing and Machine Learning Technologies for Process Monitoring and Defects Detection in Wire Arc Additive Manufacturing," *J. Manuf. Processes* **2024**, *125*, 489.
[150] Y. Fu, A. R. Downey, L. Yuan, T. Zhang, A. Pratt, Y. Balogun, "Machine Learning Algorithms for Defect Detection in Metal Laser-based Additive Manufacturing: A Review," *J. Manuf. Processes* **2022**, *75*, 693.
[151] T. Nasrin, F. Pourkamali-Anaraki, A. M. Peterson, "Application of Machine Learning in Polymer Additive Manufacturing: A Review," *J. Polym. Sci.* **2024**, *62*, 2639.
[152] A. Selot, R. Dwivedi, "Machine Learning and Sensor-based Approach for Defect Detection in MEX Additive Manufacturing Process-A Review," *J. Braz. Soc. Mech. Sci. Eng.* **2023**, *45*, 535.
[153] L. Lu, J. Hou, S. Yuan, X. Yao, Y. Li, J. Zhu, "Deep Learning-Assisted Real-Time Defect Detection and Closed-Loop Adjustment for Additive Manufacturing of Continuous Fiber-Reinforced Polymer Composites," *Rob. Comput. Integr. Manuf.* **2023**, *79*, 102431.
[154] J. Chung, B. Shen, A. C. C. Law, Z. Kong, "Reinforcement Learning-based Defect Mitigation for Quality Assurance of Additive Manufacturing," *J. Manuf. Syst.* **2022**, *65*, 822.
[155] H. Zhao, X. Wang, J. Sun, Y. Wang, Z. Chen, J. Wang, X. Xu, "Artificial Intelligence Powered Real-Time Quality Monitoring for Additive Manufacturing in Construction," *Constr. Build. Mater.* **2024**, *429*, 135894.
[156] S. Gerdes, A. Gaikwad, S. Ramesh, I. V. Rivero, A. Tamayol, P. Rao, "Monitoring and Control of Biological Additive Manufacturing using Machine Learning," *J. Intell. Manuf.* **2024**, *35*, 1055.
[157] A. Ghafarollahi, M. J. Buehler, "SciAgents: Automating Scientific Discovery through Bioinspired Multi-Agent Intelligent Graph Reasoning," *Adv. Mater.* **2025**, *37*, 2413523.
[158] B. Ni, M. J. Buehler, "Large Language Model Multi-Agent Collaborations Can Solve Mechanics Problems, Generate New Data, and Integrate Knowledge," *Extreme Mech. Lett.* **2024**, *67*, 102131.
[159] N. Samadiani, A. S. Barnard, D. Gunasegaram, N. Fayyazifar, "Best Practices for Machine Learning Strategies Aimed at Process Parameter Development in Powder Bed Fusion Additive Manufacturing," *J. Intell. Manuf.* **2024**, *36*, 4477.
[160] D. R. Gunasegaram, A. Murphy, A. Barnard, T. DebRoy, M. Matthews, L. Ladani, D. Gu, "Towards Developing Multiscale-Multiphysics Models and their Surrogates for Digital Twins of Metal Additive Manufacturing," *Addit. Manuf.* **2021**, *46*, 102089.
[161] J. Tang, Z. Zhao, Y. Guo, C. Wang, X. Zhang, R. Yan, X. Chen, "Privacy-Preserving Federated Transfer Learning for Defect Identification from Highly Imbalanced Image Data in Additive Manufacturing," *Rob. Comput. Integr. Manuf.* **2024**, *89*, 102779.
[162] J. Großeheide, Z. Tao, B. Cetin, D. Wolfschläger, W. Dewulf, R. H. Schmitt, "Enabling Multimodal Sensor Fusion in Additive Manufacturing using a Voxel-based Data Model. Production Engineering," *Prod. Eng.* **2025**, *19*, 1195.
[163] G. Wu, C. T. Cheng, T. Y. Pang, "Defect Classification and Localization in Material Extrusion with Multi-Modal Large Language Models," in *2024 IEEE Int. Conf. on Future Machine Learning and Data Science (FMLDS), Sydney, Australia* **2024**, pp. 539–544.
[164] Q. Fang, G. Xiong, F. Wang, Z. Shen, X. Dong, F.-Y. Wang, *2024 China Automation Congress (CAC), Qingdao, China*, IEEE, Piscataway, NJ **2024**, pp. 6900–6905.
[165] L. Barrault, P.-A. Duquenne, M. Elbayad, A. Kozhevnikov, B. Alastruey, P. Andrews, M. Coria, G. Couairon, M. R. Costa-jussà, D. Dale, Large concept models: Language modeling in a sentence representation space. arXiv preprint arXiv:2412.08821 **2024**.
[166] Y. Wu, B. Sicard, S. A. Gadsden, "Physics-Informed Machine Learning: A Comprehensive Review on Applications in Anomaly Detection and Condition Monitoring," *Expert Syst. Appl.* **2024**, *255*, 124678.
[167] P. Leitão, J. Barbosa, C. A. Geraldes, J. P. Coelho, in *Service Orientation in Holonic and Multi-Agent Manufacturing: Proceedings of SOHOMA 2017*, Springer, Cham **2018**, pp. 13–26.
[168] B. Chandrasekaran, Enhancing Efficiency in Manufacturing through Automated AI Agent-Based Bearing Defect Diagnostic System. **2025**, SAE Technical Paper.
[169] A. M. Ogunmolu, O. O. Olaniyi, A. D. Popoola, A. O. Olisa, O. Bamigbade, "Autonomous Artificial Intelligence Agents for Fault Detection and Self-Healing in Smart Manufacturing Systems," *J. Energy Res. Rev.* **2025**, *17*, 20.
[170] H. Fan, H. Zhang, C. Ma, T. Wu, J. Y. H. Fuh, B. Li, "Enhancing Metal Additive Manufacturing Training with the Advanced Vision Language Model: A Pathway to Immersive Augmented Reality Training for Non-Experts," *J. Manuf. Syst.* **2024**, *75*, 257.
[171] A. Garg, A. Bhattacharya, "An Insight to the Failure of FDM Parts under Tensile Loading: Finite Element Analysis and Experimental Study," *Int. J. Mech. Sci.* **2017**, *120*, 225.
[172] M. Scapin, L. Peroni, "Numerical Simulations of Components Produced by Fused Deposition 3D Printing," *Materials* **2021**, *14*, 4625.
[173] S. S. Avro, S. A. Rahman, T.-L. B. Tseng, M. F. Rahman, "A Deep Learning Framework for Automated Anomaly Detection and Localization in Fused Filament Fabrication," *Manuf. Lett.* **2024**, *41*, 1526.
[174] Z. Jin, Z. Zhang, J. Ott, G. X. Gu, "Precise Localization and Semantic Segmentation Detection of Printing Conditions in Fused Filament Fabrication Technologies using Machine Learning," *Addit. Manuf.* **2021**, *37*, 101696.
[175] Y. Fu, A. Downey, L. Yuan, A. Pratt, Y. Balogun, "In Situ Monitoring for Fused Filament Fabrication Process: A Review," *Addit. Manuf.* **2021**, *38*, 101749.
[176] Y. Fu, A. R. Downey, L. Yuan, H.-T. Huang, "Real-Time Structural Validation for Material Extrusion Additive Manufacturing," *Addit. Manuf.* **2023**, *65*, 103409.
[177] Y. Fu, A. R. Downey, L. Yuan, H.-T. Huang, E. A. Ogunniyi, "Simulation-in-the-Loop Additive Manufacturing for Real-Time

Structural Validation and Digital Twin Development," *Addit. Manuf.* **2025**, *98*, 104631.
[178] A. Farrag, Y. Yang, N. Cao, D. Won, Y. Jin, "Physics-Informed Machine Learning for Metal Additive Manufacturing," *Prog. Addit. Manuf.* **2025**, *10*, 171.
[179] F. Depaoli, S. Felicioni, F. Ponzio, A. Aliberti, E. Macii, F. Bondioli, E. Padovano, S. Di Cataldo, in *2024 IEEE 29th Int. Conf. on Emerging Technologies and Factory Automation (ETFA)*, IEEE **2024**.
[180] G. Nain, K. Pattanaik, G. Sharma, "Towards Edge Computing in Intelligent Manufacturing: Past, Present and Future," *J. Manuf. Syst.* **2022**, *62*, 588.
[181] K. P. Seng, L.-M. Ang, "Embedded Intelligence: State-of-the-Art and Research Challenges," *IEEE Access* **2022**, *10*, 59236.
[182] M. Seifi, M. Gorelik, J. Waller, N. Hrabe, N. Shamsaei, S. Daniewicz, J. J. Lewandowski, "Progress Towards Metal Additive Manufacturing Standardization to Support Qualification and Certification," *JOM* **2017**, *69*, 439.
[183] J. Rohde, U. Jahnke, C. Lindemann, A. Kruse, R. Koch, "Standardised Product Development for Technology Integration of Additive Manufacturing," *Virtual Phys. Prototyping* **2019**, *14*, 141.
[184] J. Kadkhodapour, A. S. Mirhakimi, H. Montazerian, in *Quality Analysis of Additively Manufactured Metals*, Elsevier, NewYork **2023**, pp. 119–172.
[185] S. Vogt, P. Patolla, J. Metzler, D. Reichelt, in *2024 IEEE 22nd Int. Conf. on Industrial Informatics (INDIN), Beijing, China*, IEEE, Piscataway, NJ **2024**, pp. 1–8.
[186] P. Madeleine, "Digital Twins in 3D Printing: All You Need to Know," *3Dnatives* **2024**, https://www.3dnatives.com/en/digital-twins-in-3d-printing-all-you-need-to-know-230620234/ (accessed: February 2025).
[187] E. M. Jones, Apollo lunar surface journal. http://www.hq.nasa.gov/alsj/, (accessed: 1996).
[188] M. Schluse, M. Priggemeyer, L. Atorf, J. Rossmann, "Experimentable Digital Twins—Streamlining Simulation-based Systems Engineering for Industry 4.0," *IEEE Trans. Ind. Inf.* **2018**, *14*, 1722.
[189] S. Ben Amor, N. Elloumi, A. Eltaief, B. Louhichi, N. H. Alrasheedi, A. Seibi, "Digital Twin Implementation in Additive Manufacturing: A Comprehensive Review," *Processes* **2024**, *12*, 1062.
[190] D. Gunasegaram, A. Murphy, "Towards a true digital twin for the metal additive manufcaturing process," *Metal Addit. Manuf.* **2019**, *5*, 185.
[191] K. Naminas, "Advanced Applications of Computer Vision in Manufacturing Processes," *Label Your Data*, **2023**, https://labelyourdata.com/articles/computer-vision-in-manufacturing (accessed: February 2025).
[192] I. Rojek, T. Marciniak, D. Mikołajewski, "Digital Twins in 3D Printing Processes using Artificial Intelligence," *Electronics* **2024**, *13*, 3550.
[193] R. Nascimento, I. Martins, T. A. Dutra, L. Moreira, "Computer Vision based Quality Control for Additive Manufacturing Parts," *Int. J. Adv. Manuf. Technol.* **2023**, *124*, 3241.
[194] A. Bacciaglia, F. Falcetelli, E. Troiani, R. Di Sante, A. Liverani, A. Ceruti, "Geometry Reconstruction for Additive Manufacturing: From G-CODE to 3D CAD Model," *Mater. Today: Proc.* **2023**, *75*, 16.
[195] D. Cannizzaro, A. G. Varrella, S. Paradiso, R. Sampieri, Y. Chen, A. Macii, E. Patti, S. Di Cataldo, "In-Situ Defect Detection of Metal Additive Manufacturing: An Integrated Framework," *IEEE Trans. Emerging Top. Comput.* **2021**, *10*, 74.
[196] N. Jyeniskhan, A. Keutayeva, G. Kazbek, M. H. Ali, E. Shehab, "Integrating Machine Learning Model and Digital Twin System for Additive Manufacturing," *IEEE Access* **2023**, *11*, 71113.
[197] M. H. Ali, A. W. Malik, N. Jyeniskhan, M. A. Mahmood, E. Shehab, F. Liou, "Development of Digital Twin for FDM Printer with Preventive Cyber-Attack and Control Algorithms," *IEEE Access* **2024**, *12*, 193594.
[198] E. Peretz-Andersson, S. Tabares, P. Mikalef, V. Parida, "Artificial Intelligence Implementation in Manufacturing SMEs: A Resource Orchestration Approach," *Int. J. Inf. Manage.* **2024**, *77*, 102781.
[199] L. R. Jain, V. Menon, in *2023 IEEE 35th Int. Conf. On Tools With Artificial Intelligence (ICTAI), Atlanta, GA*, IEEE, Piscataway, NJ **2023**, pp. 460–467.
[200] I. Malashin, I. Masich, V. Tynchenko, A. Gantimurov, V. Nelyub, A. Borodulin, D. Martysyuk, A. Galinovsky, "Machine Learning in 3D and 4D Printing of Polymer Composites: A Review.," *Polymers* **2024**, *16*, 3125.
[201] R. Pugliese, S. Regondi, "Artificial Intelligence-Empowered 3D and 4D Printing Technologies toward Smarter Biomedical Materials and Approaches," *Polymers* **2022**, *14*, 2794.
[202] M. A. Rahman, T. Saleh, M. P. Jahan, C. McGarry, A. Chaudhari, R. Huang, M. Tauhiduzzaman, A. Ahmed, A. A. Mahmud, M. S. Bhuiyan, "Review of Intelligence for Additive and Subtractive Manufacturing: Current Status and Future Prospects," *Micromachines* **2023**, *14*, 508.
[203] I. Rojek, D. Mikołajewski, M. Kempiński, K. Galas, A. Piszcz, "Emerging Applications of Machine Learning in 3D Printing," *Appl. Sci.* **2025**, *15*, 1781.
[204] A. Zolfaghari, M. R. Purrouhani, A. Zolfagharian, "A Response Surface Methodology Study on 4D Printing for Layered PLA/TPU Structures," *Prog. Addit. Manuf.* **2025**, *10*, 159.
[205] A. Dedeloudi, E. Weaver, D. A. Lamprou, "Machine Learning in Additive Manufacturing & Microfluidics for Smarter and Safer drug Delivery Systems," *Int. J. Pharm.* **2023**, *636*, 122818.
[206] M. Mohammadi, A. Z. Kouzani, M. Bodaghi, A. Zolfagharian, "3D-Printed Programmable Bistable Mechanisms for Customized Wearable Devices in Tremor Attenuation," *J. Mech. Behav. Biomed. Mater.* **2025**, *168*, 107006.
[207] K. Azher, A. Nazir, M. U. Farooq, M. R. U. Haq, Z. Ali, A. S. Dalaq, A. A. Abubakar, S. Hussain, M. N. Syed, A. Ullah, "Revolutionizing the Future of Smart Materials: A Review of 4D Printing, Design, Optimization, and Machine Learning Integration," *Adv. Mater. Technol.* **2025**, *10*, 2401369.
[208] Q. Fang, G. Xiong, M. Zhou, T. S. Tamir, C.-B. Yan, H. Wu, Z. Shen, F.-Y. Wang, "Process Monitoring, Diagnosis and Control of Additive Manufacturing," *IEEE Trans. Autom. Sci. Eng.* **2022**, *21*, 1041.
[209] Y. Zhou, H. Lu, G. Wang, J. Wang, W. Li, "Voxelization Modelling based Finite Element Simulation and Process Parameter Optimization for Fused Filament Fabrication," *Mater. Des.* **2020**, *187*, 108409.
[210] J. Sousa, B. Brandau, R. Darabi, A. Sousa, F. Brueckner, A. Reis, L. P. Reis, "Artificial Intelligence for Control in Laser-Based Additive Manufacturing: A Systematic Review," *IEEE Access* **2025**, *13*, 30845.
[211] J. F. Henriques, A. M. Sousa, A. P. Piedade, "4D Printing: Reality or Myth?" *4D Printing* **2025**, *1*, 5.
[212] A. Zolfagharian, M. Bodaghi, *Smart Materials in Additive Manufacturing*, Vol. *3*, Elsevier, NewYork **2024**, pp. 1–11.
[213] M. Gridach, J. Nanavati, K. Z. E. Abidine, L. Mendes, C. Mack, Agentic ai for scientific discovery: A survey of progress, challenges, and future directions. arXiv preprint arXiv:2503.08979 **2025**.
[214] A. Ghafarollahi, M. J. Buehler, "ProtAgents: protein Discovery via Large Language Model Multi-Agent Collaborations Combining Physics and Machine Learning," *Digital Discovery* **2024**, *3*, 1389.
[215] V. Gupta, K. Choudhary, B. DeCost, F. Tavazza, C. Campbell, W.-K. Liao, A. Choudhary, A. Agrawal, "Structure-Aware Graph Neural Network based Deep Transfer Learning Framework for Enhanced Predictive Analytics on Diverse Materials Datasets," *npj Comput. Mater.* **2024**, *10*, 1.
[216] T. W. Ko, B. Deng, M. Nassar, L. Barroso-Luque, R. Liu, J. Qi, A. C. Thakur, A. R. Mishra, E. Liu, G. Ceder, "Materials Graph Library (MatGL), an Open-Source Graph Deep Learning Library

for Materials Science and Chemistry.," *npj Comput. Mater.* **2025**, *11*, 253.

[217] B. Wang, B. Gao, B. Ma, S. Jiang, "Bionic Programmed Wearable Actuators based on 4D Printing of Liquid Metal-Spidroin-Liquid Crystal Elastomer Composite," *Virtual Phys. Prototyping* **2024**, *19*, e2349677.

[218] K. Nakajima, H. Hauser, T. Li, R. Pfeifer, "Information Processing via Physical Soft Body," *Sci. Rep.* **2015**, *5*, 10487.

[219] Y. Zhai, A. De Boer, J. Yan, B. Shih, M. Faber, J. Speros, R. Gupta, M. T. Tolley, "Desktop Fabrication of Monolithic Soft Robotic Devices with Embedded Fluidic Control Circuits," *Sci. Rob.* **2023**, *8*, eadg3792.

[220] S. Conrad, J. Teichmann, P. Auth, N. Knorr, K. Ulrich, D. Bellin, T. Speck, F. J. Tauber, "3D-Printed Digital Pneumatic Logic for the Control of Soft Robotic Actuators," *Sci. Rob.* **2024**, *9*, eadh4060.

[221] Y. Xia, G. M. Whitesides, "Soft Lithography," *Angew. Chem. Int. Ed.* **1998**, *37*, 550.

[222] P. Chester, C. Ehrlich, L. Warburton, D. Baker, E. Kendall, D. Crompton, "What is the Work of Recovery Oriented Practice? A Systematic Literature Review," *Int. J. Mental Health Nurs.* **2016**, *25*, 270.

[223] X. Sun, M. Mazur, C.-T. Cheng, "A Review of Void Reduction Strategies in Material Extrusion-based Additive Manufacturing," *Addit. Manuf.* **2023**, *67*, 103463.

[224] Z. Snow, L. Scime, A. Ziabari, B. Fisher, V. Paquit, "Scalable In Situ Non-Destructive Evaluation of Additively Manufactured Components using Process Monitoring, Sensor Fusion, and Machine Learning," *Addit. Manuf.* **2023**, *78*, 103817.

[225] T. J. Buchner, S. Rogler, S. Weirich, Y. Armati, B. G. Cangan, J. Ramos, S. T. Twiddy, D. M. Marini, A. Weber, D. Chen, "Vision-Controlled Jetting for Composite Systems and Robots," *Nature* **2023**, *623*, 522.

[226] A. Zanardi, J. Zilly, A. Aumiller, A. Censi, E. Frazzoli, in *2019 Int. Conf. on Robotics and Automation (ICRA), Montreal, QC*, IEEE **2019**, pp. 7899–7905.

[227] J. Liu, G. Xie, J. Wang, S. Li, C. Wang, F. Zheng, Y. Jin, "Deep Industrial Image Anomaly Detection: A Survey," *Mach. Intell. Res.* **2024**, *21*, 104.

[228] D. A. Brion, S. W. Pattinson, "Generalisable 3D Printing Error Detection and Correction via Multi-Head Neural Networks," *Nat. Commun.* **2022**, *13*, 4654.

[229] S. Dharmadhikari, N. Menon, A. Basak, "A Reinforcement Learning Approach for Process Parameter Optimization in Additive Manufacturing," *Addit. Manuf.* **2023**, *71*, 103556.

[230] J. E. Johnson, I. R. Jamil, L. Pan, G. Lin, X. Xu, "Bayesian Optimization with Gaussian-Process-based Active Machine Learning for Improvement of Geometric Accuracy in Projection Multi-Photon 3D Printing," *Light Sci. Appl.* **2025**, *14*, 56.

[231] T.-H. J. Wang, J. Zheng, P. Ma, Y. Du, B. Kim, A. Spielberg, J. Tenenbaum, C. Gan, D. Rus, "Diffusebot: Breeding Soft Robots with Physics-Augmented Generative Diffusion Models," *Adv. Neural Inf. Process. Syst.* **2023**, *36*, 44398.

[232] E. Tezsezen, D. Yigci, A. Ahmadpour, S. Tasoglu, "AI-Based Metamaterial Design," *ACS Appl. Mater. Interfaces* **2024**, *16*, 29547.

[233] L. Y. Sujeeun, N. Goonoo, H. Ramphul, I. Chummun, F. Gimié, S. Baichoo, A. Bhaw-Luximon, "Correlating in Vitro Performance with Physico-Chemical Characteristics of Nanofibrous Scaffolds for Skin Tissue Engineering using Supervised Machine Learning Algorithms," *R. Soc. Open Sci.* **2020**, *7*, 201293.

[234] M. Shirzad, A. Zolfagharian, M. Bodaghi, S. Y. Nam, "Auxetic Metamaterials for Bone-Implanted Medical Devices: Recent Advances and New Perspectives," *Eur. J. Mech. A. Solids* **2022**, *98*, 104905.

[235] M. Shirzad, J. Kang, G. Kim, M. Bodaghi, S. Y. Nam, "Bioinspired 3D-Printed Auxetic Structures with Enhanced Fatigue Behavior," *Adv. Eng. Mater.* **2024**, *26*, 2302036.

[236] L. Ren, W. Wu, L. Ren, Z. Song, Q. Liu, B. Li, Q. Wu, X. Zhou, "3D Printing of Auxetic Metamaterials with High-Temperature and Programmable Mechanical Properties," *Adv. Mater. Technol.* **2022**, *7*, 2101546.

[237] Q. Zeng, Z. Zhao, H. Lei, P. Wang, "A Deep Learning Approach for Inverse Design of Gradient Mechanical Metamaterials," *Int. J. Mech. Sci.* **2023**, *240*, 107920.

[238] H. Pahlavani, M. Amani, M. C. Saldívar, J. Zhou, M. J. Mirzaali, A. A. Zadpoor, "Deep Learning for the Rare-Event Rational Design of 3D Printed Multi-Material Mechanical Metamaterials," *Commun. Mater.* **2022**, *3*, 46.

[239] E. Roldán, N. D. Reeves, G. Cooper, K. Andrews, "Machine Learning to Predict Morphology, Topography and Mechanical Properties of Sustainable Gelatin-based Electrospun Scaffolds," *Sci. Rep.* **2024**, *14*, 21017.

[240] C. Wu, A. Entezari, K. Zheng, J. Fang, H. Zreiqat, G. P. Steven, M. V. Swain, Q. Li, "A Machine Learning-based Multiscale Model to Predict Bone Formation in Scaffolds," *Nat. Comput. Sci.* **2021**, *1*, 532.

[241] M. Li, S. Li, Y. Tian, Y. Fu, Y. Pei, W. Zhu, Y. Ke, "A Deep Learning Convolutional Neural Network and Multi-Layer Perceptron Hybrid Fusion Model for Predicting the Mechanical Properties of Carbon Fiber," *Mater. Des.* **2023**, *227*, 111760.

[242] J. Kang, M. Shirzad, J. M. Seok, W.-K. Jung, S. Y. Nam, "Mechanical Enhancement of Porous Scaffolds through Integration of Auxetic and Conventional Structures," *Mater. Lett.* **2025**, *379*, 137675.

[243] M. Shirzad, A. Zolfagharian, A. Matbouei, M. Bodaghi, "Design, Evaluation, and Optimization of 3D Printed Truss Scaffolds for Bone Tissue Engineering," *J. Mech. Behav. Biomed. Mater.* **2021**, *120*, 104594.

[244] A. J. Silvaroli, V. Chang, T. R. Heyl, J. M. Beebe, D. Ahn, S. Mangold, B. Clark, M. Wang, K. R. Shull, "Effects of Composition and Cure Parameters on the Mechanical and Optical Properties of Silicone/Methacrylate Hybrid Elastomers," *Macromolecules* **2024**, *57*, 8588.

[245] S. Lantean, G. Barrera, C. F. Pirri, P. Tiberto, M. Sangermano, I. Roppolo, G. Rizza, "3D Printing of Magnetoresponsive Polymeric Materials with Tunable Mechanical and Magnetic Properties by Digital Light Processing," *Adv. Mater. Technol.* **2019**, *4*, 1900505.

[246] A. J. Lew, M. J. Buehler, "Single-Shot Forward and Inverse Hierarchical Architected Materials Design for Nonlinear Mechanical Properties using an Attention-Diffusion model," *Mater. Today* **2023**, *64*, 10.

[247] A. J. Lew, M. J. Buehler, "Encoding and Exploring Latent Design Space of Optimal Material Structures via a VAE-LSTM Model," *Forces Mech.* **2021**, *5*, 100054.

[248] L. Moroni, T. Boland, J. A. Burdick, C. De Maria, B. Derby, G. Forgacs, J. Groll, Q. Li, J. Malda, V. A. Mironov, "Mironov, Biofabrication: A Guide to Technology and Terminology," *Trends Biotechnol.* **2018**, *36*, 384.

[249] A. F. Bonatti, G. M. Fortunato, C. De Maria, G. Vozzi, *Bioprinting: From Multidisciplinary Design to Emerging Opportunities*, Elsevier **2022**, pp. 19–49.

[250] Y. Briones, B. Pascua, N. Tiangco, I. Crisostomo, S. Casiguran, R. Remenyi, "Assessing the Landscape of Clinical and Observational Trials Involving Bioprinting: A Scoping Review," *3D Printing in Medicine* **2025**, *11*, 5.

[251] K. Ruberu, M. Senadeera, S. Rana, S. Gupta, J. Chung, Z. Yue, S. Venkatesh, G. Wallace, "Coupling Machine Learning with 3D Bioprinting to Fast Track Optimisation of Extrusion Printing," *Appl. Mater. Today* **2021**, *22*, 100914.
[252] B. Sarode, A. Kuthe, B. Petkar, A. Bagde, S. Daronde, G. Dhanuskar, in *Int. Conf. on Industry 4.0 and Advanced Manufacturing*, Springer, NewYork **2024**.
[253] C. Zhang, K. C. M. L. Elvitigala, W. Mubarok, Y. Okano, S. Sakai, "Machine Learning-based Prediction and Optimisation Framework for as-Extruded Cell Viability in Extrusion-based 3D Bioprinting," *Virtual Phys. Prototyping* **2024**, *19*, e2400330.
[254] C. Dai, Y. Sun, H. Zhang, Z. Yuan, B. Zhang, Z. Xie, P. Li, H. Liu, "New Strategies for High Efficiency and Precision Bioprinting by DOE Technology and Machine Learning," *Adv. Mater. Technol.* **2025**, *10*, 2401138.
[255] S. Rafieyan, E. Ansari, E. Vasheghani-Farahani, "A Practical Machine Learning Approach for Predicting the Quality of 3D (bio) Printed Scaffolds," *Biofabrication* **2024**, *16*, 045014.
[256] Z. Jin, Z. Zhang, X. Shao, G. X. Gu, "Monitoring Anomalies in 3D Bioprinting with Deep Neural Networks," *ACS Biomater. Sci. Eng.* **2021**, *9*, 3945.
[257] D. Kelly, V. Sergis, L. Ventura i Blanco, K. Mason, A. C. Daly, "Autonomous Control of Extrusion Bioprinting using Convolutional Neural Networks," *Adv. Funct. Mater.* **2025**, *35*, 2424553.
[258] A. F. Bonatti, G. Vozzi, C. K. Chua, C. De Maria, "A Deep Learning Quality Control Loop of the Extrusion-based Bioprinting Process," *Int. J. Bioprinting* **2022**, *8*, 620.
[259] Z. A. Sheikh, O. Clarke, A. Mir, N. Hibino, "Deep Learning for Predicting Spheroid Viability: Novel Convolutional Neural Network Model for Automating Quality Control for Three-Dimensional Bioprinting," *Bioengineering* **2025**, *12*, 28.
[260] K. Yao, J. Sun, K. Huang, L. Jing, H. Liu, D. Huang, C. Jude, "Analyzing Cell-Scaffold Interaction through Unsupervised 3D Nuclei Segmentation," *Int. J. Bioprint.* **2021**, *8*, 495.
[261] J. Song, J. Lee, N. Kim, K. Min, "Artificial Intelligence in the Design of Innovative Metamaterials: A Comprehensive Review," *Int. J. Precis. Eng. Manuf.* **2024**, *25*, 225.
[262] M. Y. Khalid, Z. U. Arif, A. Tariq, M. Hossain, R. Umer, M. Bodaghi, "3D Printing of Active Mechanical Metamaterials: A Critical Review," *Mater. Des.* **2024**, *246*, 113305.
[263] M. Bodaghi, N. Namvar, A. Yousefi, H. Teymouri, F. Demoly, A. Zolfagharian, "Metamaterial Boat Fenders with Supreme Shape Recovery and Energy Absorption/Dissipation via FFF 4D Printing," *Smart Mater. Struct.* **2023**, *32*, 095028.
[264] X. Zheng, X. Zhang, T. T. Chen, I. Watanabe, "Deep Learning in Mechanical Metamaterials: From Prediction and Generation to Inverse Design," *Adv. Mater.* **2023**, *35*, 2302530.
[265] M. Bodaghi, K. Rahmani, M. L. Dezaki, C. Branfoot, J. Baxendale, "3D/4D Printed Bio-Composites Reinforced by Bamboo Charcoal and Continuous Flax Fibres for Superior Mechanical Strength, Flame Retardancy and Recoverability.," *Polym. Test.* **2025**, *143*, 108709.
[266] S. Dimassi, F. Demoly, C. Cruz, H. J. Qi, K.-Y. Kim, J.-C. André, S. Gomes, "An Ontology-based Framework to Formalize and Represent 4D Printing Knowledge in Design," *Comput. Ind.* **2021**, *126*, 103374.
[267] X. Sun, K. Zhou, F. Demoly, R. R. Zhao, H. J. Qi, "Perspective: Machine Learning in Design for 3D/4D Printing.," *J. Appl. Mech.* **2024**, *91*, 030801.
[268] M. Ghalambaz, M. A. Sheremet, M. A. Khan, Z. Raizah, J. Shafi, "Physics-informed Neural Networks (P INNs): Application Categories, Trends and Impact," *Int. J. Numer. Methods Heat Fluid Flow* **2024**, *34*, 3131.
[269] J. Liu, E. S. Zainudin, A. B. Asarry, M. I. S. B. Ismai, C. Zhang, "Modeling of the Blockchain-Empowered Cloud 4D Printing Services Collaboration Digital Twin Platform Oriented on Supply–Demand: J. Liu et al.," *Soft Comput.* **2025**, *29*, 977.
[270] S. S. Babu, A.-H. I. Mourad, K. H. Harib, S. Vijayavenkataraman, "Recent Developments in the Application of Machine-Learning towards Accelerated Predictive Multiscale Design and Additive Manufacturing," *Virtual Phys. Prototyping* **2023**, *18*, e2141653.
[271] O. Bougzime, C. Cruz, J.-C. André, K. Zhou, H. J. Qi, F. Demoly, "Neuro-Symbolic Artificial Intelligence in Accelerated Design for 4D Printing: Status, Challenges, and Perspectives," *Mater. Des.* **2025**, *252*, 113737.