Agentic AI for Autonomous and Sustainable Additive Manufacturing: A Comprehensive Review of Text-to-CAD Frameworks, Multi-Agent Architectures, and Cross-Process Adaptability

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Abstract

This review is a thorough review on the rapid convergence of Agentic Artificial Intelligence (AI) and Machine Learning (ML) with advanced manufacturing to enable a fully autonomous "Text-to-Print" workflow. We examine the key technological pillars that bridge design intent with physical fabrication. In this review, Section 1 introduces the motivation for automation to overcome critical bottlenecks in the design-to-manufacture pipeline, specifically in Computer-Aided Design (CAD) modeling, process parameter tuning, and quality control. Section 2 provides a conceptual foundation for Agentic AI, reviewing how many agentic AI, that include Large Language Model (LLM)-based agents, multi-agent systems, and planning frameworks like Reinforcement Learning (RL) and ReAct (Reasoning then Acting) create a new era of autonomous, goal-driven manufacturing. Section 3 reviews the state-of-the-art AI-driven geometry generation, comparing procedural, parametric, and the emerging "Text-to-CAD" models (e.g., MEDA, CAD-Llama) that leverage CAD APIs as tools to increase efficiency and accessibility in CAD designing. Section 4, the core of this review, analyzes the role of ML in the industrialization of Additive Manufacturing (AM). We conduct a deep review of ML applications in process optimization, in material science, and in defect prediction, while focusing on the critical roles of Physics-Informed Neural Networks (PINNs) and Digital Twins in achieving industrial-scale quality and repeatability. Finally, Section 5 compiles these components into a complete "closed-loop learning factory" concept, analyzing end-to-end case studies of self-correcting systems and concluding with a critical assessment of the foremost challenges—data inter-operability, model explainability (XAI), and the ethical governance of autonomous design. This review additionally surfaces three key findings: Multi-Agent Systems (MAS) consistently outperform single-agent designs for complex, multi-domain manufacturing tasks; intelligent AM systems carry significant but largely untapped potential for reducing material waste and supporting sustainable manufacturing; and LLM-based agentic frameworks exhibit a cross-process adaptability—transferring reasoning across different AM processes with minimal reconfiguration—that narrow, task-specific ML models cannot easily match.

Keywords: Agentic AI, Text-to-CAD, Multi-Agent Systems, Machine Learning, Additive Manufacturing, Sustainable Manufacturing, Cross-Process Adaptability, Autonomous Manufacturing.

1. Introduction

1.1 Why We Need to Automate the Design-to-Manufacture Pipeline

The fourth industrial revolution, most commonly called Industry 4.0, is characterized by the mandate for manufacturing industries to achieve higher efficiency, greater productivity, and mass customization [1]. Automation technologies are increasingly implemented to optimize processes and achieve these goals, enabling increased production volume while ensuring uniform output. The primary motivation for automating the design-to-manufacture pipeline is to fundamentally accelerate and optimize this entire process, from initial concept to final product [1]. Artificial Intelligence (AI) and Machine Learning (ML) are the main ingredients in this transformation. They are positioned to serve not only as tools for "Task automation"—reducing the burden of repetitive, non-creative work such as data conversion or design certification—but also as “Concept Innovators."

In the former role, AI/ML reduces time spent by humans on tedious and “boring” tasks, while in the latter role, it can offer multiple novel solutions for complex engineering design tasks, integrating multimodal information spanning materials, processes, and geometries [3]. This vision is materializing in the form of "cybermanufacturing" a new service-oriented architecture (SOA) where on-demand computation, data analytics, and ML are designed to seamlessly satisfy complex manufacturing requests [4].

1.2 Critical Bottlenecks in Additive Manufacturing (AM)

Additive Manufacturing (AM), or 3D printing, has emerged as a transformative technology, offering unprecedented design freedom and the potential for mass customization.[2] However, its widespread industrial application is "currently hampered by technical challenges in process repeatability and quality management" [2].

This review identifies three primary, interdependent bottlenecks that currently pose a challenge to the full industrialization of AM:

1. Quality, Repeatability, and Defects: The layerwise fabrication process, unique to AM, introduces "specific quality challenges".[2] Variability in the final product quality, stemming from a multitude of factors, remains a "major barrier" to the adoption of AM in production environments.[6] Inconsistent results lead to losses in time and money, posing a major concern to manufacturers.

2. Process Parameter Complexity: The AM process is a "complex and multifaceted undertaking, with various parameters that can significantly influence the quality and efficiency of the printed parts".[5] The selection and optimization of these parameters—such as laser power, scan speed, or material flow rate—are "crucial in controlling the properties of AM products".[7] Traditional trial-and-error methods for finding optimal parameters are slow, costly, and inefficient.[8]

3. Design and Materials Complexity: The AM workflow begins with a digital model from Computer-Aided Design (CAD) software.[5] However, optimizing a part for the AM process, known as Design for Additive Manufacturing (DfAM), is a highly complex, data-intensive field.[9] This is layered additionally by a frequent lack of a "robust understanding of processes... and materials range".[10] Thus, simplifying the process requires careful deliberation by intelligent designers, both human and machine.

These bottlenecks are not completely discrete; in fact, they are deeply interdependent. A design choice made in the DfAM phase 9 directly and complexly impacts the optimal set of process parameters 7, which in turn determines the final part quality and the probability of defects.[2] This creates a high-dimensional, interconnected optimization problem that is intractable for human operators and traditional engineering workflows.

1.3 Agentic AI and ML as Enablers

ML is now widely applied as an effective method for "quality control, process optimization, and complex system modeling" to address these individual bottlenecks.[9] However, this review argues that a more profound paradigm shift is underway. The solution thus needs to cater to a deeply interdependent problem, and therefore is not a set of discrete ML models, but a holistic, goal-driven system that can manage the entire pipeline.

This is the concept of "autonomous fabrication", which works on the vision of "absolutely autonomous fabrication procedures, optimizing supply chains and personalizing products".[14]

The core technology that enables this vision is Agentic AI.[15] Agentic AI moves beyond simple automation (performing a known task faster and more efficiently) and toward autonomy—the ability to handle complex, open-ended, goal-driven processes from end to end.

2. The Rise of Agentic AI in Manufacturing Systems

2.1 Agentic AI in a Manufacturing Context

The field of AI in manufacturing is undergoing a "paradigm shift":- away from passive, task-specific tools and towards creating autonomous, agentic systems. In the manufacturing domain, Agentic AI "introduces a new paradigm in which manufacturing systems can autonomously define, refine, and execute goals in dynamic environments with minimal human intervention".[15] This represents a fundamental move "from reactive task optimization to proactive system-level intelligence".[16]

Unlike traditional automation, which follows pre-programmed rules, Agentic AI systems are defined by a set of more sophisticated capabilities. These include self-directed, goal-driven intelligence , "proactive planning, contextual memory, sophisticated tool use, and the ability to adapt their behavior based on environmental feedback".[15] An agentic system perceives its environment (e.g., via machine sensors), makes judgments, and acts autonomously to achieve a high-level goal.[19]

The primary catalyst for this shift has been the recent emergence of functional Large Language Models (LLMs). LLMs provide "cognitive abilities nearing human levels in planning and reasoning"[20], acting as the "core for decision-making" [21] or the "brain" of any autonomous system. The agentic framework, in turn, provides the LLM with the autonomy, memory, and tool-use capabilities required to execute tasks in the physical world.

A key advantage that stems directly from building agents on general-purpose LLMs is cross-process adaptability. A general-purpose LLM encodes broad scientific and engineering knowledge during pre-training, which means the agent it powers is not bound to a single manufacturing process. A traditional ML model trained on data from one process—say, Fused Deposition Modeling (FDM)—has no reliable footing when applied to a different process such as Laser Powder Bed Fusion (L-PBF) without significant retraining. An LLM-based agent, by contrast, can apply its general physical and materials reasoning to a new process with far less reconfiguration. In manufacturing environments where multiple processes run side by side, this flexibility has real practical value.

2.2 Multi-Agent Systems (MAS) for Complex Orchestration

While a single AI agent can be designed to accomplish a specific goal in isolation [15], real-world manufacturing problems are too complex for any single agent. They span multiple domains, from design and simulation to logistics and quality control.[20] Consequently, the "Agentic AI" architectural approach [15] for manufacturing invariably involves Multi-Agent Systems (MAS).[15] A MAS leverages "synergistic collaboration" by composing a team of "multiple specialized agents, each with unique skills and responsibilities". This architecture emulates a "multi-agent collaborative division of labor" [20] and is the necessary solution to the interdependent, multi-domain bottlenecks identified in Section 1. Beyond design elegance, this division of labor carries a measurable performance advantage. When a single agent must simultaneously handle design interpretation, code generation, execution, and visual review, its reliability degrades under the weight of competing responsibilities. Distributing these tasks across specialized agents consistently produces higher success rates—a pattern that emerges clearly when comparing single-agent and multi-agent results across the reviewed literature. A "Designer Agent" can collaborate with a "Process Agent" and a "Quality Assurance Agent" to manage the full, complex workflow.

2.3 The Human-in-the-Loop (HITL) vs. Fully Autonomous Spectrum

An unmissable debate in the industrial deployment of Artificial Intelligence is the required level of human oversight. This is not a binary choice but a spectrum; with two types of theories emerging.

Human-in-the-Loop (HITL) is a popular approach in which machines handle repetitive or data-heavy tasks, but "humans step in for validation, quality control, or decision-making".[23] While this model ensures accuracy, auditability, and ethical oversight, it can re-introduce a human bottleneck, limiting the scalability and speed that autonomy promises [24]. Human-on-the-Loop (HOTL) is a hybrid model that is the most practical and desirable architecture for industrial adoption. In a HOTL system, the "system can operate autonomously, but there's a human monitoring the process and able to intervene if needed".[25]. For the near-to-mid future, the consensus is that manufacturing systems will "still need a 'human-in-loop' [or 'on-loop'] to offer supervisory level mediation".[26]

2.4 Foundational Planning Frameworks

Agentic AI systems are defined by their ability to reason and plan. This "cognitive" work is enabled by several key frameworks that bridge the gap between abstract goals and executable actions.

1. Reinforcement Learning (RL): RL is a critical component for enabling agents to learn and adapt in dynamic physical environments. It is a key enabler of adaptive control, with a growing number of applications in "multi-agent reinforcement learning in smart factories".[27] LLM Reasoning Frameworks: For higher-level cognitive tasks, LLM-powered agents use specific reasoning patterns to decompose and solve problems.
2. Chain-of-Thought (CoT): This is a foundational prompting technique [30] that guides the LLM to "break down complex reasoning into intermediate steps".[30] By "thinking aloud," the model can more reliably perform the complex, logical decomposition required to plan a manufacturing task.[33]
3. ReAct (Reason + Act): This framework is the critical link that connects an agent's "brain" to the "world".[34] It is a "common design approach" [35]that can be defined as Chain-of-Thought + Function Calling.[35] The agent operates in a continuous loop: Reason (Thought): use CoT to analyze the problem and form a plan, Act (Action): select and execute a "tool" and Observe (Observation): receive the output from the tool, review the result, and integrate this new information.
4. Tree-of-Thought (ToT): This is a more advanced reasoning technique where the agent "explores different paths to solve a problem".[30] It generates and evaluates multiple, distinct ideas or plans at each step, forming a "tree" of possibilities, which is essential for creative design space exploration.[33]

These frameworks are not mutually exclusive; a sophisticated agent may use ToT for initial design ideation, ReAct to execute the design and simulation, and an underlying RL policy to manage real-time process control.

Table 1: Comparative Analysis of AI Agent Planning Frameworks

Framework	Core Principle	Key Capabilities	Relevance to Autonomous Fabrication
Chain-of-Thought (CoT)	Decomposing complex problems into a sequence of intermediate logical steps.30	Complex reasoning, logical deduction, arithmetic reasoning.	Planning: Decomposing a high-level user request (e.g., "design a lightweight bracket") into a logical sequence of design steps.
ReAct (Reason+Act)	Integrating reasoning (CoT) with iterative tool use (Function Calling) and environmental feedback.34	Real-world interaction, information gathering, task execution.	Execution: The core loop. Calling the CAD API (Act), getting a thermal simulation result (Observe), and planning the next step (Reason).
Tree-of-Thought (ToT)	Exploring and evaluating multiple reasoning paths in parallel or sequentially.30	Creative problem-solving, design space exploration, self-correction.	Design: Exploring multiple, distinct design alternatives (e.g., different topology options) for a single prompt before selecting the optimal one.
Reinforcement Learning (RL)	Learning an optimal action policy by maximizing a reward signal from environmental feedback.27	Real-time adaptive control, continuous optimization, self-learning.	Process Control: Dynamically adjusting laser power or flow rate in-situ based on real-time sensor feedback to maintain melt pool stability.

3. AI-Driven Geometry: From Textual Intent to Parametric CAD

3.1 The Evolution from Manual to AI-Driven Design

The "Act" step in an autonomous fabrication workflow begins with translating a design intent into a physical geometry. This remains a significant bottleneck, as "Creating Computer-Aided Design (CAD) models requires significant expertise and effort".[37] This section reviews the evolution of AI's role in automating this critical geometry generation phase.

3.2 Modeling Paradigms

The ability for an AI to "act" upon a design is contingent on the modeling paradigm used.

· Procedural and Script-Based Modeling: This is the foundation of design automation and the primary "tool" for an AI agent. Instead of a human manually editing a design, geometry is defined by executable code.[38] This includes open-source tools like OpenSCAD [39], Python scripting libraries [40], and proprietary scripting languages like AutoLisp [38] and RhinoScript.[38] A 2025 study, for example, utilizes Rhinoscript to algorithmically design and subsequently 3D print complex, bio-inspired support structures for medical applications, such as modeling a human aorta.[43]

· Parametric Modeling: This paradigm, in which designs are controlled by a set of adaptable parameters, is "widely used for generating adaptable mechanical parts".44 It offers superior "dynamic adaptability" compared to traditional, static methods, as changes to parameters can regenerate the model without arduous manual remodeling.[42]

· Text-to-CAD (Generative AI): This is the most recent paradigm, which leverages LLMs to "convert textual descriptions into CAD parametric sequences".[37] This emerging field allows users to provide natural language prompts [45] or even multimodal inputs, such as freehand sketches [46], to an AI system that then generates the corresponding CAD model.

3.3 State-of-the-Art AI-CAD Frameworks (2023-2025)

The field of Text-to-CAD is rapidly bifurcating into two main architectural approaches: fine-tuned models and agentic frameworks.

Tuned LLM Models (e.g., CAD-Llama): This approach involves fine-tuning an LLM on large, specialized datasets of CAD operations. CAD-Llama (Li et al. 2025) is a very major example in these changing times. It makes use of a "hierarchical annotation pipeline" that is somehow used in transforming raw CAD and command sequences into "semantically structured CAD code".[46] The LLM is then then later pre-trained and made adaptable and instruction-tuned on this data, enabling it and most importantly allowing it to generate high-fidelity, parametric 3D models directly from a text prompt.[46]

Agentic Frameworks (e.g., CADDesigner, MEDA): This is typically and majorly most used approach that uses a generalp urpose LLM and especially often with no CAD specific tuning as the "brain" for an intelligent agent.

CADDesigner (Ni et al. 2025) is a "ReAct-style" agent and server that can be accepted both as text and sketches.[47] Critically, it does not just generate a model; it engages in "interactive dialogue" with the user and incorporates "iterative visual feedback" to progressively refine the design, much like a human designer.[47]

MEDA (Mechanical Engineering Design Agents) is a Multi-Agent System (MAS) that scales this concept.[48]MEDA "emulate[s] human-like division of labor" [48] by employing a specialized team of agents: a "Design Expert" agent interprets the prompt and creates a modeling plan; a "CAD Script Writer" agent generates Python code for the open-source CadQuery library; an "Executor" agent runs the code; and a "CAD Image Reviewer" agent analyzes the resulting image and provides refinement feedback to the team.[48] This robust, collaborative approach achieved a 99% success rate in script execution in its evaluation.[48] This result, achieved through structured agent collaboration, is notably higher than what single-agent approaches report on tasks of comparable complexity—providing early empirical grounding for the performance advantage of multi-agent architectures in CAD generation workflows.

These agentic frameworks are arguably more flexible than tuned models. They can engage in dialogue, leverage visual feedback, and use external tools (like physics simulators), which is difficult for a static, fine-tuned model.

Table 2: Taxonomy of AI-Driven CAD Generation Frameworks (2023-2025)

Framework	Reference	Core Architecture	Input Modality	Output Format	Key Innovation /	Key Limitation
CAD-Llama	Li et al. (2025)	Tuned LLM	Text	Parametric Script (Structured Code)	High-fidelity semantic code generation.	Requires massive, specific fine-tuning dataset.
CADDesigner	Ni et al. (2025)	Single Agent (ReAct-style)	Text + Sketch	CAD Script (e.g., OpenECAD)	Iterative visual feedback and user dialogue.	Relies on general-purpose LLM's spatial reasoning.
MEDA	Regmi et al.	Multi-Agent System (MAS)	Text	Python (CadQuery) Script	"Division of labor" (Design, Write, Execute, Review).	Increased system complexity and orchestration.

3.4 Role of CAD APIs as "Tools" for Agents

A common, critical thread across all successful AI-CAD frameworks is the paradigm of "CAD-as-Code." The AI agents do not "click" buttons in a graphical user interface; they act by writing code.35 This code then interfaces with a CAD kernel through an Application Programming Interface (API).

These APIs are the "tools" in the agent's ReAct framework. Examples include the Autodesk Fusion API [39], RhinoScript [38], and open-source libraries like CadQuery.48 This approach allows the AI to generate a design (e.g., in OpenECAD) and then use the Fusion API to "convert... [it] into AutoDesk Fusion project files," where a human engineer can continue modifications.[39] For an autonomous workflow, the CAD API must be the primary, scriptable interface.

3.5 ML-Guided Scripts for Reproducibility and Optimization

The industrial power of CAD-as-Code lies not just in generation, but in optimization and reproducibility. A design defined by a script (e.g., a Python or OpenSCAD file) is a fully "computationally reproducible" artifact.[49] This is essential for auditable, trustworthy, and verifiable engineering, a standard that static mesh files cannot meet. However, this reproducibility is threatened by "reliance of codes on CAD kernels that are not open-source" (e.g., Parasolid), which limits access for academic researchers and breaks the chain of verification.[50] The true value of a parametric script is that it defines a search space. Once a design is code, its parameters can be optimized by an ML model. This is the concept of "ML guided ML" for "process parameter optimization".[41] A powerful 2025 case study in biomedicine demonstrates this by using "AI-driven generative design" and "topology optimization" to algorithmically design "advanced bone scaffolds." In this workflow, the AI iteratively refines the script's parameters to meet specific, quantifiable goals for porosity and structural strength.

This creates the logical hand-off to the next stage of the pipeline. The "Designer Agent" of Section 3 creates the parametric search space (the script). This script is then passed to the "Process Agent" and "QA Agent" of Section 4 to be physically executed, simulated, and optimized.

4. The Role of Machine Learning in the Industrialization of Additive Manufacturing (AM)

4.1 ML in AM Industrialization

The process of converting a CAD design into a physical component through additive manufacturing is highly complex. As a result, the successful industrial adoption of AM, beyond its traditional role in prototyping—largely depends on the effective use of Machine Learning. ML has been identified as a key enabler for addressing the "variability in product quality" that continues to "pose a major barrier" to the widespread application of AM.[6]

ML models are being applied across the entire AM lifecycle, including "design, process plan, build, post process, and test and validation".[6] AI-driven approaches can "automatically" acquire and apply the knowledge of experienced human operators, thereby simplifying production and reducing the risk of human error.[52]

Recent (2024-2025) reviews of the field confirm this "transformative role".[53] Xiao et al. (2024) and Chen et al. (2024) highlight the increasing application of advanced ML techniques, including "semi-supervised learning and reinforcement learning," to "further optimize and automate AM processes".[53]Concurrently, Ukwaththa et al. (2024), in the "first-ever review" of its kind, analyze the critical role of Explainable AI (XAI) in AM.[54]This work identifies the "black box" nature of many ML models as a primary obstacle to trust and adoption, noting that the use of XAI in AM is "still very limited".[54] The path to industrialization, therefore, requires not just predictive ML models, but *explainable* ones.

Table 3: Applications of Machine Learning Across the AM Lifecycle

AM Lifecycle Stage	Key Objective	ML/AI Application	Key Technologies / References
1. Design	Generate novel, performant, and manufacturable structures.	Topology Optimization; Generative Design; DfAM.	AI-driven Generative Design for biomedical scaffolds.[51]
2. Pre-Processing (Process Plan)	Optimize build parameters before printing to ensure quality and efficiency.	Process Parameter Optimization; Inverse Process Design.	ML-driven "AIDED" Framework for DED [8]; Supervised Learning.[53]
3. In-Process (Build)	Real-time monitoring, control, and defect prediction during fabrication.	In-Situ Defect Detection; Real-time Simulation; Adaptive Process Control.	CNNs for defect detection [56]; PINN-driven Digital Twins [57]; Reinforcement Learning.[27]

4. Post-Processing (Test & QA)	Certify final part quality; predict mechanical properties; characterize defects.	Predictive Quality Assurance; Defect Characterization.	ML for QA metrics [56]; XAI for validation and trust.[54]

4.2 Industrialization: Defect Prediction & Quality Assurance

Industrialization mandates a shift from one-off successes to "predictive quality assurance" with high repeatability.[60] Defect Detection and Quality Assurance (QA): ML is "pivotal in quality control, detecting defects, and ensuring consistent output".[61] This is achieved by training ML models, such as Convolutional Neural Networks (CNNs) or Support Vector Machines (SVMs) [56] to analyze data from *in-situ* monitoring systems. A 2024 study, for example, demonstrated a YOLO-based defect detection system that achieved 93% precision in real-time, highlighting its feasibility for industrial integration.[62] By analyzing and modeling process data, ML ensures "high precision" and "consistency" in the final products.[63]

4.3 Optimization of Process & Materials

ML models are uniquely adept at navigating the high-dimensional parameter space of AM. This remains a primary application of ML in AM.[55] Traditional trial-and-error is being replaced by intelligent frameworks. A 2025 paper by Shang et al. introduces the "Accurate Inverse process optimization framework in laser Directed Energy Deposition (AIDED)".[8] This machine-learning-based system is built to rapidly determine the best process parameters for laser 3D printing based on the desired industrial outcome, significantly cutting down both development time and cost. Machine learning is also used during the component- and structural-design stages, such as optimizing the composition of multi-component alloys for targeted material properties and creating complex porous structures, an approach especially useful in manufacturing metallic biomaterials.[58]

An often-overlooked but commercially significant outcome of intelligent process optimization is its impact on resource efficiency. When an ML model correctly predicts optimal build parameters before fabrication begins, failed prints and scrapped material decrease substantially. Several reviewed studies report reduced material waste as a secondary benefit of their optimization frameworks, though none treat sustainability as a primary design objective. Given the considerable material and energy demands of industrial AM, designing agentic systems with explicit sustainability targets is a high-value direction that current research has yet to fully explore.

4.4 Physics-Informed ML (PINNs)

A major challenge in using machine learning for additive manufacturing is the limited availability of high-quality data. Physical experiments are costly, slow, and typically produce sparse datasets. Physics-Informed Neural Networks (PINNs) have recently gained attention as an effective way to overcome this limitation.

A PINN is a neural network architecture that *embeds* the governing physical equations (e.g., differential equations for heat transfer or fluid dynamics) directly into the model's loss function.[57] This allows the model to "embed the physical laws governing heat transfer, fluid flow, and mechanical behavior".[57]

The advantages are twofold: the model naturally incorporates physical laws, and it can still learn effectively even when data is limited. As a result, PINNs are capable of delivering accurate, “real-time” predictions of complex and otherwise unmeasurable behaviors such as “temperature distribution, viscosity, and stress fields”.[57]

The use of this approach has emerged as a major trend during 2024–2025. A 2024 review highlights a “significant increase” in physics-informed simulations,[41] and a 2025 study similarly reports a “sharp rise” in PINN-related publications.[57] One important application is in “Accelerating Thermal Simulations in Additive Manufacturing,” particularly for processes like Laser-Powder Bed Fusion (L-PBF).[58] This physics-informed ML framework helps bridge the gap between high-fidelity simulations and real-time process control, making it a crucial enabler for industrialization.[65]

4.5 Digital Twins (DTs)

The Digital Twin (DT) is the high-level infrastructure that integrates these ML models into a cohesive system. A DT is an "accurate digital model that mirrors the characteristics, conditions, and behaviors of the physical object"[66]. It is updated in "real time" using data from Internet of Things (IoT) sensors on the physical machine [66].

While the "deployment of digital twin technologies in manufacturing is still at an early stage," with many applications being "prototypes focused on real-time observability"[67], the true vision is the "Integration of Artificial Intelligence and Digital Twins"[68].

The DT provides the high-fidelity simulation environment [69] in which an AI agent can operate. Research is actively exploring the combination of "Deep Reinforcement Learning (DRL) with digital twins to significantly enhance decision-making" [69].

This reveals a powerful symbiotic relationship. A high-fidelity DT (e.g., based on Finite Element Method) is too computationally slow for real-time control. A "pure" ML model is data-hungry. The PINN-driven Digital Twin is the solution. The DT provides the *sparse, real-time sensor data* [66] that "grounds" the PINN. The PINN [57] then serves as the predictive *engine* for the DT, using its embedded physics to accurately and rapidly predict melt pool stability, thermal stress, and other critical parameters.

This entire suite of technologies—*in-situ* monitoring, ML-based defect detection, and PINN-driven Digital Twins—constitutes the "Observation" mechanism for an autonomous agent. This is the feedback loop that enables the system to understand its own performance, and it provides the logical bridge to the final section: closing the loop for autonomous correction.

5. Toward an Autonomous “Text-to-Print” Workflow

5.1 End-to-End "Text-to-Print" Pipeline

The preceding sections have reviewed the three pillars of an autonomous fabrication system:

· The Agent (Section 2): A goal-driven AI, likely a Multi-Agent System (MAS), operating on a ReAct (Reason-Act-Observe) loop [15].

· The "Act" (Section 3): The agent's ability to "act" by generating "CAD-as-Code" and interfacing with parametric CAD APIs [39].

· The "Observe" (Section 4): The agent's "senses," provided by a "PINN-driven Digital Twin"[57] and ML-based QA models [62] that monitor the physical build.

This final section concludes these pillars into a single, "Text-to-Print" pipeline [70]. This integrated architecture is now being conceptualized as a "Generative Manufacturing System (GMS)"[72] or "Multi Agent Generative System (MAGS)"[73]. These frameworks are designed to orchestrate autonomous manufacturing resources through "conversational, human-centered decision-making"[72] and "decentralize decision-making authority across a network of autonomous manufacturing agents"[72]. This system is a "Cognitive digital twin" [72] where generative agents and LLMs actively enhance data-driven production logistics [74].

5.2 Closed-Loop Learning Factories and Self-Correction

The ultimate goal of this synthesis is the "closed-loop learning factory"[71], a system capable of "AI agents that design, simulate, print, and self-correct." This includes the ability for "self-correction of anomalies" by "intervening when deemed necessary"[71].

This vision is not distant theory; it is a present-day engineering reality. A 2025 paper by Huang and Li provides a perfect microcosm of this entire autonomous loop [75].

- System: They developed a "cost-effective, real-time monitoring and correction system for material extrusion (MEX)"[75]

- Observe: The system uses a "single-camera system" and "image processing algorithms" to perform "real-time detection" of geometric deviations, specifically "layer shifting" [75].

- Act (Correct): Upon detecting an error, the system applies a "novel correction strategy" that "effectively preserved part geometry" by adjusting the print path in real-time, balancing over- and under-correction [75]

This work "lay[s] the foundation for self-correcting, high-precision MEX processes" [75]. It demonstrates empirically that the autonomous "Observe-Correct" loop is a functional and achievable mechanism. The full "Text-to-Print" workflow is, therefore, the *scaling* of this proven concept, integrating the high-level design (Section 3) and simulation (Section 4) layers with the machine-level correction loop.

5.3 Open Challenges and Future Directions

To scale this single-machine loop to a factory-wide autonomous workflow, critical, interdependent challenges must be addressed. These can be understood as a "Triad of Trust."

Table 4: Key Challenges and Mitigation Strategies for Autonomous Fabrication

Challenge Area	Specific Problem (Barrier to Industrialization)	Proposed Mitigation / Path Forward
Interoperability	"Fragmented, heterogeneous data trapped in silos" [80] from "legacy equipment" [82] with "divergent formats" [81] prevents reliable AI agent collaboration.	Solution: Adoption of "open standards" (e.g., JSON/XML, REST APIs) and robust "Metadata management" and "Data Governance".[81]
ainability & ability (Trust)	The "black box" nature of complex ML models [54] prevents certification and human trust. A "critical gap" exists in XAI *evaluation*.[85]	Solution: Implementation of Explainable AI (XAI) methods (e.g., SHAP, LIME).[85]
		Future Work: Development of "standardized evaluation frameworks" and quantitative metrics for XAI.[85]
cal & Legal ernance	An "accountability" vacuum for autonomous decisions [88], "algorithmic bias" from training data [89], and the "erosion of human judgment".[88]	Solution: Adherence to regulatory frameworks (e.g., EU AI Act) [88] and technically designing for "Human Agency and Oversight" [90] via a "Human-on-the-Loop" (HOTL) architecture.[25]

1. Data Interoperability: An autonomous system is only as good as its data. Industrial environments are notoriously difficult, plagued by "legacy equipment" [82], "fragmented, heterogeneous data trapped in silos" [80], and "divergent formats". AI agents "struggle to collaborate" when data is inconsistent.[81] The solution is not glamorous but essential: a "fix" [81] that prioritizes Standardization (open APIs, JSON/XML), Metadata Management, and robust Data Governance.[81]

2. Model Explainability (XAI) and Reliability: As identified by Ukwaththa et al., the "black box" nature of AI [84] is a primary barrier to industrial trust, reliability, and certification. We have to differentiate, Interpretability that is basically "How does the model work? from Explainability which again is "Why did the model make this specific decision?". [86] XAI methods like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) are the today's current standard very smart solutions. A 2024 systematic review notes SHAP is "favored for its stability and mathematical guarantees" and therefore is used for various daily applications like "predictive maintenance in manufacturing". However, this same review identifies a very critical and major gap that would be : the evaluation of XAI itself. Mostly studies usually "rely on anecdotal evidence... rather than robust quantitative metrics." The field "urgently need[s] standardized evaluation frameworks" for XAI.[85]

3. Ethical Implications and Human Agency: These, autonomous systems design and build physical objects raise "ethical implications". If an autonomous agent designs a faulty part, questions of "liability, accountability, and regulatory compliance" generate [88]. This is compounded by risks of "algorithmic bias" [89] and the "erosion of human judgment"[88]. The solution is twofold: (1) Governance, through adherence to "Ethical Guidelines" [92] and regulatory frameworks like the "EU Artificial Intelligence Act" [88]; and (2) Technical, by designing systems that mandate "Human Agency and Oversight".[90] This technical solution affirms that AI systems "should support and

enhance human decision-making rather than replace it" [90], leading directly back to the "Human-on-the-Loop" (HOTL) model as the most practical, ethical, and certifiable architecture for autonomous manufacturing.

These three challenges are inextricably linked. There can be no Ethical Accountability [88] without robust Model Explainability.[85] And there can be no reliable Explainability if the models are trained on corrupted, siloed, and incomplete data caused by a lack of Data Interoperability [80]. Therefore, solving the foundational "hard" infrastructure problem of data governance and interoperability is the prerequisite for solving the "soft" but critical challenges of trust, explainability, and ethical governance.

5.4 Conclusions

This review has charted a path from the interdependent bottlenecks of modern Additive Manufacturing to a fully autonomous, "Text-to-Print" workflow. This workflow is not based on a single, monolithic AI model, but on a sophisticated *architecture*.

The proposed architecture is a Multi-Agent System (MAS, or Generative Manufacturing System (GMS), that orchestrates specialized agents. This system operates on a ReAct (Reason-Act-Observe) loop. The *lingua franca* for the "Act" step is "CAD-as-Code," executed via parametric scripting APIs [48]. The "Observe" mechanism is a "PINN-driven Digital Twin" that provides real-time, physics-informed feedback. As demonstrated by current 2025 research, this system is capable of "closed-loop" self-correction at the machine level [75].

Beyond this core architectural finding, this review surfaces three additional key observations from the synthesized literature.

First, a measurable performance advantage of Multi-Agent Systems (MAS) over single-agent designs is evident for complex, multi-domain manufacturing tasks. A single agent handles well-scoped, isolated jobs adequately, but when multiple competing constraints must be balanced simultaneously—structural integrity, material behavior, and build-process compatibility—MAS architectures handle this complexity more reliably by distributing cognitive responsibility across specialized agents. The near-perfect script-execution rates reported in MEDA [48] and comparable systems [20] lend clear empirical weight to this observation.

Second, this review identifies an under-explored but commercially significant benefit: the potential of intelligent AM systems to support sustainable manufacturing. Across multiple reviewed studies, intelligent process optimization demonstrably reduces failed builds and material scrap. Yet no reviewed work treats sustainability as a primary design objective for an agentic system. Closing this gap is among the most practical and impactful directions available for near-term research.

Third, LLM-based agentic frameworks demonstrate a cross-process adaptability that narrow, task-specific ML models cannot easily replicate. Because a general-purpose LLM encodes broad engineering and materials knowledge, an agent built on such a model can transfer its reasoning strategies across different AM processes—from Fused Deposition Modeling (FDM) to Laser Powder Bed Fusion (L-PBF)—with minimal reconfiguration. This stands in direct contrast to traditional data-driven models, which are trained on process-specific datasets and require significant rework when the process changes.

The final, scaled system must be designed under a Human-on-the-Loop (HOTL) supervisory model to ensure safety, accountability, and trust. The primary barriers to this vision are not conceptual but practical: the "Triad of Trust" (Data Interoperability, Model Explainability, and Ethical Governance). The future of this field, hence, lies in building the standardized, open, and auditable data infrastructure upon which they can be trusted to operate [92].

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