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Integration of Artificial Intelligence and Human–Machine Collaboration in Additive Manufacturing: A Review in the Context of Industry 5.0

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Abstract: Additive Manufacturing (AM) enables high levels of customization and flexibility in modern production systems. At the same time, the transition toward Industry 5.0 introduces a human-centered and sustainable manufacturing paradigm. This paper reviews the integration of artificial intelligence (AI), particularly machine learning (ML), with AM processes, highlighting the role of human–machine collaboration. The study identifies a key research gap: the lack of integrated frameworks combining AM, AI, and human-centered design. A conceptual model for intelligent and adaptive manufacturing systems is proposed, aligned with Industry 5.0 principles [1], [2], [3].
Keywords: Additive Manufacturing, Artificial Intelligence, Human–Machine Collaboration, Industry 5.0, Human-Centered Design

INTRODUCTION

The manufacturing industry is undergoing a transformation driven by digitalization, automation, and increasing demand for customization. Industry 4.0 introduced cyber-physical systems and data-driven production, significantly improving efficiency and productivity. However, this paradigm has been criticized for marginalizing the human role and overlooking sustainability [2], [3], [4].

Industry 5.0 emerges as a complementary paradigm that emphasizes human-centricity, resilience, and sustainable production. These core dimensions redefine the role of technology in industrial systems, shifting the focus toward a balanced interaction between humans and intelligent technologies, as illustrated in Figure 1 [4]. In parallel, additive manufacturing (AM) enables flexible and personalized production but continues to face challenges related to process variability and quality control [5], [6].

Figure 1. Core pillars of the Industry 5.0 paradigm: human-centricity, sustainability, and resilience [4]

Artificial intelligence (AI), especially machine learning (ML), offers solutions through predictive modeling and process optimization. Nevertheless, existing research often treats AM, AI, and human interaction separately, revealing a critical gap: the absence of integrated systems combining these domains [7], [8].

This paper contributes to the field by providing a structured and integrated perspective on the convergence of additive manufacturing, artificial intelligence, and human-centered design within the Industry 5.0 paradigm [5].

2. From Industry 4.0 to Industry 5.0

Industry 4.0 introduced highly automated and interconnected production systems based on IoT, cyber-physical systems, and data analytics. While effective, these systems often reduce human involvement and prioritize efficiency over adaptability and sustainability [2], [3], [4].

Industry 5.0 extends this paradigm by reintroducing the human as a central element. It is built on three key pillars: human-centricity, sustainability, and resilience. In this context, humans collaborate with intelligent systems, contributing creativity and contextual understanding, while AI provides data-driven insights [9].

Enabling technologies such as AI, digital twins, AR/VR, and collaborative robots support this transition by enhancing, rather than replacing, human capabilities [10], [11].

For additive manufacturing, this shift means moving from prototyping and efficiency optimization toward mass personalization, adaptive processes, and human-centered production.

3. Fundamentals of Additive Manufacturing

Additive manufacturing is based on the layer-by-layer fabrication of components from digital models [12]. The process typically involves several interconnected stages, including computer-aided design (CAD), slicing of the digital model into successive layers, physical fabrication, and post-processing operations. Due to this sequential deposition mechanism, the geometry of the final component is progressively built by adding material layer by layer, as illustrated in Figure 2 [13]. AM processes are influenced by multiple interdependent parameters, including geometric, thermal, and kinematic variables, which determine part quality in terms of accuracy, strength, and surface finish. This complexity leads to significant process variability, especially due to material–process interactions such as interlayer adhesion and thermal effects [12], [13].

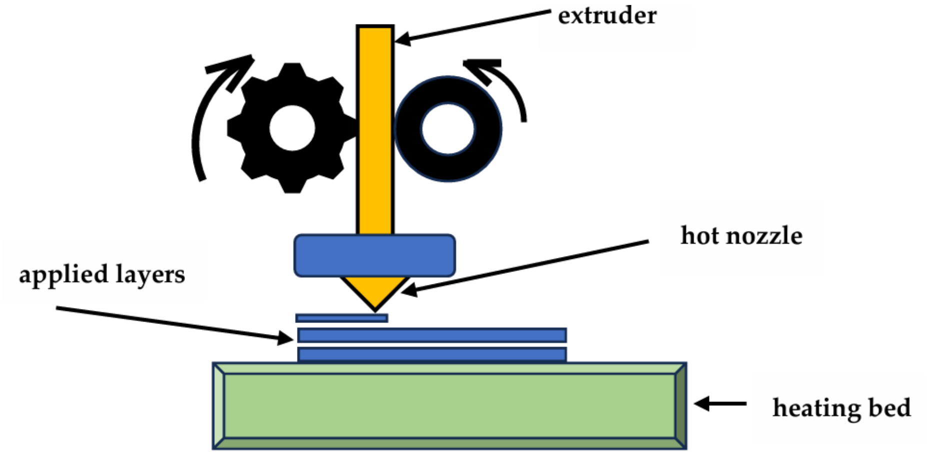

Figure 2. Schematic representation of the layer-by-layer fabrication process in additive manufacturing [13]

Major AM technologies include FDM, SLA, SLS/SLM, and DED, each offering different advantages in terms of cost, precision, and material compatibility. Among these, FDM is widely used due to its accessibility and flexibility, although it suffers from anisotropic properties and sensitivity to parameters [12], [14].

Despite its advantages, AM faces challenges such as lack of standardization, quality variability, and scalability limitations. These issues highlight the need for intelligent and adaptive systems integrating data analysis and process control.

4. Role of Artificial Intelligence in Additive Manufacturing

Building on the complexity of additive manufacturing processes discussed previously, artificial intelligence plays a key role in enabling predictive and adaptive control [13].

The complexity of AM processes makes traditional modeling approaches insufficient. Artificial intelligence (AI), particularly machine learning (ML), enables predictive and adaptive control by learning from process data and identifying patterns that are difficult to capture using conventional methods [2], [8]. Supervised learning methods, including regression models and neural networks, are widely used to predict mechanical properties and optimize process parameters, while semi-supervised learning reduces the need for labeled data and reinforcement learning enables adaptive control strategies in dynamic environments.

Deep learning techniques, especially convolutional neural networks (CNN), are increasingly applied for defect detection and real-time monitoring, transforming AM into an actively controlled and data-driven process. In this context, recent studies highlight the integration of AI with data acquisition systems, big data analytics, and model-based approaches to enhance process understanding and performance [13].

Digital twins further enhance these capabilities by providing virtual representations of physical systems, enabling simulation, prediction, and continuous model updating based on real-time and simulated data [15]. This interaction between physical processes, data analytics, and intelligent models is illustrated in Figure 3, where process variables, sensor data, and simulation outputs are integrated within a unified framework [16].

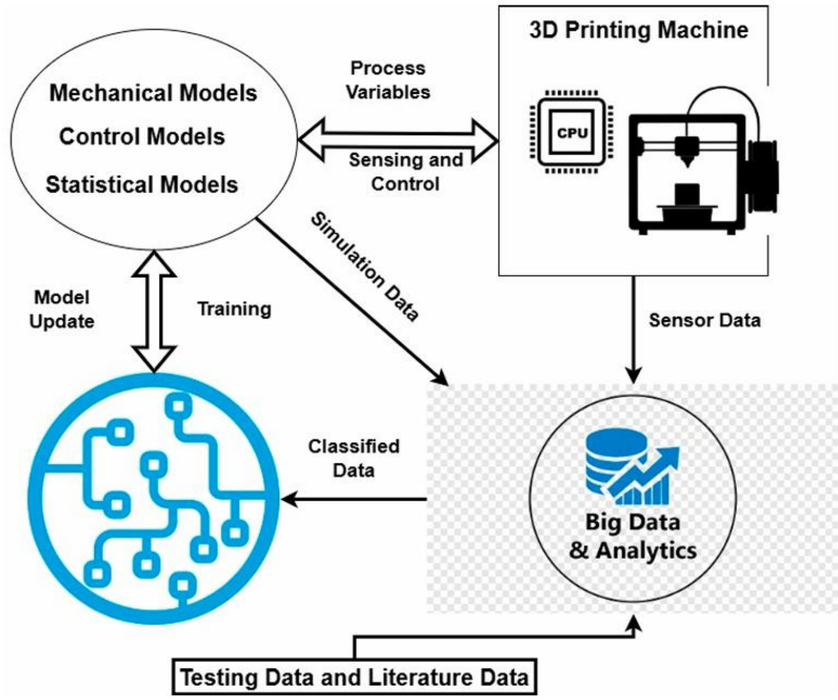

Figure 3. General framework of data-driven and model-based approaches integrating AI and digital twin concepts in additive manufacturing [16]

However, challenges remain, including data scarcity, model generalization, integration complexity, and interpretability. Addressing these issues requires hybrid approaches that combine physics-based models with data-driven techniques, improving both prediction accuracy and system robustness.

5. Human–Machine Collaboration in Additive Manufacturing within Industry 5.0

Beyond technological advancements, the effective integration of AI in additive manufacturing requires a strong focus on human–machine collaboration [9].
The transition toward Industry 5.0 fundamentally redefines the role of the human operator in manufacturing systems. In contrast to the automation-driven paradigm of Industry 4.0, where humans were often relegated to supervisory roles, Industry 5.0 promotes a **collaborative interaction between humans and intelligent systems** [9].

In the context of additive manufacturing (AM), this collaboration is particularly relevant due to the complexity, variability, and customization potential of the processes involved [9].

5.1 The Human-Centered Manufacturing Paradigm

Industry 5.0 introduces a shift from technology-centric to human-centered manufacturing systems, where human capabilities are augmented—not replaced—by advanced technologies. Within this paradigm, human–machine interaction is structured as a collaborative system that integrates human, digital, and physical components, in line with the human–cyber–physical system (HCPS) concept [5].

In this context:

- humans contribute with intuition, creativity, and contextual understanding
- AI systems provide data-driven insights and predictive capabilities
- decision-making becomes a shared and dynamic process supported by continuous interaction

The concept of human-in-the-loop (HITL) is central, ensuring that human expertise remains actively integrated into monitoring, validation, and control processes. As illustrated in Figure 4, this interaction is distributed across multiple layers-product, economic, and ecological-highlighting the interconnection between human, information, and physical systems [5], [9].

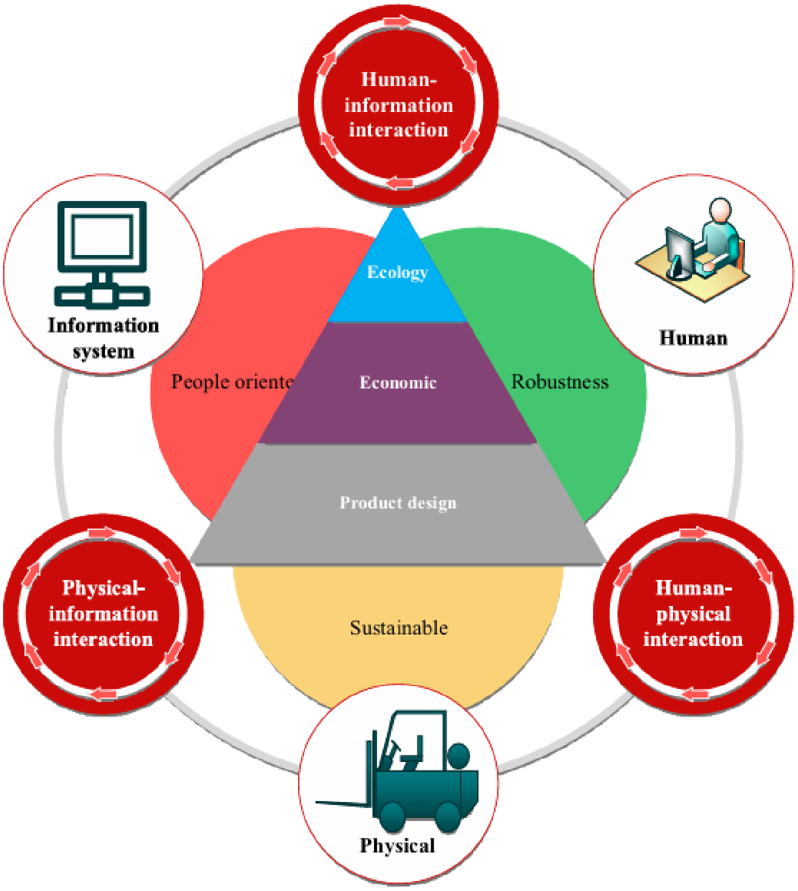

Figure 4. Human–Machine Interaction Model in Industry 5.0 [5]

This approach leads to:
• increased adaptability in complex environments
• improved decision quality through the combination of human and AI capabilities
• enhanced operator engagement and satisfaction within advanced manufacturing systems

5.2 Role of the Operator in Additive Manufacturing Systems

Unlike conventional manufacturing, additive manufacturing requires a higher level of operator involvement, including:
• continuous parameter adjustments
• interpretation of process anomalies
• validation of final product quality
This makes the human operator an essential component of the system.
In Industry 5.0 environments, supported by technologies such as digital **twins and artificial intelligence**, the operator interacts continuously with both the physical process and its virtual model. As illustrated in Figure 5, this interaction is structured through a cyclic framework (Connect–Collect–Combine–Process–Simulate–Act), which enables real-time data exchange, process monitoring and simulation before execution [17].

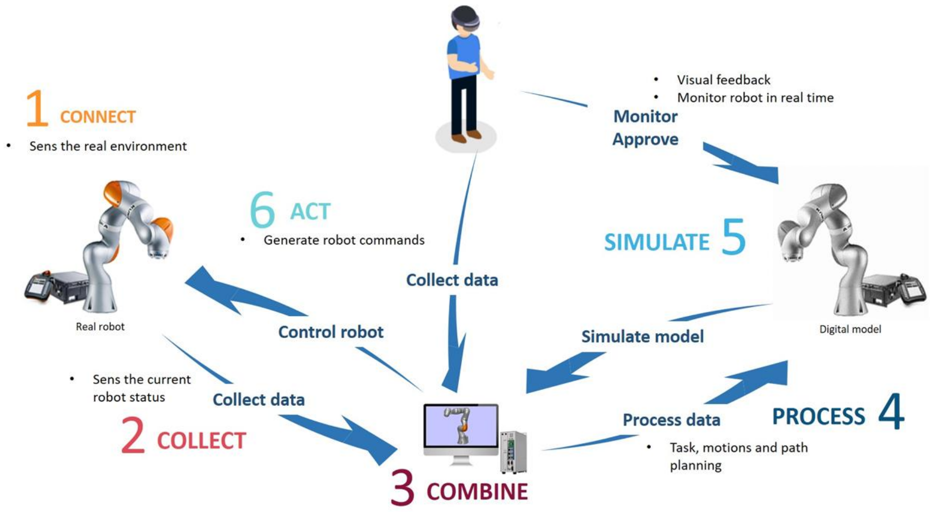

Figure 5. Digital Twin-Based Operator–System Interaction Framework [17]

Within this framework, the operator evolves into:

- a decision-maker supported by AI tools
- a process supervisor with active intervention capability
- a co-designer in personalized production systems

This transformation reflects the transition toward augmented intelligence, where human expertise is enhanced by intelligent systems, enabling more efficient, flexible and human-centered manufacturing processes [9], [17].

5.3 Enabling Technologies for Human–Machine Collaboration

Several technologies facilitate effective human–machine interaction in additive manufacturing:

5.3.1 Augmented and Virtual Reality (AR/VR)

AR and VR technologies enable immersive interaction with digital models and production environments. In Additive Manufacturing, these technologies support the visualization of 3D models before fabrication, simulation of printing processes, and operator training and guidance [11].

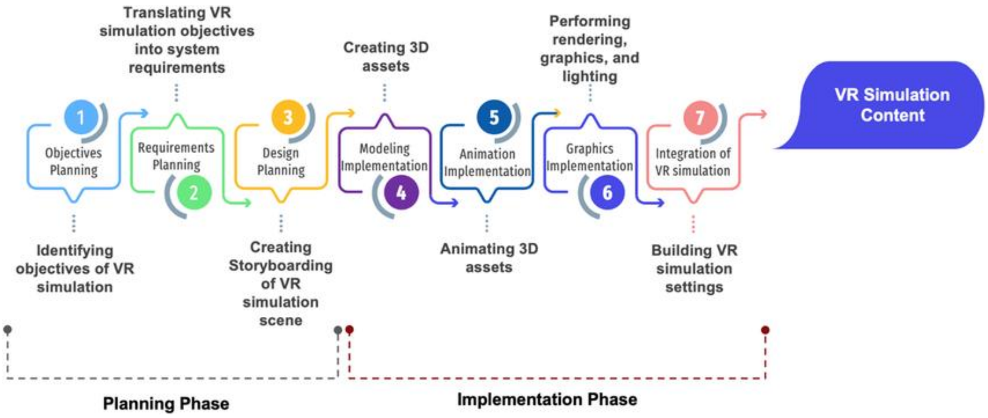

Figure 6. VR Manufacturing Simulation Workflow [18]

In particular, virtual reality systems allow the development of structured simulation environments, where manufacturing scenarios can be designed, modeled, and tested prior to physical execution. As illustrated in Figure 6, VR-based systems follow a multi-stage workflow that includes planning, 3D modeling, simulation, and integration, enabling the creation of high-fidelity virtual manufacturing environments [18].

These capabilities improve process understanding, support operator training, and contribute to reducing errors in complex manufacturing tasks.

5.3.2 Digital Twins

Digital twins provide a virtual representation of the physical manufacturing process, enabling real-time interaction between the physical system and its digital counterpart. In Additive Manufacturing, this allows operators to:

- monitor system behavior in real time
- simulate process scenarios
- detect and anticipate defects

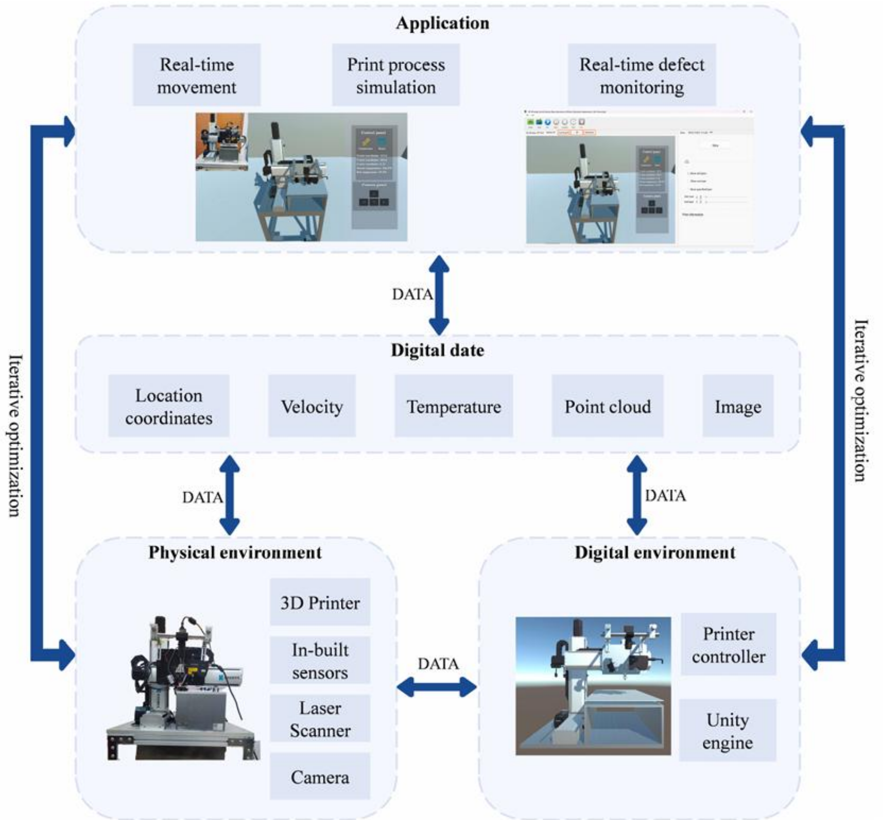

Figure 7. Digital Twins in Additive Manufacturing [16]

As illustrated in Figure 7, digital twin systems integrate physical components, digital environments, and real-time data, enabling continuous monitoring, simulation, and process optimization [16].

5.3.3 Intelligent Interfaces and Decision Support Systems

Modern AM systems increasingly incorporate user-friendly interfaces that:

- present real-time process data
- suggest optimal parameter settings

- alert operators to potential issues

These interfaces act as **decision support systems**, bridging the gap between complex data and human understanding [7].

5.3.4 Collaborative Robotics (Cobots)

Although less common in AM compared to other manufacturing processes, collaborative robots can assist in:

- material handling
- post-processing operations
- hybrid manufacturing systems

Cobots enhance efficiency while maintaining safe human interaction.

5.4 Ergonomic and Cognitive Considerations

A key aspect of human–machine collaboration is ensuring that systems are designed according to human capabilities and limitations [19], [20].

Important factors include:

- **Physical ergonomics** – posture, movement, and workspace design
- **Cognitive ergonomics** – mental workload, decision complexity, information processing
- **User experience** – interface usability and clarity

As illustrated in Figure 8, human-centered system design integrates human, technological, and environmental factors across different levels of complexity, supporting a holistic approach to system development [19].

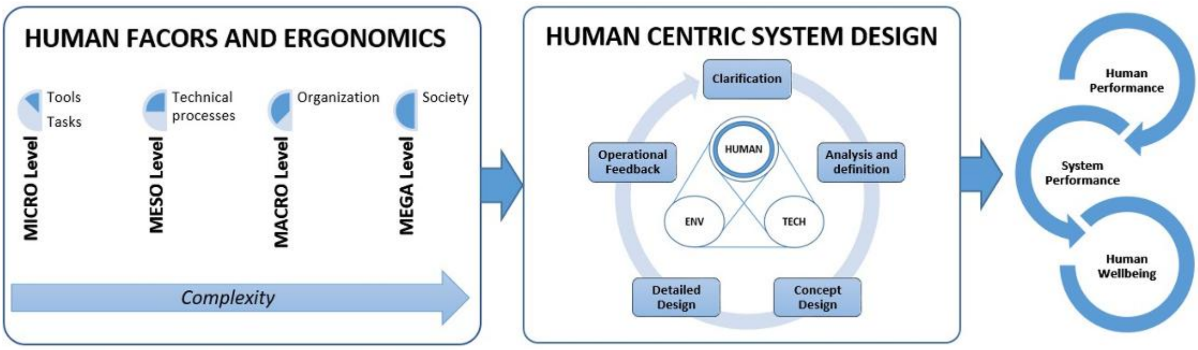

Figure 8. Human-Centered Design Framework [19]

Integrating ergonomic principles with digital technologies can improve both performance and worker well-being. However, excessive reliance on automation may lead to:

- reduced situational awareness
- operator disengagement
- overtrust in AI systems

Therefore, a balanced approach is necessary.

5.5 Human–AI Collaboration in Decision-Making

In additive manufacturing, decision-making often involves selecting optimal process parameters under uncertain conditions [13], [21].

AI systems can:

- analyze large datasets
- predict outcomes
- recommend optimal configurations

However, human operators remain essential for:

- validating results
- interpreting unexpected situations
- making context-aware decisions

This collaborative approach ensures:

- higher robustness
- improved flexibility
- ethical and responsible decision-making

5.6 Toward Personalized Manufacturing Systems

One of the defining features of Industry 5.0 is mass personalization, where products are tailored to individual needs. In this context, additive manufacturing, combined with artificial intelligence and human input, enables more flexible and responsive production systems.

As illustrated in Figure 9, AI-augmented additive manufacturing systems operate based on a closed-loop architecture, where sensor data collected during the printing process are continuously analyzed to detect deviations and optimize process parameters in real time [22].

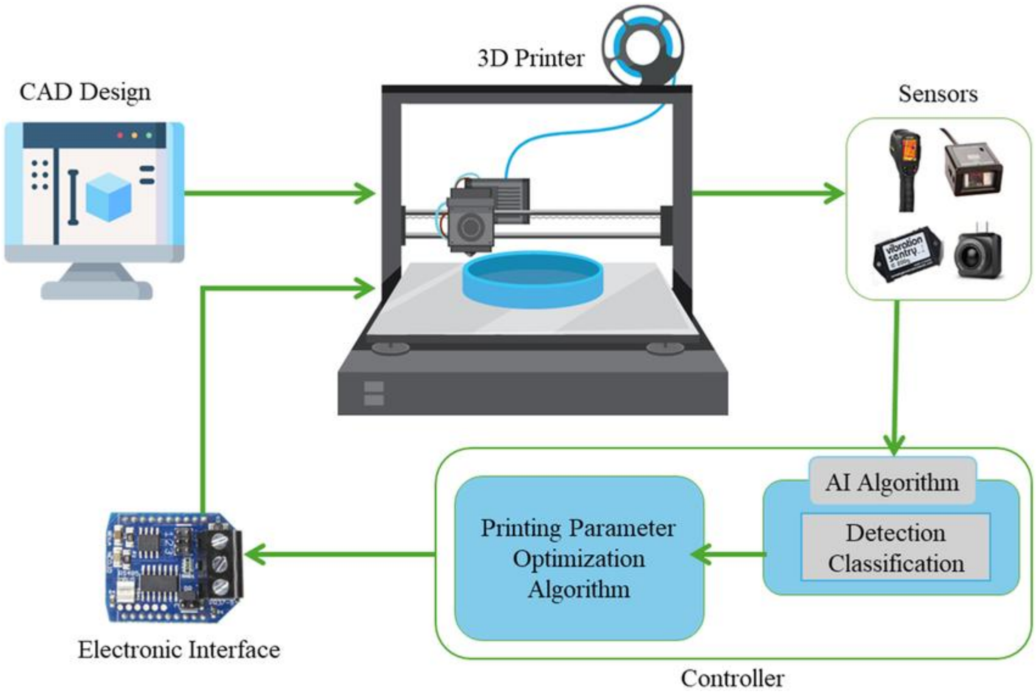

Figure 9. AI-augmented additive manufacturing system with closed-loop monitoring and real-time process optimization[22]

This integration supports:

• customization of geometry and functionality through digital design (CAD)
• adaptation of process parameters based on real-time data and user requirements
• rapid iteration and prototyping enabled by continuous feedback and optimization

In this framework:

• AI optimizes process parameters and supports decision-making
• humans define design requirements and validate outputs
• additive manufacturing enables the physical realization of customized products

This synergy leads to the development of production systems that are:
• flexible
• adaptive
• user-centered

5.7 Challenges in Human–Machine Collaboration

Despite its advantages, several challenges must be addressed:

- **Integration complexity** between human and AI systems
- **Lack of standardized interaction frameworks**
- **Training requirements** for operators
- **Trust and acceptance of AI technologies**
- **Ethical considerations** in decision-making

Moreover, designing intuitive interfaces that effectively communicate complex data remains a significant challenge [5], [9].

5.8 Future Perspectives

Future research should focus on:

- developing adaptive interfaces tailored to user expertise
- integrating ergonomic data into AI models
- enhancing transparency and explainability of AI systems
- creating standardized frameworks for human–machine collaboration

In particular, the combination of additive manufacturing, artificial intelligence, and human-centered design represents a promising direction for next-generation manufacturing systems [5], [9].

6. Toward an Integrated Intelligent Additive Manufacturing System

Current research lacks integrated systems combining AM, AI, and human-centered design. This paper proposes a conceptual framework consisting of three interconnected layers: the AM process layer, the AI layer, and the human–machine interaction layer.
The system operates through a continuous feedback loop:
input parameters → AI prediction → human validation → manufacturing execution → data feedback [2].
The AM layer generates process data, the AI layer performs prediction and optimization, and the human layer ensures interpretability and adaptability [23].
This integrated approach enables:

- continuous learning and improvement
- adaptive process control
- personalized production

The framework is particularly relevant for automotive applications, where customization and performance are critical [23].
Implementation challenges include data availability, system integration, operator training, and lack of standardization. Future work should focus on real-time systems, hybrid models, and industrial validation.

7. Conclusions and Future Research Directions

This study highlights the convergence of additive manufacturing, artificial intelligence, and human–machine collaboration within Industry 5.0. While each domain has advanced significantly, their integration remains limited [20].

The proposed framework demonstrates the potential for developing intelligent, adaptive, and human-centered manufacturing systems. Such systems enable mass personalization, improved efficiency, and enhanced resilience [19].

Future research should focus on experimental validation, real-time monitoring, and the development of explainable AI models integrated with human feedback[13].

Ultimately, the success of Industry 5.0 will depend on the ability to integrate technological intelligence with human creativity and responsibility.

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