Artificial Intelligence Capabilities in Additive Manufacturing: A Review of Integration Across the 3D Printing Process

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Abstract. Artificial Intelligence (AI) has emerged as a powerful enabler for enhancing 3D Printing processes, contributing to increased accuracy, efficiency, and automation. This paper presents a structured review of AI capabilities developed for 3D Printing based solely on qualitative document analysis conducted between 2021 and 2025. The review categorises AI applications into three functional stages: pre-printing (e.g., image segmentation, CAD optimisation), in-process (e.g., real-time monitoring, defect detection, closed-loop control), and post-processing (e.g., quality evaluation, parameter refinement). By analysing scholarly and industry sources, the paper identifies prevailing technologies—such as convolutional neural networks (CNNs), machine learning models, and vision-based feedback systems—that are actively shaping additive manufacturing. It also highlights trends in AI deployment tailored to specific sectors such as healthcare and aerospace. While these developments demonstrate strong technical promise, the review also notes that most research is confined to controlled environments and lacks strategic alignment with broader adoption frameworks. The paper concludes by discussing how AI capabilities—if generalised and scaled—can address key barriers to adoption and help transition 3D Printing from early adopters to early majority users.

Keywords: Artificial Intelligence, 3D Printing, Technology Integration.

1 Introduction

Additive manufacturing, commonly known as 3D Printing, has rapidly evolved from a niche prototyping method to an increasingly viable production technology across various industries [1]. Its capacity for on-demand manufacturing, design flexibility, and material efficiency has made it attractive for sectors ranging from healthcare and aerospace to automotive and construction [2], [3], [4]. Despite growing visibility, widespread adoption of 3D Printing remains constrained by several persistent technical challenges—namely print accuracy, quality consistency, process reliability, and scalability [5], [6]. These limitations restrict its transition from early adopters to broader industrial acceptance [7].

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In parallel, Artificial Intelligence (AI) has become a foundational driver of innovation across sectors, offering tools for process automation, defect detection, decision support, and data-driven optimisation [8]. In manufacturing, AI enables dynamic control over complex operations and reduces human dependency in quality assurance and maintenance processes [9]. As such, AI presents a significant opportunity to address critical performance and usability gaps that currently hinder the full-scale adoption of 3D Printing technologies.

Drawing upon this critical juncture, this paper is guided by the overarching research question: "What cutting-edge AI capabilities are currently being developed for implementation in 3D printing technologies, and how can these capabilities effectively address the prevailing barriers to 3D printing adoption?" This inquiry aims to provide a comprehensive overview of the latest advancements in AI applied to 3D printing. By dissecting these developments, this research serves as a vital reference for both makers and researchers, offering insights into the future trajectory of 3D printing and highlighting how AI can serve as the primary catalyst in overcoming its most pressing adoption challenges. Furthermore, this study will delineate the specific AI functionalities required by the 3D printing sector, thereby providing clear direction for researchers and AI developers dedicated to advancing this transformative technology.

This paper presents a structured review of AI capabilities that have been developed and applied in the context of 3D Printing especially the Fused Deposition Modelling (FDM) type as the main focus. Drawing solely on qualitative document analysis conducted between 2020 and 2025, the review categorises these capabilities into three core operational phases: pre-printing, in-process, and post-processing. Each category explores how specific AI tools—such as computer vision, machine learning models, and neural networks—are being used to enhance efficiency, reduce defects, and automate decision-making in additive manufacturing workflows. To facilitate a clearer understanding, Fig. 1 outlines the 3D printing process from a systems perspective, serving as a crucial foundation that helps readers easily pinpoint where the AI solutions presented in this paper will be integrated.

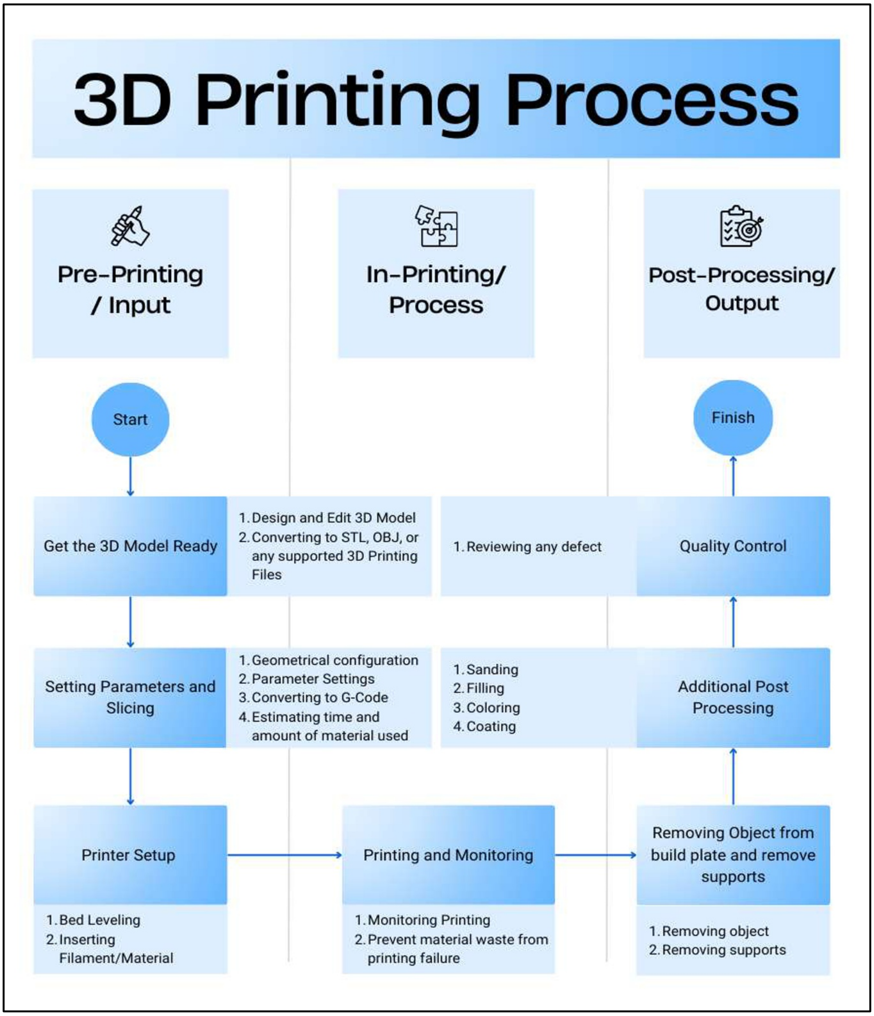

Fig. 1. 3D Printing Process adapted [10]

By synthesising findings from recent academic, news, and industrial publications, this review aims to offer a comprehensive view of current AI integration efforts in the 3D Printing domain. While the focus remains technical, the paper also reflects on the potential of these developments to resolve adoption bottlenecks and support a transition toward broader industrial implementation. In doing so, it contributes to the growing discourse on the role of AI in enabling the next phase of additive manufacturing maturity.

2 Method

This study employs a qualitative review approach grounded in document analysis to examine the capabilities of Artificial Intelligence (AI) that have been developed and applied in the context of 3D Printing [11], [12]. The objective of this method is to systematically synthesise knowledge from existing academic and industry sources, offering a structured overview of how AI has been integrated across various stages of the additive manufacturing workflow. No primary data collection such as interviews or surveys was conducted; the analysis is entirely literature-based.

The document analysis was conducted through targeted searches of peer-reviewed journals, conference proceedings, industry white papers, and relevant online sources. These were accessed via institutional databases—primarily the University College London (UCL) library system—as well as public websites, including platforms such as YouTube and online news outlets, to capture emerging insights not yet available in academic literature. The review focused on documents published between 2020 and 2025 to ensure coverage of the most recent developments. Search keywords included “Artificial Intelligence for 3D Printing,” “AI in Additive Manufacturing,” “Machine Learning in 3D Printing,” and “AI-based Process Optimisation in Additive Manufacturing.”

The selection and screening process followed the PRISMA methodology. Fig. 2 presents the PRISMA flow diagram, which outlines the stages of document identification, screening, exclusion, and inclusion applied in this study.

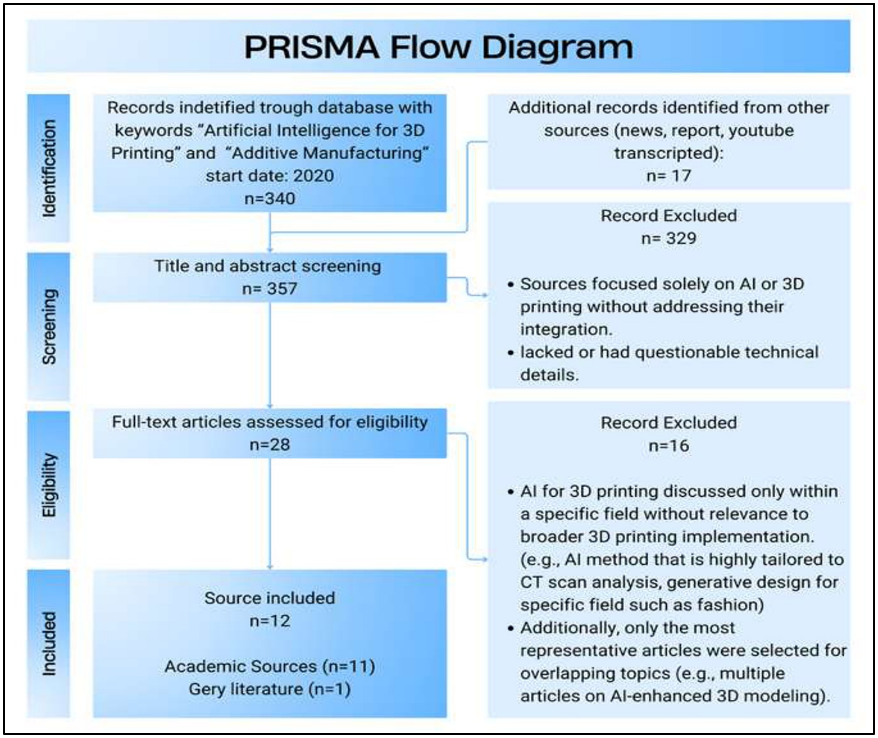

Fig. 2. PRISMA Flow Diagram for Document Analysis

The initial search yielded 357 documents. These were filtered through a multi-stage process involving title screening, abstract review, and full-text relevance assessment. Selection criteria included the explicit discussion of AI integration into 3D Printing processes, the generalisability of findings across different application domains, and the presence of technical detail regarding AI methods and their operational roles. After applying these filters, 28 documents were shortlisted, with 12 selected for detailed thematic analysis.

The analytical process involved using NVivo 12 to code and categorise the relevant literature based on the function and application of AI within the 3D printing workflow. NVivo facilitated the systematic identification of recurring themes by enabling the organisation and comparison of data across multiple sources. Through this process, AI capabilities were categorised into three major operational stages as mentioned in Fig. 1. Within each stage, key themes were identified based on recurring technological functions—such as image segmentation, real-time monitoring, or defect detection—and were further classified according to the type of AI employed, including convolutional neural networks (CNNs), supervised learning, and computer vision systems. This structured coding approach allowed for the synthesis of patterns and relationships across studies, supporting a more nuanced understanding of how AI enhances different stages of the additive manufacturing process.

In addition to describing the technical functions of these capabilities, the analysis also considered their potential contributions to solving known barriers to 3D Printing adoption, such as quality inconsistency, lack of process automation, and the high rate of print failure. This mapping helped assess not only what has been developed but also how these developments may influence broader industrial uptake. The resulting synthesis forms the basis for the following sections, which present and discuss AI capabilities at each phase of the 3D Printing process.

3 AI Capabilities in Pre-Printing

The pre-printing phase in 3D Printing encompasses activities such as data acquisition, 3D models generation, design optimisation, and preparation of printing parameter and instruction. This stage is critical, as errors or inefficiencies in model design and file preparation can lead to print failures, material waste, and extended production times. AI technologies have been increasingly applied in this phase to automate and enhance design processes, improve model accuracy, and optimise geometrical configurations for more reliable outputs. Table 1 list the AI capabilities for Pre-printing.

Table 1. AI Capabilities for 3D Printing Pre-Printing

AI Capability and Description	AI Method and Hardware/Software Example	Stage
AI-Assisted 3D Model Preparation		
Image Segmentation and Enhancement for 3D Design [12]	Genetic Algorithms (GA), Conditional Generative Adversarial Networks (cGANs) for applying DfAM constraints.	Design prediction: Research Prototype Generative Design: Commercial
AI supports the design process specifically for additive manufacturing, optimising designs for complexity, material usage, and performance[13].	Mimics 2.5, Nvidia Clara Generative Design and Topology Optimisation for 3D Design, Deep Learning, CNN [14] Autodesk Generative Design, ANSYS	Commercial
AI provides simulations that predict how different designs will perform, helping create optimised designs [9], [13].	Generative Design Algorithms AI Build	Early Commercial
AI-Assisted Parameter and Slicing Settings		
Cost Estimation and Production Planning. AI estimates 3DP costs based on design and process complexity [2].	Predictive Modelling, Regression Analysis DELMIA, Arena Simulation, Ultimaker CURA	Commercial
AI recommend parameter and slicing optimisation and	Reinforced Machine Learning, CNN	Early Commercial

AI Capability and Description	AI Method and Hardware/Software Example	Stage
automatically detect any potential error (such as potential overheat on edges, unstable printing result, etc). AI provides real-time guidance and support during printing [16].	AI Build, AMAIZE by 1000 Kelvin	
Enhanced Slicing User Interface and Accessibility using generative AI [16].	LLM, NLP AI Build	Early Commercial
Other Capabilities Outside 3D Printing Process		
Material Development and Optimisation AI aids in the development and selection of new materials, optimising material composition and properties [15], [16].	Machine Learning, AI-driven simulations, Quantum Computing BIOVIA Materials Studio, IBM Q	Commercial
Market Trend Analysis and Demand Forecasting AI forecasts demand and helps align production with market needs [2].	ML, Predictive Analytics SAP IBP	Commercial

One of the most prominent applications of AI in the pre-printing stage is in medical image segmentation and 3D model generation. Studies such as Ma et al. [17] have demonstrated how convolutional neural networks (CNNs) can accurately segment complex anatomical structures from CT or MRI scans, significantly improving the quality and speed of converting medical data into printable CAD models. Tools like Mimics 25.0 and Nvidia's Clara platform exemplify commercially available solutions that incorporate AI to facilitate this process. These capabilities are particularly beneficial in bioprinting and personalised prosthetics, where anatomical precision is paramount.

Beyond the medical domain, AI has also been leveraged to automate and refine the design-to-slicing workflow. Machine learning algorithms are used to optimise print paths, infill structures, and orientation strategies to reduce support material usage and improve build efficiency. CNNs and other pattern recognition tools have been employed to identify weak points in the geometry of CAD models and suggest modifications that improve printability without compromising design intent [16].

Another notable contribution of AI at this stage lies in generative design and topology optimisation. AI systems can evaluate multiple design alternatives rapidly, balancing structural integrity with material efficiency [9], [14]. This is particularly valuable in industries such as aerospace and automotive, where reducing part weight while maintaining performance is a critical design goal.

Despite these advances, most pre-printing AI applications are developed within narrow domains and are not yet generalisable across industries. Furthermore, most of the solutions are in early commercial, with limited integration into mainstream CAD or slicing software. The high variability of input data and the lack of standardised datasets for training AI models present additional challenges for scaling these technologies.

Nevertheless, the application of AI in the pre-printing phase demonstrates strong potential to reduce complexity, minimise manual intervention, and shorten lead times. These improvements directly address some of the most cited barriers to 3D Printing adoption, particularly those related to usability and process reliability. As such, further development and commercialisation of AI-driven tools in this phase could play a key role in making 3D Printing more accessible and efficient for broader industrial use.

4 AI Capabilities in In-Process

The in-process phase of 3D Printing is where material deposition, fusion, and shaping occur in real-time according to pre-defined instructions. Ensuring accuracy and consistency during this phase is crucial, as any anomalies—such as temperature fluctuations, misalignments, or material inconsistencies—can result in print defects or failed builds. Given the complexity and variability of printing conditions, this stage is particularly well-suited for AI integration. Recent developments in AI have focused on enabling real-time monitoring, defect detection, and adaptive control mechanisms that can intervene mid-process to ensure print quality. Table 2 recap Ai capabilities for in-printing process.

Table 2. AI Capabilities for In-Process 3D Printing

AI Capability and Description	AI Technology and Hardware/Software Example	Stage
Real-Time Process Monitoring and Control	**CNNs, Computer Vision, Machine Learning, RL**	**Early Commercial**
AI is used for real-time monitoring to inform users the printing progress and defect detection [17], [13].	**Bambu Lab 3D Printers, Bambu Handy, Bambu Studio, TensorFlow, PyTorch, VisionPro**	
Live Parameter Optimisation	**Genetic Algorithms, Bayesian Optimisation, Neural Networks**	**Prototype and some early commercial**
AI optimises process variables and modifying parameters during printing to prevent defects and ensure optimal output quality during printing [13].	**Bambu lab 3D Printer, Bambu Studio, Bambu Handy, AI Build, MATLAB, OptiSLang**	
Thermal Management	**Simulation Models, AI Predictive Analytics**	**Prototype**
AI tools predict and manage thermal issues in metal additive manufacturing [9].	**AI-enhanced 3DP systems, AMAIZE, AI Build**	

One of the most impactful applications of AI in this phase is the implementation of real-time monitoring systems. Using sensors such as infrared cameras, pyrometers, and acoustic emission detectors, AI models—particularly convolutional neural networks (CNNs)—can process large streams of visual and thermal data to identify signs of error as they emerge. These systems are designed to detect anomalies such as layer delamination, void formation, or overheating, which may not be visible to the human eye or detectable by conventional threshold-based monitoring tools [14], [17].

Beyond detection, more advanced AI systems have been developed to enable closed-loop control during printing. These systems not only recognise defects but also automatically adjust process parameters such as print speed, extrusion rate, and temperature in response. This creates a feedback loop that allows the printer to self-correct without human intervention, significantly improving the reliability and consistency of prints. Examples in the literature describe integration of machine learning models that continuously learn from historical and real-time data, improving their responsiveness and precision over time [14], [17].

Another key area of AI deployment is process parameter optimisation. AI algorithms can model the complex relationships between process variables and print outcomes, identifying ideal parameter sets that maximise quality while reducing cycle time and material use. Reinforcement learning and Bayesian optimisation have been explored for this purpose, particularly in metal additive manufacturing where heat distribution and residual stresses are difficult to predict using traditional simulations [17].

Despite these technological advancements, challenges remain in achieving broad deployment of AI in in-process control. Many solutions are developed in controlled laboratory settings or are tailored to specific printer models or materials, limiting their generalisability. The implementation of AI systems also requires high-fidelity data acquisition and synchronisation across hardware, which can be costly and technically demanding. Additionally, there is often limited transparency in how some machine learning models arrive at their decisions, raising concerns about trust and interpretability in safety-critical applications.

Nevertheless, the integration of AI in the in-process stage represents one of the most mature and technically promising areas for enhancing 3D Printing performance. These capabilities directly address barriers related to quality assurance, repeatability, and process stability—challenges that have long inhibited 3D Printing from scaling beyond prototyping into full industrial production. By embedding intelligence into the print process itself, AI has the potential to transform 3D Printing into a more autonomous, self-optimising manufacturing method.

5 AI Capabilities in Post-Processing

Post-processing is a critical yet often labour-intensive stage in the 3D Printing workflow. It includes activities such as part inspection, defect analysis, surface finishing, support removal, and quality certification. While frequently overlooked in early-stage research, post-processing plays a significant role in determining the final quality, functional performance, and regulatory compliance of printed components—especially in high-stakes sectors like aerospace and healthcare. Recent developments have shown that AI can be effectively leveraged to automate and enhance key aspects of this stage, improving consistency and reducing human workload. Table 3 list the AI capabilities for post-printing.

Table 3. AI Capabilities for 3D Printing Post-Processing

AI Capability and Description	AI Technology and Hardware/ Software	Stage
Defect Detection and Surface Quality Assessment [17]	Computer Vision systems and Deep Learning (CNNs and autoencoders)	Research
Predictive Quality Assurance	Predictive Analytics, ML Models, Time-Series Analysis	Prototype

AI Capability and Description	AI Technology and Hardware/ Software	Stage
AI models predict print quality from process data and environment factors to ensure consistency [17], [18].	IBM SPSS Modeler, SAS Analytics	
Predictive Maintenance	Predictive Analytics, Time-Series Analysis, ML	Research Stage
AI predicts maintenance needs, reducing downtime and extending lifespan [19].	IBM Maximo, Siemens MindSphere	
Inventory Management for On-Demand Production	ML, Predictive Analytics	Prototype
AI ensures materials/ components are stocked appropriately for on-demand production [19].	Oracle NetSuite, SAP IBP	

One of the most direct applications of AI in post-processing is in defect detection and surface quality assessment. Using computer vision systems paired with deep learning algorithms—such as CNNs and autoencoders—AI can analyse images of printed parts to detect surface anomalies, dimensional deviations, and internal defects with greater consistency and speed than manual inspection. These models can be trained on datasets of known defect types and calibrated for various surface textures and material finishes, enabling them to identify even subtle inconsistencies that may affect part performance [17].

AI is also being applied in predictive maintenance and traceability, where it analyses historical print data and environmental conditions to anticipate future failures or degradation. By correlating post-print defects with specific process conditions or equipment behaviours, machine learning models can inform preventative interventions, thereby improve long-term machine reliability and reducing downtime. These insights also support process certification and documentation—an important requirement in regulated industries where traceability and compliance are paramount [17].

Another emerging area is the refinement of future print parameters based on post-processing feedback. AI systems can learn from past defects to recommend adjustments in design, slicing, or process settings for future builds, effectively closing the loop between post-processing outcomes and pre-processing decisions. This type of adaptive learning can help manufacturers gradually improve yield and performance across repeated builds, even when using different materials or geometries [18], [19].

Despite these promising developments, AI integration in post-processing remains less mature compared to the pre-printing and in-process phases. The main challenges include the need for large, labelled datasets to train accurate defect classification models, as well as the diversity of parts, materials, and post-processing techniques that complicate standardisation. Additionally, many AI tools remain proprietary or embedded in high-end industrial platforms, limiting accessibility for small to mid-sized manufacturers. Nonetheless, the application of AI in post-processing offers clear benefits in terms of efficiency, scalability, and quality assurance. As the industry moves toward more demanding use cases for 3D Printing—such as functional parts and end-use components—automated inspection and continuous improvement systems will become essential. AI technologies can bridge the current gap between prototyping and production readiness by ensuring that printed parts meet rigorous standards without excessive manual oversight, thereby supporting broader adoption of additive manufacturing in industrial contexts.

6 Discussion

The review of AI capabilities across the pre-printing, in-process, and post-processing stages reveals a clear trajectory: artificial intelligence is increasingly positioned as a transformative enabler for the industrialisation of 3D Printing. While each stage has unique applications, a common theme emerges—AI addresses core barriers that have historically limited the scalability, consistency, and reliability of additive manufacturing.

In the pre-printing phase, AI improves model generation and design validation, especially in complex domains such as healthcare. These capabilities reduce the dependency on specialist expertise and minimise errors early in the production pipeline, thereby enhancing accessibility and process efficiency. Although many of these applications are still domain-specific, they show the potential to democratise design and lower entry barriers for non-expert users, which is crucial for broader adoption.

The in-process phase exhibits the most advanced integration of AI, particularly in real-time monitoring and closed-loop control. These systems directly confront one of the most cited adoption bottlenecks in additive manufacturing: inconsistent print quality and high failure rates. By embedding intelligence into the printing process itself, AI not only automates correction mechanisms but also enables more reliable production outputs. This supports the shift from experimental and prototyping use cases toward mainstream industrial production, especially in sectors that demand high repeatability and certification.

Post-processing applications, while still emerging, offer long-term strategic benefits. AI-assisted defect detection and predictive quality analytics can substantially reduce labour intensity, accelerate inspection, and enhance traceability—factors that are increasingly important as regulatory scrutiny grows in industries like aerospace, healthcare, and automotive. Additionally, when post-processing insights are fed back into design and slicing workflows, AI can support continuous improvement and adaptive manufacturing strategies.

However, despite this technological promise, several limitations must be acknowledged. First, many AI applications remain siloed—developed as isolated solutions rather than as part of an integrated manufacturing ecosystem. Second, there is a lack of generalisability across printer models, materials, and industries. Third, the infrastructure requirements for high-quality data acquisition and processing—both hardware and human expertise—can be prohibitive for smaller firms. Finally, few studies consider the organisational, cultural, or training challenges involved in adopting AI-driven workflows, which can significantly delay or derail implementation.

To fully realise the benefits of AI in 3D Printing, future research and development must shift towards system-level integration, standardisation, and cross-functional usability. In particular, greater attention should be paid to how AI capabilities align with established technology adoption frameworks. Strategic mapping of AI's contribution to usability, cost-efficiency, and automation may reveal clearer pathways for accelerating the adoption curve—helping 3D Printing transition from a specialist tool to a mainstream production method.

7 Conclusion

This paper has presented a structured review of Artificial Intelligence (AI) capabilities developed for 3D Printing, focusing on their integration across the pre-printing, in-process, and post-processing phases. Drawing solely from document-based analysis, the review highlights how AI has been applied to enhance design preparation, real-time control, defect detection, and process optimisation. These developments demonstrate strong potential to address long-standing technical barriers that have limited the scalability and industrial adoption of additive manufacturing.

In the pre-printing stage, AI enables more accurate and efficient model generation, particularly in specialised domains like medical imaging. During the printing process itself, real-time monitoring and closed-loop control systems powered by machine learning significantly improve quality and reliability. In post-processing, AI supports quality assurance and adaptive feedback mechanisms, contributing to greater consistency and reduced manual overhead.

While these capabilities are promising, the review also underscores that most implementations remain either experimental or domain-specific, lacking the system-level integration and standardisation needed for widespread adoption. Furthermore, organisational readiness and data infrastructure continue to be overlooked in many technical studies, presenting a gap between capability development and real-world deployment. Nonetheless, AI remains a critical enabler for the future of 3D Printing. If strategically integrated, it can support the technology's transition from early adoption to broader industrial acceptance by improving usability, reliability, and efficiency. Future work should therefore focus not only on advancing AI capabilities, but also on embedding them into coherent, cross-functional manufacturing ecosystems that are accessible, scalable, and aligned with industry needs.

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