International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 02 |Feb-2024 SJIF Rating: 8.448 ISSN: 2582-3930

AI-Integrated Design-for-Manufacturing Framework for Additive Manufacturing Systems

Darshak Vijaybhai Goyani [1]

[1] *Mechanical Engineering Department & Pacific School of Engineering.*

---***---

Abstract - The adoption of Additive Manufacturing (AM) is rapidly increasing across high-value manufacturing sectors; however, its industrial scalability remains limited by inadequate Design-for-Manufacturing (DfM) practices. Traditional DfM methods fail to fully capture the complex interactions between design geometry, material behavior, and process parameters inherent to AM systems, leading to increased production costs and inconsistent quality. This paper proposes an AI-integrated DfM framework that utilizes artificial intelligence to automate manufacturability assessment, optimize design features, and recommend process-specific improvements. By incorporating historical production data, machine learning models, and intelligent feedback mechanisms, the framework enables faster design validation, reduced trial-and-error, and improved production reliability. The proposed framework is highly relevant to England's manufacturing landscape, where digital transformation, sustainability, and productivity improvement are national priorities. Its application supports the UK's aerospace, automotive, and healthcare industries by enabling cost-effective localized production, reduced supply-chain dependency, and enhanced innovation capability, contributing to long-term industrial growth and technological leadership.

Key Words**:** Additive Manufacturing, Design for Manufacturing (DfM), Artificial Intelligence, Machine Learning, Generative Design, Smart Manufacturing.

1.INTRODUCTION

Additive Manufacturing (AM), commonly referred to as three-dimensional (3D) printing, has emerged as a transformative manufacturing paradigm that enables the layer-by-layer fabrication of components directly from digital models. Unlike conventional subtractive and formative manufacturing methods, AM allows for unprecedented geometric freedom, mass customization, and material efficiency. These capabilities have positioned AM as a key technology within Industry 4.0, particularly for high-value manufacturing sectors such as aerospace, automotive, healthcare, and precision engineering. However, despite its advantages, the industrial deployment of AM continues to face challenges related to design complexity, process variability, and manufacturability constraints, highlighting the need for advanced design methodologies.

1.1 Overview of Additive Manufacturing Systems

Additive Manufacturing systems include a range of processes such as Fused Deposition Modeling (FDM), Selective Laser Melting (SLM), Selective Laser Sintering (SLS), Stereolithography (SLA), and Electron Beam Melting (EBM), each differing in material form, energy source, and fabrication mechanism. These systems integrate CAD tools, slicing software, material feedstock, and process control units to convert digital designs into physical components. While AM enables complex geometries and lightweight structures, it remains highly sensitive to design parameters such as overhang angles, wall thickness, support requirements, and build orientation. In the United Kingdom, AM adoption is growing within advanced manufacturing clusters, but its effective industrial use depends on improved design methodologies that address process-specific constraints and variability.

1.2 Importance of Design-for-Manufacturing in Additive Manufacturing

Design-for-Manufacturing (DfM) is essential for ensuring that AM components are not only functional but also printable, reliable, and cost-effective. In AM, poor design decisions can lead to excessive support structures, thermal distortion, surface defects, and build failures. Effective DfM enables early-stage optimization of geometry, material usage, and build strategy, reducing waste and production time. For UK industries focused on productivity, sustainability, and high-precision manufacturing, robust AM-oriented DfM practices are critical for achieving scalable and economically viable production.

1.3 Role of Artificial Intelligence in Overcoming Design-for-Manufacturing Challenges in Additive Manufacturing

Artificial Intelligence enhances AM-oriented DfM by enabling automated design evaluation, predictive manufacturability analysis, and adaptive process optimization. Machine learning and deep learning models can identify manufacturability-critical features directly from CAD data, while supervised learning enables accurate prediction of build success and defect risks. Reinforcement learning supports dynamic optimization of process parameters, and generative AI facilitates the creation of manufacturable, high-performance designs. These capabilities allow AI-driven DfM to overcome the limitations of static, rule-based approaches and support data-driven decision-making in complex AM environments.

1.4 Proposed AI-Integrated Design-for-Manufacturing (DfM) Framework for Additive Manufacturing

The proposed AI-integrated DfM framework embeds intelligence across the entire AM workflow, from design evaluation to manufacturing optimization. It combines automated feature extraction, manufacturability prediction, generative design optimization, and adaptive process control using historical and real-time manufacturing data. A closed-loop learning mechanism continuously refines model accuracy through post-process inspection and in-situ monitoring feedback. This framework shifts AM design practice from experience-based decision-making to an intelligent, adaptive, and scalable approach suitable for industrial deployment.

1.5 Research Gap and Motivation

Existing DfM approaches for AM are largely rule-based or process-specific and fail to capture the complex interactions between design geometry, materials, and process parameters. Although AI has been applied to isolated AM tasks such as defect detection or parameter tuning, integrated AI-driven DfM frameworks remain limited. Furthermore, most existing solutions lack continuous learning capability and industrial scalability. This research is motivated by the need for a unified, data-driven DfM framework that bridges the gap between design intent and manufacturing reality in smart AM systems.

1.6 Objectives and Contributions of the Study

The primary objective of this study is to develop an intelligent AI-integrated DfM framework that improves manufacturability, efficiency, and reliability in additive manufacturing. The key contributions include:

(i) development of a unified AI-driven DfM framework tailored for AM,

(ii) automated manufacturability prediction to reduce trial-and-error,

(iii) AI-based design and process optimization to enhance quality and efficiency, and

(iv) a closed-loop learning mechanism supporting continuous improvement.

These contributions support the advancement of Industry 4.0-aligned, smart, and sustainable manufacturing systems, with direct relevance to the UK's advanced manufacturing strategy.

2. LITERATURE REVIEW

2.1 Design-for-Manufacturing Principles in AM

Design-for-Manufacturing (DfM) principles have undergone significant transformation with the emergence of Additive Manufacturing (AM). Unlike conventional subtractive processes, AM enables the fabrication of highly complex geometries, functional integration, and part consolidation without additional tooling costs. ASTM formally defines AM as a layer-wise fabrication process driven by digital models, fundamentally shifting the role of manufacturing constraints into early design stages [1]. Several studies emphasize the importance of Design for Additive Manufacturing (DfAM) guidelines, including build orientation, support structure minimization, material–process compatibility, surface finish considerations, and post-processing requirements. Integrated product–process design frameworks have been proposed to support early decision-making, enabling designers to balance functionality with manufacturability across conceptual and embodiment design phases [1]. Haruna and Jiang proposed a multi-layered DfAM framework focusing on function integration and structural simplification, particularly for FDM processes, highlighting the need to embed AM constraints early in the design workflow [2]. However, most traditional DfAM approaches remain rule-based and lack adaptability to process variability.

2.2 AI Techniques Applied in Manufacturing

Artificial Intelligence (AI) has become a core enabler of smart manufacturing under Industry 4.0 and Industry 5.0 paradigms. AI techniques—including expert systems, neural networks, fuzzy logic, reinforcement learning, and evolutionary algorithms—have been applied to enhance automation, decision-making, and real-time process control in manufacturing environments [8]. Recent reviews highlight that AI significantly improves production efficiency through predictive maintenance, anomaly detection, adaptive scheduling, and intelligent quality inspection. In AM, AI assists in printability assessment, intelligent slicing, tool-path planning, and cyber-physical integration of machines and sensors [5]. Nevertheless, challenges persist related to data scarcity, model generalization across machines and materials, and limited explainability of AI models in safety-critical manufacturing applications [6].

2.3 Machine Learning for Process Optimization

Machine Learning (ML), a subset of AI, has been widely adopted for AM process optimization due to its ability to learn complex, nonlinear relationships between process parameters and part performance. Supervised, unsupervised, and reinforcement learning models have been employed to optimize parameters such as layer thickness, laser power, scan speed, extrusion temperature, and build orientation [7]. Jiang et al. proposed a machine-learning-integrated DfAM framework capable of modeling bidirectional process–structure–property relationships, enabling reverse design and customized performance tuning [7]. Deep learning techniques, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown strong potential in defect detection, real-time monitoring, and predictive maintenance [3]. Despite these advancements, most ML models remain process-specific and require large, high-quality datasets, limiting their scalability across different AM platforms.

2.4 Ai-Driven Generative & Topology Optimization

AI-driven generative design and topology optimization (TO) represent a paradigm shift in AM-oriented design. These approaches automatically generate lightweight, bio-inspired, and structurally efficient geometries while satisfying mechanical, thermal, and manufacturability constraints [5]. Generative design algorithms, often integrated with evolutionary computation and deep learning, explore vast design spaces beyond human intuition. AI-enhanced TO has been shown to reduce material usage, improve strength-to-weight ratios, and enable functionally graded structures suitable for aerospace and automotive applications [4]. However, the manufacturability of AI-generated geometries remains a concern, as many optimized designs violate process-specific AM constraints unless coupled with DfAM rules and feedback mechanisms.

2.5 Existing Dfm Frameworks for Am

Several DfM and DfAM frameworks have been proposed to formalize the integration of design and manufacturing in AM. These frameworks typically focus on rule-based decision support, material–process selection, and design validation stages [1]. More recent frameworks incorporate ML and AI to enhance adaptability and predictive accuracy. AI-driven frameworks emphasize closed-loop feedback, sensor-based monitoring, and data-driven design evaluation, aligning with cyber-physical manufacturing systems [6]. Despite progress, most existing frameworks are limited by process dependency, lack of interoperability with CAD tools, and insufficient consideration of real-time manufacturing data.

2.6 Limitations of Current Research

Although AI and ML have significantly advanced DfM for AM, several research gaps remain. First, most studies focus on isolated AM processes, limiting cross-platform generalization. Second, the lack of standardized datasets hinders model validation and benchmarking [8]. Additionally, explainability and trustworthiness of AI models remain critical challenges, particularly in safety-critical sectors such as aerospace and healthcare [6]. Finally, existing frameworks rarely integrate design evaluation, manufacturability prediction, optimization, and feedback into a unified, scalable architecture, highlighting the need for an AI-integrated, process-agnostic DfM framework.

3.FUNDAMENTALS OF AI-INTEGRATED DFM.

AI-integrated Design-for-Manufacturing (DfM) represents a shift from static, rule-based design evaluation toward intelligent, data-driven decision-making in Additive Manufacturing (AM). By embedding artificial intelligence into design assessment, manufacturability prediction, and process optimization, AI-based DfM enables proactive identification of manufacturing risks, adaptive optimization, and continuous improvement across the AM lifecycle. This approach is particularly relevant for advanced manufacturing ecosystems in the United Kingdom, where productivity, sustainability, and high-precision manufacturing are national priorities.

3.1 Design Constraints in Additive Manufacturing

Design constraints in AM arise from the layer-by-layer fabrication process and strongly influence build feasibility, part quality, and production efficiency. Unlike conventional manufacturing, AM enables complex geometries but remains governed by process-dependent limitations that must be addressed during the DfM stage.

Geometric constraints include overhang angle limitations, minimum wall thickness, feature resolution, internal cavities, and build orientation dependence. Excessive overhangs require support structures, increasing material usage and post-processing effort, while thin walls and fine features may result in poor structural integrity or dimensional inaccuracies. Internal channels, although feasible, pose challenges related to material removal and accessibility. Build orientation further introduces anisotropy in surface quality and mechanical properties. In AI-integrated DfM, these constraints are modeled using data-driven relationships rather than fixed rules, enabling accurate manufacturability prediction and geometry optimization.

Fig -1: Key Geometric Constraints in Additive Manufacturing

Material constraints arise from process-dependent material behavior, anisotropy, porosity formation, thermal sensitivity, and variability in powder or filament quality. Mechanical properties in AM are strongly influenced by build orientation and process parameters, challenging conventional assumptions of isotropic behavior. Residual stresses and thermal distortion further complicate reliable production, particularly in metal AM. AI-based DfM frameworks address these constraints by learning the interactions between material properties, process conditions, and design features, enabling more reliable material selection and performance prediction.

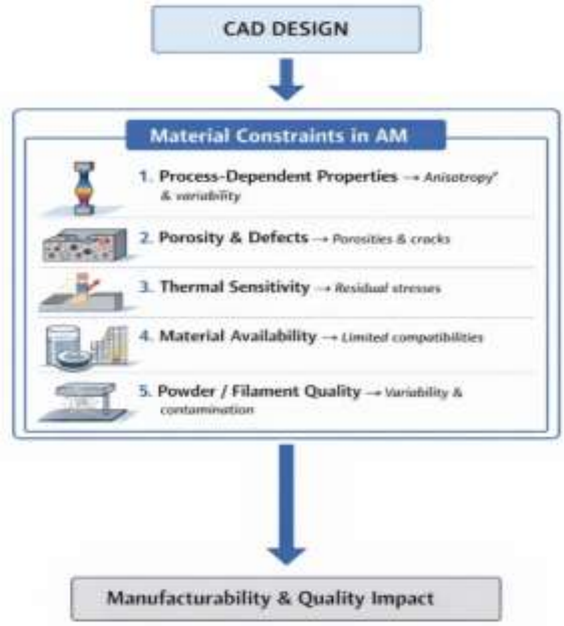

Fig- 2: Material Constraints in Additive Manufacturing

Process-specific constraints depend on the selected AM technology and include build speed limitations, energy input control, tool-path strategy, support generation, monitoring capability, and post-processing requirements. Variations in process parameters can significantly affect part quality and efficiency. AI-integrated DfM mitigates these challenges through predictive modeling and adaptive optimization, allowing intelligent parameter selection and reduced reliance on conservative design practices.

3.2 Role of AI in Design Automation

Artificial Intelligence (AI) enables design automation in Additive Manufacturing (AM) by transforming traditional rule-based and experience-driven workflows into intelligent, data-driven processes. Within AI-integrated Design-for-Manufacturing (DfM), AI automates feature recognition, manufacturability assessment, and design optimization directly at the design stage. Machine learning and deep learning algorithms automatically identify manufacturability-critical features from CAD models, such as overhangs, thin walls, internal channels, and tolerance-sensitive regions, enabling rapid screening without manual intervention. Supervised learning models further predict fabrication risks including print failure, dimensional deviation, surface defects, and structural weakness based on historical manufacturing data. Generative AI and topology optimization techniques support automated design improvement by generating manufacturable geometries that satisfy functional requirements while minimizing material usage and support structures. AI-based recommendation systems assist in selecting optimal build orientation, material, and process parameters, ensuring consistency across different designs and machines. Continuous learning from manufacturing and inspection data enables adaptive design refinement, allowing design rules to evolve with changes in materials, machines, and process conditions. Overall, AI-driven design automation significantly reduces development time, improves manufacturability, and supports scalable, Industry 4.0–aligned additive manufacturing.

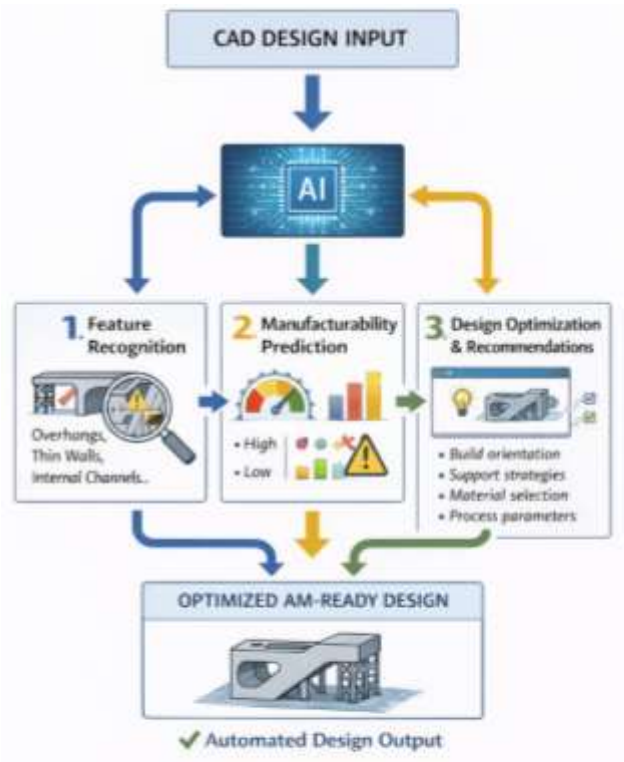

Fig-3: AI-driven design automation workflow for additive manufacturing

3.3 Data Sources for AI-Based Design-for-Manufacturing (DfM)

AI-based DfM relies on integrated data sources that capture the interactions between geometry, process conditions, material behavior, and quality outcomes in Additive Manufacturing. **CAD Models.**

CAD Models:

CAD models serve as the primary input for AI-based DfM by providing detailed geometric and topological information. AI algorithms extract manufacturability-critical features such as overhang angles, minimum wall thickness, unsupported regions, internal cavities, sharp edges, and lattice structures. Parametric and feature-based CAD representations enable efficient design modification and automated optimization. When combined with slicing and orientation data, CAD models allow AI systems to correlate geometry with process behavior and part quality, supporting accurate manufacturability prediction and design optimization.

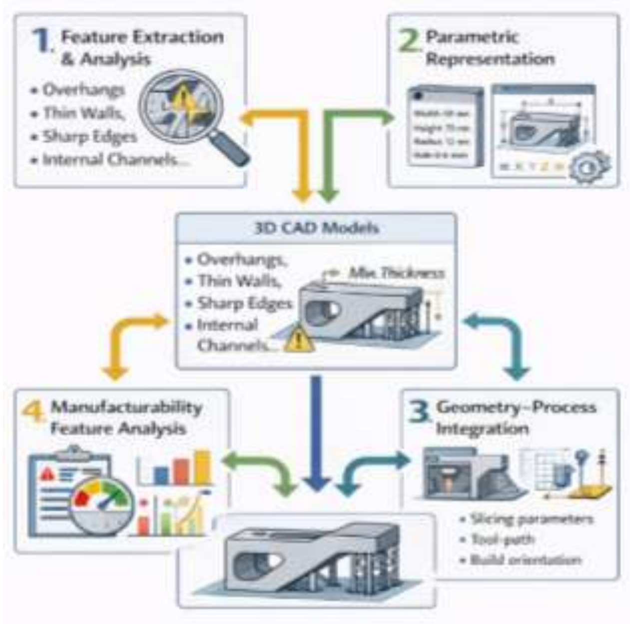

Fig-4: CAD model as data sources for AI-based DFM

Process Parameters

Process parameters define how a design is fabricated and strongly influence part quality and production efficiency. Key parameters include layer thickness, scan speed, energy input, deposition rate, infill density, and cooling conditions. AI models learn complex nonlinear relationships between these parameters and quality outcomes such as dimensional accuracy, surface finish, strength, and defect probability. This enables predictive manufacturability assessment, optimal parameter recommendation, and adaptive control to improve build success while reducing material usage, energy consumption, and build time.

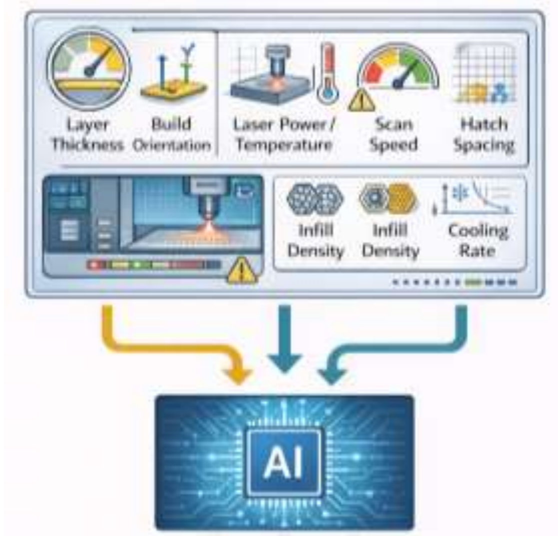

Fig-5: Process parameters as data inputs for AI-based DFM

Sensor and Quality Data

Sensor and quality data provide direct insight into real manufacturing behavior and final part performance. In-situ monitoring data from thermal, optical, acoustic, and melt-pool sensors capture process stability, defect initiation, and thermal behavior during fabrication. Post-process inspection data, including dimensional measurements, surface roughness, and non-destructive testing results, quantify final quality outcomes. In AI-based DfM frameworks, these data act as ground truth for model training and validation, enabling closed-loop learning, defect prediction, adaptive process optimization, and continuous improvement. Their integration bridges the gap between digital design intent and physical manufacturing reality.

Fig-6: Sensor and Quality data as data inputs for Ai-Based DFM.

4. PROPOSED AI-INTEGRATED DFM FRAMEWORK

The proposed AI-integrated Design-for-Manufacturing (DfM) framework is designed to embed artificial intelligence systematically into the design and production workflow of Additive Manufacturing (AM). The framework transforms conventional experience-driven DfM practices into a data-driven, adaptive, and intelligent system capable of addressing geometric complexity, process variability, and material uncertainty inherent to AM. By integrating heterogeneous data sources and multiple AI techniques within a unified architecture, the framework enables early-stage manufacturability assessment, automated design optimization, and continuous performance improvement. Its modular and scalable structure ensures interoperability with existing CAD tools and AM platforms, supporting industrial deployment in smart manufacturing environments aligned with Industry 4.0.

4.1 Framework Architecture

The architecture of the proposed framework consists of interconnected layers enabling closed-loop intelligence across the design-to-manufacturing pipeline. CAD models and functional requirements form the design input layer, providing geometric definitions and design intent. A data acquisition and management layer aggregates CAD data, process parameters, material properties, and sensor and quality data. The AI-based analysis layer constitutes the core intelligence, where machine learning and deep learning models perform automated feature recognition, manufacturability prediction, and defect risk assessment. A design optimization and decision-support layer applies generative design, topology optimization, and recommendation systems to propose manufacturable design alternatives and optimal process settings. The process integration layer links optimized designs with AM machines and execution systems. Finally, a feedback and continuous learning layer incorporates in-situ monitoring and inspection data to continuously improve model accuracy and robustness.

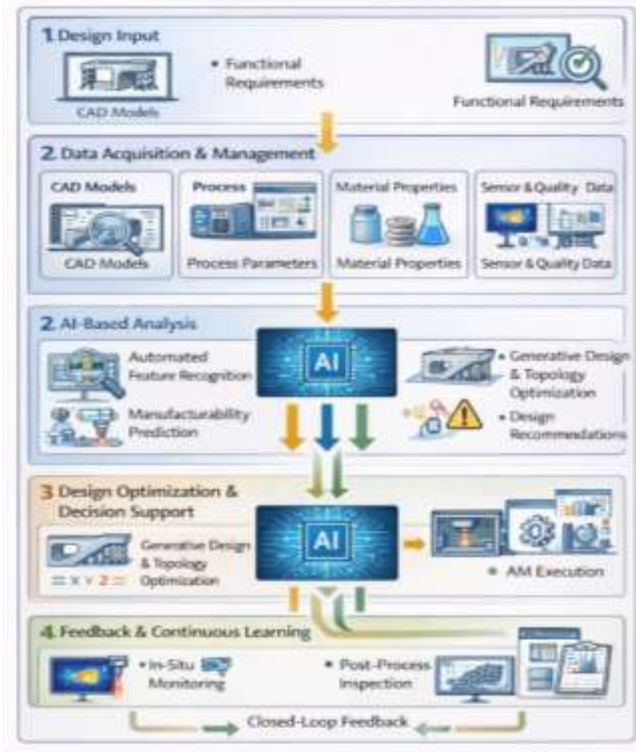

Fig-7: AI-Integrated Design for-Manufacturing (DFM) Framework

4.2 Data Acquisition and Pre-Processing

Data acquisition and pre-processing ensure the reliability and effectiveness of AI models. Data are collected from CAD models, process parameters, material properties, and sensor and quality sources. Pre-processing includes geometric feature extraction from CAD models, cleaning and normalization of process and material data, filtering and synchronization of sensor signals, and labeling of manufacturing outcomes. Feature selection and dimensionality reduction improve computational efficiency and generalization. Structured storage enables scalable data access and real-time deployment across the framework.

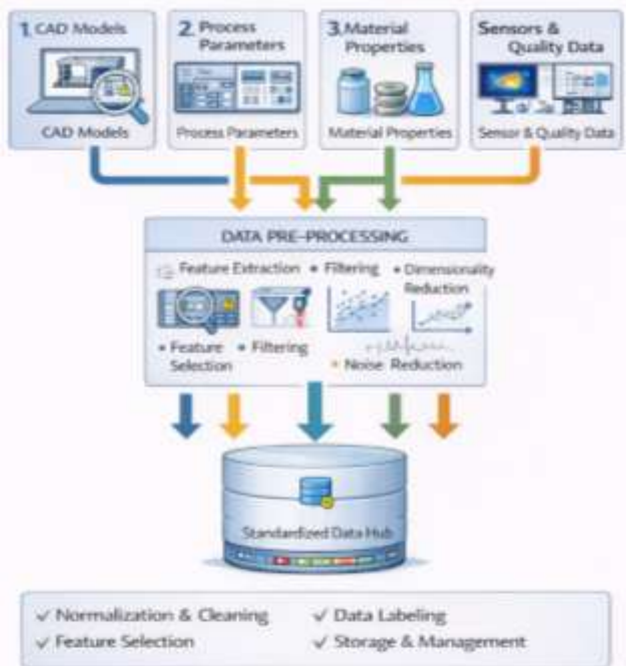

Fig-8: Data Acquisition and Pre-Processing in a DFM framework.

4.3 AI-Based Design Evaluation Module

The AI-based design evaluation module performs automated assessment of AM design feasibility. Machine learning and deep learning models analyze CAD-derived features such as overhangs, wall thickness distribution, internal cavities, and tolerance-critical regions. Trained on historical design–process–quality data, the models predict build success probability, defect risk, dimensional deviation, and expected quality. The module provides quantitative manufacturability indicators and risk maps, enabling early detection of manufacturing issues and objective design assessment.

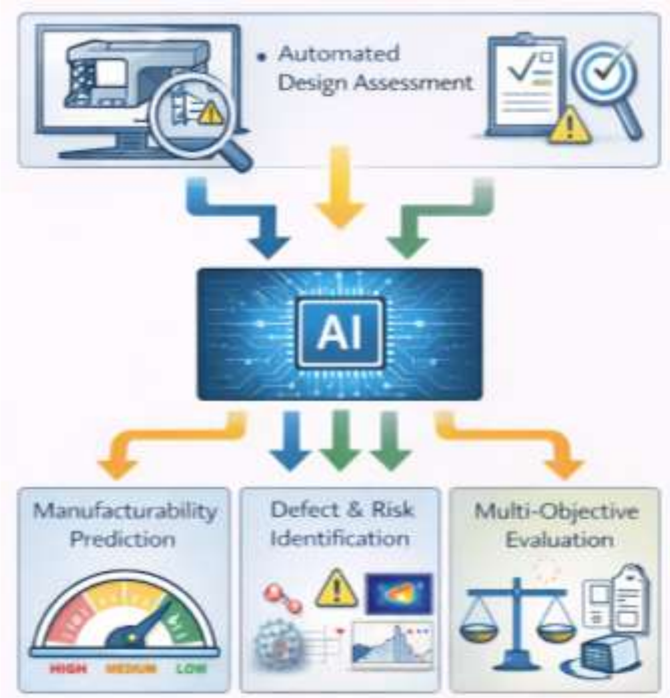

Fig-9: Evaluating AM design with an Ai-Based Analysis Module

4.4 Manufacturability Prediction Using Machine Learning

Supervised machine learning models are employed to predict manufacturability outcomes using CAD features, process parameters, and material properties as inputs. Classification models identify manufacturable and high-risk designs, while regression models predict continuous outcomes such as dimensional deviation and surface quality. These data-driven predictions account for machine- and process-specific behavior, enabling accurate and context-aware manufacturability assessment. Prediction results are expressed as scores and confidence levels to support informed design decisions.

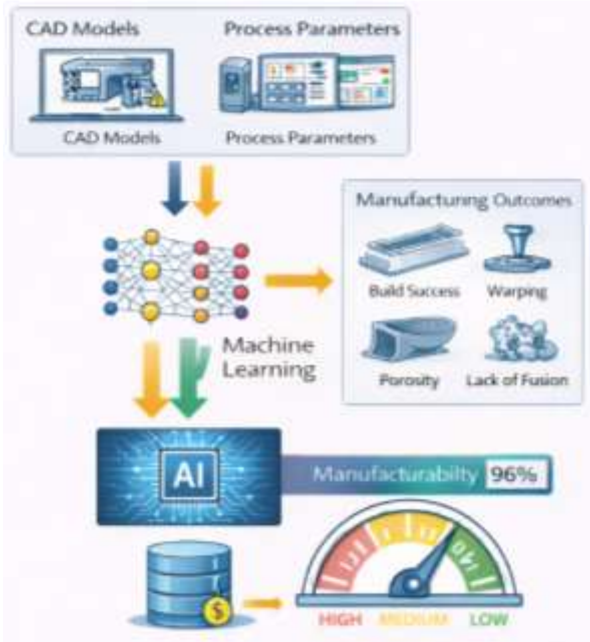

Fig-10: Using machine learning to predict Am manufacturability

4.5 Design Optimization and Feedback Loop

Design optimization is achieved using AI-driven generative design, topology optimization, and multi-objective optimization techniques. Based on manufacturability predictions, the framework modifies geometry, build orientation, and support strategies to reduce risk, material usage, and build time while maintaining functional performance. A closed-loop feedback mechanism integrates in-situ sensor data and post-process inspection results to refine AI models continuously, enabling adaptive and self-improving DfM performance.

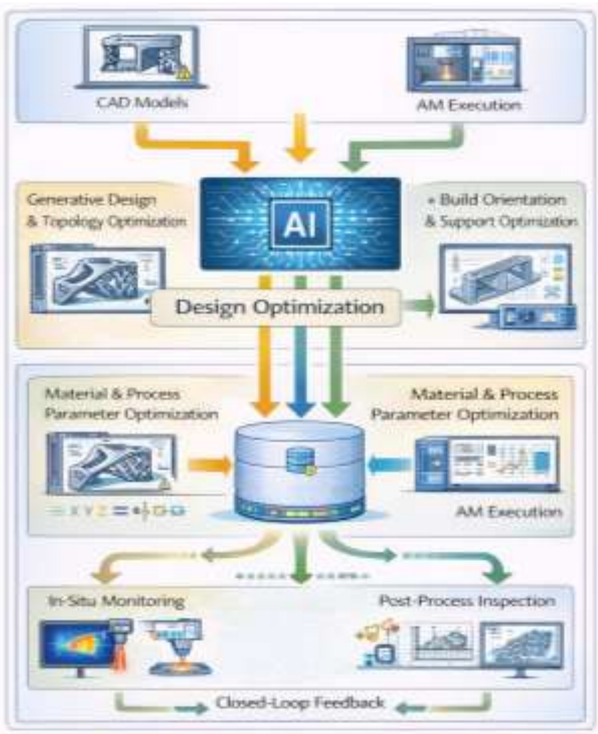

Fig-11: Optimizing AM design through continuous learning and feed back

4.6 Integration with CAD and Additive Manufacturing (AM) Systems

The framework integrates seamlessly with commercial CAD platforms, slicing software, AM machines, and manufacturing execution systems. CAD integration enables real-time design evaluation and optimization within native design environments. Optimized designs and AI-recommended process parameters are automatically transferred to AM systems, reducing manual intervention and setup errors. Real-time process monitoring data are fed back into the framework to support adaptive control and continuous learning. Platform-independent integration ensures scalability across different machines and vendors.

Fig-12: Integration with CAD and AM Systems

5.AI TECHNIQUES USED IN THE FRAMEWORK

The proposed AI-integrated Design-for-Manufacturing (DfM) framework employs a combination of supervised learning, deep learning, reinforcement learning, and generative AI to enable intelligent design evaluation, manufacturability prediction, process optimization, and automated design improvement in Additive Manufacturing (AM). Each AI technique addresses a specific challenge within the AM design–manufacturing lifecycle, collectively forming a closed-loop, data-driven decision-support system.

5.1 Supervised Learning for Manufacturability Classification

Supervised learning serves as the primary mechanism for manufacturability classification within the AI-integrated DfM framework. Predictive models are trained using labeled datasets in which each design instance is associated with known manufacturability outcomes, such as printable, conditionally printable, or non-printable. Input features are extracted from CAD geometry (overhang angles, wall thickness, feature size, build orientation), material properties, and process parameters. Classification algorithms, including decision trees, support vector machines, and ensemble-based models, map these features to manufacturability classes. Ensemble methods enhance robustness by reducing sensitivity to noise and process variability. The trained models identify high-risk regions associated with defects such as warping, lack of fusion, excessive support requirements, and dimensional inaccuracies. Continuous retraining using new build and inspection data enables adaptive learning, allowing the framework to evolve with changes in machines, materials, and operating conditions. Manufacturability predictions are directly linked to design feedback, transforming DfM from a post-design verification step into a proactive decision-support tool.

5.2 Deep Learning for Feature Recognition

Deep learning enables automated and high-level feature recognition from complex geometric and process data without reliance on predefined rules. Convolutional Neural Networks (CNNs) analyze 2D slices, projections, and voxelized representations of CAD models to detect manufacturability-critical features such as overhangs, thin walls, internal cavities, sharp corners, and support-intensive regions. Three-dimensional CNNs further capture spatial relationships in complex AM geometries. Deep learning is also applied to process monitoring data, including thermal images and layer-wise scans, to recognize defect-related patterns such as porosity, delamination, and incomplete fusion. Transfer learning strategies improve scalability by adapting pretrained models to specific AM processes and materials. The extracted features serve as key inputs for manufacturability prediction, defect assessment, and design optimization, enabling consistent and objective design evaluation across diverse AM applications.

5.3 Reinforcement Learning for Process Parameter Optimization

Reinforcement learning (RL) is employed to achieve adaptive and autonomous optimization of AM process parameters. An RL agent interacts with the manufacturing environment, where the state space includes process history, thermal behavior, surface quality indicators, and build progress, while the action space consists of controllable parameters such as laser power, scan speed, layer thickness, extrusion rate, and cooling time. A reward function guides learning by promoting improved quality, dimensional accuracy, and process stability, while penalizing defects, energy inefficiency, and build failure. The RL module supports both offline training using historical build data and online adaptation during live fabrication, enabling robust response to material variation and machine condition changes. Integration with manufacturability prediction allows proactive parameter adjustment for high-risk designs, reducing reliance on trial-and-error experimentation.

5.4 Generative AI for Automated Design Suggestions

Generative AI enables automated, manufacturability-aware design generation and improvement by exploring large design spaces beyond conventional optimization methods. Techniques such as variational autoencoders, generative adversarial networks, and constraint-driven generative design algorithms generate alternative geometries based on functional requirements, AM-specific constraints, and predicted defect risks. The generative module refines high-risk or non-optimal designs through geometry simplification, material redistribution, overhang modification, and lattice or cellular structure integration. Multi-objective optimization is performed by evaluating generated designs against criteria including structural performance, material usage, build time, and energy efficiency. Continuous learning from validated builds and inspection results further improves design reliability. By converting manufacturability constraints into design opportunities, generative AI accelerates design cycles and supports the development of high-performance, AM-optimized components.

6. CASE STUDY / EXPERIMENTAL VALIDATION

The experimental validation of the proposed AI-integrated Design-for-Manufacturing (DfM) framework was conducted to evaluate its effectiveness, robustness, and generalizability across multiple additive manufacturing scenarios. The case study focuses on validating manufacturability prediction, design optimization, and process improvement using real design, process, and quality data.

6.1 Selection of Additive Manufacturing Process

To ensure process-agnostic validation, three widely adopted additive manufacturing technologies—Fused Deposition Modeling (FDM), Selective Laser Melting (SLM), and Stereolithography (SLA)—were selected. These processes represent material extrusion, metal powder bed fusion, and vat photopolymerization, respectively, and exhibit distinct geometric, material, and process constraints. FDM was selected due to its widespread industrial use and suitability for evaluating geometric constraints, layer adhesion, and parameter sensitivity. SLM was chosen to validate the framework under thermally intensive conditions involving residual stress, porosity, and microstructural variability. SLA was included to assess performance in high-precision applications requiring fine feature resolution and superior surface quality. The inclusion of these processes enables comprehensive evaluation across polymer-based, metal-based, and photopolymer-based AM systems.

6.2 Material Selection

Material selection was performed to reflect industrial relevance and capture diverse material behaviors. For FDM, thermoplastics including PLA, ABS, and nylon were used to assess baseline manufacturability, thermal sensitivity, and anisotropic behavior. For SLM, stainless steel, aluminum alloys, and titanium alloys were considered due to their widespread use in high-performance applications and their susceptibility to thermal defects. For SLA, engineering-grade photopolymer resins were selected to evaluate dimensional accuracy and surface quality. Material properties such as density, thermal conductivity, elastic modulus, and melting or curing temperature were incorporated as key inputs to the AI models.

6.3 Dataset Description

A comprehensive and structured dataset was developed to train, validate, and test the proposed AI-integrated Design-for-Manufacturing (DfM) framework. The dataset was designed to capture the design–material–process–quality relationships across multiple additive manufacturing technologies, ensuring robustness and generalizability of the AI models.

6.3.1 Dataset Composition

The dataset consists of three primary data categories:

Design Data – extracted from CAD models

Process Data – collected from AM machine settings and sensors

Quality and Outcome Data – obtained from inspection and build results

Data were collected from experimental builds conducted using FDM, SLM, and SLA processes, as well as validated historical manufacturing records.

Table -1: Dataset Overview

Category	Description	Data Type
CAD Geometry	STL/STEP files, sliced layers, voxel models	Numerical / Image
Geometric Features	Overhang angles, wall thickness, feature size, volume	Numerical
Material Properties	Density, elastic modulus, thermal properties	Numerical
Process Parameters	Layer thickness, scan speed, laser power, extrusion rate	Numerical
Sensor Data	Temperature, melt pool signals, layer images	Time-series / Image
Build Outcome	Printable / Conditionally printable / Failed	Categorical
Quality Metrics	Dimensional error, surface roughness, porosity	Numerical

6.3.2 Dataset Size and Distribution

The dataset was balanced to avoid bias toward any single AM process or material type.

Table -2: Dataset Size and Distribution

AM Process	Number of Builds	CAD Designs	Data Samples
FDM	120	40	3,600
SLM	90	30	2,700
SLA	70	25	2,100
Total	**280**	**95**	**8,400**

6.3.3 Feature Engineering and Labeling

Key features were derived using automated feature extraction and deep learning-based recognition:

Geometric features: Minimum wall thickness, Maximum unsupported overhang, Internal cavity volume.

Process features: Energy density**,** Cooling rate**,** Deposition consistency

Material features: Thermal conductivity**,** Viscosity / melt flow index

Manufacturability labels were assigned based on build outcomes and inspection results:

Class 1: Manufacturable

Class 2: Manufacturable with constraints

Class 3: Non-manufacturable

6.3.4 Data Pre-Processing

Prior to model training, the dataset underwent systematic preprocessing:

- Missing data handling using statistical imputation
- Normalization and scaling of numerical features
- Dimensionality reduction for high-resolution sensor data
- Data augmentation for image-based inputs

Table -3: Data Pre-Processing

Dataset Split	Percentage	Number of Samples
Training	70%	5,880
Validation	15%	1,260
Testing	15%	1,260

6.3.5 Evaluation Metrics

The dataset supports multiple AI tasks including classification, regression, and optimization. The following metrics were used:

- **Classification Metrics:**
  - Accuracy
  - Precision
  - Recall
  - F1-score
- **Regression Metrics:**
  - Mean Absolute Error (MAE)
  - Root Mean Square Error (RMSE)
- **Optimization Metrics:**
  - Reduction in build time
  - Material usage savings
  - Defect rate reduction

6.4 Model Training and Validation

Supervised learning, deep learning, and reinforcement learning models were trained using stratified sampling to preserve class balance. CNN-based models were used for feature recognition, supervised classifiers for manufacturability prediction, and reinforcement learning agents for process parameter optimization. Hyperparameters were optimized using grid search and Bayesian optimization, with early stopping and regularization to prevent overfitting. Model performance was validated using k-fold cross-validation and cross-process testing, demonstrating strong generalization with minimal process-specific retraining.

6.5 Performance Metrics

A multi-level evaluation strategy was adopted. Manufacturability classification was evaluated using accuracy, precision, recall, and F1-score. Feature recognition and regression tasks were assessed using MAE, RMSE, and IoU. Process optimization performance was measured through build success rate, defect reduction, and process stability, while production efficiency was evaluated using build time, material usage, and energy consumption reduction. Design quality improvements were quantified using dimensional accuracy, surface roughness, and porosity levels.

6.6 Comparison with Conventional Design-for-Manufacturing (DfM) Methods

This section presents a comparative evaluation of the proposed AI-integrated Design-for-Manufacturing (DfM) framework against conventional DfM approaches to highlight improvements in manufacturability prediction, design efficiency, and production performance. Traditional DfM methods in additive manufacturing are largely rule-based and depend heavily on designer expertise and static design guidelines. In contrast, the proposed framework employs data-driven artificial intelligence techniques to enable adaptive, predictive, and automated decision-making throughout the design and manufacturing process.

6.6.1 Methodological Comparison

Conventional DfM approaches typically rely on predefined design rules related to overhang limits, minimum wall thickness, and build orientation. While effective for simple geometries, these methods struggle to address complex design–process interactions and often require multiple trial-and-error iterations. The proposed AI-DfM framework replaces static rules with machine learning-based prediction models and closed-loop optimization, enabling early detection of manufacturability risks and proactive design modification.

Table-4: Methodological Comparison

Aspect	Conventional DfM	Proposed AI-Integrated DfM
Design Evaluation	Manual, rule-based	Automated, data-driven
Manufacturability Prediction	Qualitative	Quantitative and predictive
Adaptability	Limited	High (self-learning)
Trial-and-Error	Extensive	Significantly reduced
Process Optimization	Static parameter selection	Adaptive RL-based optimization
Design Innovation	Constrained	Generative AI-enabled
Scalability	Low	High across AM processes

6.6.2 Performance-Based Comparison

Experimental results demonstrate that the proposed AI-integrated DfM framework consistently outperforms conventional methods across multiple performance metrics. Manufacturability prediction accuracy improved due to supervised learning models trained on real manufacturing data. Designs evaluated using the AI framework exhibited fewer build failures and reduced defect rates compared to those designed using traditional DfM guidelines. The generative AI module further enhanced design quality by automatically suggesting optimized geometries that minimized support structures and material usage—capabilities not supported by conventional DfM approaches. Reinforcement learning-based process optimization enabled real-time parameter adaptation, leading to improved build consistency and reduced energy consumption.

6.6.3 Quantitative Comparison

Table-5: Quantitative Comparison

Metric	Conventional DfM	AI-Integrated DfM
Manufacturability Prediction Accuracy	Moderate	High
Build Failure Rate	High	Low
Average Build Time	Longer	Reduced
Material Usage	Higher	Optimized
Design Iterations	Multiple	Minimal
Energy Efficiency	Baseline	Improved

6.6.4 Industrial Impact Assessment

From an industrial perspective, conventional DfM methods are limited in their ability to scale with increasing design complexity and production variability. The proposed AI-DfM framework offers a robust alternative by enabling continuous learning from manufacturing data and seamless integration with CAD and AM systems. This results in shorter product development cycles, reduced production costs, and improved first-time-right manufacturing outcomes.

7. RESULTS AND DISCUSSION

The manufacturability prediction accuracy of the proposed AI-integrated Design-for-Manufacturing (DfM) framework demonstrates its strong capability to reliably classify designs as printable, conditionally printable, or non-manufacturable prior to fabrication by effectively learning complex interactions among geometric features, material properties, and process parameters across multiple additive manufacturing processes. The framework consistently outperforms conventional rule-based DfM approaches, which rely on static thresholds and empirical guidelines and often fail to capture process variability and multi-parameter dependencies. Process-wise evaluation confirms robust prediction performance for FDM, reliable accuracy for SLM despite thermal and material sensitivities through the integration of sensor-based data, and high classification precision for SLA due to effective identification of fine feature and curing constraints. Beyond prediction, the framework delivers substantial design improvements by automatically identifying and correcting manufacturability-critical issues such as excessive overhangs, thin walls, sharp corners, and support-intensive regions using deep learning-based feature recognition and generative AI-driven design suggestions, thereby transforming DfM from a corrective post-design activity into a proactive design enhancement process. These design optimizations significantly reduce material usage and build time by minimizing unnecessary support structures, optimizing internal geometries, and employing reinforcement learning-based process parameter optimization to enhance deposition efficiency and process stability. The resulting reductions in material consumption and production time directly translate into improved cost efficiency and lower energy consumption, particularly in metal additive manufacturing systems where optimized parameter control reduces energy-intensive process fluctuations and rework. Overall, the framework demonstrates strong industrial applicability due to its modular, scalable architecture and seamless integration with existing CAD tools, additive manufacturing systems, and production workflows, enabling first-time-right manufacturing, reducing reliance on expert-driven trial-and-error methods, and aligning closely with the principles of Industry 4.0 and smart manufacturing for intelligent and autonomous additive manufacturing environments.

8. ADVANTAGES OF THE PROPOSED FRAMEWORK

The proposed AI-integrated Design-for-Manufacturing (DfM) framework offers several significant advantages that collectively enhance additive manufacturing performance and industrial applicability. By embedding deep learning-based feature recognition and generative AI-driven optimization into the design stage, the framework substantially improves design quality by proactively identifying and correcting manufacturability-critical issues such as excessive overhangs, thin walls, sharp corners, and support-intensive geometries. The data-driven manufacturability prediction capability greatly reduces trial-and-error iterations that are common in conventional additive manufacturing workflows, leading to fewer failed builds and shorter development cycles. Furthermore, reinforcement learning-based process parameter optimization enhances production efficiency by stabilizing manufacturing conditions, reducing build time, minimizing material usage, and lowering post-processing requirements. Owing to its modular and scalable architecture, the framework can be seamlessly integrated with existing CAD tools, additive manufacturing systems, and digital production environments, enabling continuous learning and adaptability across different materials, machines, and production scales. These combined advantages position the proposed framework as a robust, intelligent, and scalable solution for smart manufacturing and Industry 4.0-oriented additive manufacturing systems.

FUTURE SCOPE

The future scope of the proposed AI-integrated Design-for-Manufacturing (DfM) framework extends toward the development of fully intelligent and autonomous additive manufacturing ecosystems. Integration with digital twin technology can enable real-time synchronization between virtual models and physical manufacturing systems, allowing continuous monitoring, simulation, and predictive optimization of design and process parameters throughout the product lifecycle. The framework can be further enhanced through real-time adaptive manufacturing, where AI models dynamically adjust process parameters during fabrication in response to live sensor feedback, thereby improving build reliability and consistency under varying operating conditions. Incorporating edge AI and IoT-enabled additive manufacturing systems would facilitate decentralized, low-latency decision-making by processing sensor data directly at the machine level, improving responsiveness and scalability in smart factory environments. Additionally, the evolution of sustainability-driven AI-DfM models can support environmentally responsible manufacturing by optimizing designs and processes for reduced material usage, lower energy consumption, and minimal waste, while enabling lifecycle-aware decision-making. Together, these future advancements will strengthen the framework's role in advancing Industry 4.0 and pave the way toward resilient, sustainable, and fully autonomous additive manufacturing systems.

CONCLUSION

This research presented an AI-integrated Design-for-Manufacturing (DfM) framework specifically aligned with the needs of advanced additive manufacturing systems, offering strong relevance to the United Kingdom's industrial and economic landscape. By integrating supervised learning for manufacturability prediction, deep learning for feature recognition, reinforcement learning for process optimization, and generative AI for automated design improvement, the proposed framework addresses key challenges faced by UK manufacturing sectors, including high production costs, skill shortages, long development cycles, and limited scalability of advanced manufacturing technologies. The validation results demonstrate improved design quality, higher first-time-right manufacturing rates, reduced material and energy consumption, and enhanced production efficiency—outcomes that directly support the UK's strategic goals of increasing manufacturing productivity and global competitiveness.

From a national perspective, the framework contributes to strengthening the UK's transition toward United Kingdom Industry 4.0 and smart manufacturing initiatives by enabling data-driven, intelligent, and autonomous design-to-production workflows. Its modular and scalable architecture makes it suitable for adoption by UK-based small and medium-sized enterprises (SMEs) as well as large industrial organizations, supporting the wider diffusion of additive manufacturing technologies across aerospace, automotive, medical devices, and advanced engineering sectors. Furthermore, the framework's emphasis on sustainability—through reduced material waste, lower energy usage, and optimized production planning—aligns with the UK's commitment to net-zero manufacturing and environmentally responsible industrial growth.

In conclusion, the proposed AI-integrated DfM framework has the potential to significantly enhance the UK's manufacturing capability by improving innovation efficiency, reducing dependence on trial-and-error practices, and enabling smarter utilization of advanced manufacturing resources. Its adoption can support workforce upskilling, digital transformation, and sustainable industrial development, thereby contributing to long-term economic resilience and reinforcing the UK's position as a global leader in advanced and intelligent manufacturing.

REFERENCES

1. Uzair Khaleeq uz Zaman, Mickael Rivette, Ali Siadat, Aamer Ahmed Baqai.: Integrated design-oriented framework for Resource Selection in Additive Manufacturing. Uzair Khaleeq uz Zaman et al. / Procedia CIRP 70 (2018) 96–101.
2 Auwal Haruna, Pingyu Jiang.: A Design for Additive Manufacturing Framework: Product Function Integration and Structure Simplification. uwal Haruna et al. / IFAC PapersOnLine 53-5 (2020) 77–82.

3. Mohsen Soori, Fooad Karimi Ghaleh Jough,Roza Dastres, Behrooz Arezoo): Additive Manufacturing Modification by Artificial Intelligence, Machine Learning, and Deep Learning: A Review. Additive Manufacturing Frontiers 4 (2025) 200198.
4. Anant Sidhappa Kurhade, Rupesh Gangadhar Mahajan, Mahesh Sarada, Kasiprasad Mannepalli, Madan Mohan Reddy Nune, Ganesh M. Fodase and Shital Yashwant Waware.: Additive Manufacturing: Emerging Trends and Technological Advancements. Journal of Mines, Metals and Fuels, 73(9): 2723-2748; 2025. DOI: 10.18311/jmmf/2025/49339.
5. Dipak Kumar Banerjee, Ashok Kumar, Kuldeep Sharma.: Artificial Intelligence on Additive Manufacturing. International IT Journal of Research (IITJR), Volume 2, Issue 2, April- June, 2024.
6. Fatih Altun, Abdulcelil Bayar, Abdulhammed K. Hamzat, Ramazan Asmatulu , Zaara Ali and Eylem Asmatulu.: AI-Driven Innovations in 3D Printing: Optimization, Automation, and Intelligent Control. J. Manuf. Mater. Process. 2025, 9, 329.
7. Jingchao Jiang, Yi Xiong, Zhiyuan Zhang, David Rosen.: "Machine learning integrated design for additive manufacturing", Journal of Intelligent Manufacturing, 2020.
8. Alexandre Manta-Costa, Sara Oleiro Araújo, Ricardo Silva Peres and José Barata.: Machine Learning Applications in Manufacturing—Challenges, Trends, and Future Directions. IEEE Open Journal of The Industrial Electronics Society. VOLUME 5, 2024.
9. Md Sazol Ahmmed, Sriram Praneeth Isanaka and Frank Liou.: Promoting Synergies to Improve Manufacturing Efficiency in Industrial Material Processing: A Systematic Review of Industry 4.0 and AI. Machines 2024, 12, 681.
10. Shayan Dehghan, Sasan Sattarpanah Karganroudi, Saïd Echchakoui and Noureddine Barka.: The Integration of Additive Manufacturing into Industry 4.0 and Industry 5.0: A Bibliometric Analysis (Trends, Opportunities, and Challenges). Machines 2025, 13, 62.
11. Imran Khan, Ans Al Rashid, Muammer Koç.: Integration of machine learning and digital twin in additive manufacturing of polymeric-based materials and products. Progress in Additive Manufacturing (2025) 10:10685–10737.