



A Review of the Fused Deposition Modeling (FDM) Process: An Integrated Analysis of Materials, Manufacturing Parameters, Mechanical Properties, Defect Formation, and Quality Assessment

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ABSTRACT :

Fused Deposition Modeling (FDM) is widely used in polymer additive manufacturing, although printed component performance depends on several interacting material and process-related factors. This review examines 60 selected publications from 2022 to 2026, covering thermoplastic materials, manufacturing parameters, mechanical properties, defect formation, and quality assessment. The literature is organized into an integrated, process-oriented framework connecting material selection and printing conditions with interlayer bonding, structural performance, manufacturing defects, and quality verification. Five comparative tables and two conceptual schemes summarize material characteristics, defect mechanisms, inspection methods, and optimization trade-offs. The analysis indicates that printing parameters influence mechanical performance and manufacturing quality differently across conventional, reinforced, flexible, and recycled polymers. Conventional testing remains essential, while sensor-based monitoring, computer vision, and machine learning offer complementary opportunities for defect detection and process refinement. The review also highlights limitations associated with experimental comparability, process reproducibility, internal defect characterization, and the generalization of intelligent monitoring approaches. Future research directions include standardized testing, multimodal quality assessment, fatigue characterization, and material-specific optimization. The resulting synthesis provides a structured reference for evaluating and improving FDM manufacturing processes.

Keywords: Fused Deposition Modeling; Fused Filament Fabrication; Additive Manufacturing; Manufacturing Parameters; Mechanical Properties; Defect Formation; Quality Assessment; Process Optimization.

Introduction

Fused Deposition Modeling (FDM), also known as Fused Filament Fabrication (FFF), is one of the most widely used additive manufacturing processes for producing polymer components through successive material deposition. Its relatively low equipment costs, manufacturing flexibility, and compatibility with different thermoplastic materials have supported its development from rapid prototyping toward functional manufacturing applications. Gao et al. [1] highlighted the importance of printing parameters in determining the mechanical performance of FDM components, while recent research has continued to investigate the relationships between processing conditions and manufactured part quality. In particular, Raza et al. [2] reviewed recent advancements in FDM materials and parameter optimization, emphasizing the importance of selecting appropriate manufacturing conditions for different polymers.

The selection of printing materials represents a fundamental stage in the FDM process. Common thermoplastics, including polylactic acid (PLA), acrylonitrile butadiene styrene (ABS), and polyethylene terephthalate glycol-modified (PETG), offer different combinations of mechanical performance, thermal behavior, processability, and production cost. Zotti et al. [3] examined the development, properties, and applications of polymer composites manufactured using FDM, demonstrating the importance of material composition for functional applications. Kumar et al. [4] also analyzed the mechanical properties of additively manufactured polymer composites, highlighting the influence of reinforcement materials and manufacturing conditions on component performance. These findings indicate that material selection cannot be considered independently of manufacturing parameters and the requirements of the final application.

The influence of manufacturing parameters has consequently become a major research direction in FDM. Layer height, printing speed, nozzle temperature, build orientation, raster angle, and infill characteristics can affect mechanical resistance, dimensional accuracy, surface roughness, and manufacturing efficiency. Gao et al. [1] provided an extensive overview of these relationships, while Rathod et al. [5] recently examined parameter optimization strategies for improving the mechanical properties of FFF components. Their findings highlight the importance of identifying suitable printing conditions while considering the interactions between multiple process variables. However, differences in materials, equipment configurations, and experimental procedures make direct comparisons between published results difficult. A broader classification connecting manufacturing parameters with material characteristics, mechanical performance, and quality evaluation is therefore necessary.

The mechanical performance of FDM-printed parts is still a key factor in their usefulness. When assessing the structural behavior of printed polymers, it is common practice to measure their tensile strength, flexural strength, impact resistance, stiffness, and interlayer bonding. Omer et al. [6] looked at how new innovations in interlayer bonding affect structural integrity, whereas Kumar et al. [4] spoke about mechanical performance in polymer composite production. Mechanical anisotropy and decreased component dependability might result from insufficient bonding between deposited layers, according to their research. Material qualities, manufacturing orientation, temperature conditions, and internal structures are some of the elements that interact to produce the mechanical response of printed components. Results obtained from one set of tests may not always be generalizable to different materials or printing conditions.

The creation of manufacturing flaws is another crucial part of the FDM process. Void formation, porosity, inadequate interlayer adhesion, delamination, warping, and dimensional aberrations may all be introduced by the layer-by-layer deposition technique. Improper printing settings, shaky material deposition, temperature gradients, or inconsistent filament properties may all lead to these kinds of flaws. The mechanical performance of fiber-reinforced thermoplastic components, as well as the correlations between structural discontinuities and internal flaws, have recently been the focus of research on material extrusion additive manufacturing [7]. Additional research on FDM dimensional accuracy was conducted by Equbal et al. [8], who emphasized the role of process management and manufacturing circumstances in reducing geometric errors. Research like this shows that optimizing process parameters and material choice are crucial to understanding fault development.

In order to evaluate the repeatability and dependability of the FDM process, quality evaluation is crucial, and it goes beyond only finding manufacturing flaws. Different methods for inspecting manufactured components are available, including dimensional measurements, mechanical testing, visual inspection, microscopy, and non-destructive testing. While traditional surface examination may miss interior discontinuities and structural flaws, research on improved non-destructive testing techniques has shown promise in this area [7]. Defect identification during FDM printing was examined by He et al. [9] in their evaluation of machine condition monitoring methods. These strategies included computational approaches and sensor-based measures. These additions show that quality evaluation isn't only something that should be thought about after components are made; it should be examined at every stage.

New innovations have brought digital monitoring and smart ways to increase the dependability of FDM processes. Xu et al. [10] explored the possibility of combining production data with computational monitoring by looking at a digital twin method for fault detection in FDM printing. Material behavior prediction, process parameter optimization, and manufacturing defect identification are some of the other areas that have investigated machine learning approaches. With an eye on data-driven methods for process optimization and quality control, Xie et al. [11] examined these uses across additive manufacturing technologies. The availability of relevant datasets, suitable validation techniques, and the ability of these approaches to work under diverse production settings determine their application, however.

The current literature on FDM often focuses on individual components rather than how they interact to affect manufacturing results, even though there is a lot of study on the topic. Optimization of process parameters [5], interlayer bonding [6], dimensional precision [8], and condition monitoring [9] all provide useful but distinctly focused reviews. Contributions with a broader scope have also investigated FDM materials, production circumstances, and application needs [12]. A more recent synthesis that reliably links material properties, production factors, defect causes, mechanical effects, and methods for evaluating quality is still helpful, however. By working together, researchers may better understand the strengths and weaknesses of current production and inspection methods, draw connections across seemingly unrelated areas of study, and compare and contrast experimental results.

Through five interrelated topics—materials, production parameters, mechanical characteristics, defect generation, and quality assessment—this review aims to organize and critically analyze current research on the Fused Deposition Modeling method. We pay close attention to the connections between the mechanical performance of produced parts, printing parameters, fault causes, and material properties. We take a look at both traditional inspection techniques and new computational tools, including AI and ML, to see how they might help with finding defects and evaluating process quality. Finding consistent patterns, contradicting results, present constraints, and future study paths is the goal of this review, which is organized into comparison tables and conceptual categories based on published findings. The planned group will serve as a central resource for scholars studying FDM production, mechanical characterisation, defect avoidance, and quality assurance.

Literature Review and Process-Oriented Classification

2.1. Literature Organization and Analytical Approach

Through a process-oriented lens, this paper investigates the interrelationships between FDM materials, production settings, mechanical characteristics, defect generation, and quality evaluation. Review articles and experimental studies published between 2023 and 2026 make up the material evaluated in this section. Instead of seeing these contributions as separate lines of inquiry, the suggested method establishes connections between them by means of a series of steps including material choice, production setup, defect creation, performance assessment, and process improvement.

Based on 60 chosen papers from 2022–2026, this research presents a narrative, process-oriented evaluation. The literature covers the main steps of FDM production and includes review papers as well as sample computational and experimental investigations. Connecting materials, processing parameters, mechanical performance, flaws, and quality assessment, the synthesis centers on themes and their significance. Neither a comprehensive systematic review nor a statistical meta-analysis are its stated purposes.

Evaluating the performance of FDM-printed components requires simultaneous consideration of production settings and material properties, according to recent evaluations. The combined effect of processing conditions on structural and thermal properties was investigated in a thorough assessment of thermoplastic composites [13], and the interaction between printed-part quality, process parameters, and material selection was addressed by Palanisamy et al. [14]. The impact of production factors on mechanical behavior and surface roughness was further investigated by Umer et al. [15].

Conductive polymers used for printed sensors and electrodes are one example of the functional materials that must be considered in light of the growing variety of filament compositions [16].

Nevertheless, optimizing only for maximal mechanical strength is not feasible. In material extrusion production, Sun et al. [17] showed how important it is to reduce internal voids, while Nguyen et al. [18] looked at the trade-off between mechanical performance and manufacturing time. Important limitations in multicomponent production include material compatibility and interlayer adhesion, according to research on polymer interfaces [19]. Processing conditions impact structural performance via material-dependent processes, as shown by experimental results including thermal treatment [20], carbon-fiber-reinforced nylon [21], and PLA components [22].

Thus, this study views FDM not as a set of separate parameter studies but as an integrated production system. Material properties, controllable production parameters, fault causes, mechanical implications, and quality assessment methods are the five main aspects that make up the categorization. Research is evaluated based on the factors studied and the findings that were actually recorded, without supposing that results from other polymers, specimen shapes, or testing methods may be immediately used interchangeably.

2.2. Comparative Analysis of Existing FDM Research

Multiple factors interact to determine the success of manufacturing advances, according to recent experimental research. Researchers have looked at vibration-assisted PLA manufacture as a way to enhance mechanical characteristics and surface quality [23], and they have also tested ultrasonic vibration on ABS and PLA specimens [24]. To achieve a happy medium between competing performance goals, multi-objective optimization techniques like the Grey-Taguchi method [25] have been developed. Further evidence of the significance of comparing production parameters to the functional needs of the target component is provided by application-oriented studies of PLA acetabular liners [26].

The data-driven methods for process optimization, property prediction, and quality evaluation have been outlined in recent reviews on machine-learning-assisted FDM manufacturing [27], and causality-guided fault diagnosis [28] has been studied for detecting manufacturing anomalies when visual interference is present. Recent research on defect-induced geometric deformation [30] focuses on dimensional conformity, while experimental studies employing the Taguchi technique [29] provide a typical optimization viewpoint. The results of using lightweight convolutional neural networks [31] to detect obvious printing flaws are conditional on the training data and the operational settings, but they do provide some hope.

It is important to pay close attention to the connection between parameter selection and the development of defects. Using temporal imaging information, researchers have looked at layer-wise defect detection [32], and surface quality in terms of roughness and printing-related abnormalities [33]. Another method that has been used to differentiate extrusion-related flaws is camera-based classification [34]. Further proof that flawed interfaces and void creation might impact mechanical integrity was found in experimental studies of PLA interlayer bonding [35]. To enhance polymer components made by extrusion, more recent studies have suggested defect-oriented methods [36].

Quality, according to their research, defies proper representation by any one geometric or mechanical measure. A more appropriate approach would be to assess the manufacturing process using a number of metrics related to structural integrity, surface quality, dimensional accuracy, defect detection, and process stability. Related research has focused on predicting surface quality with material flow measurements [37], diagnosing feeder motors using electrical signals [38], and studying how different deposition patterns affect mechanical performance and surface roughness [39]. In Table 1 we can see the key areas of study and how they connect to the suggested categorization.

Table 1 – Process-oriented classification of the reviewed FDM literature

Research direction	Representative studies	Main investigated relationship	Role in the present review
Materials and composites	[13], [16], [19], [21]	Material composition, processing compatibility, interlayer behavior	Material selection
Manufacturing parameters	[14], [15], [18], [25], [29]	Printing settings, mechanical performance, manufacturing efficiency	Parameter optimization
Mechanical characterization	[20], [22], [23], [24], [26]	Structural performance, bonding, mechanical improvement	Performance evaluation
Defect formation	[17], [30], [35], [36]	Voids, geometric deviations, insufficient adhesion	Defect mechanisms
Surface and dimensional quality	[33], [37], [39]	Surface roughness, material flow, printed geometry	Quality assessment
Digital defect detection	[27], [28], [31], [32], [34], [38]	Image analysis, process data, fault identification	Computational monitoring
Advanced manufacturing strategies	[40], [41], [42]	Deposition paths, high-performance polymers, multi-objective evaluation	Process improvement

The classification in Table 1 is thematic rather than mutually exclusive, since several studies address more than one manufacturing dimension. This distinction is important because the same process variable may simultaneously influence mechanical resistance, dimensional accuracy, manufacturing time, and defect occurrence.

2.3. Integrated Framework for FDM Process Evaluation

A suggested integrated framework is based on the literature evaluation and links controllable production circumstances to their corresponding outputs. Material properties and process parameters are the starting points of the framework, which then moves on to material deposition and interlayer bonding,

and finally integrates defect development as a mechanism that influences the performance of the final component. The data needed to determine whether the chosen production circumstances meet the desired standards is subsequently provided by quality assessment.

Recent advances lend credence to the idea that this framework may accommodate various quality assessment methods. Surface quality prediction using in-process material flow data has been studied [37], and feeder motor problems may be identified using electrical signal analysis [38]. Mechanical performance and surface roughness might vary depending on the deposition strategy [39]. Previous research has focused on stress-oriented printing routes [40], high-performance PEEK-based composites [41], and multi-objective optimization of surface roughness, dimensional errors, and material density [42].

Each of these additions lend credence to the idea that FDM production is best understood as a cycle, with material choice and printing settings dictating the starting points for production and mechanical characterization and defect assessment providing the data needed to refine the process. There is no one best configuration that can be applied to all materials and applications, according to the evaluated results. Instead, while choosing parameters, it's important to think about the printed component's intended use, the equipment at your disposal, the relevant fault mechanisms, and the quality standards.

The suggested theoretical structure is shown in Fig. 1. Its goal is to provide structure to the connections found in the literature so that the comparative analyzes that follow may be more easily understood. It is not an innovative optimization method that has been verified experimentally. In what follows, we take a closer look at each facet of the framework, dissecting its material-dependent parameter effects, defect creation processes, mechanical repercussions, and the applicability of both traditional and computational approaches to quality evaluation.

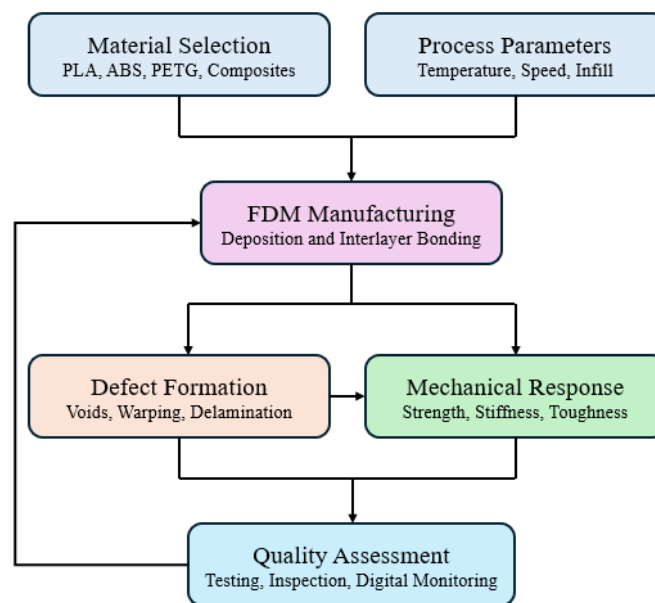


Fig. 1 - Proposed process-oriented framework linking material selection, manufacturing parameters, defect formation, mechanical properties, and quality assessment, with feedback for process optimization.

Integrated Analysis of the FDM Process

3.1 Materials and Manufacturing Parameters

To regulate the performance of FDM-printed components, the first step is to choose the materials and production settings. While PLA, ABS, PETG, and TPU are common thermoplastics, they all have unique printing properties when it comes to heat behavior, flexibility, rigidity, dimensional stability, and adhesion between layers. It is important to choose the printing settings based on the material properties and the functional needs of the produced part, according to reviews discussing polymer composites [3, 13] and process optimization [5, 15].

Due to its appropriateness for geometrically complicated components and its comparatively easy manufacturing, PLA is often the subject of investigation. Megersa et al. [29] investigated how printing factors affected its tensile behavior, whereas Li et al. [22] looked at its orthotropic mechanical characteristics. To go even deeper into how process variables affect interlayer bonding, Gajjar et al. [35] conducted further research. These findings show that different manufacturing orientations, deposition circumstances, and bonding quality may cause mechanical responses to differ, even within the same family of materials.

There are several thermoplastics that bring new factors into production. PETG offers an alternative for uses necessitating a distinct equilibrium between mechanical behavior and processing properties, whereas ABS necessitates proper heat management to restrict dimensional distortion. The filament feeding and deposition stability issues are compounded when working with flexible materials like TPU. Equipment compatibility, processing temperatures, and reinforcement-related effects must be carefully considered when working with reinforced materials, such as carbon-fiber-filled nylon

[21] and high-performance PEEK-based composites [41]. These materials expand the range of applications for FDM.

According to Table 2, there is a correlation between materials and production factors. Because different filament grades, printers, specimen geometries, and testing protocols have different processing needs and performance characteristics, the comparison can only be described as qualitative.

Table 2. Qualitative comparison of FDM materials and manufacturing considerations.

Material	Main characteristics	Manufacturing considerations	Relevant quality concerns	Supporting references
PLA	Relatively stiff; straightforward processing; limited thermal resistance	Layer orientation, temperature, infill, raster configuration	Brittle response, interlayer weakness, dimensional variation	[22], [29], [35]
ABS	Tougher behavior in some applications; greater thermal processing demands	Bed temperature, enclosure conditions, cooling, interlayer temperature	Warping, shrinkage, delamination	[18], [24]
PETG	Balance of strength, ductility, and processability	Extrusion temperature, cooling, deposition speed	Stringing, surface irregularities, dimensional accuracy	[2], [14]
TPU	Flexible and deformable thermoplastic	Feed stability, printing speed, filament handling	Extrusion instability, dimensional variation	[2], [14]
Reinforced nylon	Enhanced stiffness potential; fiber-dependent behavior	Printing orientation, filament conditioning, nozzle compatibility	Porosity, anisotropy, fiber–matrix bonding	[21]
PEEK-based composites	High-performance engineering applications; demanding processing requirements	Elevated processing temperatures, thermal control, equipment capability	Inadequate bonding, thermal distortion	[41]

Note: The characteristics are material- and grade-dependent. The table does not represent a universal ranking of mechanical performance.

A better way to look of manufacturing parameters is as a collection of interrelated variables rather than a set of static values. Load transfer via printed structures is affected by raster angle and build orientation, while nozzle temperature and layer height determine the shape of the deposited beads and the bonding conditions. Consumption of materials, production time, and structural reaction are further affected by infill pattern and density. The correlations were examined by Gao et al. [1], and the significance of evaluating mechanical performance and manufacturing time combined was proved by Nguyen et al. [18]. Therefore, rather of optimizing one performance indicator, choosing the right FDM configuration involves balancing material compatibility, process stability, mechanical requirements, and production efficiency.

Newer studies have broadened the scope of material-dependent FDM performance analysis even further. In order to provide a comparative view on frequently used thermoplastics, Prajapati et al. [43] examined the mechanical and physical properties of PLA, ABS, TPU, and PETG. In their experimental investigation of the tensile performance of PLA, ABS, and PETG, Menargues et al. [44] found that parameter effects differ between materials. These effects were caused by changes in extrusion temperature, printing speed, infill configuration, layer height, and wall count. The relationships between extrusion temperature, infill configuration, void formation, and mechanical behavior in TPU components were studied by Sardinha et al. [45] for flexible polymers, and by Gallup et al. [46] for hyperelastic constitutive response of TPU as a function of printing conditions. New factors in production have emerged as a result of studies focusing on sustainability. While Firtikiadis et al. [48] used response surface methods to optimize the tensile strength of recycled PETG specimens, Hasan et al. [47] explored the impact of printing settings on recycled PLA components. The mechanical characteristics of PLA mixes made by extruding filaments from virgin and recycled materials were described by Aly et al. [49]. Using various infill designs and exposure settings, Rihar and Hozdić [50] studied the mechanical and microstructural reactions of PETG and carbon-fiber-reinforced PETG. Taken together, these studies show that while optimizing FDM processes, it's important to consider variations in recycled material properties, internal architecture, polymer mix, and performance needs relevant to each application.

3.2 Mechanical Properties and Defect Formation

Internal structure and manufacturing history have a significant impact on the mechanical performance of components that have been FDM-printed. Printed components may include direction-dependent features because to deposited roads and interfaces, in contrast to traditionally produced homogenous specimens. The tensile strength, stiffness, flexural behavior, and fracture resistance are all affected by the patterns of material deposition and the bonding circumstances because of this property.

The significance of temperature history and bonding between neighboring layers has been emphasized in studies on interlayer adhesion [6, 20].

Further research using PLA [22, 35] and fiber-reinforced polymers [21] confirms that mechanical performance is affected by both material properties and the printed structure's orientation. Further techniques to optimizing parameters [25, 26] and vibration-assisted manufacturing [23, 24] have also been considered for enhancing certain mechanical properties.

The creation of defects offers a significant rationale for the observed performance variances in printed parts. poor interlayer adhesion may allow deposited layers to separate, voids and poor fusion can decrease the effective load-bearing area. Conventional strength measures may still be adequate, although assembly accuracy may be compromised by warping and dimensional variations. Ashebir et al. [7] investigated flaws and non-destructive testing techniques in extrusion-based fiber-reinforced thermoplastic composites, whereas Sun et al. [17] studied void reduction methodologies.

The connections between production circumstances, possible flaws, mechanical repercussions, and appropriate assessment methods are outlined in Table 3.

Table 3. Manufacturing conditions, possible defects, and corresponding evaluation methods.

Manufacturing condition	Potential defect	Possible consequence	Evaluation method
Inadequate extrusion temperature	Insufficient interlayer bonding	Reduced interlayer strength	Tensile testing, microscopy
Unsuitable cooling conditions	Warping, distortion	Dimensional deviations	Dimensional inspection
Unstable material flow	Under-extrusion, voids	Local structural discontinuities	Visual inspection, image analysis
Inappropriate raster orientation	Weak loading direction	Anisotropic mechanical response	Directional mechanical testing
Inadequate filament conditioning	Extrusion irregularities, possible porosity	Variable mechanical and surface quality	Material inspection, microscopy
Excessive process instability	Layer displacement, deposition errors	Geometric and structural defects	Camera-based monitoring
Inappropriate infill configuration	Insufficient internal support	Reduced load-bearing capacity under relevant loading	Mechanical testing, structural inspection

Note: The relationships are potential mechanisms derived from the reviewed literature, not universally observed outcomes. References [6], [7], [17], [22], [30], and [35] support the principal mechanisms represented.

Changing only one printing setting is not enough to avoid defects, as seen in the comparison. Consideration of loading requirements, material behavior, and application-specific defect types is essential when evaluating manufacturing conditions. Additionally, when enhancing one quality, it's possible to unintentionally compromise another, leading to issues like increased material consumption, decreased dimensional stability, or increased production time.

Fatigue behavior in FDM-printed components has recently come to the forefront of research, alongside traditional static mechanical characterization. Utilizing finite element modeling, Adibeig et al. [51] investigated the quasi-static mechanical response and fatigue life estimate for PLA specimens fabricated by FFF. In their study, Zahir et al. [52] examined the effects of infill design, surface condition, numerical life prediction, and rotating-bending stress on the performance of PLA HD and ABS components. In their comprehensive analysis of continuous glass-fiber-reinforced PLA composites, Javadian et al. [53] found that reinforcement orientation, internal voids, and fiber-matrix debonding were important factors in fatigue behavior and failure causes. According to their research, the structural dependability of FDM components that are loaded repeatedly cannot be described just by static tensile strength. Consequently, while assessing components meant for use in functional engineering, it is important to take into account factors such as fatigue-related damage processes, manufacturing-induced discontinuities, and cyclic loading conditions.

3.3 Quality Assessment and Intelligent Monitoring

At the verification step of FDM manufacturing, known as quality assessment, data is gathered to ascertain whether the printed part satisfies its specifications. Microscopy, non-destructive testing, mechanical testing, surface inspection, and dimensional measurements are all examples of conventional procedures. Surface roughness in additively made polymers was evaluated by Golhin et al. [33], while Equbal et al. [8] investigated dimensional accuracy in FDM. Methods like these are still useful since they quantify geometric or structural excellence.

Nevertheless, a number of traditional methods assess the part only after it has been manufactured. Although destructive testing is useful for discovering mechanical constraints, it may not be possible to fix faulty components while they are being manufactured. As a result, technologies that can monitor the process while material deposition is happening have been the focus of current study.

Condition monitoring techniques for FDM defect detection were evaluated by He et al. [9], and digital twin technology was examined by Xu et al. [10] to facilitate defect identification. Convolutional neural networks[31,34], temporal image analysis[32], and causality-guided algorithms under visual interference[28] have all been used to investigate image-based defect detection. Electrical signals from filament feeding systems [38] and material flow measurements [37] have also been investigated in other contributions.

By delving into the connections between process inputs and quality-related outputs, machine learning technologies broaden the scope of these monitoring capabilities. Machine learning has many uses in FDM production, such as predicting properties and evaluating quality, as discussed by Deokar et al. [27]. In a more comprehensive examination of machine learning in additive manufacturing, Xie et al. [11] highlighted the significance of validating models, generalizing results, and maintaining high-quality data.

It would be a mistake to assume that intelligent monitoring can fully replace traditional testing methods. When it comes to obvious deposition faults, approaches based on cameras are great, but when it comes to interior voids and bonding problems, you may need to try something else for sensing or inspection. Similarly, when tested under other circumstances, a model's performance may deviate from what was expected based on the original printer, material, or lighting setup.

The main techniques to quality evaluation that have been studied in the literature are compared in Table 4..

Table 4. Conventional and computational quality assessment methods in FDM.

Method	Main input	Evaluated output	Main advantage	Main limitation	References
Mechanical testing	Printed specimens, applied loads	Strength, stiffness, deformation	Direct mechanical characterization	Often destructive	[22], [29]
Dimensional inspection	Measured part geometry	Dimensional deviations	Direct verification of tolerances	Limited internal defect information	[8]
Microscopy and non-destructive inspection	Surface or internal structure	Voids, discontinuities, bonding defects	Structural defect characterization	Equipment and accessibility constraints	[7]
Camera-based inspection	Images or video frames	Visible printing defects	Potential in-process monitoring	Lighting, occlusion, unseen internal defects	[31], [34]
Process signal monitoring	Material flow, motor signals	Process abnormalities	Uses manufacturing-related measurements	Signal interpretation and calibration	[37], [38]
Machine learning	Process parameters, images, sensor data	Quality predictions or defect classes	Models complex relationships	Dataset dependence and generalization	[11], [27]
Digital twin approaches	Process and model information	Process-state or defect-related assessment	Integration of digital and physical information	Model updating and implementation complexity	[10]

The comparison shows that various techniques of evaluating quality provide further data. Computational monitoring approaches may help detect process issues sooner, dimensional measurements confirm geometric conformance, and mechanical testing assess structure performance. By integrating these methods, we may get a deeper comprehension of the quality of FDM production.

New advances in computational manufacturing have broadened the scope of quality evaluation to include predictive modeling and process correction, in addition to traditional inspection methods. In order to forecast printing time, dimensional tolerance, residual stresses, deformation, and artificial intelligence (AI)-assisted digital twin framework, Ben Brayek et al. [54] used high-fidelity simulations in conjunction with machine learning. Using data collected from cameras and multi-output machine learning, Fu and Li [55] created a system for real-time monitoring and mistake correction. For the purpose of forecasting dimensional correctness, tensile strength, and porosity in material extrusion production, Ogunsanya et al. [56] examined artificial neural networks and ensemble models. By combining data from many cameras, Yu et al. [57] were able to overcome the problems with single-camera monitoring and develop a system for online fault identification and autonomous repair. Opportunities for defect detection and process monitoring were highlighted in Pereira et al.'s [58] further study of machine learning algorithms for quality control in extrusion-based additive manufacturing. The validity of FDM quality evaluation may be shown by these research by combining visual data with experimental measurements, computer models, and prediction algorithms. However, rigorous validation techniques, assessment with diverse materials, equipment, and operating circumstances, and representative training data are all necessary for dependable implementation.

3.4 Integrated Process Optimization and Research Gaps

Based on what we know from the literature, process optimization is best approached as a cycle that incorporates quality assurance and manufacturing decision-making. The initial processing requirements are determined by the material selection, while the deposited shape, interlayer bonding, defect occurrence, and component performance are affected by the manufacturing settings. In order to find improper configurations and improve the production process, quality assessment gives feedback.

Grey-Taguchi techniques [25], experimental parameter optimization [29], stress-oriented deposition routes [40], and adaptive neuro-fuzzy inference modeling [42] are some of the optimization approaches that have been investigated recently. While each of these approaches has its own unique goals,

they show how crucial it is to look at a variety of KPIs instead of depending only on mechanical strength.

Based on the research that were studied, Fig. 2 presents a potential optimization sequence that is decision-oriented. Choosing an appropriate material and outlining functional requirements are the first steps in the framework. Fabrication and quality assessment follow the establishment of appropriate process parameters. A change is made to the process configuration is made if the printed part does not meet the chosen quality standards. For the intended use, the configuration may be kept if the conditions are met.

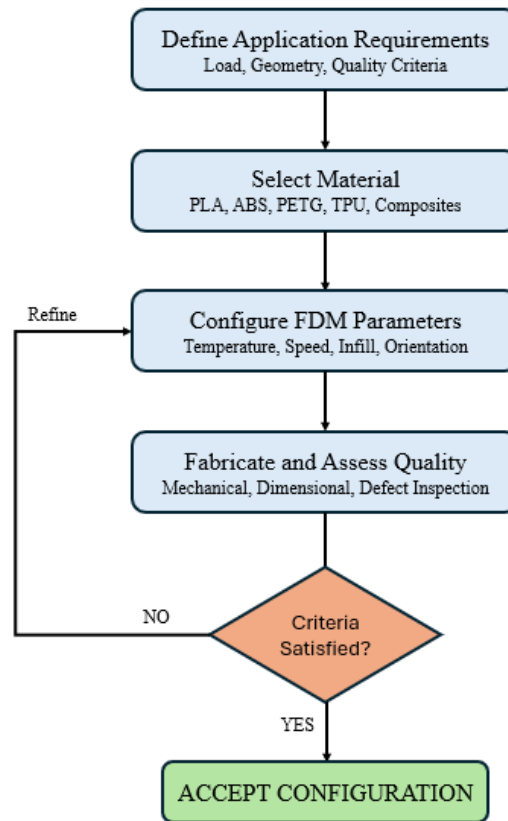


Fig. 2 - Proposed decision-oriented framework for FDM process optimization through material selection, manufacturing parameter configuration, quality assessment, and iterative refinement.

This is only a conceptual sequence, not an actual optimization technique that has been tested and proven. Its goal is to provide a user-friendly framework for industrial decision-making by incorporating the linkages found in the literature.

There are still some pertinent research constraints. To begin, it is difficult to directly compare published results because to the wide variety of printers, materials, specimen setups, and testing procedures. Secondly, there is a lack of uniformity in the experimental methods used to quantify the interactions between production factors. Thirdly, just because something seems perfectly square on the outside doesn't mean there aren't any flaws within. Finally, it is not always possible to generalize the performance of intelligent monitoring technologies to other production settings without first validating them.

Therefore, it is imperative that future studies place an emphasis on validated optimization methods across various materials and equipment, multimodal quality evaluation, documented parameter settings, and repeatable testing protocols. There would be more support for comparisons between published research if mechanical findings, manufacturing circumstances, material parameters, and defect measures were all reported consistently.

According to the integrated analysis, ensuring successful FDM manufacture requires a series of coordinated choices concerning mechanical characterisation, quality verification, defect avoidance, process setup, and material compatibility. The suggested framework does not aim to find a single best set of parameters, but rather to provide a formal foundation for choosing and assessing production circumstances based on needs particular to each applications.

One such use of the integrated framework is as a starting point for comparing optimization goals for various materials and uses. Printing times and material consumption could go up if process configurations are optimized for tensile performance, and surface quality and geometric precision might suffer if deposition rates are increased. Similarly, smart monitoring systems may help with early defect detection, but they come with their own set of challenges when it comes to data collection, validation of models, and calibration. With the use of key process parameters, verification indicators, and possible trade-offs, Table 5 summarizes these connections and identifies optimization targets. Do not take the suggested comparison as an all-inclusive evaluation of FDM production circumstances; it is qualitative in nature.

Table 5. Integrated FDM process optimization objectives, verification indicators, and potential manufacturing trade-offs.

Objective	Main variables	Verification	Trade-off	References
Mechanical strength	Orientation, infill, temperature	Tensile/flexural tests	Time, material use	[22], [29], [44]
Dimensional accuracy	Cooling, speed, temperature	Dimensional deviation	Efficiency	[8], [30]
Surface quality	Layer height, deposition path	Surface roughness	Print duration	[33], [39]
Defect reduction	Thermal and flow stability	Voids, delamination	Process complexity	[17], [35]
Fatigue resistance	Orientation, bonding, infill	Cycles to failure	Design constraints	[51]–[53]
Sustainable manufacturing	Recycled polymers, settings	Strength, material reuse	Material variability	[47]–[49]
Production efficiency	Speed, infill, toolpath	Build time	Part performance	[18], [44]
Intelligent monitoring	Sensors, cameras, ML	Detection performance	Data requirements	[55]–[58]

For flexible thermoplastics, optimization according to the material's specifications is crucial. By conducting experimental investigations into the tensile characteristics of FDM-printed TPU specimens, Jakab and Lendvai [59] demonstrated how the deposition configuration affects strength, stiffness, and elongation. The impacts of nozzle diameter and raster orientation were also considered. Following this, Ma et al. [60] used Taguchi design and analysis of variance to look at how printing speed, layer height, infill pattern, temperature, and combination of the four affected TPU tensile performance. Parameter optimization, as these results show, has to be tailored to the properties of individual materials and the needs of certain applications. This review's recommended integrated framework is more of a decision-support structure than a definitive set of ideal production characteristics, so take it with a grain of salt.

Conclusions

Materials, production parameters, mechanical characteristics, defect generation, and quality evaluation were the primary foci of the sixty papers chosen for this study, which dealt with the Fused Deposition Modeling technique. Material properties, printing parameters, interlayer bonding, and internal structural flaws all interact to determine how well FDM-printed components operate.

Based on the results of the comparison, it is clear that optimizing manufacturing parameters requires thinking about mechanical performance, dimensional accuracy, surface quality, and production efficiency all at once. Computer vision, machine learning, and sensor-based monitoring provide complementary potential for defect identification and process optimization, complementing conventional mechanical testing and dimensional inspection.

Two conceptual frameworks that connect material selection, production parameters, component performance, and quality verification, as well as comparison tables and an integrated, process-oriented categorization, constitute this review's primary contribution. Nevertheless, it is not possible to directly compare published findings due to variations in materials, equipment, and experimental protocols.

Standardized testing protocols, enhanced characterisation of fatigue behavior and internal flaws, multimodal monitoring, and validation of intelligent optimization approaches across materials should be the focus of future research. Without supposing an ideal printing configuration for all cases, these advancements have the potential to make FDM production more repeatable and dependable.

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