

Review

Understanding and Resolving 3D Printing Challenges: A Systematic Literature Review

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Abstract: Additive manufacturing (AM), or 3D printing, enables efficient fabrication of complex and customized components. Despite its growth across industries, users frequently encounter print failures due to design errors, process limitations, and inadequate monitoring. While existing research has explored various aspects of these failures, much of it remains fragmented, with limited consolidated overviews that map common problems, troubleshooting strategies, and guidelines across the AM workflow. This study conducted a systematic literature review using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology to identify and categorize common 3D printing problems and their solutions. Relevant studies published between 2000 and 2024 were extracted from major databases. A total of 126 peer-reviewed articles were selected and analyzed. Three major categories of recurring challenges were identified: (1) design and pre-processing errors; (2) geometric errors and dimensional deviations; (3) failures in in-process error detection and response. A variety of mitigation strategies have been proposed across the literature, including STL and slicing optimization, thermal management, machine calibration, and sensor-based real-time monitoring. These approaches reflect the multifactorial nature of 3D printing failures, which often arise from the complex interplay of design, material, and process parameters. This review provides a structured summary of failure types and mitigation strategies across the AM workflow.

Keywords: additive manufacturing; guideline; PRISMA; troubleshooting

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1. Introduction

3D printing, also referred to as additive manufacturing (AM), is a technology that fabricates physical objects by sequentially depositing material layers based on digital files. Due to its capability to rapidly and cost-effectively produce complex structures, 3D printing has become a core technology in various industries, including the aerospace, healthcare, and automotive sectors [1]. The use of 3D printers for customized production offers significant advantages in small-scale mass production, earning technical recognition from a wide spectrum of users, ranging from individual creators to large-scale manufacturers [2]. Notably, the 3D printing market experienced remarkable growth in 2023, surpassing \$20 billion for the first time, driven by advancements in metal 3D printing technologies and a transition toward mass production [3,4].

Despite its innovative potential, users often encounter a variety of challenges when learning and effectively utilizing 3D printing technologies. Issues that arise during the printing process, such as reduced print quality and design and mechanical setting errors, can pose significant difficulties for both novice and experienced users alike [5]. Whilst

previous studies have proposed various analyses and solutions to 3D printing issues, most have remained limited to specific case-based or post hoc approaches, lacking comprehensive coverage of problems across the entire process workflow [6]. Additionally, many existing studies tend to address only narrowly defined problems within specific AM processes, which contributes to the persistence of a broader research gap. It is important that knowledge of AM-related errors and their corresponding solutions be made accessible not only to specialists, but also to a wider range of users who interact with these technologies. To support this need, there is value in conducting reviews that take a more comprehensive and structured approach to synthesizing fragmented findings across diverse AM contexts.

While narrative reviews are often sufficient for summarizing research trends, we adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology to enhance the transparency and reproducibility of the literature selection and analysis process. The use of PRISMA helps minimize the influence of researcher bias and provides a logical and standardized framework for systematically identifying and synthesizing relevant studies—even for those who may not be long-standing experts in the field. Building on this foundation, this study aims to propose a proactive approach that systematically identifies and analyzes potential problems that may arise throughout the 3D printing process, categorized by components and stages. Specifically, we apply the PRISMA methodology, which is commonly used to enhance transparency and quality in systematic reviews and meta-analyses [7], to comprehensively review existing literature on 3D printing-related issues and their corresponding solutions. Through this systematic review, we aim to develop practical guidelines that help 3D printing users prevent printing failures and ensure successful output. To guide this investigation, we formulated the following research questions:

Q1: What types of problems are commonly encountered when using 3D printing technologies across different stages of the process?

Q2: What solutions have been proposed in the literature to address these problems, and how might they inform practice and future research?

2. Methodology

2.1. Literature Search Strategy

This study conducted a systematic literature review based on the PRISMA guidelines to identify common issues encountered during the use of 3D printers and their corresponding solutions. PRISMA encourages transparency in the process of identifying, selecting, and reporting research, including the search strategy, classification method, inclusion and exclusion criteria, and the use of automation tools. This methodology enhances the reliability of literature selection and enables researchers to define clear research questions and apply consistent criteria for analysis [8]. Due to its robustness and reproducibility, PRISMA is widely adopted across disciplines to yield trustworthy results.

To ensure comprehensive coverage, the literature search was conducted across major academic databases, including Google Scholar, ScienceDirect, PubMed, and IEEE Xplore. The search targeted publications from 1 January 2000 to 31 July 2024. Keywords used in the search included combinations of terms such as “3D printing”, “3D printer”, or “additive manufacturing” with “error(s)”, “guideline(s)”, or “troubleshooting”, specifically within the article titles. This ensured that studies addressing errors and guidance related to 3D printing and additive manufacturing were inclusively identified. The keyword combination logic used in this title-based search is summarized in Figure 1.

Keyword combination logic



Figure 1. Keyword combination logic used in the title-based search.

2.2. Literature Selection Process

The literature selection process was conducted using the PRISMA flow diagram (Figure 2) and followed specific inclusion and exclusion criteria. Studies were included if they addressed problems encountered during the use of 3D printers and proposed corresponding solutions. Eligible sources included original research articles, experimental studies, review articles, and case studies focusing specifically on technical or methodological aspects of 3D printing.

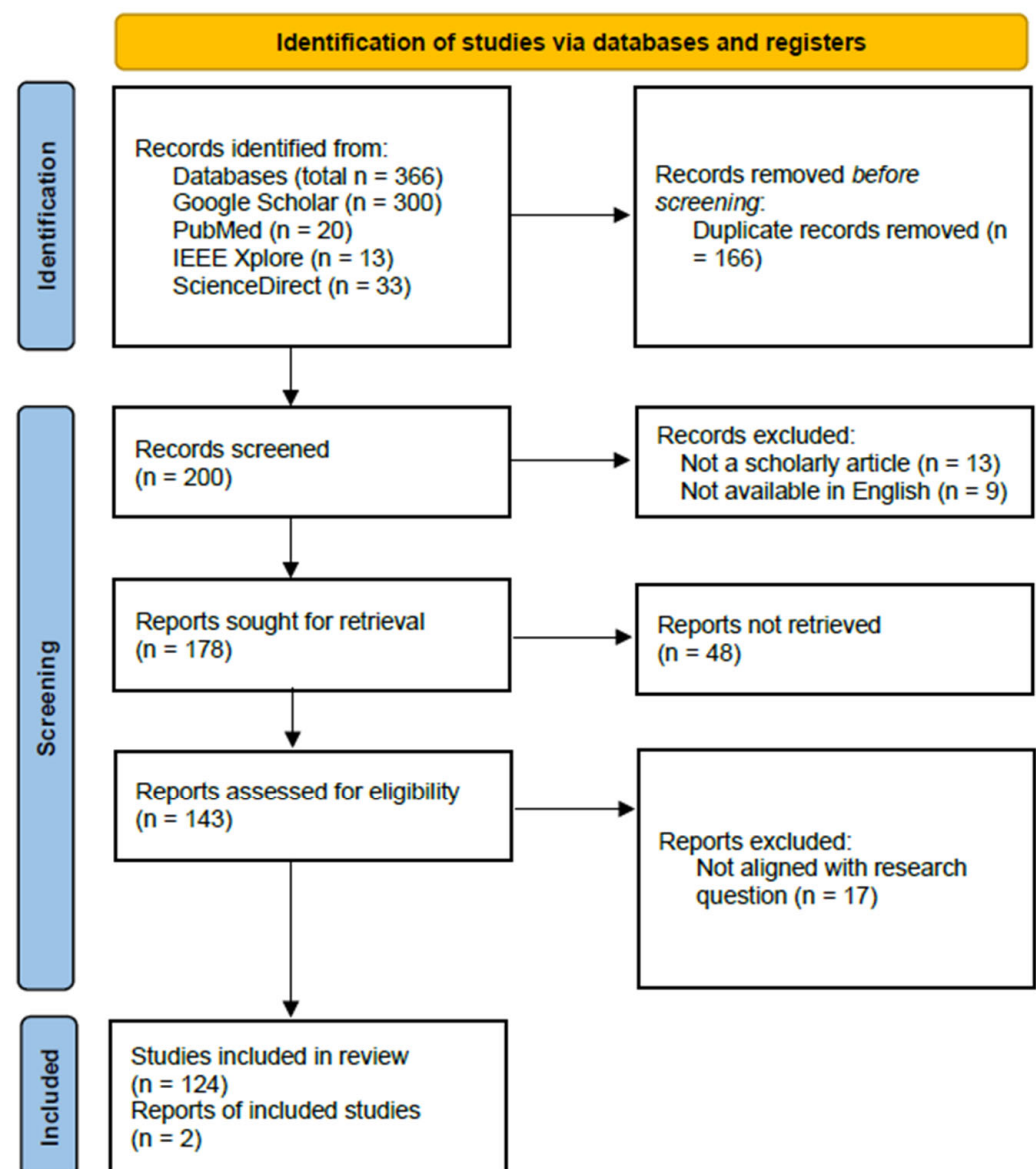


Figure 2. PRISMA flow diagram of the study selection process.

The selection proceeded through a two-stage exclusion process. In the first stage, studies were excluded if only abstracts were available, if full-text access was not accessible, if the papers were not written in English, or if the documents were not in scholarly article format (e.g., books, reports). The second stage excluded studies that focused solely on specific industries, assessed the performance of printed products without addressing failure causes, or provided only general overviews without concrete troubleshooting approaches.

The initial search yielded a total of 366 studies. After removing duplicates, 200 unique studies remained. Applying the first exclusion criteria resulted in 143 eligible papers. A second round of screening was then conducted, and studies that did not align with the research questions were excluded. As a result, a final set of 126 studies was selected for full analysis and data extraction. No automation tools were used during the selection process; all screening and eligibility assessments were conducted manually based on the predefined criteria.

2.3. Data Extraction and Analysis

From the final selection of 126 studies, data were extracted based on predefined criteria, including the study title, publication year, research objectives, key problems encountered during 3D printer use, and corresponding solutions. The data extraction process followed the PRISMA methodology, with two researchers independently conducting the extraction. In cases of disagreement, a third researcher reviewed the discrepancies and facilitated resolution.

In this process, we examined the publication recency, research focus, and objectives of each study, and assessed their methodological rigor and experimental design to ensure validity and reliability. Particular emphasis was placed on identifying recurring issues such as printing errors, quality degradation, and mechanical failures, as well as the solutions proposed to address them. A structured coding process was applied to organize the extracted data, allowing for the consistent categorization of problem types and associated solutions across studies. This analysis enabled us to classify common problem types and extract representative troubleshooting strategies reported across the literature.

Additionally, to evaluate consistency among the findings, similar studies were comparatively analyzed. Major findings and contributions were synthesized according to the research questions. Finally, the limitations of existing research were discussed and future research directions were proposed, providing key insights for the continued advancement of 3D printing studies.

3. Analysis of Troubleshooting Problems in 3D Printing Technologies

AM encompasses a range of process technologies, each characterized by distinct technical attributes depending on the materials used and the specific forming mechanisms involved. The results of the literature analysis revealed that across various AM techniques there are recurring types of issues and corresponding strategies proposed to address them. Accordingly, this study first identifies the common categories of problems that arise throughout AM processes. For each problem type, representative failure cases are outlined along with the specific solutions proposed in the reviewed literature.

To aid interpretation of the following analysis, we refer to the ISO/ASTM 52900 classification, which categorizes AM into seven primary process types [9]. While this study does not aim to conduct a modality-specific comparison, it is acknowledged that certain troubleshooting challenges may vary across different AM processes. A summary of each process, along with its definition and representative technologies, is provided in Table 1.

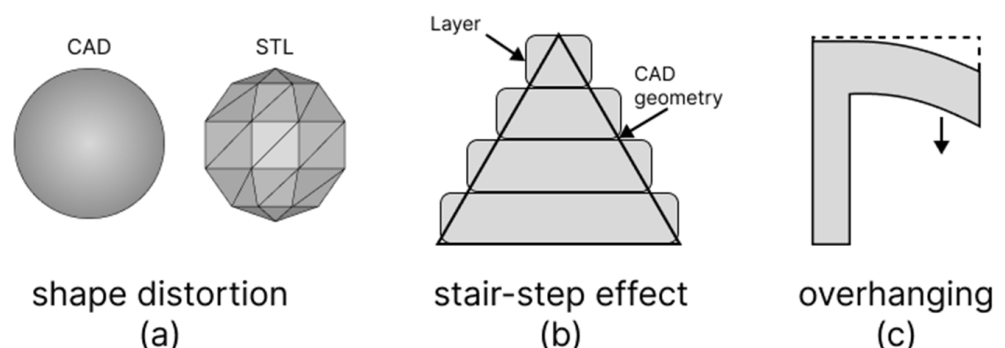
Table 1. Categories of additive manufacturing processes with definitions and examples.

Process	Definition	Example Technologies
Binder Jetting (BJ)	A liquid bonding agent is selectively deposited to join powder materials.	ExOne, ZPrinting, and VoxelJet.
Directed Energy Deposition (DED)	Focused thermal energy is used to fuse materials by melting as they are being deposited.	LENS, WAAM, and EBAM.
Material Extrusion (ME)	Material is selectively dispensed through a nozzle or orifice.	FDM/FFF, Contour Crafting.
Material Jetting (MJ)	Droplets of feedstock material are selectively deposited.	PolyJet, MJP, and NPJ.
Powder Bed Fusion (PBF)	Thermal energy selectively fuses regions of a powder bed	SLS, SLM, DMLS, and EBM.
Sheet Lamination (SHL)	Sheets of material are bonded to form a part.	LOM, and CBAM.
Vat Photopolymerization (VPP)	Liquid photopolymer in a vat is selectively cured by light-activated polymerization.	SLA, DLP, and CLIP.

3.1. Design and Pre-Processing Errors

In AM the quality of printed objects is influenced not only by post-processing conditions but also by the appropriateness of the design and pre-processing steps performed prior to printing. Key pre-printing procedures include CAD-based modeling, STL file conversion, slicing parameter configuration, build orientation setup, and material and temperature parameter input. These preliminary steps have a direct impact on the dimensional accuracy, surface quality, and mechanical properties of the printed parts. Errors at the design or pre-processing stage often lead to cumulative issues that are difficult to correct in later stages of the process.

According to the literature, the major issues arising during the design and pre-processing stages are as follows. First, during the process of converting CAD models into STL files composed of small triangles, geometric fidelity may not be sufficiently preserved, which can lead to information loss and result in shape distortions [10]. This phenomenon is illustrated in Figure 3a. Such distortions are particularly problematic for models with curves or complex geometries, where chordal errors frequently occur. To reduce these errors, a denser mesh is often used, but this increases the file size and computational load during slicing [11].

**Figure 3.** Visual examples of (a) shape distortion, (b) stair-step effect, and (c) overhang deformation.

Second, during slicing, where G-code is generated based on the STL file, the quality and precision of the output are directly influenced by user-defined parameters. A representative example is layer thickness, which affects the trade-off between precision and

speed. Thinner layers yield higher resolution but slower print times, whereas thicker layers increase speed at the cost of surface quality. Especially in curved regions, visible layer boundaries can create a phenomenon known as the stair-step effect, which may be partially mitigated by adjusting the build orientation [12]. This effect is illustrated in Figure 3b. To reduce such artifacts, the “Discrete Interpolable-Area Error Profile (DIA-EP)” algorithm has been proposed, applying thinner layers to highly curved areas and thicker layers to flatter surfaces [13]. Additionally, the type of path generation algorithm and its resolution settings are significant factors affecting print quality [14]. Notably, different application domains have adopted tailored strategies to address such fidelity challenges. In medical additive manufacturing, particularly for patient-specific implants or anatomical models, maintaining fine geometric fidelity is critical; hence, adaptive slicing and ultra-fine layer resolution are often prioritized, despite longer build times. In contrast, industrial applications such as tooling or prototyping may tolerate greater dimensional deviation in favor of increased throughput, often leveraging coarser slicing or post-processing techniques. Building on these developments, recent algorithmic approaches such as adaptive slicing and AI-driven design tools have been introduced to further enhance pre-processing accuracy and geometric fidelity.

Third, within the same slicing process, build orientation is another critical factor. Due to the layer-by-layer nature of AM, build orientation influences layer structure, need for and number of support structures, material consumption, print time, and ultimately, durability and post-processing difficulty [15]. One notable issue is the “supporting error”. Without adequate support in inclined or overhanging areas, the geometry may collapse or warp. A representative example of such unsupported deformation is illustrated in Figure 3c. In high-precision parts, improper placement or angle of support structures can lead to print failure or deformation [16]. Therefore, build orientation should not be considered merely a visual or esthetic factor but a critical design parameter closely linked to functional quality and manufacturing efficiency.

Since these errors are typically irreversible after printing and often result in significant quality degradation, pre-print simulation-based verification, high-resolution mesh generation, and adherence to standardized design guidelines are essential. Recent research [11] also highlights the importance of pre-evaluating toolpath quality at the G-code level. Techniques such as applying G2/G3 commands for curved path optimization or using post-processing algorithms like Arc Welder have been proposed to enhance toolpath precision. As such, design and pre-processing errors are among the leading causes of print quality degradation and must be considered as both the starting point and a core control node in the overall AM process.

3.2. Geometric Errors and Dimensional Deviations

AM has gained significant attention for its ability to precisely fabricate complex geometries and efficiently produce customized components in small quantities. Despite these advantages, multiple studies have focused on addressing quality and printing errors that occur throughout the AM process [17,18]. During printing, relatively minor issues such as dimensional deviations or surface roughness may arise; in severe cases, geometric distortions and structural instabilities can lead to critical defects such as cracks, porosity, or warping. Unsupported features such as overhangs and bridges can collapse without proper support structures, potentially resulting in severe print failures like the “spaghetti error”, which renders the component unusable. These precision-related concerns are particularly critical in medical applications, where AM is widely used for surgical implants, patient-specific prosthetics, and anatomical phantoms [19]. Such components must closely conform to individual anatomical features, often with acceptable dimensional deviations

restricted to within a few micrometers as inaccuracies can directly affect patient safety and treatment efficacy [20]. Accordingly, extensive research has been conducted to identify and compensate for dimensional and geometric inaccuracies in medical AM, focusing on process optimization and improving geometric fidelity [21].

The literature review revealed that discrepancies between the designed CAD model and the printed output were among the most frequently observed issues. While design and pre-processing errors have been discussed in detail in Section 3.1, this section focuses on the physical and mechanical factors that contribute to geometric inaccuracies during the actual printing process.

First, thermal variations and the accumulation of residual thermal stress are widely reported as the primary causes of geometric errors. Printed materials tend to shrink during the cooling process, and interlayer temperature gradients can result in asymmetric thermal stress [22]. These stresses may cause overall warping, localized lifting, or tilting of the print, potentially leading to collisions with the recoater or print failures [23]. Although the severity of these effects varies with process and material, they are commonly observed across AM technologies. For example, in material extrusion (ME) processes such as fused deposition modeling (FDM), warping may occur due to filament shrinkage upon cooling [24]. In powder bed fusion (PBF) processes like selective laser melting (SLM) and electron beam melting (EBM), rapid heating and cooling can create steep thermal gradients, resulting in high residual stress [25]. These thermal effects often lead to geometric distortions such as warping or shrinkage. These geometric accuracy concerns tend to be more stringent in medical applications due to patient-specific requirements, whereas industrial contexts may prioritize repeatability and structural performance. Figure 4 illustrates (a) a schematic of layer deformation caused by thermal stress and (b) a simplified shrinkage model comparing the designed geometry to the printed output.

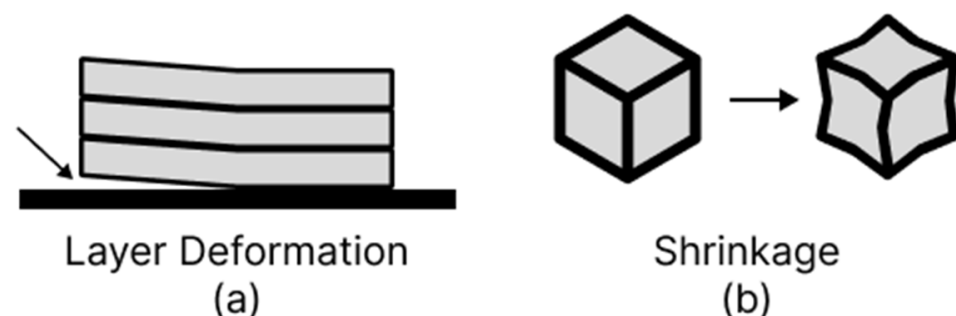


Figure 4. (a) Layer deformation and (b) shrinkage illustrations.

Second, mechanical vibrations and minor misalignments in the system can accumulate over time and significantly affect print accuracy. Instabilities during machine operation, including vibrations and inconsistent movements, directly influence nozzle positioning and path tracking accuracy, resulting in interlayer misalignment and geometric distortion [26]. Low repeatability in the Z-axis or backlash in the drive mechanisms may cause cumulative misalignment, degrading the consistency of printed layers. Bed leveling errors, where the build plate is not parallel to the reference plane, can also lead to uneven initial layers, poor adhesion, and compromised overall geometric integrity [27]. These issues are often exacerbated by mechanical wear and tear, such as a relaxation of synchronous belts or bearing degradation, causing a gradual decline in print quality over time [28]. In stepper motor-driven systems, excessive vibration during head or platform movement can lead to tracking errors, step skipping, and visible surface artifacts such as ringing or layer registration errors [29].

Third, various process conditions and equipment-related variables have also been reported as key contributors to printing errors. For instance, in PBF processes spatially non-uniform laser energy distribution or suboptimal hatch path planning can lead to reduced flatness and surface accuracy of printed parts [30]. In ME processes, imbalanced material extrusion often results in defects. In particular, temporary interruptions in material flow or excessive self-overlapping in localized regions during extrusion may produce uneven layer thickness, thereby compromising the geometric accuracy of the printed object [22]. In Vat Photopolymerization (VPP), especially in masked stereolithography (mSLA), differences in resin viscosity and curing time can cause variations in surface accuracy and shrinkage behavior, potentially leading to geometric distortion and dimensional mismatch [31]. In Directed Energy Deposition (DED), if the balance between powder feed rate and laser energy input is not properly maintained then irregular melt pool dynamics may occur, resulting in non-uniform layer formation and reduced consistency in deposition [32]. Although the specific causes vary across AM technologies, instability in process parameters universally contributes to degradation in print quality. As such, these process-dependent factors must be systematically considered across all AM platforms.

In conclusion, geometric errors and dimensional inaccuracies in AM are rarely the result of a single cause. Instead, they arise from the complex interplay of multiple factors, including thermal fluctuations, mechanical vibrations, alignment errors, and process parameter variations. Such issues are frequently linked to material shrinkage behaviors, machine repeatability issues, non-uniform deposition paths, and inconsistencies in curing conditions. These problems are not limited to any one AM method but are inherent risks across all additive manufacturing processes. The following table (Table 2) summarizes the issues and proposed solutions related to geometric errors and dimensional deviations. All proposed solutions listed in the table were extracted from the respective referenced studies.

Table 2. Selective literature on the geometric errors and dimensional deviations.

Author(s) (Year)	AM Technology	Issue	Root Cause	Proposed Solution
Auškalnis et al. (2022) [33]	VPP	Photopolymer shrinkage.	Accumulated error during intraoral scanning (IOS); resin shrinkage during printing.	- Shrinkage-compensated design adjustment. - Standardization of post-curing conditions.
Tian et al. (2024) [34]	PBF	Micro-geometry defects.	Node detachment, radius variation, and surface distortion during SLM printing.	- Precision prediction and error quantification. - Geometric parameter modeling and sensitivity analysis.
Pinto et al. (2015) [21]	MJ	Stair-stepping and overbuilding.	STL quality degradation due to an improper tessellation threshold and mesh resolution.	- Layer thickness tuning and material optimization.
Cajal et al. (2013) [35]	VPP	Volumetric dimensional deviation.	Kinematic position error per axis and cumulative mismatch in STL-based build location.	- Real-time probing-based measurement. - Multidimensional compensation model. - Volume correction and reprinting based on STL data.
Das et al. (2015) [36]	PBF	Stair-stepping.	Errors in flatness, verticality, and roundness depending on build orientation and slice thickness.	- Mathematical modeling of geometric errors. - Output orientation optimization. - Visual analysis via quadtree-based support structure calculation.

Table 2. Cont.

Author(s) (Year)	AM Technology	Issue	Root Cause	Proposed Solution
Majarena et al. (2017) [26]	ME	Positional and linearity errors.	Positional deviation during axis movement; loss of precision over longer paths.	- Calibrated scanner-based measurement. - G-code correction using positional error matrices. - Reprinting based on modified toolpath.
Li and Anand (2021) [30]	PBF	Flatness error.	Residual stress and asymmetric thermal shrinkage from hatch pattern and scan direction.	- ANN-based deformation prediction. - Backward interpolation for distortion calculation. - GA-based multilayer hatch angle optimization.
Majd et al. (2023) [37]	ME	Infill density deviation.	Discrepancy between target and actual infill, irregular infill geometry, and extrusion profile.	- Neural network for predicting the volumetric percentage error. - Proposed algorithm for infill optimization. - Dataset-based training on infill patterns and parameters.
Zgórniak and Stachurski (2010) [38]	MJ	Dimensional deviation.	Recurrent dimensional deviation depending on print location and orientation.	- Systematic error analysis by XYZ orientation. - Statistical compensation guidelines. - Direction optimization for prototype development.
Moodleah and Kirimasthong (2023) [13]	ME	Geometric error during slicing.	Irregular point cloud and inaccurate inter-layer boundary leading to cumulative shape error.	- Geometric error calculation using triangular interlayer regions. - Adaptive slicing and G-code tuning.

To effectively address these challenges, a comprehensive, end-to-end quality management framework is essential. This should encompass not only path optimization during the design and slicing stages but also post-print 3D scanning-based verification, geometry compensation tailored to process characteristics, shrinkage-aware design compensation, and statistical prediction-based calibration strategies. Only through such holistic control mechanisms can consistent geometric fidelity and dimensional precision be achieved in complex AM workflows.

3.3. Failures in In-Process Error Detection and Response

AM is a process that often requires continuous operation over several hours. During this time, the quality of the printed output can be affected in real time by various physical factors such as temperature fluctuations, vibrations, and the wear of mechanical components. Consequently, even when the initial setup is highly precise, unforeseen variables that occur during the printing process can frequently lead to print failures. This issue is particularly critical in long-duration prints, where constant user supervision is not feasible. In such cases, the need for systems capable of detecting and autonomously responding to errors in real time has been increasingly emphasized. To help readers intuitively understand the structure and data flow of such systems, Figure 5 presents a simplified schematic illustration of a typical sensor-integrated real-time monitoring setup in AM.

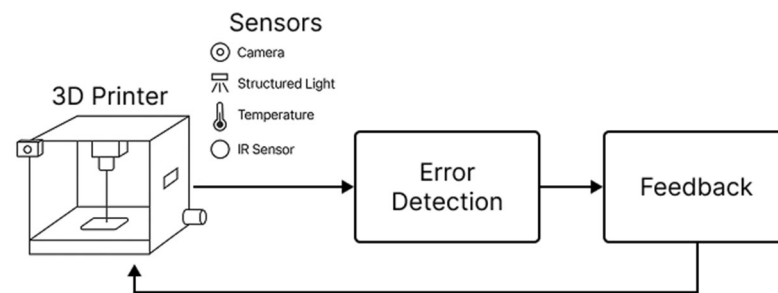


Figure 5. Sensor layout and feedback flow in real-time AM monitoring.

Representative issues observed in this category include the following. First, interlayer deposition errors, such as missing geometry or over-deposition, can compromise the structural integrity of the final product if not immediately detected as the same defect may propagate throughout the remaining layers [39]. Second, minor anomalies such as material extrusion imbalance, machine vibration, or misalignment between axes can significantly degrade the dimensional accuracy of the printed object. However, conventional sensor-based systems often lack the sensitivity or responsiveness required to detect and correct such deviations in real time [29]. Third, if the system fails to quickly identify the exact location and nature of an error after it occurs then a delayed response can result in increased material waste and reduced output quality [40].

In response to these challenges, a few studies have proposed technological approaches that enable real-time error detection and adaptive response during the AM process [41,42]. The following table (Table 3) summarizes selected prior studies and outlines the key techniques and underlying principles proposed to address the problem of in-process error detection and reaction failures. These techniques are designed to detect various abnormalities that may occur during printing, or to enable preemptive control measures. Their ultimate goal is to enhance both the accuracy and speed of error detection and response in additive manufacturing systems.

Table 3. Selective literature on the in-process error detection and response.

Author(s) (Year)	Issue	Technique Used	Technique Description	Advantages
Auškalnis et al. (2022) [33]	Layer deposition error	Structured light-based 2D phase domain error detection.	Detects printing errors in a 2D phase domain, minimizing the need for full 3D reconstruction.	Faster error detection compared to 3D point cloud analysis and enables automatic correction of error regions.
Zhang et al. (2019) [28]	Print anomalies	EFMSAE (error fusion of multiple sparse auto-encoders).	Unsupervised learning-based condition monitoring using multi-sensor data.	Early detection of micro-defects in delta 3D printers using low-cost sensors which enables real-time response.
Duan et al. (2018) [29]	Equipment vibration	LPFBS (limited-preview filtered b-spline).	Feedforward control technique generating predictive B-spline paths for short intervals and adjusting them in real time to correct vibration-induced errors.	Reduces surface roughness and positional misalignment during high-speed printing and enables sensor-free real-time correction on low-cost printers.
Peña et al. (2022) [43]	Geometric errors	CH (conoscopic holography).	Uses non-contact optical interferometry sensors to measure geometric deviation per layer and quantify radial deviations.	Enables fast acquisition of high-density 3D shape data and allows precise, non-contact monitoring of layer-wise deviations in FFF processes.

3.4. Overall Classification and Solution Approaches

In the previous sections, we examined three primary categories of errors in additive manufacturing (AM). Building upon that foundation, this section presents a broader classification by organizing the selected studies according to both the identified problem domains and the types of solution approaches proposed. A total of 126 studies were initially selected based on their relevance to the research questions. However, upon closer examination, 12 of these studies were found to lack a clear alignment with either the defined error categories or the specified solution strategies. To maintain analytical consistency, these studies were grouped under a separate “Other” classification. Table 4 presents the classification of the reviewed literature according to the defined error domains and corresponding solution approaches: (3.1) design and pre-processing errors, (3.2) geometric errors and dimensional deviations, and (3.3) failures in in-process error detection and response. Each study is also classified based on its proposed solution approach, either through the development of software-based algorithms, hardware-based physical systems, or user-controlled operational strategies. For clarity, the table excludes hardware-based interventions during the design/pre-processing stage (3.1) and user-setting-based strategies in the in-process stage (3.3) as these combinations are not logically applicable within the AM workflow. As shown in the table, a substantial number of studies emphasize software-based solutions, such as computational modeling, machine learning-driven parameter optimization, or geometric compensation algorithms aimed at improving accuracy and detecting failures in real time. In contrast, hardware-focused or user-directed solutions appeared less frequently overall; however, a notable number of user-driven strategies were observed within the 3.2 category. This can be attributed to the fact that many studies incorporating the keyword “guideline” proposed user-controllable methods specifically designed to enhance model accuracy.

Table 4. Mapping of representative AM studies by problem domain and solution approach.

Sub-Section	Solution Approach	References
3.1	Development of software-based algorithm.	[13,37,44–49]
	User-controlled operational strategies.	[11,16,20,50–52]
3.2	Development of software-based algorithm.	[12,14,25–27,29,30,32,34–36,53–83]
	Development of hardware-based physical system.	[14,62,74,75,84–87]
	User-controlled operational strategies.	[17,21,23,27,31,33,38,69,78,88–104]
3.3	Development of software-based algorithm.	[18,28,39,105–120]
	Development of hardware-based physical system.	[18,41,42,105,109–112,117,120–124]

From a broader perspective, all studies underscore the importance of systematic error modeling and compensation techniques to improve final-part accuracy and reduce manufacturing defects. For instance, in Section 3.1 (Design and Pre-processing Errors), several algorithms have been proposed to correct slicing and modeling errors by minimizing approximation deviations in model contours [44]. In contrast, Section 3.2 (Geometric Errors and Dimensional Deviations) focuses on geometric compensation of FDM processes, employing methods such as virtual reference points or machine learning regressors to address issues like build platform misalignments or layer-wise shrinkage [34]. In some cases, although the primary focus was on dimensional deviations, several studies have developed algorithms that address these issues by modifying the design and pre-processing steps typically covered in Section 3.1 [53]. Finally, studies corresponding to Section 3.3 (Failures in In-Process Error Detection and Response) incorporate hardware components, such as sensors, to capture critical data in real time, which then serve as inputs for algorithms designed to enable early detection and mitigation of failures [105]. Overall, these findings confirm

that software-driven compensation and predictive modeling techniques hold promising potential for improved AM performance. However, to translate these strategies effectively into practice, structured collaboration between design engineers—who ensure that models meet geometric and functional constraints—and control system experts—who develop real-time feedback mechanisms to detect and correct fabrication errors—will be essential.

4. Discussion

This study employed a systematic review methodology following the PRISMA guidelines to ensure a transparent and comprehensive literature survey. A broad search strategy was designed to capture relevant studies on 3D printing failures and mitigation techniques, spanning multiple academic databases. The identification, screening, and eligibility phases were documented using a PRISMA flow diagram, resulting in a final corpus of peer-reviewed articles that directly addressed the research questions. By adhering to PRISMA's structured approach, the review minimized selection bias and provided an overview of the state-of-the-art. This rigorous process underpins the reliability of the findings and allowed for the extraction of key themes. In particular, the included studies converged on three primary categories of challenges in additive manufacturing: (1) design and pre-processing errors; (2) geometric errors and dimensional deviations; (3) failures in in-process error detection and response. These categories formed the basis for organizing the results and are discussed in detail below in relation to the research objectives.

Challenges in the design and pre-processing errors arise from the early stages of the 3D printing workflow, specifically during the design of the 3D model and the preparation of that model for printing, which includes file conversion and slicing. Common problems identified in the literature include a range of design-for-manufacturing issues and setup mistakes that can predispose a print to fail. For example, the accuracy and printability of a part are highly dependent on its design, meaning that 3D printing is not well-suited for certain geometrical features such as unsupported overhangs, extremely thin vertical columns, or large flat horizontal spans without support. Models that ignore these constraints often suffer from collapse, severe sagging, or incomplete layers during printing. Another prevalent issue is the loss of fidelity when converting a CAD model into the triangulated STL format for slicing. The STL approximation represents curved surfaces as a mesh of flat facets, introducing discretization errors that cause subtle geometry distortions. These pre-processing errors can lead to gaps or misalignments between layers, especially for small features or curved surfaces, ultimately affecting the dimensional accuracy and surface quality of the final part. Furthermore, improper slicing configurations such as selecting a suboptimal part orientation, inadequate support structures, or incorrect process parameters are frequently reported for failed builds. Such mistakes can result in issues like poor bed adhesion, internal stresses, or unstable structures during the print.

To minimize errors arising in the design and pre-processing stages, Design for Additive Manufacturing (DfAM) provides a systematic framework that incorporates the physical limitations of the manufacturing process into the design phase itself. This framework is further supported by software tools capable of automatically validating and correcting design features [1]. For instance, in the context of metal powder bed fusion, distortion and buckling in thin-walled structures can be mitigated through the use of design maps that correlate wall thickness and fillet radius, thereby enabling designers to model components with greater confidence [25]. Additionally, Budinoff and McMains (2021) introduced a toolkit that automatically analyzes a 3D model for known problem features such as warping-prone corners, likely weak overhangs, and insufficient support regions, and suggests modifications in geometry or orientation to improve manufacturability [125]. These pre-processing solutions, often integrated into slicing software, have shown success

in preventing common failure modes such as part toppling or excessive material deposition in unsupported areas.

The second major category of challenges pertains to the accuracy and fidelity of the printed object's geometry. Even when a part is well-designed and correctly sliced, the physical printing process can introduce geometrical distortions, dimensional inaccuracies, and surface quality issues. A multitude of studies confirm that achieving high dimensional accuracy and repeatability in 3D printing is non-trivial, with errors stemming from both machine limitations and material behavior. For instance, FDM inherently produces layer-by-layer artifacts that can roughen surfaces and slightly alter dimensions. As the extruded filament cools and solidifies, it may shrink unevenly, leading to warping or internal stresses that cause subtle deformations [24]. Such thermally induced deformation means that printed features can deviate from their intended geometry: holes might come out undersized or shafts oversized due to material contraction and the finite extrusion width. Another well-documented source of error is the aforementioned STL model approximation. The conversion of curved CAD surfaces into flat facets introduces a chordal error, which is when the printed object's surface can deviate by a small amount from the true shape and is often noticeable in fine details or circular features. Compounded with the discrete layer thickness, this leads to a "stair-stepping" effect on sloped surfaces and dimensional offsets that accumulate over the height of the part [12]. Consequently, researchers have observed that without compensation even optimally designed parts may not meet tight tolerance requirements. In summary, typical geometric problems include the warping and curling of parts, dimensional shrinkage or expansion, and surface roughness or texture deviations. These issues were frequently highlighted in the surveyed literature as key barriers to using 3D printed components.

Addressing the research question on solutions to improve geometric accuracy, researchers have investigated both hardware- and software-based approaches. On the hardware side, one solution is improved printer calibration and control. High-end machines employ closed-loop controls to ensure each layer is deposited within the correct tolerances. Heating enclosures and controlled cooling systems are used to mitigate warping by maintaining a uniform temperature field around the part, thereby reducing the thermal gradients that cause distortion. On the software side, error compensation algorithms have been proposed. These algorithms pre-emptively modify the print instructions to counteract known sources of deviation. Likewise, some tools adjust the toolpath to account for filament expansion, effectively calibrating out systematic errors. A study on FDM dimensional accuracy noted that tweaking the STL mesh can lessen the chordal discrepancy and improve the match between the printed part and the CAD model. Another set of solutions involves post-processing for dimensional correction; for instance, targeted annealing or vapor smoothing can relieve internal stresses and improve dimensional fidelity after printing. While post-processing veers outside the printing process itself, it is sometimes necessary to meet tight dimensional specs.

The third challenge category identified is the failure to detect and respond to errors during the printing process itself. Even with a perfect design and a well-calibrated printer, unforeseen issues can arise mid-print such as material jams, layer misalignment, support structure failure, or loss of adhesion that could lead to a failed print. A recurring theme in the reviewed studies is that traditional 3D printers operate in an open-loop manner with minimal real-time feedback, making in-process failures disturbingly common. In answer to research question 1, the types of problems often occurring during the print include filament feed problems (e.g., clogged nozzles or filament running out), thermal anomalies like overheating or cooling leading to poor layer bonding, and mechanical issues such as stepper motors skipping. One particular failure mode is the so-called "spaghetti print",

where due to a dislodged part or missed layer the printer continues extruding filament into empty space, creating a tangled mess of filament. Without intervention, the print is irrecoverable and results in wasted material and time. Overall, the lack of timely detection means that many prints fail only after significant waste has occurred.

To tackle these in-process issues, researchers have been actively developing solutions centered on real-time monitoring and control systems. One prominent approach is the use of sensor arrays to continuously observe the printing process. Various sensor modalities have been explored, such as visual monitoring with cameras, thermal imaging, acoustic sensors, and vibration/strain sensors attached to the printer. Each of these can capture different signatures of a printing anomaly. For instance, a camera can detect visible defects such as layer delamination, excessive stringing, or part detachment, while a microphone or accelerometer might pick up the sound or vibration pattern of a clogged extruder or stepper motor skip. Once an anomaly is detected, the next step is the response; simpler systems might just alert the operator or pause the print, whereas more sophisticated implementations attempt automated error correction. For example, machine learning algorithms like neural networks have been trained to not only recognize specific failure patterns from sensor data but also to adjust printing parameters on-the-fly to correct them. These types of interventions have shown promise in reducing wasted prints, although they remain largely in experimental stages and are not yet widespread in consumer printers.

Recent studies published since 2023 reflect an emerging trend in AM research toward more integrated, intelligent, and scalable error mitigation strategies. For example, Girard and Zhang (2025) introduced a structured light-based method that detects errors in the 2D absolute phase domain, enabling selective 3D reconstruction and real-time G-code-based correction and thereby demonstrating efficient integration of fast error detection and closed-loop control in AM processes [39]. Similarly, Ntousia et al. (2023) proposed a printability prediction framework that combines neural network-based geometric error estimation with probabilistic modeling of design and process parameters, offering a technology-agnostic tool to support quality assurance across AM platforms from the early design stage [5]. Kwon et al. (2024) further contribute to this trajectory by introducing an AI-driven troubleshooting system that leverages community-annotated data for real-time failure diagnosis and user support [6]. Furthermore, a number of studies emphasize the value of open-source platforms and collaborative ecosystems, which are expected to accelerate the development and democratization of robust AM error-handling solutions. Sani et al. (2024) complement these developments by presenting a comprehensive review of closed-loop AI-augmented additive manufacturing (AI2AM), which integrates real-time monitoring, parameter optimization, and defect correction to enhance the reliability and efficiency of AM systems [126]. Ulkir (2024) further adds to this trajectory by experimentally evaluating the mechanical and thermal behavior of metal-reinforced PLA composites and optimizing FDM process parameters to enhance part quality through the data-driven control of layer thickness, infill density, and nozzle temperature [127]. Additionally, recent advancements in DfAM have led to the development of automated design validation tools and real-time STL repair or slicing optimization techniques, which aim to minimize print failures during the early stages of the AM workflow. Together, these efforts highlight a growing emphasis on real-time, data-driven, and user-supportive frameworks that integrate error detection, prediction, and correction across the AM workflow. This trend reflects a broader shift toward intelligent automation, where adaptive control, predictive modeling, and community-enabled tools work in concert to enhance reliability and accessibility in additive manufacturing.

While the systematic approach of this review provides a high-level understanding of 3D printing challenges and solutions, there are several limitations to acknowledge. First, the

scope of the literature survey was constrained to studies available in indexed databases and published in English. It is possible that relevant insights, especially practical knowledge in industry or in non-English publications, were not captured, which may bias the findings toward academic settings. Secondly, the quality and focus of the included studies varied. Some papers provided quantitative data on failure rates or solution effectiveness, whereas others were more anecdotal or conceptual. As a result, our synthesis sometimes had to generalize across different printer technologies and materials. Another limitation lies in the classification of challenges into three categories. In reality, these issues are interrelated as design flaws can lead to in-process failures, and geometric inaccuracies can stem from both design and process. Thus, there is an inherent simplification in our discussion.

5. Conclusions

In conclusion, this PRISMA-guided review has synthesized current knowledge on why 3D prints fail and how to prevent such failures, covering design-stage pitfalls, machine- and material-induced errors, and shortcomings in process monitoring. The challenges of design and pre-processing errors, geometric inaccuracies, and inadequate error detection are significant, but not insurmountable. The literature offers a toolkit of solutions that improve print success rates and part quality. Moving forward, addressing the limitations noted and pursuing the recommended research directions will be critical. By performing this research, the AM community can close the gap between prototype and production, ensuring that 3D printing evolves into a reliably high-quality manufacturing technology. The continued collaboration between design engineers, materials scientists, and control system experts will accelerate progress toward 3D printers that are not only innovative in what they can create, but also consistent and dependable in how they create it.

Future research should aim to address these limitations by expanding the scope of analysis to include non-English literature, gray literature, and practice-oriented case studies from industrial settings. This broader inclusion could enrich the understanding of practical failure modes and solution strategies that are currently underrepresented in academic sources. In addition, more granular classification frameworks may help to capture the interdependencies between design-, geometry-, and process-related errors more accurately. Finally, increased attention to benchmarking datasets, open-source validation tools, and collaborative development environments may facilitate reproducible, scalable, and community-driven progress in AM error detection and correction. In particular, future studies may build upon the PRISMA-based review framework to establish comprehensive troubleshooting guidelines that serve both researchers and practitioners in the AM field.

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