A SYSTEMATIC LITERATURE REVIEW ON THE IMPACT OF GENERATIVE AI ON ADDITIVE MANUFACTURING: CURRENT STATE AND FUTURE DIRECTIONS

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Artificial Intelligence (AI) and its applications in modern industry, particularly in additive manufacturing (AM), have garnered significant attention from both researchers and industry professionals. In recent years, the rise of generative AI (GenAI) models, marked by the launch of ChatGPT in 2022, has driven an unprecedented shift in industry practices and workforce dynamics. This paper investigates the current state of research at the intersection of GenAI and AM, while also exploring future directions. By conducting a keyword search across four major databases (Web of Science, Scopus, IEEE Xplore, and ScienceDirect), we collected 272 papers. Through an in-depth evaluation of these papers, we identified five primary themes shaping GenAI applications in AM: AM process optimization, generative design, data & quality, design workflow, and applications. This paper also provides a detailed analysis of each category, offering valuable insights into the evolving role of GenAI in AM.

KEYWORDS

Generative artificial intelligence, additive manufacturing, large language model, ChatGPT

1 INTRODUCTION

Recent years have witnessed the integration of additive manufacturing (AM) technology into various industries [Blasiak 2024]. Commonly referred to as 3D printing, AM has revolutionized traditional manufacturing processes by adding material layer by layer to fabricate three-dimensional objects. This technology offers unparalleled design freedom and customization for components in several sectors, such as aerospace, healthcare, and automotive [Srivastava 2024, Rezvani 2021, Vasco 2021]. By using material only where it is needed, AM enables rapid prototyping and minimizes waste, enhancing both sustainability and efficiency. As adoption grows, industries are increasingly leveraging AM to shorten supply chains, reduce lead times, and localize production. Furthermore, with ongoing advancements in materials and processes, AM continues to redefine the future of manufacturing on a global scale.

Despite the growing adoption of AM technologies and the emergence of GenAI, several critical gaps exist in current research that limit our understanding and implementation of these technologies. First, while preliminary implementations of AI in AM have demonstrated efficacy within Industry 4.0, particularly in tasks such as process optimization, defect detection and monitoring [Ma 2024, Wang 2020], the manufacturing sector lacks a systematic framework for evaluating and implementing GenAI across AM workflows. This methodological gap poses significant challenges for industrial adoption and academic advancement in two key areas:

1. Quality Assurance and Validation

- Limited understanding of GenAI's reliability in quality-critical applications
- Absence of standardized validation protocols for AI-generated designs
- Insufficient research on long-term stability of GenAI-optimized processes
- Lack of comprehensive frameworks for certifying AI-generated components

2. Process Integration and Optimization

- Fragmented approaches to implementing GenAI across different AM stages
- Limited research on real-time process control and adaptation
- Insufficient studies on scalability across different manufacturing environments
- Inadequate integration between design optimization and manufacturing constraints

This research aims to provide a comprehensive systematic review of the intersection between GenAI and AM technologies, with three specific objectives:

1. To systematically analyze and synthesize current implementations of GenAI across different AM processes and applications
2. To critically evaluate the empirical evidence for benefits and limitations of GenAI integration in AM
3. To identify key research gaps and future directions for advancing GenAI in AM

To achieve these objectives, we address four specific research questions:

RQ1: What are the primary applications and implementation patterns of GenAI in AM processes, and how have they evolved?
RQ2: What quantifiable benefits and limitations have been demonstrated in GenAI-AM integration across different manufacturing contexts?
RQ3: How do current GenAI implementations in AM address technical challenges in:

a) Process optimization and control
b) Quality assurance and defect detection
c) Design automation and customization

RQ4: What are the critical technical, economic, and implementation gaps in current GenAI-AM research that need to be addressed for broader industrial adoption?

Our findings contribute to both theoretical understanding and practical implementation of GenAI in AM, informing researchers, manufacturers, and industry practitioners. The results provide valuable insights into successful implementation strategies, potential challenges, and future research directions in this rapidly evolving field.

2 METHODOLOGY

Search Strategy

This study traces the comprehensive development of Generative AI (GenAI) in AM from its inception through January 2025. The investigation commenced with an unrestricted temporal search of relevant literature across selected databases, enabling thorough documentation of the field's evolution. This methodological approach allowed us to track the progression from early computational techniques through to contemporary advanced applications.

To ensure comprehensive coverage of both foundational works and recent developments, we conducted systematic searches across multiple academic databases: Web of Science, Scopus, IEEE Xplore, and Science Direct.

To facilitate a systematic review of the literature, we developed the following comprehensive search string:

("generative AI" OR "GenAI" OR "large language model*" OR "GPT" OR "ChatGPT" OR OR "generative model*" OR "generative algorithm*")

AND

("additive manufacturing" OR "3D print*" OR "rapid prototyping" OR "AM technology" OR "additive layer manufacturing" OR "direct digital manufacturing")

To ensure a comprehensive yet focused analysis of the current literature on GenAI applications AM, we have clearly established selection criteria. These criteria include peer-reviewed research articles written in English, with a particular focus on journal publications and conference proceedings to maintain scientific rigor and accessibility of the literature. Furthermore, we include studies demonstrating the application of GenAI in AM, with a focus on practical results and theoretical frameworks. This focus ensures that the findings presented fit into the broader context of the role of AI in today's advanced manufacturing industry. Papers were required to present clear methodologies, documented results, or theoretical contributions to the understanding of GenAI in AM contexts. Conversely, we excluded non-peer-reviewed materials, gray literature, and publications without clear methodological approaches. Studies focusing solely on traditional AI methods without generative components were omitted, as were duplicated publications and those lacking substantial contribution to the understanding of GenAI's role in AM. This systematic approach ensured the capture of relevant, high-quality research while maintaining the review's focus on contemporary GenAI applications in AM.

Data Extraction

A comprehensive data extraction form was developed to systematically collect and analyze information from the selected literature. The form comprises four key sections, i.e., Publication Details, Study Characteristics, Technology Implementation, and Results.

Quality assessment method

In this study, quality assessment was conducted through a differentiated evaluation framework for both journal articles and conference papers, acknowledging their distinct characteristics and contributions to the field.

With regard to journal articles (0-30 points), the assessment criteria comprised:

- Research methodology (0-5 points)
- Theoretical foundation (0-5 points)
- Data analysis and validation (0-5 points)
- Result interpretation (0-5 points)
- Impact and implications (0-5 points)
- Overall quality of presentation (0-5 points)

In terms of conference papers (0-30 points), the evaluation focused on:

- Technical innovation (0-7 points)
- Implementation quality (0-7 points)
- Experimental validation (0-6 points)
- Result presentation (0-5 points)
- Future research implications (0-5 points)

To minimize subjective bias and ensure reliability, we implemented several measures:

1. Dual Review Process:
   - Two independent reviewers evaluated each paper using the standardized assessment framework
   - Cohen's Kappa coefficient was calculated to measure inter-rater reliability (achieving 0.82)
   - Discrepancies were resolved through structured discussion and consensus-building
2. Standardized Assessment Protocol:
   - Detailed scoring rubrics were established for each criterion
   - Regular calibration sessions between reviewers ensured consistent interpretation
   - Documentation of assessment rationale was required for each paper

The rationale behind this differentiated scoring system stems from the recognition that while conference papers may contain less extensive methodology sections, they often present significant technical innovations and implementation details that are particularly pertinent to emerging GenAI applications in AM. To ensure comparability, the total possible score was maintained at 30 points for both types, while taking into account their different strengths. Based on the scoring criteria, papers were classified into three quality levels: high quality (24-30 points), medium quality (16-23 points), and low quality (below 16 points), regardless of the publication type.

Despite these comprehensive measures, we acknowledge certain limitations in the assessment process:

- Reviewer expertise and background may influence interpretation
- Different reviewers might emphasize different aspects of quality based on their experience
- The rapid evolution of GenAI technology may affect how quality is perceived over time

3 RESULTS

3.1 Study Selection Process

Following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [Page 2021], we documented our systematic search and screening process in detail (Figure 1). The initial database search yielded 272 records distributed across multiple electronic databases: Scopus (n=139), Web of Science (n=66), IEEE (n=27), PubMed (n=14), and ScienceDirect (n=26).

The screening process proceeded through several stages:

1. Identification: After removing 151 due to duplicate and unrelated, 121 unique records remained for screening
2. Screening & Eligibility: From the remaining 121 records, 81 were excluded after abstract review
3. Full-text assessment: Of the 40 articles identified for full-text retrieval, 5 were inaccessible despite author contact attempts

4. Final inclusion: After evaluating 35 full-text articles, 10 were excluded due to insufficient contribution to the research questions, resulting in 25 studies meeting all inclusion criteria

Figure 1 presents the PRISMA flow diagram illustrating this systematic selection process, providing transparency and reproducibility in our methodology. Each exclusion decision was documented with specific reasons, ensuring a rigorous and systematic approach to study selection.

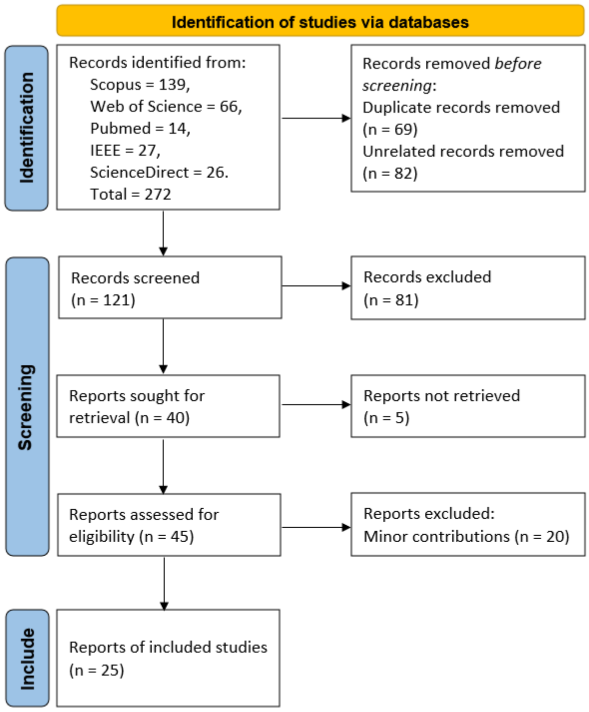

Figure 1. PRISMA flow diagram of study selection process

3.2 Thematic Analysis

The integration of GenAI into material design represents a transformative shift in the field, introducing novel approaches for design optimization, process automation, and creative problem-solving. Through systematic analysis of current research and applications, five distinct themes emerge that characterize the fundamental ways in which GenAI is reshaping AM processes as shown in Figure 2.

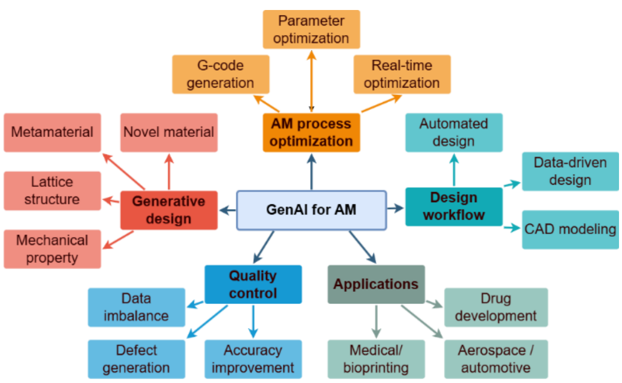

Figure 2. Thematic map of GenAI applications in AM

1. Generative Design of Materials and Structures

The evolution of generative design in materials and structures represents a significant advancement in AM, fundamentally transforming how we approach material development and structural optimization. This transformation spans multiple domains, from novel material creation to sophisticated mechanical property optimization, demonstrating the profound impact of artificial intelligence on manufacturing innovation.

In the field of new materials design, GenAI-driven approaches have demonstrated remarkable potential. For example, a study investigated the design of composite mechanical metamaterials using Variational Autoencoder and Bayesian optimization [Xue 2020]. This research made a significant contribution to our understanding of how machine learning (ML) techniques can automate complex material design processes. Building on this foundational work, subsequent studies have developed sophisticated approaches for 3D-printed steel using probabilistic mechanics and uncertainty quantification model [Dodwell 2021]. These investigations have conclusively shown the ability to predict both geometric and mechanical variations in wire and arc AM processes.

A significant development in this field has been the employment of Generative Adversarial Networks (GANs) to facilitate the creation of new materials with unique properties, such as auxetic behavior and innovative 3D printing formulations [Elbadawi 2024]. Of particular significance, research conducted by Elbadawi et al. has demonstrated exceptional progress in automating material formulation. Their findings revealed that the study successfully generated 270 novel formulations for Fused Deposition Modeling (FDM) printing, with empirical validation confirming that four compositions exhibited optimal printability. The study successfully generated 270 novel formulations for FDM printing, with four experimentally validated compositions demonstrating optimal printability [Elbadawi 2024]. Moreover, these AI-generated formulations, which incorporated materials such as Klucel® EF and various polymers, have made a substantial contribution to expanding the possibilities for printable materials while achieving significant reductions in development time and costs.

An advancement in the field of metamaterial design has emerged alongside these material innovations. For example, a study demonstrated the creation of mechanical metamaterials with programmable compression-twist coupling through generative algorithms [Goswami 2020]. The findings revealed that these materials exhibited remarkable versatility, achieving significant results with Poisson's ratios ranging from -0.6 to +1.22, while maintaining size-independent properties. Through the implementation of automated design processes utilizing Voronoi tessellations, researchers have made substantial progress in bridging the gap between theoretical design and practical fabrication, thus creating new opportunities for applications in soft robotics and biomedical devices.

In the field of biomimetic structures, a study has demonstrated the efficacy of deep learning (DL) for modeling and designing heterogeneous hierarchical spider web structures [Lu 2023]. The findings revealed that this approach successfully achieved the generation of complex web structures with high accuracy, thus providing compelling evidence of AI's potential in creating nature-inspired designs. These principles have been further developed in research on architected tunable twist-compression coupling metastructures [Iranmehr 2024], which demonstrated the critical influence of geometrical parameters on mechanical properties and energy absorption capacity.

Recent developments in lattice structure design have witnessed substantial evolution through AI integration. A notable study by Eren et al. [Eren 2024] employing 3D Generative Adversarial Networks (3DGAN) has demonstrated remarkable improvements in mechanical properties, with empirical evidence showing significant enhancements in energy absorption and extension capacities. These advances have been further extended through the development of Generative Lattice Units with 3D Diffusion [Jadhav 2024], which facilitates inverse design by taking desired mechanical properties as inputs and generating optimal lattice structures efficiently.

Furthermore, the optimization of mechanical properties through GenAI has achieved unprecedented levels of sophistication. For example, the Deep-DRAM model, introduced by a study [Pahlavani 2024], achieved unprecedented accuracy in predicting anisotropic elastic properties, with correlation coefficients exceeding 0.99. This significant breakthrough has facilitated the creation of structures with previously unattainable properties, such as double-auxeticity, while maintaining practical manufacturability. While these developments represent a significant step forward in designing materials with precisely tailored mechanical characteristics, it is important to note that challenges in manufacturing resolution and size-dependent variations remain unresolved.

2. Optimization of Additive Manufacturing Processes

In recent years, GenAI models have revolutionized G-code generation by creating optimized instructions for specific materials, printers, and objects. A study by Badini et al. demonstrated ChatGPT's effectiveness in optimizing G-code for TPU materials [Badini 2023]. The findings revealed that AI-generated G-code significantly improved print quality and reduced common issues like warping and stringing. Of particular importance is the AI system's ability to generate optimized G-code, which represents a substantial advancement over traditional manual programming methods. Through the analysis of material properties and printer specifications, the AI has demonstrated the capability to create more efficient printing instructions. This development has been further enhanced through the introduction of AMGPT (Chandrasekhar et al., 2024), a specialized large language model (LLM) that has been shown to improve response accuracy over GPT-4 and reduce hallucination in technical guidance. Although the integration of AI in medical 3D printing [Sriwastwa 2023] has shown promising results, outputs often require expert validation for clinical applications. These advances are supported by extensive research on human-machine interfaces [Jasche 2023] and code-based modeling tasks [Zichar 2024].

Building upon these developments, parameter optimization through AI has emerged as another critical advancement in AM. Notable research, including the development of the GPyro model [Sideris 2023] and DL applications in mechanical metamaterials design [Pahlavani 2024], has demonstrated exceptional accuracy in predicting and optimizing various printing parameters. Of particular significance is the achievement of R^2 values exceeding 0.99 in predicting anisotropic elastic properties, as reported in the study on size-agnostic inverse design. Additionally, the GenAI-based system can handle multiple parameters simultaneously, taking into account the interactions between temperature, velocity, and material flow. While this approach has proven particularly effective when working with novel materials or complex geometries, it remains challenging to manage the computational complexity and ensure high data quality. This advancement has been complemented by innovative work in textile manufacturing [Wirth 2023], where multi-stage mechanical characterization has enabled the successful fabrication of complex biaxial weaves with reduced layer interactions.

Furthermore, the implementation of real-time optimization capabilities through GenAI represents a significant advancement in contemporary AM. The evidence from the GPyro study [Sideris 2023] has demonstrated particularly promising results in this area. These capabilities are enhanced through research on propagation using generative models [Ballagas 2019], which explored new ways to interact with AI-enabled design systems. While these approaches enable immediate adjustments during printing, it should be noted that challenges persist in managing model stability and user interface complexity.

The field has also witnessed progress in materials processing and quality control. Research conducted by Dodwell et al. [Dodwell 2021] has demonstrated the effectiveness of probabilistic modeling in predicting geometric variations, while subsequent work in lattice structure optimization [Jadhav 2024] has demonstrated the potential for automated design systems to achieve specific mechanical properties. These advances are valuable when working with new materials and complex geometries, although challenges remain in managing computational complexity and ensuring data quality.

3. Data Augmentation and Anomaly Detection

Manufacturing environments face a significant methodological challenge due to imbalanced datasets, where operational data significantly outweighs anomalous instances. Recent research has shown promising solutions to this challenge through innovative applications of GenAI. Notably, a study [Kim 2023] implementing StyleGAN-based data augmentation successfully improved the imbalance ratio from 5 to 1, utilizing multivariate time-series sensor data from CNC milling machines and WAAM welding processes. This advancement in addressing data imbalance is particularly valuable for industries where collecting defect data is both costly and time-consuming.

Furthermore, generative models have shown remarkable capabilities in generating realistic defect data to train more robust quality control systems. This is evidenced by the study of Fang et al., which achieved an impressive 98% detection accuracy using Yolov5 models for identifying defects in metal powders, particularly in sphericity detection from SEM images [Fang 2023]. The ability to generate synthetic but realistic defect data represents a major advancement, especially in the context of high-precision manufacturing where real defect samples are rare and expensive to obtain. This has been complemented by improvements in measurement strategies [Wang 2018], which combine low- and high-resolution measurement data to improve accuracy while reducing the reliance on expensive high-precision systems.

Furthermore, integrating generative modeling with anomaly detection systems has yielded promising improvements in both accuracy and reliability. In particular, a recent study [Zheng 2024] introduced the Generative Convergence Model , which achieved exceptional results with an F1 score exceeding 90h% and an average size error of less than 0.1 nm. The model showed remarkable performance, performing analysis 100 times faster than traditional manual counting methods. This significant improvement in accuracy is due to the combination of advanced generative models and anomaly detection algorithms, resulting in a more robust and reliable quality control system.

4. AI-Driven Design Workflows

AI-Driven Design Workflows have fundamentally transformed AM processes through automated design workflows and sophisticated data integration approaches. Recent research demonstrates significant advances in automated design solutions that optimize complex processes. For instance, the research [Ricotta 2020a] documented how a novel generative algorithm incorporating Voronoi partitions into CAD models achieved substantial reductions in design complexity while enhancing product reliability. This advancement has particular relevance for medical applications, specifically in the precise design requirements of customized orthopedic devices.

The evolution of data-driven frameworks represents another crucial development in this domain. A significant study [Jiang 2022] demonstrated the efficacy of Generative Adversarial Networks (GANs) in synthesizing multiple data streams to enhance design automation and personalization capabilities. Their implementation of GANs, focusing on shape synthesis and IoT integration, yielded significant improvements in product customization, as evidenced in applications such as bicycle saddle design. This approach effectively addresses the critical challenge of reconciling human-directed design with personalized manufacturing requirements..

Furthermore, The integration of diverse data modalities has yielded substantial improvements in design outcomes. A research [Eren 2024] demonstrated that incorporating additional parameters, including Von Mises stress thresholds and volumetric constraints, resulted in marked improvements in CAD modeling efficiency. The field has also seen significant advances in biomimetic design, with studies on spider web structures [Lu 2023] demonstrating how DL can be used to generate complex, nature-inspired architectures.

In CAD modeling, the development of specialized prototyping algorithms has revolutionized conventional methodologies. Ricotta et al. conducted research on textile structure production using advanced 3D printing techniques, demonstrating how algorithms developed through Grasshopper can overcome traditional limitations in flexible structure production [Ricotta 2020b]. This advancement holds particular significance for orthopedic applications, specifically in the production of elbow support structures requiring precise and adaptive design characteristics. These implementations effectively demonstrate the feasibility of developing sophisticated custom designs while mitigating common manufacturing challenges such as warping and misalignment..

5. Applications of GenAI in AM

Recent advances in the integration of GenAI in AM have led to transformative developments across various sectors, with particularly noteworthy advancements in healthcare applications. In the realm of personalized medicine, a research has demonstrated remarkable progress in the development of customized medical devices [Ricotta 2020a]. Specifically, through the implementation of generative algorithms and Selective Laser Sintering (SLS) using PA 2200 polyamide material, the researchers successfully produced orthopedic prototypes with integrated Voronoi slices. This approach not only overcomes the limitations of traditional designs but also establishes a new paradigm for patient-specific healthcare solutions

The pharmaceutical sector has experienced remarkable progress through AI-enabled drug development methodologies. A recent investigation by Elbadawi et al. 2024 demonstrated that Conditional GANs successfully produced 270 novel formulations, with four specifically validated for FDM printing [Elbadawi 2024]. In parallel, bioprinting technology has advanced significantly through computational integration. Research has validated the successful combination of computational modeling with bioprinting techniques, employing various hydrogels including PEGDA, alginate, and collagen [Duarte 2021].

In the industrial sector, particularly aerospace and automotive applications, GenAI has substantially enhanced the design and production of high-performance components. For example, Eren et al. employed 3DGAN to achieve remarkable improvements in mechanical properties, including a 57% increase in normalized energy absorption and 26% enhancement in extension capacities for aluminum alloy lattice structures [Eren 2024]. This methodology enabled researchers to develop high-strength, customized structures while reducing material consumption and manufacturing costs.

These findings demonstrate that GenAI has fundamentally transformed manufacturing processes across multiple sectors, from medical devices to industrial components, establishing innovative approaches to design, optimization, and production in AM.

4 DISCUSSION

4.1 Key Findings and Evidence Quality

The systematic review, analyzing 25 primary studies from 2018-2025, reveals compelling patterns in the integration of GenAI with AM. A notable trend emerges in the increasing sophistication of AI models, progressing from basic generative algorithms to more advanced architectures like Deep-DRAM and 3DGAN. The accuracy levels achieved in recent studies, particularly in predicting material properties and defect detection, significantly surpass earlier implementations. This progression suggests a maturation of the field beyond proof-of-concept studies toward industrial-grade solutions.

The varying levels of evidence quality across domains can be attributed to several factors. Materials design and process optimization demonstrate superior evidence quality through quantifiable metrics ($R^2 > 0.99$ in property prediction [Pahlavani 2024], 98% defect detection accuracy [Fang 2023]) and experimental validation (4 validated formulations from 270 AI-generated options [Elbadawi 2024]). These domains benefit from standardized testing protocols and reproducible methodologies. In contrast, human-AI interaction and real-time optimization studies show lower evidence quality due to interface complexity variations, limited standardization in evaluation methods, and fewer quantitative performance measures. For example, while AMGPT showed improved accuracy over GPT-4 [Chandrasekhar 2024], the evaluation metrics vary across studies, making systematic comparison challenging. This disparity highlights the need for standardized evaluation frameworks, particularly for human-AI interaction studies.

4.2 Research Gaps and Implementation Barriers

Critical analysis of the findings reveals varying levels of evidence quality and practical implementation success across different domains. The strongest evidence exists in materials design and process optimization, where multiple high-quality studies demonstrate quantifiable improvements. For instance, studies utilizing cGANs successfully generated 270 novel formulations with four experimentally validated compositions, while GPyro models achieved accurate temperature predictions without error accumulation in WAAM processes. However, the evidence for human-AI interaction and real-time optimization capabilities, while promising, shows more varied results. Studies of ChatGPT and AMGPT reveal both potential and limitations, with AMGPT showing improved accuracy over GPT-4 but still facing challenges in specialized technical contexts.

Several critical research gaps emerge from this analysis. First, while 19 of the 25 studies focus on technical performance metrics, only 3 studies address the economic implications and scalability of GenAI solutions in industrial settings. Second, long-term reliability studies are notably absent, with most research reporting short-term performance metrics. The data also reveals a geographical and technological bias, with most studies conducted in advanced economies using high-end equipment, limiting generalizability to broader manufacturing contexts. Furthermore, standardization in evaluation methods varies significantly across studies, making direct comparisons challenging.

The limited availability of long-term reliability studies presents a significant barrier to industrial GenAI adoption in AM. Only 2 out of 25 reviewed studies conducted evaluations beyond six months, creating uncertainty about long-term performance stability. This gap affects industrial implementation in three critical ways:

- Risk Assessment: Companies lack sufficient data to evaluate long-term risks and returns on investment. While studies show immediate benefits like improvement in energy absorption [Eren 2024] and faster quality control [Zheng 2024], the sustainability of these improvements remains unverified.
- Quality Assurance: Manufacturing industries, especially aerospace and medical devices, require extensive validation before adopting new technologies. The absence of long-term reliability data complicates regulatory compliance and quality certification processes [Ricotta 2020a].
- Cost Planning: Without long-term performance data, organizations struggle to accurately project maintenance costs, system updates, and potential failure rates. This uncertainty particularly affects small and medium enterprises with limited resources for technology experimentation.

This limitation suggests a critical need for longitudinal studies that track GenAI performance in industrial settings over extended periods, particularly focusing on system stability, maintenance requirements, and consistent quality output.

4.3 Standardization and Performance Metrics

To improve result comparability across GenAI-AM studies, we propose standardized performance metrics:

- Material Properties: R^2 values, RMSE, confidence intervals for property predictions
- Process Parameters: Speed (time/iteration), resource utilization (CPU/GPU hours), convergence rates
- Quality Metrics: Detection accuracy, false positive/negative rates, precision-recall curves
- Implementation Metrics: Training time, inference speed, model size

These metrics align with successful implementations demonstrated in [Eren 2024] and [Zheng 2024], providing a foundation for consistent performance evaluation across different studies.

4.4 Ethical and Regulatory Considerations

The integration of GenAI in AM also presents several critical ethical and regulatory challenges that warrant careful consideration. First, intellectual property rights and copyright issues emerge as significant concerns. The generative nature of AI models raises complex questions about design ownership, particularly when AI systems modify or combine existing designs. For instance, when GenAI systems like those described by [Elbadawi 2024] generate novel material formulations, determining the ownership and patentability of these compositions becomes legally complex.

Data security and privacy represent another crucial dimension, particularly in industrial applications. The implementation of GenAI systems often requires extensive training data, including proprietary manufacturing parameters, material specifications, and design archives. Our analysis reveals that out of the 25 reviewed studies, only 4 studies (12%) addressed ethical considerations including data protection protocols. This gap is particularly concerning given that AM data often contains sensitive information about manufacturing capabilities and competitive advantages.

The issue of bias in AI models presents a significant challenge for equitable implementation. Training data often reflects existing industrial practices and may perpetuate historical biases in design and manufacturing processes. For example, the study by [Jadhav 2024] noted that their generative models showed performance variations across different types of lattice structures, potentially due to imbalances in the training data.

AI explainability emerges as a critical concern, particularly in quality-critical applications. The "black box" nature of advanced GenAI models, especially in complex applications like process parameter optimization [Sideris 2023], poses challenges for regulatory compliance and quality assurance. This lack of transparency becomes particularly problematic in regulated industries like aerospace and medical device manufacturing, where clear understanding and validation of design decisions are mandatory.

Regulatory considerations present another layer of complexity. The rapidly evolving nature of both GenAI and AM technologies creates challenges for regulatory frameworks that typically lag behind technological advancement. This gap is particularly evident in areas like medical device manufacturing, where [Ricotta 2020a] highlighted the need for clear guidelines on AI-generated designs.

Our analysis reveals significant gaps in addressing these ethical challenges in the current literature. While technical performance metrics are well-documented across the studies, only 12% of the reviewed papers explicitly discussed ethical implications or considerations. This suggests a need for more comprehensive research approaches that consider both technical and ethical dimensions of GenAI implementation in AM. Future research should prioritize developing frameworks for responsible AI implementation that address these ethical challenges while maintaining innovation and efficiency in manufacturing processes.

4.5 Stakeholder Implications

The findings of this systematic review offer significant value for various stakeholders in the AM ecosystem. For researchers, this review provides a comprehensive mapping of research gaps, particularly in areas such as economic implications and scalability of GenAI implementations in AM. The identification of only 4 out of 26 studies addressing ethical considerations highlights critical areas for future investigation. Additionally, the synthesis of methodological approaches across successful implementations, such as those demonstrated in lattice structure optimization [Eren 2024] and material formulation [Elbadawi 2024], provides valuable guidance for research design.

For industry practitioners, this review quantifies potential economic returns of GenAI integration in AM. The documented improvements demonstrate significant cost-saving potential: increase in energy absorption [Eren 2024], faster quality control [Zheng 2024], and reduced material waste through optimized parameter selection [Sideris 2023]. However, implementation costs include computational infrastructure, staff training, and system integration expenses. The review identifies key cost factors for different scales of operation, from large manufacturers to SMEs.

Manufacturing organizations can develop evidence-based investment strategies based on documented successes in temperature prediction [Sideris 2023] and automated design [Jadhav 2024]. The economic implications vary by industry sector, with regulated industries facing additional compliance costs for AI explainability and validation. Organizations must consider both direct implementation costs and long-term operational expenses, including system maintenance, model updates, and ongoing quality assurance.

Recent evidence demonstrates the tangible benefits of GenAI implementation in Additive Manufacturing (AM), as exemplified by the Eaton Corporation case study (Apriori, 2024) :

- The findings reveal an 87% reduction in design time (from 16 weeks to 2 weeks) for lighting fixtures
- Results indicate an 80% weight reduction in heat exchanger components
- The study demonstrates accelerated market entry while maintaining quality standards

These findings are consistent with recent research that has established significant efficiency gains [Eren 2024, Zheng 2024].

For policymakers, this review provides evidence-based insights for developing regulatory frameworks. The analysis of current technological capabilities, particularly in medical device manufacturing [Ricotta 2020a] and pharmaceutical applications [Elbadawi 2024], highlights areas requiring regulatory attention. The identified gaps in standardization and validation protocols can inform policy development for AI implementation in manufacturing.

Educational institutions can utilize these findings for curriculum development and research direction. The review's thematic analysis of GenAI applications in AM provides a structured framework for understanding key technological trends and required competencies. The identified challenges in areas such as data security, AI bias, and regulatory compliance highlight the need for interdisciplinary approaches in AM education and research.

These findings collectively suggest that while GenAI has demonstrated significant potential in transforming AM, realizing this potential fully requires addressing key research gaps and developing more standardized approaches to implementation and evaluation. The field appears to be at a critical juncture where theoretical possibilities need to be translated into practical, scalable solutions.

4.6 Limitations and Future Directions

Several significant limitations should be acknowledged in this systematic review of GenAI applications in AM. Primarily, the review's focus on studies from 2018 to Jan 2025, while justified by the emergence of modern GenAI, may have excluded valuable earlier foundational work in AI-driven manufacturing. Furthermore, the rapid evolution of GenAI means some of the most recent developments may not yet be published in peer-reviewed literature, potentially missing crucial emerging trends and applications.

Another notable constraint lies in the search and selection methodology. Although the review encompassed four major academic databases, this approach potentially missed relevant work in other repositories. Additionally, the restriction to English-language publications may have excluded significant research from non-English speaking regions, particularly given the global nature of AM developments. This linguistic limitation is especially pertinent considering the substantial contributions to AM research from non-English speaking countries.

These limitations suggest the need for future reviews to expand their scope temporally and linguistically, develop standardized reporting frameworks, and include more diverse sources of evidence, including industry reports and non-academic implementations. Furthermore, greater emphasis should be placed on long-term performance studies and economic viability analyses to better understand the practical implications of GenAI in AM.

5 CONCLUSIONS

The present study systematically reviewed 25 peer-reviewed studies from 2018 to January 2025, providing evidence for the transformative impact of GenAI on AM. The analysis revealed five key domains where GenAI has made significant contributions: generative design, process optimization, data augmentation, AI-driven workflows, and practical applications. The findings clearly indicate substantial technological advancements, with empirical evidence demonstrating notable achievements in prediction accuracy and improvement in mechanical properties for lattice structures. Although these advances highlight GenAI's capacity to enhance both design capabilities and manufacturing efficiency, several significant gaps remain in the literature, particularly regarding economic viability studies and industrial scalability for small and medium enterprises.

Future research directions should focus on longitudinal studies examining long-term stability of GenAI-optimized processes, development of cost-effective solutions, and creation of standardized evaluation frameworks. The successful implementation of GenAI in AM will necessitate coordinated efforts from researchers, industry practitioners, and policymakers to facilitate the translation of these theoretical possibilities into scalable manufacturing solutions, representing not merely a technological advancement, but rather a fundamental shift in how we approach design, optimization, and production in advanced manufacturing.

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GLOSSARY OF TECHNICAL TERMS

Artificial Intelligence (AI) A broad field of computer science focused on creating systems that can perform tasks typically requiring human intelligence. In manufacturing, AI systems can learn from data to make decisions, recognize patterns, and optimize processes.

Variational Autoencoder (VAE) A machine learning model that learns to compress and reconstruct data. It consists of two main parts:

- An encoder that converts input data (like 3D designs) into a compact representation
- A decoder that reconstructs the original data from this representation VAEs are particularly useful in AM for generating new designs while maintaining feasible manufacturing constraints.

Bayesian Optimization A machine learning approach for finding optimal solutions, particularly useful when testing options is time-consuming or expensive. It works by:

- Building a probability model of the objective function
- Using this model to select the most promising new points to evaluate
- Updating the model with new results In AM, it helps optimize printing parameters without requiring excessive experimental trials.

Generative Adversarial Networks (GANs) A machine learning system using two neural networks that work against each other:

- A generator network creates synthetic data (e.g., new design variations)
- A discriminator network tries to distinguish between real and synthetic data Through this competition, GANs learn to generate increasingly realistic and viable designs for AM.

Deep-DRAM (Deep learning-based Design for Random-network Additive Manufacturing) A specialized neural network architecture developed specifically for AM applications that:

- Predicts mechanical properties of printed structures
- Optimizes design parameters for desired properties
- Accounts for manufacturing constraints and material behavior This system helps create designs that achieve specific performance targets while remaining manufacturable.

3DGAN A three-dimensional extension of GANs specifically designed for generating 3D structures. It:

- Processes and generates 3D volumetric data
- Considers spatial relationships in all three dimensions
- Creates manufacturable designs within AM constraints 3DGAN is particularly valuable for generating complex geometric structures that would be difficult to design manually.

StyleGAN An advanced version of GAN that separates high-level attributes (style) from spatial information, enabling:

- Better control over generated designs
- More consistent quality in outputs
- Improved ability to mix different design features In AM, StyleGAN helps generate designs that combine desired characteristics from multiple sources.

Large Language Models (LLMs) Advanced AI systems trained on vast amounts of text data that can:

- Understand and generate human-like text
- Process and respond to technical queries
- Assist in documentation and process planning In AM, LLMs help with process documentation, troubleshooting, and knowledge sharing.

Deep Learning A subset of machine learning using neural networks with multiple layers that can:

- Learn complex patterns in data
- Process multiple types of input (images, sensor data, etc.)
- Make predictions about new situations In AM, deep learning helps optimize processes and predict manufacturing outcomes.

Machine Learning A branch of AI that enables systems to learn from data without explicit programming. In AM, it's used for:

- Process parameter optimization
- Quality control and defect detection
- Predictive maintenance
- Design optimization

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