

The convergence of additive manufacturing and artificial intelligence with LLMs for smart product design

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Abstract

The development of smart product design through the integration of additive manufacturing (AM) and artificial intelligence (AI) has become a game changer in the production value chain of Industry 4.0. This is premised on today's trend of moving away from mechanical technologies to digitization processes driven by AI. This trend has harnessed an AI-driven intelligent approach in creating new avenues for manufacturing process and system optimization in the era of Industry 4.0 and the emerging Industry 5.0. Conversely, there are concerns about how AI-driven design optimization can improve product manufacturability and performance. Thus, this study discusses the key processes, challenges, and opportunities in integrating AM and AI for smart product design. The study further suggests the possible utilization of the recent large language models (LLMs) and customized robots as designers to enable AM capabilities for optimizing smart product design and product performance, reducing production time, and possibly producing more product units at a much lower cost, instead of employing AM only. With the aid of this study and the AM-AI with LLMs taxonomy outlined, the convergence shows promising potential in synthesizing intelligent and smart product designs.

Keywords: *additive manufacturing, artificial intelligence, industry 4.0, large language model, product design, industry 5.0*

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1. Introduction

The industrial landscape has undergone a significant transformation with the rise of Industry 4.0, which has driven the merging of digital and physical technologies to manage manufacturing processes. Artificial intelligence (AI) and additive manufacturing (AM) are key technologies leading this change. Imagine a future factory where the combination of these technologies can conveniently manage each printed layer for a product assembly, from utilizing real-time data from sensors to optimizing the design environment platform's geometry, process parameters, and structural performance estimates before the next powder layer solidifies. A synergistic relationship between AM and AI is quickly becoming vital for this success, in line with the vision of Industry 4.0 and the emerging Industry 5.0, which focuses on sustainability, human-machine collaboration, and hyper-customization. AI's adaptive control, predictive analytics, and generative design abilities make the process more efficient. AM's inherent design freedom enables the direct conversion of computer-aided design (CAD) into physical parts with minimal waste. As factories transform to Industry 5.0, smart manufacturing allows data acquisition from machines for smart processes, offering flexibility that delivers high-quality products at economically friendly prices [1]. This 21st-century innovation has transformed the composition of the workforce, boosted industrial growth, improved economics, and enhanced productivity [2]. AI supports intelligent decision-making and process optimization, while AM, often called 3D printing, allows the creation of complex geometries and customized pr-

oducts. Combining AM with AI could revolutionize product design by producing intelligent, flexible, and efficient goods [3, 4]. Today, many manufacturing companies are required to seek greater flexibility in design and production. The increasing demand for customized and high-value products drives this shift. As a result, customized manufacturing has emerged, where design and fabrication are tailored to individual client needs. This includes mass customization, build-to-order, and small production runs [5–7].

Despite the growing research on advances in AM driven by AI, the field still lacks conceptual consistency. Research on AM's role in smart manufacturing ecosystems is plentiful [8, 9]; however, most of this research treats AI and AM separately, according to Dehghan et al. [10]. The industrial deployment assessment by Windmann et al. [11] highlighted data silos, outdated hardware, and staff skill gaps as major challenges. However, they did not provide a unified framework. Furthermore, studies have shown that AI, autonomous robots, and digital twins can reduce design cycles; nonetheless, they failed to systematically connect these innovations to AM's layer-by-layer dynamics [12–16]. Building on these gaps in the literature, this work offers a conceptual discussion based on different studies' perspectives to support the convergence of AI and AM themes, ensuring that the taxonomy of AI-AM convergence is comprehensive and easy to understand for harnessing its enormous potential. By examining the current status of AM-AI integration, its uses, advantages, and challenges,

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this study seeks to provide a perspective to enhance interdisciplinary knowledge in this area. The convergence of AM and AI in smart product design is specifically examined in this paper, emphasizing potential avenues for future study.

The amalgamation of AM and AI in product design is essential for the realization of Industry 5.0's objectives of hyper-customization, sustainability, and human-machine collaboration. Nonetheless, a cohesive framework elucidating how these technologies facilitate intelligent product design is pertinent. Large language models (LLMs) possess unexploited potential to coordinate comprehensive design-manufacture pipelines; nevertheless, systematic understanding of their function within AM ecosystems is limited. This fragmentation obstructs practitioners from utilizing cross-disciplinary synergies and impedes the advancement of completely autonomous "robot-designer" workflows. This work presents a generalized manufacturing process, AM with product design, the role of AI and smart manufacturing in Industry 5.0, AI and product manufacturing, including design for additive manufacturing (DfAM), and concludes with the challenges and prospects of AI-guided AM based on a three-mode taxonomy centered around the pathway to LLM-driven autonomous design agents.

2. Customized manufacturing processes

The manufacturing sector's reaction to the demands of a more contemporary and dynamic environment is mass customization, a hybrid of mass production and customized production. New chances and difficulties for uniqueness in consuming are always being created by society. The modern individualist drives a specially customized car, wears clothing that suits them, and consumes their own cereals that they purchase online [17]. This customized product must be properly identified with the proper material characterization so that a suitable welding technique can be applied to forestall any distortion of the material's internal lattice, which can lead to unexpected deformation [18, 19].

In other words, products that meet the specific demands of each consumer are in high demand in a buyer's market. Manufacturing businesses must balance providing competitive pricing with expanding the external diversity that the market demands [20]. Mass customization aims to meet each unique consumer's demands at a price point that appeals to a sizable portion of the market. Typical mass customization strategies offer a middle ground between uniformity and unadulterated uniqueness [21]. In order to achieve economies of scale at the component level and to simplify development and production capabilities, product family design should strive for an adequate number of exterior product variations in addition to a reasonable amount of internal diversity [22, 23].

Thus, personalization of manufacturing processes techniques seeks to meet each consumer as an individual with implicit demands; however, the existing mass customization strategies feature passive and restricted customer engagement. High levels of product modification, user experience, and co-creation allow for personalization, making the finished product, as well as the fundamental design and structure, flexible and adjustable and, as a result, less predictable [24, 25]. For instance, "Industry 4.0" refers to a broad spectrum of contemporary ideas, many of which are difficult to precisely distinguish from one another and classify

according to a field. Industry 4.0 combined the benefits of 3.0 and networked computers to allow for reciprocal communication and decision-making with or without human intervention [26–28]. Additionally, this Industry 4.0 is primarily driven by cutting-edge technologies which include cyber-physical systems and the Internet of Things (IoT). The intelligent manufacturing idea is now a reality [29, 30].

Smart devices are becoming increasingly intelligent due to AI and the ease with which more data can be accessed. Industries become more efficient, well-structured, and optimized as a result [20, 29]. In the end, the real power of industry comes from a network of digitally linked machines that share information [29, 31]. Emerging technological innovation is developing quickly, with the ultimate goal of benefiting humanity in every manner. New technologies are emerging at the same time as improvements in industrial processes. Therefore, Industry 4.0 employs technologies which include big data analytics, IoT, AI, AM [31, 32], and other technologies, as depicted in **Figure 1**. The whole manufacturing process in Industry 4.0 is outfitted with sensors, actuators, and self-governing systems, and the development of so-called "smart factories," which are autonomously operated, is made possible by the use of "smart technology," which is associated with completely digitalized models. This smart factory aids manufacturing processes that are economically sustainable with quality control systems that drive intelligent manufacturing and scheduling [4, 28, 33].

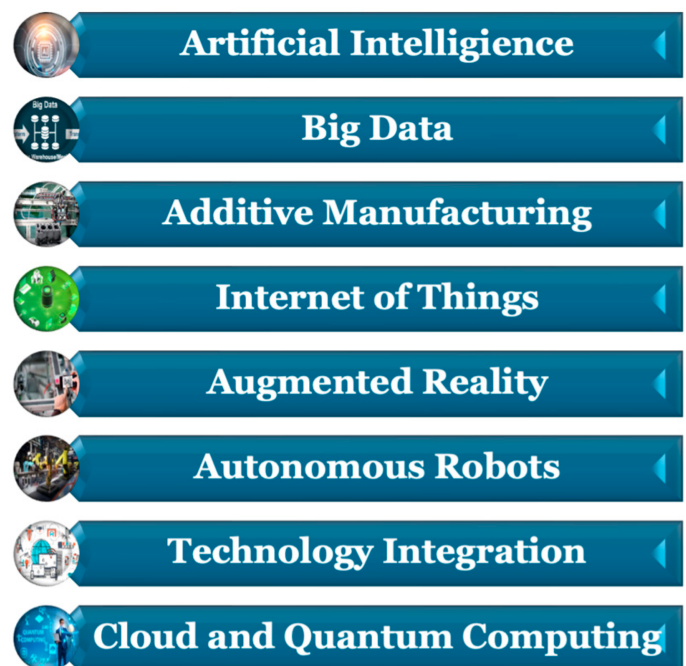


Figure 1 • Industry 4.0 and 5.0 technologies transforming smart product design.

3. Additive manufacturing and product design

The process of fusing, binding, or solidifying components like powders and liquid resin is known as additive manufacturing. It employs three-dimensional (3D) CAD modeling to construct the component layer by layer. Terms such as 3D printing, solid

freeform fabrication, rapid prototyping, direct digital manufacturing, and rapid manufacturing can describe AM methods [34]. In other words, AM is a cutting-edge digital manufacturing technique that utilizes CAD models to create 3D items, often layer by layer. It offers benefits like shorter lead times and lower costs, as well as the capability to fabricate complex parts with intricate geometries and patterns, unique microstructures, and distinctive characteristics, compared to traditional manufacturing processes. Consequently, AM has garnered significant attention in recent years from both academic and industrial research communities worldwide [35, 36].

AM processes are iterative, as shown in **Figure 2**, and follow three phases, namely, design, manufacturing, and testing, to generate components using 3D computer data or Standard Tessellation Language files, which provide geometry information about the product. AM is an excellent tool when low production volumes, high design complexity, and frequent design changes are required. Even with all of AM's benefits, its application is still limited due to its low accuracy and long build times compared to Computer Numerical Control (CNC) machines. It does not have the same restrictions as CNC machining since it splits the part into cross-sections at a resolution equal to the process. However, accuracy and assembly time can be improved by employing the proper part orientation. Enhancing precision, cutting down on building time, and optimizing part orientation can all lower the cost of producing a part [37, 38].

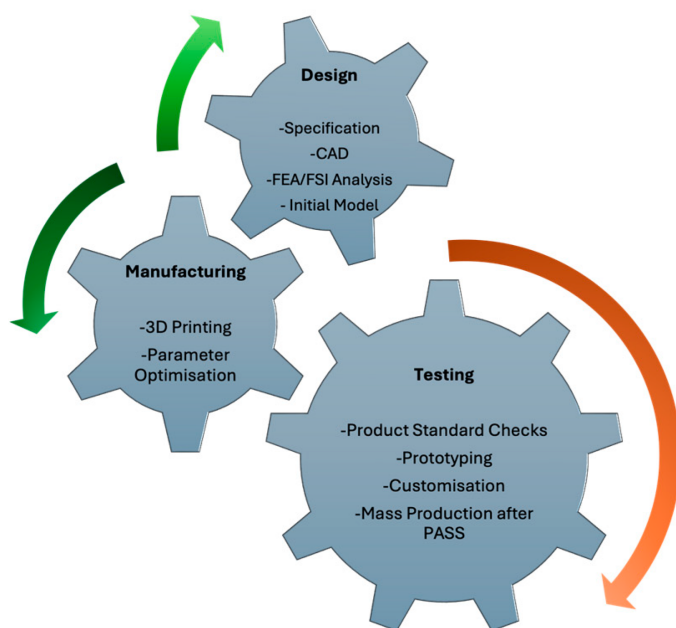


Figure 2 • Phases in iterative intelligent additive manufacturing.

4. The role of AI and smart manufacturing in the industrial revolution

AM is seen as a key component of the newest industrial revolution, which is promoting the integration of sophisticated information technology and intelligent production systems. Several industries have embraced AM, ranging from aerospace to electronics and robotics [27, 35, 39–41]. Because of its high demands and small manufacturing scale, the aerospace industry is one of those that gain the most from AM technology and sustainability effects [41].

To address the issue of waste from aviation sector manufacturing procedures, researchers looked into a project run by the EU FP7 MERLIN. This project produced an improved AM technique called Laser Material Deposition (LMD), which is utilized in the production of bladed discs for aero engines. The trash from the prior method, known as “swarf,” that could not be recycled is eliminated by this new procedure and useful for many AM applications [42]. Furthermore, it was demonstrated that the LMD method saved 30% of the time and 60% of the materials in the Fraunhofer ILT [40, 43]. According to Elhazmiri et al. [36] and Godina et al. [44], additive AM is essential to Industry 4.0. The various manufacturing processes and stages resulting in the final product distinguish AM from traditional manufacturing. These roles include the following.

4.1. Savings of time and materials

In traditional manufacturing, materials are molded into the desired shape using subtractive processes like milling, cutting, and machining. In contrast, AM generates far less material waste and creates products by putting materials where they are needed. Waste minimization is one advantage of this method. The capacity of AM to produce complex designs that would have been impossible with conventional methods is what many innovators find most fascinating. It enables engineers to change objects, produce small quantities of goods at a reasonable cost, and increase production by reducing costs and lead times. It also enables engineers to design components with complex structures and materials that do not require assembly [45, 46].

4.2. Efficient delivery

AM is becoming the preferred technique for many industries, including consumer products, healthcare, automotive, and aerospace, in order to ensure accuracy and efficient delivery. It is also evident that big blue-chip businesses understand its potential to improve supply chains, shorten lead times, and improve product design in order to gain a competitive edge over nearby rivals [21, 46]. Process efficiency customization is made possible by AM's ability to produce complex designs and unique items; however, when AM is deployed, decentralized production streamlines supply chains and lowers transportation costs. Traditional manufacturing processes often involve complex tooling and assembly procedures; AM simplifies these processes by producing components directly, reducing complexity and failure spots [27, 47].

With the use of machine learning (ML), an AI technology, a machine or system may automatically learn from data and make predictions or judgements without explicit programming [48]. Medical diagnostics [49, 50], material property prediction [51], smart manufacturing [52], autonomous driving [53], natural language processing [54], and object identification [55] are among the study fields where ML is becoming more and more popular. ML algorithms are frequently divided into three categories: reinforcement learning, unsupervised learning, and supervised learning.

A semi-supervised ML paradigm called reinforcement learning enables the model to engage with the surroundings and learn which activities will result in the highest rewards. The model learns from its own behaviors and does not require any training dataset. Reinforcement learning has been widely used in many

applications [56, 57]. On the other hand, in supervised learning, a set of computer programs may learn from a collection of labeled data in the training set, which increases the programs' ability to identify unlabeled data from a test set accurately. The datasets can take many formats, such as text, audio snippets, or photos. The cost function is an objective function that determines the discrepancy between the expected and actual output values. After every iteration (or epoch) of the training process, the parameters (or weights) of neurons in neighboring layers are modified to lower the cost function [58]. Conversely, unsupervised learning relies on unlabeled data and is a data-driven ML technique deployed to unravel patterns that are hidden or in dissimilar state (i.e., clustering in a given random dataset).

5. AI and product manufacturing

Every day, the manufacturing sector generates a huge amount of data. This data comes in a variety of formats, such as monitoring data acquired from production lines, weather conditions, and all the performance parameters. Different countries have given this process different names (Germany—Industry 4.0; USA—Smart Manufacturing; South Korea—Smart Factory) [20, 31]. The product quality and its processes may be expanded sustainably with the aid of the valuable information that has been retrieved from the big data. But the drawback of having so much data is that it might cause confusion or lead to incorrect conclusions. The industrial sectors always benefit from a well-established system for handling such large amounts of data. Additionally, it should be mentioned that having such a trustworthy data system available aids in process quality improvement, cost reduction, and customer expectation comprehension [59]. ML has drawn the attention of numerous researchers and investigators from around the world in a variety of fields which include engineering services, biomedical engineering, auto industry, communication, and pharmaceuticals. It should be observed that ML offers wide range capacity in smart manufacturing including scheduling, capacity analysis, material resource planning, quality control, maintenance planning, and enterprise resource planning [60]. The genetic algorithm was employed by Rolf et al. [61] to solve a hybrid flow scheduling application. The findings of the created model were better than those of the industry-accepted approach. The evaluation of the splicing intensity of an uncontrolled beam sample was achieved with support vector regression, thus enabling the current paradigm of ML in the field of product manufacturing.

6. AI and design for additive manufacturing

It must be observed that ML may also enhance AM's capabilities. Artificial neural networks, for example, have the potential to enhance production quality by monitoring the whole manufacturing process, controlling geometric changes, and detecting deviations in the process or component problems. Blockchain technology may facilitate traceability applications in a range of AM industries, especially those with exacting production processes, such as the aviation and medical sectors. Although it varies from traditional Design for Manufacturing and Assembly (DfMA) in a number of areas, DfAM is a subset of Design for Manufacturing (DfMA). Designers are reconsidering the standard DfMA method used in AM since it may create intricate structures that are not

feasible to manufacture with conventional manufacturing techniques [62]. Because AM can produce the complete product in a single step, it also skips the assembling process. DfAM can be described as taking into account both the distinctions between AM and traditional manufacturing methods and the special potential of generalized DfAM enabled by ML based on established rules of design compliance [63]. Integrating ML into design for AM facilitates the development of eco-friendly products and aids in establishing both design guidelines and requirements for cellular structures. [64, 65]. Thus, the subsequent sections are dedicated to the discussion of the value of ML across the elements in DfAM and the domains of AM and AI convergence, as depicted in **Figure 3**.



Figure 3 • Overview of the major application domains for AM and AI convergence towards product design.

6.1. Design of topologies and optimization

A technique for building structures that maximizes material distribution within a design region while accounting for particular stresses and constraints is called Topology Optimization (TO) [66]. TO methods are technologically demanding, particularly for mass-scale and challenging-to-make components, because they usually include several designs and prototype repetitions. After the ML models are well-learned, they may offer beneficial suggestions without requiring a restart, enabling the ML-centric method to supplement the traditional TO method. Regrettably, little research has been carried out on using ML to develop topologies for AM applications. While a clustering approach was employed during the designing process, Lui et al. [22] and Yao et al. [67] presented a unique ML framework that cut across AM with its design characteristics. The process did not employ TO methods; instead, lightweight components that were extracted from a set in the original model were employed to replace the heavy ones. To fix a mechanical issue, a convolutional neural network (CNN) was used to upskill the intermediate topologies

learnt by standard TO approaches. In order to predict the best designs at an intermediate stage, the TO algorithm was stopped after just a few rounds. The learnt CNN method may predict the topology and its optimization, which can be more efficient than simplified isotropic material with penalization (SIMP) with a few odd pixel-wise adjustments. The developed network outperformed SIMP in terms of both performance and numerical precision, and may be used to handle heat flux concerns and thresholding. This demonstrates the wide generalizability of the CNN model without necessitating an understanding of the nature of the problem [68, 69], as seen in **Figure 4**.

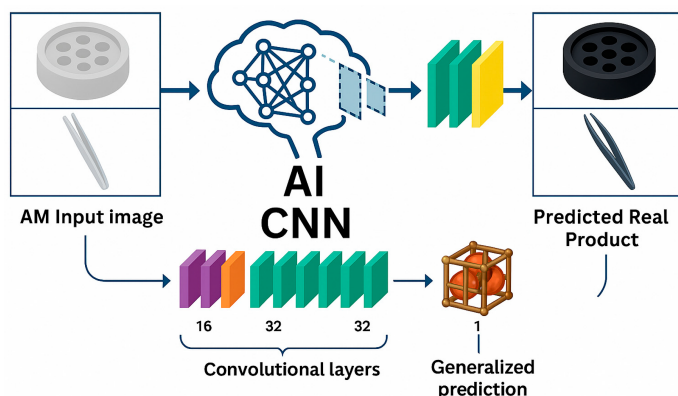


Figure 4 • Hypothetical CNN prediction of optimal product design manufactured with AM. The number 1 is the structure of the generalised prediction, while numbers 16, 32, and 32 indicate the number of feature maps (filters) in each convolutional layer of the CNN, which typically uses more filters as it goes deeper into a CNN, to recognise more complex and abstract features. In this hypothetical generalised example, (16) is the first convolutional layer: it detects simple patterns like edges and textures. (32) second convolutional layer: combines those patterns into more complex shapes, and (32) third convolutional layer: refines and detects even more detailed features.

6.2. Design of materials

It should be observed that metamaterials are composites with unique qualities that have been developed by industry experts and materials specialists in order to achieve certain desired characteristics. The Edisonian approach of creating metamaterials by hand is very challenging and time-consuming. Thus, applying ML techniques can significantly speed up the synthesis of metamaterials such as bioinspired composite design [70]. Researchers and materials specialists can now forecast material characteristics to create new metamaterials because of recent advances in ML. Additionally, as several researchers have demonstrated, AM methods may bring to life concepts that were previously impossible to manufacture. Modern ML in materials and AM methods have a lot of unrealized synergistic potential. Additionally, Karimzadeh M. et al. [71] examined the role of ML in the design and optimization of functionally graded materials, facilitating the development of novel materials with spatially varying physical and mechanical properties. These designs have the potential to help in manufacturing intelligent products [72].

Developers have encountered challenges in knowing the quality of a product developed with a certain set of processing parameters due to the optimization of processes that remain problematic [73, 74]. As a result, a number of procedures, including print-

ing prototypes and confirming their effectiveness, are required to guarantee product performance, which makes the design expensive, time-consuming, and uncertain. Consequently, it might be quite beneficial to have a direct correlation between regulating factors and product performance. Although calculations and tests are useful methods for making a link, it might be challenging to obtain the best variables when there are several intertwined input parameters. To improve operational efficiency, ML approaches may be applied as replacement models [34, 75]. Process parameter development and optimization have historically been carried out using simulation techniques or experiment design in order to additively create novel materials. But when it comes to metal AM, creating an experimental plan frequently calls for a drawn-out and expensive research procedure.

6.3. Characterization of powder spreading

The level of consistency for powder distribution greatly influences the quality of the finished components in the PBF process. Inadequate powder application might result in several flaws or possibly the failure of the entire fabrication because of warping or swelling. Defects in powder spreading can take many different forms, such as debris covering the powder bed, recoater dragging impurities, recoater impacting humped or curled-up components, or recoater blade damage. Furthermore, it would be ideal to do away with the requirement for specially designed detectors for particular abnormalities. In order to do this, a method for automatically identifying and categorizing powder spreading flaws across the fabrication has been implemented [76], alongside other emerging methods, most particularly ML techniques [75], with significant benefits towards sustainability [46].

7. AI-guided AM: challenges and prospects

7.1. General challenges

The creation of ML software and the availability of learning data are prerequisites for using AI in 3D printing. In AM, in situ monitoring and process learning have drawn more attention recently. In terms of research, ML has been used in several areas related to process customization, manipulation, and optimization. Controlling characteristics, including defect density, local flaws, internal stresses, design correctness, and microstructural variabilities, is one concern. However, because there are so many factors in data analysis, it is not easy to regulate these parameters. The result is influenced by design decisions, part shape, material kinds, process parameters, and environmental conditions. AI/ML may be extremely helpful in comprehending the impacts of some controlled factors, while other variables function as noise or extra parameters whose impact can only be discovered over time [22, 75, 76]. AM has used AI/ML methods, such as supervised, unsupervised, and reinforcement learning. In order to minimize mistakes, minimize flaws, or customize the microstructure, unsupervised and reinforced learning algorithms can change parameters inside a build, create patterns and models, and learn from the process locally. Feedback control, data processing, data analysis, and local monitoring are necessary for this strategy. It calls for thorough data gathering, quick processing, analysis, and useful feedback. When deterministic methods are not enough to make local judgements, statistical analysis could be necessary [22].

Industry 4.0's combination of AM and AI has the potential to completely transform the manufacturing industry. Nevertheless, this integration has a number of challenges in addition to its many advantages. These include:

- i. Technical challenges;
- ii. Data security concerns;
- iii. High implementation costs;
- iv. Skills gaps;
- v. Dependence on data quality.

The technical difficulties involved in combining AI with AM are one of the main disadvantages. AM systems must precisely control the manufacturing process, and AI algorithms must be able to comprehend and react to the massive volumes of data produced throughout the manufacturing process. But integrating these two technologies can be difficult, and technical problems including incompatibilities, data formats, and software integration can occur. Data security issues are a major disadvantage of combining AI and AM. Large volumes of data, such as design files, manufacturing parameters, and quality control data, are produced by AM systems. For AI algorithms to learn and forecast, they need access to this data. Nevertheless, this information may be private and susceptible to online attacks. Inadequate security measures can allow data to be compromised, resulting in financial losses, industrial interruptions, and theft of intellectual property [60]. A large investment in new tools, technology, and training is also necessary for the integration of AI with AM. The implementation of these technologies may be too costly for small and medium-sized businesses (SMEs). Additionally, these systems can be expensive to maintain and update, which makes it difficult for businesses to obtain a return on their investment. Expertise in data science, ML, and AM are among the specific talents needed to integrate AI with AM. However, there is a substantial scarcity of skilled individuals in these areas, making it tough for organizations to locate the personnel they need to install and manage these technologies [4, 27]. The quality of the data utilized to train AI algorithms in AM has a significant impact on their accuracy and dependability. Hence, the accuracy of the AI algorithms may be impacted by noisy, inconsistent, or incomplete data produced during the AM process. Additionally, the data might not accurately reflect the manufacturing process, which could result in projections that are skewed or incorrect [33]. Hence, these challenges can be addressed with the following recommendations:

- The use of LLMs in product design;
- Creating customized robots as designers for specific design areas and applications.

7.2. LLM and prospects

The integration of LLMs with AI/ML techniques in AM holds considerable promise for transforming product design. LLMs could evaluate and understand significant design data, manufacturing specifications, material properties, and user feedback. This enables the development of optimal designs, the prediction of potential issues, and the customization of products to meet specific needs. LLMs can assist in navigating the difficulties associated

with the myriad variables in AM data analysis, such as design choices, geometric configurations, material classifications, and process parameters [77–79]. By understanding the relationships among these elements, LLMs can aid in controlling attributes such as defect density, localized abnormalities, and microstructural variations. Furthermore, LLMs can enhance in situ monitoring and process learning by evaluating real-time data and providing feedback for process optimization. This may lead to improved design accuracy, reduced errors, and tailored microstructures, resulting in a much lower cost of unit production than using AM only, as highlighted in **Figure 5**.

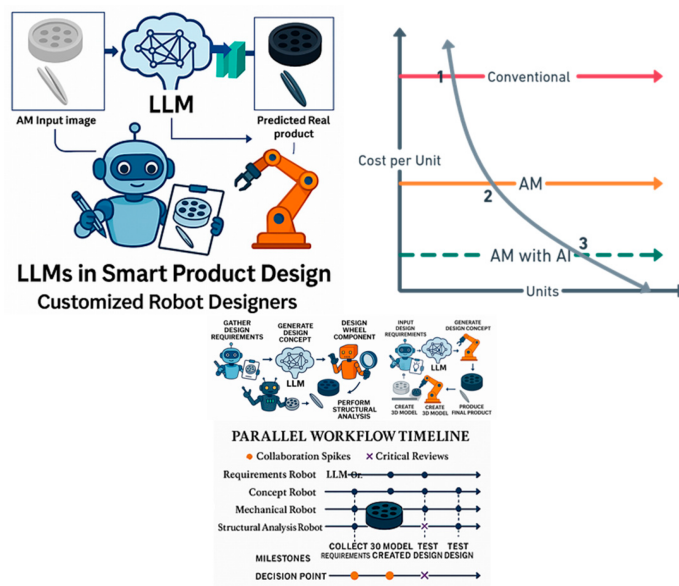


Figure 5 • Prospects of AM and AI convergence in smart product design. Point 1: Highest unit cost (conventional manufacturing), Point 2: Lower unit cost (additive manufacturing—3D printing), and Point 3: Lowest unit cost (additive manufacturing enhanced with AI).

Additionally, the future of product design may involve customized robots integrated with LLMs that act as autonomous designers. These robots could understand design specifications, develop new solutions, and implement those ideas through advanced manufacturing techniques. Combining LLMs with robotic systems enables a closed-loop design and manufacturing process. Robots as designers might assess real-time feedback from production and adjust their designs accordingly, leading to ongoing improvements and optimization. These robots could be customized for specific sectors like aerospace, automotive, or medical devices, and equipped with specialized skills and capabilities. They might collaborate with human designers, offering artistic inspiration and technological support. The robots would use AI/ML techniques, including supervised, unsupervised, and reinforcement learning, to reduce errors, fix defects, or customize microstructures, while employing feedback control, data processing, data analysis, and localized monitorin

As AI-driven AM advances, establishing trust, upholding ethical norms, and improving human-machine collaboration are imperative concerns. Three interrelated taxonomies, namely, ethics and governance, bias reduction, and workforce improvement, with the advancement of LLM-driven robotic designers, are pertinent to formulate a technically informed and creatively advanced plan. These perspectives outline a framework for AI-driven AM that

is ethically sound, unbiased, and fundamentally centered on human values. Integrating transparent governance, bias mitigation, workforce empowerment, and leveraging advanced LLM robotics into AM may usher in an era of smart, sustainable, and equitable production.

- i. **Ethics and Governance:** Transparent and accountable AI is crucial in high-stakes production environments. Industrial standards, such as the European Commission's Ethics Guidelines for Trustworthy AI, emphasize the principles of human oversight, technical robustness, privacy, transparency, justice, and societal benefit [80]. In manufacturing, this requires establishing transparent process controls, substituting "black box" neural predictors with interpretable modules, such as surrogate models for laser power modulation in powder bed fusion, which engineers can assess and validate [81, 82]. As analyzed by Ahangar et al. [83], federated learning architectures facilitate the interchange of insights among supply chain nodes while preserving proprietary data ownership. Integrating continuous model-governance cycles, monitoring drift, assuring policy adherence, and documenting decision rationales will anchor AI-AM systems in responsible product design innovation.
- ii. **Recognition and Reduction in Bias:** Bias can infiltrate AM processes through skewed process logs or unrepresentative sensor data. Brintrup et al.'s [76] research on ethical AI in manufacturing demonstrates how biases in training data may perpetuate defects or economic inequalities among stakeholders. Mitigation strategies include dataset audits using adversarial samples to reveal edge-case issues, optimization procedures that promote fairness by reweighting under-represented process conditions, and post hoc explainability tools to clarify prediction mechanisms and identify inherent biases [72]. This approach encourages cross-validation in synthetic microstructure contexts to detect latent covariance patterns before they cause production problems.
- iii. **Workforce Augmentation and Human-Machine Cooperation:** AI-enhanced AM requires redefining skills instead of replacing human ingenuity. Industry 5.0 envisions robots as collaborative partners, machines performing repetitive tasks while humans oversee strategy, quality control, and innovation. This indicates that AM operators skilled in comprehending LLM-generated design recommendations achieve 30% faster iteration cycles and 40% fewer error corrections [15]. Concurrently, Freire et al. [82] disclosed, through a factory-floor user study, that operators value LLM chatbots for rapid troubleshooting but ultimately depend on human experts when nuance or tacit knowledge is required. Upskilling projects should therefore integrate the foundational understanding of AM with proficiency in AI, training technicians to validate big language model outputs, enhance models, and incorporate sensor feedback into digital twins. Massive language models will evolve from text-based assistants to embodied design agents within AM systems. Fan et al. [84] introduced an "embodied intelligence" system wherein LLM agents automatically transform high-level briefs into G-code toolpaths, optimize topologies via in-context learning, and modify designs in real time via sensor feedback loops. The GenAI for Manufacturing consortium at MIT established

that GPT-4-derived agents can deliver multi-material composite instructions with 85% accuracy compared to human experts, expediting the rapid manufacturing of bioinspired lattices [85]. To realize this vision, robust integration layers, combining semantic parsers, physics-informed neural networks, and digital-twin APIs, would need to converge into modular, secure platforms.

8. Conclusions

The development of the manufacturing sector depends on innovative research on production methods, materials, and product design. Manufacturing techniques must be creative and inventive to meet the ever-increasing complexity requirements for new products. AM and AI have gained popularity recently because of their many benefits and challenges, which have been thoroughly examined and reviewed by the scientific community. This study has carried out a comprehensive conceptual discussion of AM and AI with LLM convergence. The importance of part orientation, build time estimation, and cost computation has all been thoroughly examined. For instance, AM and AI's primary challenges are limited part size, anisotropic mechanical properties, the creation of overhang surfaces, high costs, low precision, warping, layer misalignment, mass production, and material utilization constraints. More research and investigation are needed on these problems. Selecting the appropriate portion orientation is crucial in AM and AI, as it reduces build times, enhances geometrical and dimensional accuracy, and lowers support volume and part production costs. AM remains the foundation of Industry 5.0, offering unparalleled flexibility, efficiency benefits, and decentralized production capabilities. The seamless integration of AM into smart factories driven by LLM agents will encourage product innovation and the rethinking of industrial paradigms and influence the industry's future.

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