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Technical Paper

When AI meets additive manufacturing: Challenges and emerging opportunities for human-centered products development

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A R T I C L E I N F O

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A B S T R A C T

Nowadays, additive manufacturing (AM) has been increasingly leveraged to produce human-centered products, such as orthoses and prostheses as well as therapeutic helmets, finger splints, and other personalized devices. This study reviews the state-of-the-art research in human-centered AM with a highlight on the role of artificial intelligence (AI). Notably, AI is increasingly involved in the decision-makings throughout the three stages of AM product development, i.e., design, fabrication, and assessment, and it brings emerging opportunities for cost-effective human-centered products development. Therefore, in this paper, recent research in AI-enabled customized design, fabrication, and assessment has been summarized. Furthermore, research opportunities and challenges for broader adoptions of AI in AM applications are thoroughly discussed, particularly for human-centered AM products.

1. Introduction

The increasing demand of highly personalized, high value-added products urges manufacturing enterprises to enhance their flexibility in design and manufacturing practices. This fast-growing trend also leads to a critical field in manufacturing called customized manufacturing, in which the design and fabrication are based on a customer or user's unique specifications, including build-to-order (BTO) parts, one-offs, short production runs, as well as mass customization [1]. Customized manufacturing has been applied in many fields. Typical examples include small high-value-products such as bespoke jewelry, and medical devices tailored to specific human body such as clear aligners and therapeutic helmets [2]. Among these applications, it can be observed that one of the most attractive aspects is to fabricate the human-centered products and devices, which requires very high levels of customization while maintaining highly competitive quality and cost.

Recently, the emerging additive manufacturing (AM) technology is playing a key role in accelerating the development and broader adoption of customized manufacturing. Given its high flexibility, toolless fabrication, and potential to quickly scale up, AM can be well-suited to the customized manufacturing in the development of human-centered products, e.g., the biomedical products [3]. Fig. 1a reported by the SmarTech Analysis shows the current and projected trend of the rapid growth of the AM market from 2014 to 2027 [4]. AM consists of a large variety of processes, which are developed to handle complex geometries and novel materials through layer-by-layer fabrication [5]. These AM processes can be applied to different areas where human-centered customized products are needed, such as orthopedics, sports, and dentistry. Compared to the solely task-focused product development, human-centered product development focuses more on the customers/users, particularly, their individual needs and requirements. Although it becomes more complex, it significantly improves the product effectiveness, human well-being, user satisfaction, as well as the accessibility and sustainability. Thus, human-centered product development has attracted more and more attentions in advanced manufacturing [6].

For example, as illustrated in Fig. 1b [7], the AM penetration rate in orthoses and prostheses (O&P) production has been increasing rapidly, indicating that AM is expected to be one of the major components in the O&P market. In the literature, Chen et al. [8] provided a comprehensive review for the AM applications in human-centered O&P. Nadagouda et al. [2] identified that AM can be applied in the personalized medicines through five aspects, namely, regenerative medicine, implants, cardiovascular medicine, orthopedics, and dentistry.

Although AM has provided unprecedented opportunities in the

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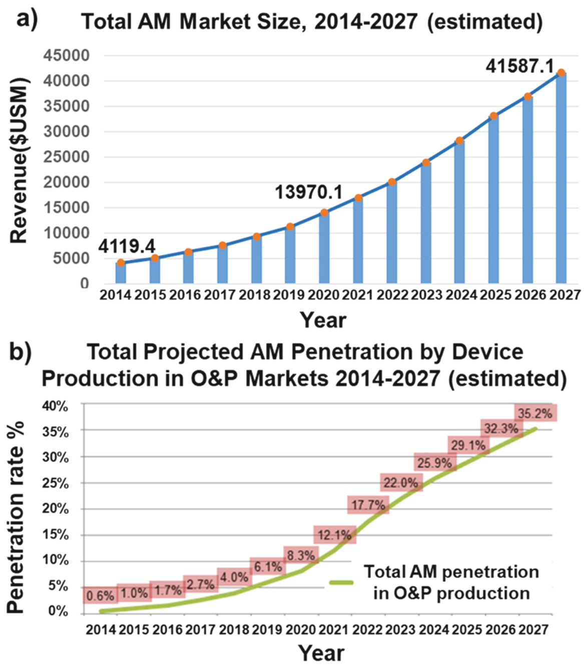

Fig. 1. (a) The fast-growing trend of the AM market size, reported by the SmarTech Analysis [4]; and (b) the increasing AM penetration rate in O&P production market, reported by the SmarTech Analysis [7].

development of human-centered products, particularly, in the medical related applications, there are still many practical challenges that limit its broader adoptions, including personalized material and product design, customized process optimization, and quality assurance. Therefore, driven by the advancement of artificial intelligence (AI), various strategies have been developed in the literature to overcome the barriers in design, fabrication, and assessment of customized AM [8]. In general, AI is the ability of machines, computers, or robotics to implement or "mimic" the cognitive functions associated with human minds, for example, the ability of learning and problem-solving. The capability of AI techniques grows very fast in recent decades, and it has demonstrated the excellent potential in many fields, such as bioinformatics [9], service systems [10], and advanced manufacturing [11]. More importantly, the recent studies have also identified that the incorporation of AI, such as deep neural networks (DNN), can successfully enable the cognitive learning, reasoning, and self-correction activities for many advanced manufacturing applications [11]. According to [11], in the advanced manufacturing research communities, the attention of AI keeps increasing over the past 40 years with a steady increase of the related publications.

Notably, AI is extensively adopted in various aspects of AM and it is difficult to provide an exclusive list. Instead, this paper focuses on two major objectives: (1) explore the state-of-the-art research in AI-enabled development of human-centered products using AM; and (2) identify emerging opportunities and challenges to further integrate AI and AM to better meet the demands in the human-centered product manufacturing. With these goals in mind, this paper is organized following the structure which highlights the three major stages of customized AM, as illustrated in Fig. 2. First, a state-of-the-art review for the AI-enabled human-centered AM is summarized in Section 2, which is according to the three stages in customized AM, namely, product design (Section 2.1), fabrication (Section 2.2), and assessment (Section 2.3). Subsequently, the opportunities and challenges in AI-enabled customized AM are identified in Section 3, and the overall conclusions are drawn in Section 4.

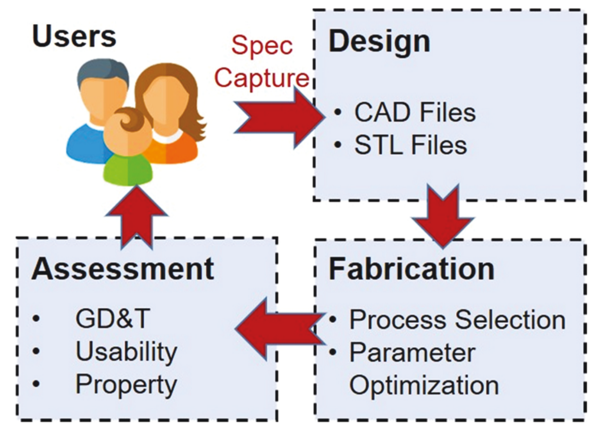

Fig. 2. A generic workflow for human-centered AM product development.

2. AI-enabled human-centered AM: state of the art

As illustrated in Fig. 2, this section summarized the state of the art for the AI-enabled human-centered AM in terms of each individual stage, namely, design customization, process optimization, and product quality assessment.

2.1. AI-enabled design customization in AM

AM of human-centered products starts from the design stage. In the literature, design for AM (DfAM) has been extensively explored with the principal of designing and optimizing the product as well as the manufacturing processes to achieve desired quality and performance with minimized time and cost [12]. As AM products usually have complex geometries (especially the human-centered AM discussed in this paper), DfAM needs to account for a variety of design variables and their complicated interactions. This, in turn, poses a significant challenge for traditional design approaches. To address this challenge, recent years have witnessed an increasing uptake of AI and machine learning in DfAM. With rich data collected in AM design, fabrication, and inspection, AI methods are leveraged to conduct design search and optimization in a fast and cost-efficient way. For example, designers have implemented AI in the geometry optimization of AM products [12–14]. Notably, the geometries of designed products, as well as their support structures, need to be carefully optimized to achieve desired property or minimized mass or costs. As opposed to sorely depending on the knowledge and experience of the designer, the use of AI significantly accelerates the design process by time-efficient exploration of comprehensive design space. Yao et al. [15] integrates hierarchical clustering with support vector machine (SVM) methods to identify a subset of AM design features based on specific design tasks. Leary et al. [16] developed an optimization approach to modify the theoretically optimal topology to enable support-free fabrication process. Tang et al. [17] leveraged machine learning as a surrogate model in the design optimization for customized porous lattice shoe soles.

Also, AI has been increasingly employed in the material design in DfAM. As discussed in [18], AM is associated with a special need for material design and development as materials used for traditional manufacturing techniques may need to be modified for AM processing. The AM material design, such as revising the components of known materials and developing new materials, can be accelerated by AI. For example, data mining approaches have been used to modify the aluminum alloys to make the material better suited for the processing of laser bed powder fusion (LBPF) [18]. Also, genetic algorithms, decision trees, and other AI-related approaches are also used in the design of alloys with specific desired properties [18].

Furthermore, in the interface of material science and AM, machine learning and deep learning approaches have been widely used to assist in the design of metamaterials that to be fabricated using AM. Metamaterials are with extremely complex geometries to achieve desired performances that may not be obtained from natural materials, such as negative Poisson ratio [19]. The benefit of AI is more profound when such complex geometries are designed. For example, Tang et al. [20] used an experiment-obtained meta-model with the artificial neural network approach to identify the manufacturing constraints, which were further considered to redesign the arm of quadcopter in the lattice structure to improve the stiffness. Despres et al. [21] proposed a graph autoencoder for the geometric optimization of microlattice architectures. With a large training data set generated using the genetic algorithm, the graph autoencoder was used to identify optimal lattice structure to achieve the desired mechanical property, i.e., force-displacement characteristics. In [22], the authors explored both the solid and lattice spaces to optimize the geometry of solid lattice hybrid structures. A bidirectional evolutionary structural optimization model was used to optimize the strut thickness in the structure. Wang et al. [23] leveraged Laplace-Beltrami spectrum to describe the geometry of unit cells of metamaterials and established an indexed library, coined as “metamaterial genome”. Such a library facilitated efficient design and evaluation of unit cells, which could be further assembled into the full structure. In [24], a variational autoencoder and a graph-based optimization approach were integrated to generate microstructures with desired properties and ensure the compatibility between adjacent microstructures in the assembly process to achieve the final multiscale metamaterial.

Notably, how to establish the process-structure-property (P-S-P) relationships is a major concern in geometry optimization and material development. In the literature, AI has been leveraged to establish such highly-nonlinear relationships. For example, Jung et al. [25] employed a Gaussian process regression model with limited full-field simulation results to develop the S-P relationship for various microstructures. Jiang et al. [12] constructed DNN models to build bi-directional links between the three components, i.e., process, structure, and property. Yan et al. [26] used a data-driven approach for comprehensive multi-scale, multi-physics modeling of the P-S-P relationships and established a design loop for AM processing and materials. In [27], the authors managed to visualize the P-S-P data with a self-organizing map for data-driven microstructure design.

2.2. AI-driven AM process optimization

2.2.1. AM process selection

AM process selection has been extensively investigated in the literature. Mançanares et al. [28] introduced various AM technologies and presented an Analytic Hierarchy Process (AHP) based method to rank the most appropriate AM technologies and machines based on key relevant machine parameters. Wang et al. [29] reviewed decision theory-based methods for AM process selection published by 2017. Furthermore, they reviewed the limitations of the shared sequential decision process and proposed a new iterative design approach for the “a posteriori” articulation instead of the “a priori” articulation of those existing methods. Furthermore, the inherent nature of AM makes it necessary to integrate product design, material selection, and process selection of AM in a holistic manner. Therefore, most recent AM process selection methods jointly considered process selection with product design [30,31] and material selection [32–34]. Similarly, the AM process selection is often integrated with DfAM [35–37]. For example, Vaneker et al. [36] presented a holistic framework for DfAM that involves three stages of product development, i.e., AM process selection, product redesign, and product optimization.

Due to the high complexity of the problem, various multi-criteria decision-making schemes have been extensively used. A few typical examples include AHP [28,30,32,33,35], Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) [38], fuzzy logic based operators [39], and hybrid schemes that integrate multiple methods [40]. Among all those schemes, two categories of selection criteria have been primarily considered, which are, (1) technical and economic viability include manufacturability analysis, cost, build time, accuracy, part weight and buy-to-fly ratio [30,33,35], and (2) sustainability include energy demand and CO_2 emissions for the entire product lifecycle [41].

2.2.2. AM parameter optimization

There are multiple review papers that are dedicated to the process optimization of various AM processes [42–44]. Similar to the generic optimization framework, the AM parameter optimization problem can be formulated using three critical components: (1) decision variables, (2) constraints, and (3) objective function. In this section, the relevant literature is summarized for each component, respectively. The decision variables involved in AM process optimization may include the slicing parameters (such as build orientation [45], layer thickness [46,47], and printing paths [44]) which are universal for different AM processes, and all the adjustable process parameters which vary with the specific AM process (such as laser power, laser scanning speed, and hatch spacing for laser-based AM [42,48]). The constraints usually enforce the feasible region of the decision variables [49]. For example, to make sure the fabricated parts satisfy the quality requirements, Tian et al. [47] modeled the geometric accuracy as a function of the AM process parameters and set the accuracy to remain within the upper and lower bound while minimizing the part-level energy consumption. Furthermore, the constraints need to be specified based on the machine capabilities. Regarding the objective functions (i.e., goals), there are single-objective and multi-objective AM parameter optimization methods. Single-objective problems usually only have one specific objective, such as optimizing the manufacturing costs [50], part quality (such as density, microstructure, geometric accuracy, and surface quality) [44,48,51–53], energy and material consumption [47,54], and mechanical properties [55]. On the other hand, multi-objective problems aim to jointly optimize two or more objectives. For example, Alizadeh et al. [46] proposed a data-driven method to jointly optimize the energy consumption and final part geometric accuracy. Furthermore, there are multiple studies that aimed to simultaneously optimize multiple geometric accuracy features or multiple mechanical properties [56–58].

With respect to modeling the objective functions, two categories of methods have been proposed to describe the effect of process parameters on the final outcomes. Data-driven approaches usually leverage experimental data generated from systematic Design of Experiments (DoE). Furthermore, accelerated optimization methods were proposed to reduce the sample size while achieving comparable optimized results [56,59]. Subsequently, supervised machine learning techniques (both regression and classification) have been extensively used [46–48,58,60]. For example, artificial neural networks are leveraged to establish the relationship between process parameters and density, dimensions and surface quality [61]. Alternatively, computation-based approaches developed physics-based models to characterize the relationship between AM parameters and the outcomes [43,62,63]. To alleviate the computational intensity of those high-fidelity physics-based models, surrogate modeling techniques have been extensively used [64–66]. After the relationship between process parameters and the outcome of interests are established, the AM process optimization can be achieved by using the desired outcome to solve for the process parameters.

Therefore, it may be noted that AI and machine learning play a critical role in the AM process optimization. This observation aligns with the discussions in multiple review papers [42–44]. For example, Jiang and Ma [44] has envisioned that machine learning methods can be a powerful tool for AM process optimization. Furthermore, Shamsaei et al. [42] introduced a few recent studies on using AI in AM process optimization while pointing out a few challenges in adopting AI in AM optimization. More detailed discussions about the challenges will be summarized in Section 3.

2.3. AI-assisted quality assessment in AM

This section deals with the last step of the human-centered customized products development in AM, i.e., assessment. The assessment in AM is a broad topic, and it can be considered from multiple aspects, such as metrology [67–70], sustainability [71–74], dimensionality [75–78], and property [79,80], which have been widely explored and surveyed. Meanwhile, these studies also identified the importance of quality assessment in AM, particularly, for the development of human-centered customized products, as they are usually highly quality critical in practice, such as the therapeutic devices and prosthetic implant. Thus, a number of studies have developed various approaches for effective and efficient quality assessment [81,82] in the AM.

In general, the quality assessment for AM-built human-centered products consists of two aspects, namely, subjective assessment and objective assessment (Fig. 3). Subjective assessments are usually qualitative analysis and can be conducted through usability tests, ergonomics methods, etc. [83]. On the other hand, objective assessment involves quantitative analysis of process/product quality. For example, as a group of commonly applied quality assessment techniques, traditional geometric dimensioning and tolerancing (GD&T) approaches have been successfully incorporated to assess the AM-built customized medical devices [84], such as the personalized ankle-foot orthoses using selective laser sintering (SLS) [75], and anthropological dental collections [85].

Recently, in the era of industry 4.0, as the environment of AM has become data-rich, AI techniques have also attracted AM researchers' attention, and a number of AM-oriented AI approaches have been developed for AM quality monitoring and control. The importance and great potential of AI in the AM quality assurance have been recognized in multiple recent review articles [86–89]. Since these articles have already surveyed the existing studies before 2019 in a comprehensive manner, we aim to mainly review the most recent AI-assisted AM quality assessment techniques reported since 2020. Notably, the existing studies are mainly focused on incorporating AI to assist the objective assessment.

According to the recent studies, AI contributes to two main objectives in the quality assessment of AM: (1) quality monitoring, and (2) quality prediction and control. For both objectives, AI is expected to characterize the patterns in the AM systems data, which include metrological data [90], heterogeneous sensor signals (such as vibrations [91] and acoustics [92]), images (including optical [93], XCT [94], and thermal images [95]), point cloud [96], and their integrations [97], thereby providing the assessment outcomes. More specifically, quality monitoring can be mainly categorized into defect detection, geometric deviation inspection, and process shift identification. For example, to achieve timely defect detection, Liu et al. [98] proposed an integrated manifold learning approach using high dimension sensor data, and Baumgartl et al. [99] implemented a DNN model for analyzing the in-process image data. For the geometric deviation monitoring and process shift detection, based on the point cloud data, Li et al. [100] incorporated machine learning algorithms to implement geometrical defect detection, and Ye et al. [101] proposed a point cloud fusion algorithm for surface geometrical shift detection in process. Furthermore, for the porosity assessment, which is critically needed in many powder-based AM, Tian et al. [102] developed a fused neural network model for porosity detection, and Liu et al. [103] established a physics-informed machine learning model for the porosity assessment in metal AM. Moreover, Esfahani et al. [104] developed an *in-situ* process certification method based on image series analysis and machine learning.

Fig. 3. Two aspects of the quality assessment for the AM-built human-centered products.

For the quality prediction and control in AM, recent studies mainly focus on the prediction, prescriptive compensation, and correction for the critical quality characteristics, such as the defects, geometric deviation and process condition. For example, in quality prediction, Akhil et al. [105] developed an image-based surface texture prediction approach for selective laser melting (SLM) using machine learning. Xia et al. [106] leveraged different supervised machine learning models to predict the layer-wise surface roughness in wire arc AM. Wang et al. [107] extended the convolution learning framework to predict the 3D geometric deformation in AM. In addition, for the prescriptive compensation and control, the emerging AI techniques such as the transfer learning and adversarial networks demonstrated their strong capabilities in AM. For instance, Cheng et al. [108] developed a hybrid transfer learning framework for geometric accuracy control, and Li et al. [109] incorporated the conditional adversarial networks to implement 3D geometric deviation in material extrusion AM.

According to the most recent studies reviewed above, it can be observed that integrating the cutting-edge AI techniques (such as DNN, transfer learning, and adversarial learning) to handle the complex assessment tasks and further maximize the value of data has become a key research trend. Although the application of AI in AM has been extensively investigated, the research in the assessment for AM-based human-centered customized product development is still relatively limited, particularly, the incorporation of AI to facilitate the subjective quality assessment.

3. Challenges and opportunities for future research

Although the current research progress in the AI-driven customized AM product development is very significant, many gaps still exist. In this section, three important topics are summarized as recommendations for future research.

3.1. Data complexity in AI-enabled customized AM

The successful application of AI methods heavily relies on sufficient data of high quality, and the actual demand for data is positively correlated with the complexity of the data generated. Consequently, one of the most critical challenges in the scale-up of AI-enabled human-centered AM product development is to address the data complexity issues. The highly customized design and complex fabrication process complicates the data generated from AM in the following two aspects.

3.1.1. High data heterogeneity

The heterogeneity of AM data can be summarized as three aspects: (1) data format heterogeneity is resulted from the multiple stages of the product development; (2) machine-to-machine heterogeneity comes from different AM machines and/or different sensing setups; and (3) sample-to-sample heterogeneity is attributed to high design variability due to product customization. Consequently, directly applying the conventional AI techniques may not work well. Therefore, there is an urgent need in developing effective AM-oriented AI methodologies. For example, various powerful machine learning methods, such as transfer learning [110], adversarial learning [111], multitask learning [112], and federated learning algorithms [113], can be tailored for the specific characteristics of AM data.

3.1.2. High dimensionality vs. limited data availability

The high dimensionality issue is a long-term problem, and it has been extensively investigated. Particularly, the representation learning techniques, such as the popular autoencoder [114,115], data decomposition [95,116,117], and manifold learning [98], have been widely applied to the complex high dimensional AM data. However, it still lacks a systematic and flexible methodology to effectively handle the high dimensional data collected from the highly customized manufacturing scenarios in human-centered AM. Thus, dimensionality reduction are still open and important directions in this area. On the other hand, customized AM also suffers from the limited data availability issue, which is also a broad topic, and it consists of multiple aspects, including small sample sizes, incomplete data, invalid data, imbalanced data, unlabeled data, and duplicated data. Although a large variety of techniques are available to address these issues, methodologies that can jointly handle these data insufficiency issues are still limited.

Addressing the above-mentioned commonly occurred data complexity issues will enable a more effective and efficient human-centered customized products development in AM, which could further facilitate the functionality of AM. Moreover, it is also worth noting that the potential solutions to address these data complexity issues can also greatly benefit other critical areas, such as the infrastructure systems (e.g., data quality assurance) [118] and healthcare analytics [119], since the similar data issues are also widely noticed in these fields.

3.2. Data sharing and cyber-physical security

As suggested by Shamsaei et al. [42], the key to any successful AI applications in AM is sufficiently comprehensive training data which can be used for reliable model estimation. However, data availability has become a major limitation in the successful adoption of AI or machine learning related techniques in AM applications, and the case is even more prominent for customized AM applications which are associated with very limited labeled data for training.

We summarize three levels of challenges in successful AI-enabled customized AM in terms of data sharing. First, the current AI-enabled modeling and optimization studies are usually focused on one product design at a time, and the models estimated from one design cannot be directly extended to a new design. In customized AM, however, very small or even single-piece batches are very common. Therefore, it is prohibitively expensive to generate a sufficiently large data set for each individual design for either experimental or computation-based approaches. Second, even though transfer learning can be leveraged to aggregate the data collected from different part designs [110,120–123], the proprietary nature of customized AM leads to significant privacy concerns that prohibit raw data sharing and aggregation among multiple AM users [124,125]. Third, excessive data sharing and exchange during the design and fabrication for AI-enabled customized AM will be exposed under high risks of cyber-physical attacks. As illustrated in Fig. 4, excessive data transfer and sharing is necessary in the AM fabrication. AM related cyber-physical attacks include AM design data theft and design/process tampering [126–129]. The significant flexibility of AM and the single-piece production batches can further broaden the attack space of the customized AM products, making them more vulnerable than products fabricated by conventional manufacturing processes and even AM products fabricated in large batches [130,131].

Accordingly, there are three major research questions to be addressed for successful AI-enbled customized AM.

Research Question 1: How to properly aggregate AM data of diversified part designs for process optimization, monitoring, and control for brand-new designs in customized AM. Even though transfer learning schemes have been used in the data-driven modeling for AM, the high variability in AM product design has not been properly addressed. The different product designs have a significant impact on the P-S-P relationships and thus need to be properly factored in the AI models for more reliable analysis and prediction. One of the promising solutions involves leveraging computational models to explain the variability induced by product designs, leading to physics-informed AI models. A few recent works have already demonstrated success in some specific AM process modeling problems [132–134], which can be further extended to benefit broader applications in customized AM.

Research Question 2: How to establish a data sharing mechanism to facilitate secured data sharing between multiple users without disclosing users' privacy information and among different product lifecycle stages. The design, process, and assessment data generated in the customized AM applications contain significant privacy information of the users. Therefore, privacy protection is of critical importance in data sharing for customized AM. One promising direction is to leverage the privacy-preserving machine learning which has demonstrated significant success in computer science [135–137]. In addition, some case studies have demonstrated the great potential for privacy-preserving machine learning and federated learning in the manufacturing [138,139] and health care applications [140]. In addition, a collaborative data sharing mechanism among different stages in the AM produce lifecycle can facilitate effective data management and smart decision making through efficient data communications [141].

Research Question 3: How to develop effective measures to enhance the cyber-physical security by protecting various AM data (including CAD design, g-code, and process data) from data theft and tampering during the data sharing and exchange. Even though there are extensive studies in the protecting cyber-physical security of AM, there is still a significant need for an effective and efficient framework to assure the security in both cyber and physical domains. For data security, the blockchain and encryption techniques have been used in securing g-code and process data for AM [142–145]. However, those solutions still need to be comprehensively tested to evaluate their effectiveness and efficiency for customized AM applications.

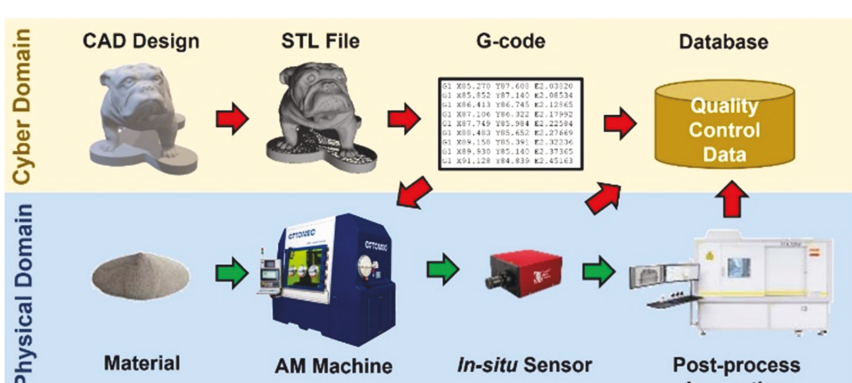

Fig. 4. Material and information flow in the cyber-physical systems of AM (Reproduced from [130]).

For process/part authentication, most of the current studies focus on one specific AM process and a few typical potential attacks [146–149]. However, due to the infinite attack space, it is challenging to develop a comprehensive training data for process/product authentication. To address this issue together with the small batch characteristics of customized AM, leveraging AM design information and process knowledge would essentially reduce the demands in large sample sizes for AI methods. For example, physical hashes and other physically uncloneable identities can be established from the implemented g-codes for part authentication of each individual design [150–152].

3.3. Human-in-the-loop manufacturing

It is worth mentioning that human interventions are expected in the AM of human-centered products. Comparing with machines, humans offer a much higher level of flexibility and intelligent decision-making capability. It is believed that human and machine need to collaborate to fulfill complex manufacturing tasks (e.g., the design and manufacturing of human-centered products discussed in this paper). The great potential of human-in-the-loop manufacturing has also been identified in many recent related literature [153–155]. Thus, it is important to integrate humans into the design, fabrication, and quality inspection processes. Recent advances in robots, AI, Internet of Things (IoT), and metaverse technologies provide unprecedented opportunities for humans to better interact and intervene product design and manufacturing (Fig. 5). Nevertheless, leveraging those technologies to facilitate human-in-the-loop AM of human-centered products are still in its infancy. In this section, we would like to briefly discuss three sub-directions for future research.

3.3.1. IoT-enhanced human-machine/robot cooperation

The human-machine/human-robot cooperation has long been an active research area that aims at improving productivity, reducing costs, and minimizing human errors [156]. It also plays a very important role in the recent development of human-centered manufacturing [157]. The rapid maturation of natural language processing (NLP), gesture recognition, among others, significantly enhanced the ability of machines and robots in identifying and interpreting human actions. This provides a great opportunity to share or transfer human skills into the manufacturing process. Moreover, the emerging technology of the IoT (also known as Industry 4.0) maps human operators, machines, robots, and other entities in a networked structure, which enables the seamless communication, data exchange, and information sharing among entities [158,159]. This, in turn, further removes the barriers in human-machine/human-robot cooperation and improves the level of flexibility and responsiveness. An increasing number of studies have been reported, which proposed new approaches to leverage the IoT for better human-machine/human-robot cooperation. For example, Garcia et al. [160] developed a natural human-machine interfaces to integrate the decision-making capabilities of human operators into an IoT-enabled platform for the control, coordination, and cooperation with an industrial robot for assembly. Cimini et al. [161] also discussed the mutual impact of the IoT and human in the human-in-the-loop cyber-physical production system and highlighted the opportunities. In this direction, some remaining challenges, among others, that need to be further explored and tackled in future research include: (1) how to better facilitate the delivery of mutual understandable and executable messages among humans and machines/robots, (2) how to better extend the cooperation scope from one human and one machine/robot to multiple human operations and a large number of machines/robots (e.g., swarm robots [162]) even when the entities are with different locations (e.g., far from each other). New simulation, optimization, and control models are needed to collectively ensure the effective and efficient coordination.

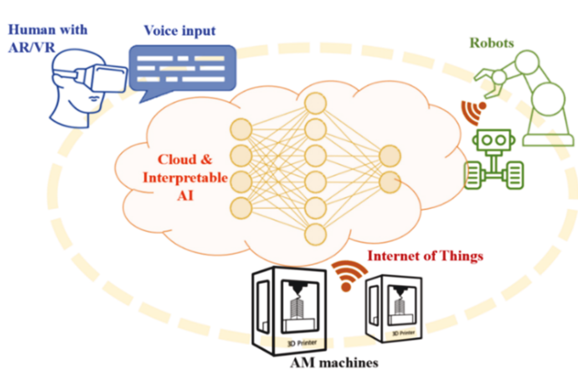

Fig. 5. Human-in-the-loop AM with robots, AI, IoT, and AR/VR.

3.3.2. Interpretable AI for human operators

Many AI algorithms, especially those involving deep learning, lack the interpretability and are oftentimes considered as blackboxes. To human operators in human-centered AM, “how and why the decision is made” is sometimes more important than “what decision is made”. Thus, it is important to improve the interpretability of AI algorithms so as to unveil the blackboxes for well-informed decision making. In the literature, interpretable AI has been increasingly discussed for years. In addition to the widely used interpretable models such as logistic regression and decision trees, many researchers attempted to address the “lack of interpretability” problem of deep learning by either improving the interpretability of DNN models or finding alternatives that demonstrate comparable performance. For example, Argarwal et al. [163] developed neural additive nets to allow more interpretability with state-of-the-art accuracy. Zhou and Feng proposed a deep forest model [164], in which random forests were leveraged to replace neurons for the construction of a deep learning structure so that the model was more interpretable [96]. For more existing works on interpretable machine learning, please refer to [165]. Still, there are some challenges to be addressed, including how to maintain a comparable accuracy while enhancing model interpretability, how to better quantify the perceived interpretability of human operators, and how to leverage only a limited number of training samples as human-centered AM is likely to have very small sample sizes.

3.3.3. AR/VR for the design and manufacturing

The development of virtual reality (VR), augmented reality (AR) and related technologies provides a great opportunity to overlay machine-generated information in graphical representations and demonstrate in the real-world environment [166], which also offers great opportunities to the improvement of AM systems [167,168]. Such contextualized information helps human operators better understand the underlying dynamics of manufacturing processes and machine conditions so as to make informed decisions. For example, with AR, workers wearing HoloLens were able to interact with the *in-situ* obtained 3D geometry of the part for quality inspection [169]. Also, VR/AR has been increasingly adopted to assist human in the visualization of the DfAM process. Eckertz et al. [170] employed AR to accelerate the design-and-review process that iterates between the designer and the customer. In [171], the authors discussed the advantages of VR over traditional CAD tools in assisting engineers to design and evaluate complex parts. It is anticipated that AR/VR will empower a higher-level of interactivity among various participants in the human-centered AM processes. To achieve that, some open questions remain for future research to address, including (1) how to improve the resolution and accuracy of AR/VR models to better emulate the design and manufacturing processes and provide augmented information to human operators; (2) how to incorporate real-time streaming data collected using advanced sensors and cameras into AR/VR models and contextualize the information to human operators; and (3) how to integrate AI in the AR/VR visualization to promote the interoperation between the operators and the machines.

4. Conclusions

This paper aims to review the most recent research in the AI-enabled human-centered AM products development, and identify the trend and future research opportunities in this area. In this work, the existing studies are categorized into three aspects based on the sequential stages in AM, namely, design, fabrication, and assessment. Enabling AI in the product design stage provides a promising solution to account for a variety of design variables and their complicated interactions in design and thereby achieve desired performance in production. Moreover, with the integration of AI in the AM fabrication and assessment stages, the fabrication process for the customized human-centered products can be optimized, and the quality performance can be assessed thoroughly as well in an efficient manner.

The three steps in the human-centered AM products development summarized above also indicated the remaining challenges and future research opportunities, as identified in three directions: (1) develop advanced AM-oriented AI techniques to handle the data with high heterogeneity, high dimensionality, but low availability in the highly customized scenarios; (2) make full use of physics knowledge in the AI methods for customized AM applications while assuring process security and data privacy; and (3) integrate humans into the design, fabrication, and quality inspection processes, through interpretable AI, IoT-enhanced human-machine corporation, AR/VR, etc.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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