Design for Artificial Intelligence: Proposing a Conceptual Framework Grounded in Data Wrangling

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The intersection between engineering design, manufacturing, and artificial intelligence offers countless opportunities for breakthrough improvements in how we develop new technology. However, achieving this synergy between the physical and the computational worlds involves overcoming a core challenge: few specialists educated today are trained in both engineering design and artificial intelligence. This fact, combined with the recency of both fields' adoption and the antiquated state of many institutional data management systems, results in an industrial landscape that is relatively devoid of high-quality data and individuals who can rapidly use that data for machine learning and artificial intelligence development. In order to advance the fields of engineering design and manufacturing to the next level of preparedness for the development of effective artificially intelligent, data-driven analytical and generative tools, a new design for X principle must be established: design for artificial intelligence (DfAI). In this paper, a conceptual framework for DfAI is presented and discussed in the context of the contemporary field and the personas which drive it. [DOI: 10.1115/1.4055854]

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1 Introduction

Engineering design and manufacturing have been on an exciting trajectory in parallel with advancements in computation and internet connectivity. In only a few generations the world has transitioned from paper drawings stored in bulky file cabinets [1,2] to millions of computer-aided design (CAD) models accessible from anywhere in the world at the touch of a mouse click [3–5]. Entire professions, such as drafters, have largely declined [6], while new movements, such as that of the "maker" and rapid prototyping hobbyist have exploded in popularity [7].

The proliferation of 3D CAD applications has helped drive the adoption of advanced and robotic manufacturing [8]. What used to require careful manual attention can now be accomplished by computer-numeric controlled (CNC) machine tools, additive manufacturing (AM) machines, and many other automated solutions [9]. These advancements have fueled transformative progress in what types of geometries can be manufactured, how quickly they can be prototyped, and how much data can be mined to continuously improve the efficiency and profitability of manufacturing [10]. This emphasis on data monitoring and internet of things (IoT) has opened up new possibilities for "smart factories" using advanced, distributed, and automated data monitoring techniques [11,12].

These advancements in digitally driven design and manufacturing [13], although massively important, have led the design community into a false sense of security. Technology and the development of the digital thread are increasingly linking engineering design, engineering analysis, and manufacturing into interconnected processes. Thinking of these areas as separate, siloed fields limits the potential for high performance in all three. While technologies like computer-aided manufacturing (CAM) software can perform useful and impressive tasks, they are limited in their capability by the ability of software developers to translate complex expert manufacturing knowledge into automated tools.

Recognizing the challenges of manually designing algorithms for increasingly complex engineering processes, many have turned to AI, and particularly machine learning (ML), as a potential future of advancing engineering design software [14–20]. ML has shown great success for text, image, sensor, and video analysis [21–25]. Perhaps the two most exciting attributes of ML are its ability to reuse the same algorithms to solve a wide variety of problems and to automatically train these software algorithms to solve a problem [26,27]. These benefits, combined with recent advances in parallel processing hardware, mobile computing, and cloud-based computing, have led to a surge in ML research across industries [28–31].

The generality of ML makes it easy to begin considering how large datasets might be useful for many potential problems that are adjacent to those in other fields. Examples may be found in a variety of problem types of varying levels of complexity. For instance, 3D object recognition [32–36] is a natural extension of 2D image recognition [37,38]. Additionally, segmentation of image areas [37,39] can be similarly approached as the segmentation 3D volumes [40–44], in such applications as identifying critical features or estimated defect zones [45–50]. Even video can be seen as a specific case of time-series analysis [51], which is particularly relevant to manufacturing processes with transient heat flow and material deposition or removal phenomena [52–57]. These time-series phenomena are a topic of particular interest in the rapidly maturing area of smart factories [11,12,58,59], in which sensor data are streamed to analytical and dashboard systems in real-time [60–62]. Analogous time series could also be analyzed at the design stage [63]. Rather than harvesting sensor data from a physical machine to monitor activities in a factory, simulation data could be harvested and automatically analyzed at a larger scale to monitor and optimize an engineering team before manufacturing is even attempted.

As exciting as the advancements in ML are the prospect of applying ML to engineering design and manufacturing also reflects a false sense of security in the industry. ML and AI may finally be

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emerging from the "trough of disillusionment" in some industries [64]. However, the application of ML to engineering design fields is far from trivial, which may decrease business risk tolerance. One reason other fields may be more rapidly innovating ML technologies is that nonengineering data are often more common and relatable to a wider community. For instance, the internet is teeming with 2D graphics, images, text, and video which are consumed daily by billions of people. Contrastingly, 3D CAD models are only familiar to and interacted with perhaps a few hundred thousand individuals on a daily basis [65]. If advanced simulation technology data (such as data derived from finite element analysis (FEA), topology optimization, and implicit modeling) are taken into account, the number of existing examples and experts able to interpret them shrinks even further. Additionally, ML in "manufacturing" and "engineering design," although linked through the digital thread and overall engineered product lifecycle, are often themselves markedly different in goals, difficulty, and implementation, adding to this complexity.

The consequence of general data and expert scarcity [66] has ripple effects in the field of engineering design and manufacturing AI. In addition to the obvious challenge of smaller datasets being more challenging to work with for ML, a deeper data quality issue is present as well. Whereas individuals in the general population can produce relatively accurate labels [67–69] for something like 2D images or text, producing equivalently accurate labels for complex engineering design data may be challenging, time-consuming, or impossible for all but the most experienced engineering specialists [3,70,71]. Consider the case of trying to label an arbitrary 3D CAD model with the "best manufacturing method" to build it [72]. Such a question is a multi-objective optimization problem that may be highly susceptible to human bias, orientation-dependent, or require extensive physical and/or economic analysis. Answering such fundamental questions are very challenging without the context of the original design and function of the part. The labor required to create robust and useful datasets may actually prove prohibitive to medium and large-scale adoption of ML in industry.

For the near-term, engineering design software will largely continue to depend on the time-tested traditional modeling and analysis techniques that have transformed the manufacturing sector for the last decades. In order for the benefit from data-driven approaches like ML to be realized, the academic and industrial engineering community must work together to prepare for and support long-term innovation by strategically adjusting how engineering-design-practicing institutions operate on an ongoing basis. We propose design for artificial intelligence (DfAI) as a strategy for addressing these objectives. DfAI is a set of goals, principles, and heuristics that aim to improve the effectiveness, adoption, and innovation of engineering design and manufacturing AI. DfAI is not a rigid, fully mature construct, due to the rapidly evolving nature of AI; rather it is an evolving set of additional user requirements that strive to enhance how we architect design repositories, design engineered products, and conduct engineering software development. Like other design for X (DfX) principles, such as design for manufacturing (DfM), DfAI aims to improve design by explicitly focusing on specific goals and practices associated with the activities related to AI development. However, DfAI is differentiated from many DfX principles because it must have a broader impact on the long-term development of design-process-enhancing software, rather than being restricted to only the shorter-term impact of manufacturing a particular product. Creating useful engineering design or manufacturing AI based on learnings from past engineering design and manufacturing data requires guiding principles to address this breadth.

2 Short-Term Excellence Versus Long-Term View, A Challenge for the Future of Design

Engineering is ultimately economically and product-driven meaning that the unit of work for engineers is relatively short-term. The role of design and manufacturing engineers requires them to manage the creation, troubleshooting, continuous improvement, and sales of manufactured goods. From a software standpoint, CAD, CAM, Product Lifecycle Management (PLM), Product Data Management (PDM), Enterprise Resource Management (ERP), Material Requirements Planning (MRP), and other technologies have grown to support digitized end-to-end design and manufacturing.

Although beneficial for business, focusing solely on improvements and optimization of the products being designed and manufactured today could stifle the transformative potential of AI technologies. For an optimized business, driven by its bottom-line, discerning appropriate budget and allocation of resources for long-term research and development is certainly challenging. Thus, a great dilemma presents itself: How can institutions become motivated to make serious investments in engineering and design AI when they must still accomplish their challenging day-to-day missions? We propose that this immense challenge to advancing DfAI can be addressed through three foci (see Fig. 1).

The three foci are (a) raising AI literacy in industry, (b) redesigning engineering systems to better integrate with AI, and (c) enhancing the engineering AI development process. These three foci are intentionally broad to help facilitate an inclusive, encompassing conversation. To address them practically, we propose the adoption and continuous improvement of DfAI as a guiding principle of engineering design and manufacturing. Each of these foci is explored in more detail in the following sections.

2.1 Raising Industrial Artificial Intelligence Literacy.

The first focus is to raise industrial literacy of the realities of AI for design and manufacturing. Simply defining AI, let alone developing it, can be a challenging task, and a greater understanding of the landscape of AI's present and future could go a long way. Specifically, raising AI-literacy could be achieved by increasing the synergy between (a) academic and industrial engineering design and manufacturing experts and (b) engineering AI researchers and those of adjacent fields.

More collaborative projects between academic labs and industry could help make scientific studies more applicable to the real world. Major compromises are needed from both sides to make this easier-said-than-done goal a reality. Companies must be willing to invest in labor to contribute to these projects as well as intellectual property, which is often a barrier to increasing community

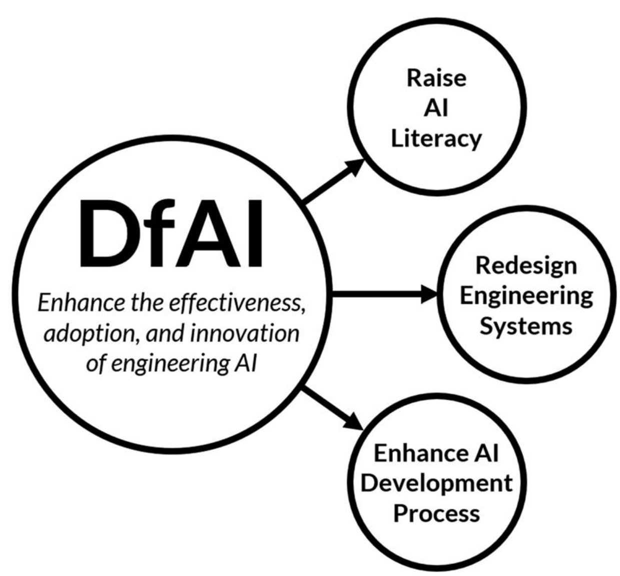

Fig. 1 The three, overall foci that are driven by the adoption of DfAI principles

knowledge. More strategic distinction of what can and cannot be shared by a company, although more expensive to determine than a completely defensive, conservative IP strategy, could end up paying off in the long run by helping create new community-driven technologies that could later enhance that organization's capabilities. Academic labs also must compromise to better fit industrial needs. Some improvements could be made by increasing the scale and timeline of research projects, perhaps by combining the resources of labs or planning projects that transcend the normal schedules of the academic cycle. Increasing scale in this way could help alleviate the resource imbalance that often comes with relatively large companies and relatively low-staffed academic labs.

Increasing synergy between engineering AI researchers and those in adjacent fields, such as medical and general data science, could have numerous benefits. The demand for specialization in higher education creates powerful expertise in niche topics but might run the risk of losing sight of the larger community. One of the most powerful benefits of deep learning is its ability to be reused for many different problems, sometimes with only slight modifications. We must stop viewing advancements in individual fields as existing in their own spheres of influence. From a practical standpoint, this means providing greater support for interdisciplinary work and increasing industrial networks beyond their specific manufacturing or service sector.

2.2 Redesigning Engineering Systems to Meet Artificial Intelligence Growth Demands. The second DfAI focus is to redesign the systems that power design and manufacturing to enable next-generation hierarchical data scalability and transformability. Hierarchical data scalability is the capacity to manage exponentially more design, simulation, and quality control data. As an example, imagine creating a quality control digital thread for a manufacturing company that measures their parts for simple length accuracy at key dimensions. Such measurements are simple numbers and binary pass/fail values, easily stored in a typical database. Achieving hierarchical data scalability would mean going above and beyond the current need of storing those quality control results by preparing for the development of future, more advanced data, such as a full 3D volumetric scan of each part that is suitable as input to a quality control AI construct. Failure to prepare for that possibility while the system is being developed might hinder the progress of implementing such an AI construct in the future, perhaps by years, due to the investment now required to completely redesign the system.

Like scalability, hierarchical data transformability also strives to prepare for an AI-driven future. It is the ability to efficiently operate on that data, transforming it through a series of automated operations. While the example of preparing for scalability relates closely to the use and adoption of specific AI, transformability addresses the need to develop that AI. Obtaining, cleaning, and validating data can be a substantial portion of the labor and cost of even attempting to create such technologies. Reducing the burden of these challenging, often miserable tasks, can only be done by compiling and understanding that data at the outset. Ensuring data is machine-readable, as accurate as possible, labeled with all possible knowledge, and populated with standardized, descriptive metadata could help motivate the development of AI by reducing the up-front investment to produce proof-of-concept and prototype technologies. Although some standards exist, digitally driven manufacturing is far from being fully standardized in practice. There exists a diverse landscape of file formats and institutionally specific knowledge. Thus, a combination of improved standards around engineering and design data management and organizational data storage enhancements are necessary to support hierarchical data transformability.

2.3 Enhancing the Artificial Intelligence Development Process. The third focus is to improve the rate of adoption of design engineering and manufacturing AI by enhancing the techniques, tools, and expertise of the community developing that AI. Like manufacturing data management, this area could also stand to adopt greater standardization. However, standardization alone is not enough and may be misguided if attempted too early. Thus, the education of both generalist and specialist experts in the engineering and manufacturing AI space should be enhanced through specialized curricula, research programs, and knowledge-sharing venues that specifically advance this subfield of engineering and manufacturing.

Many general-purpose AI development tools are becoming increasingly accessible and performant. For instance, tools like TensorFlow [73] and scikit-learn [74] have decreased the barrier for entry to apply ML/AI to new problems. However, developing tools is only part of the solution. The specific ways in which the community approach problems, prioritize resources, build teams, and shares results are also important. Furthermore, understanding how to succeed in complex, team-driven design projects like AI development is not always trivial [75]. Achieving success in this third focus includes both developing enhanced community and institutional practices around AI-centric projects and enhancing existing engineering tools, such as CAD applications and PLM software, to integrate well with new ML and AI development and deployment platforms.

3. DfAI Principles and Applications

We propose several interconnected DfAI principles, with the acknowledgment that they are initial principles that should evolve with and be expanded by the engineering AI community in the future (see Fig. 2).

The proposed principles primarily relate to the data surrounding engineering design and additional steps that improve that data for use in ML and AI development. The first DfAI principle, digitization, means striving to capture *all* engineering design data in a digital format *and* store that data in a reliable place. At some organizations, improving digitization could mean actions as simple as scanning paper drawings or replacing paper lab notebooks with software. At others, it could mean better capturing verbal, sketched, and whiteboard design collaboration. The next DfAI principle, data linkage integrity, relates to ensuring the many interconnected files and data points related to products are digitally linked. Ideally, all aspects of a project are hierarchically linked in some way and appropriately scalable. Examples of ensuring data are hierarchical could mean ensuring different parts of an assembly are related to each, different products are related to business initiatives, or different versions of designs are related to each other and their relative performances in reference to user requirements and specifications. This DfAI principle is closely related to the next, machine readability. Ensuring data linkage is more closely related to the abstract concept of linking different parts of the digital thread together, whereas ensuring machine readability relates more to an organization's future ability to automatically slice and analyze those data. Another DfAI principle, metadata quality, could improve machine readability. By ensuring high-quality descriptive attributes accompany design data, programs that intend to consume that data are easier and less time-consuming to create. We propose data valuation as a DfAI principle. This principle relates less to practical engineering design activities and more toward fostering long-term motivation for engineering AI development. By improving the understanding of data value, both direct value and value toward future AI R&D opportunities, the return on investment (ROI) of infrastructure changes to support AI may be justified. Finally, the principles that define DfAI should evolve over time, expanding and redefining alongside changes to engineering design, manufacturing, and AI technology.

DfAI takes advantage of the extensible nature of the DfX family by applying the same meta-process of developing goals and heuristics as other DfX strategies. Unlike many other DfX strategies, the area of improvement is broader in DfAI. In typical DfX techniques,

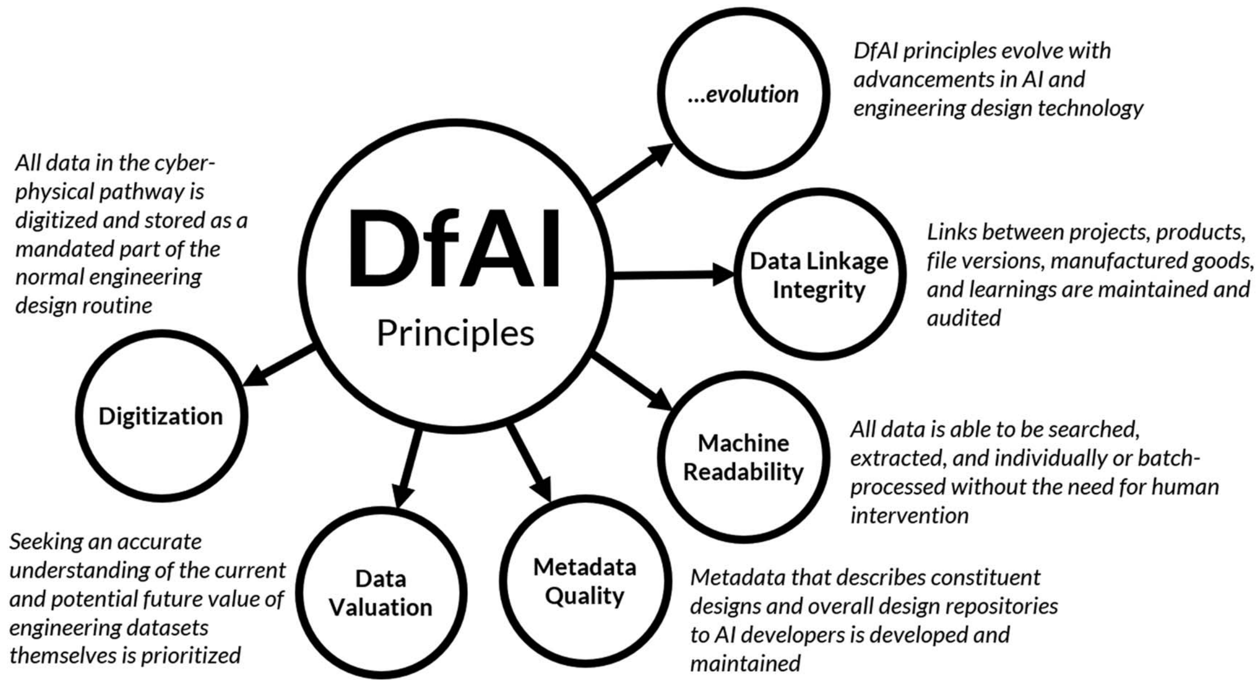

Fig. 2 Proposed DfAI principles

such as design for manufacturing (DfM), the area of application relevant to DfM is the design and manufacture of particular products. While DfAI also applies to the design and manufacture of particular products as a relevant area of improvement, it should also be applied to broader aspects of the engineering design process at a product portfolio, institutional practice, and design community levels. The areas to which DfAI, which are interdependent and not listed in priority order, is applied include (see Fig. 3):

(1) The design, manufacture, and testing of physical products and assemblies ("Products")
(2) The design and use of design repositories and the digital threads which support them ("Design Repositories")
(3) The design, manufacture, and use of manufacturing operational procedures, machines, lines, factories, and supply chains ("Practices & Infrastructure")
(4) The design, development process, and use of analytical and artificially intelligent tools affect the cyber-physical manufacturing process ("AI Development")

3.1 Conceptual Case Study for Applying DfAI Principles. Design and manufacture of engineered products do not occur in a vacuum, but rather in a complicated, financially driven landscape of industry. To help illustrate the motivation for applying DfAI principles to areas related to manufacturing, consider a hypothetical case study of a new company inventing small electric aircraft to be manufactured at a large scale for the shipping industry. At the outset of creating the company, proving technology through research and development, developing the business through market research and sales, and preparing to scale up operations through raising capital and preparing to build factories and hire works are expensive and risky activities. Relatively short-term factors such as speed-to-market and rapidly reaching profitability may eclipse all other needs. Suppose the company could take two general paths: path (a), a manual, data-devoid future, and path (b) a highly automatable and data-rich future. In path (a), the company pursues only the minimum viable product, does not spend excess resources on data collection, and does not consider how they may develop the end-to-end supply and manufacturing chain to be automatable in the future. In path (b), the company invests in an extensive data collection, validation, storage, and retrieval system to capture data through the lifecycle of design, manufacturing, and logistics into the future and creates dedicated roles to build, maintain, and link those systems to the growing organization. Path (a) is most likely to be less-cost-intensive during up-front development and requires fewer technical individuals. Now imagine 10 years later, and the company's competitors begin introducing extensive data-driven design and manufacturing artificial intelligence that reduce their operating cost below the company's capabilities. The difference in cost for path (a) versus path (b) companies to develop technology as-needed that competes after the companies are entrenched and mature may be staggering, perhaps threatening their feasibility.

3.2 Applying DfAI to Product Development. We contend that DfAI principles can be applied to product development to improve the design, manufacture, and testing of physical products and assemblies in the long term. To consider how, one must

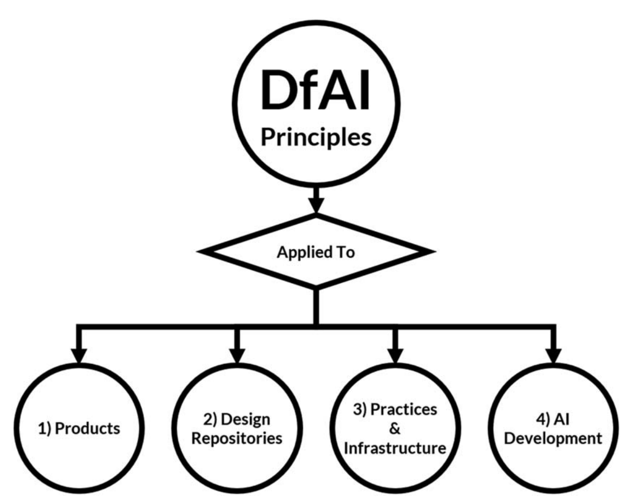

Fig. 3 Broad application areas that could benefit from DfAI principles

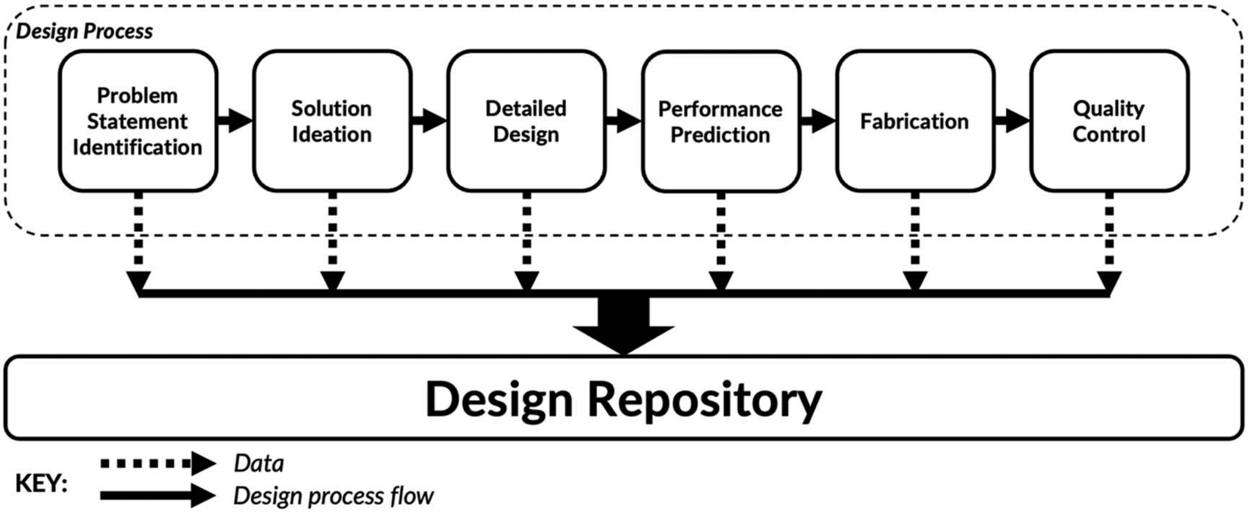

Fig. 4 Data from each stage of the design process should be considered for DfAI principles before being added to a design repository

envision the entire lifecycle of an engineered product from ideation to retirement and how each step is interconnected. Two examples of contemporary areas of development are manufacturing machine optimization and design process enhancement. Manufacturing machine optimization often involves intelligently determining machine settings, build orientations, and toolpath control strategies that will most cost-effectively manufacture the highest quality part. Design process enhancement typically involves automatically suggesting either big-picture heuristics, such as which manufacturing process is best suited for a design or other, smaller-scale tasks such as automatically generating a physical form that meets the design project's problem statement or simulating and predicting the performance of a given form.

Although both of these engineering AI examples strive to better meet the ultimate goal of creating a product that addresses the user requirements and specifications of a problem within constraints, they do so at different stages of the design and manufacturing process. While early generation AI efforts may be able to address these stages individually with self-contained AI modules, later-generation, paradigm-shifting innovations likely require cohesive interconnection between all stages. For instance, optimizing a machine is often great for making incremental improvements for producing a single design, but won't provide much insight in how to achieve step-change improvements with entirely new designs [76]. At the other end, design AI could help envision better products to meet user requirements in a theoretical sense, but might fail to account for the rapid advancements in the physical manufacturing and material science spaces. Harmony between these two areas, and the other areas of the design process, are necessary.

3.3 Applying DfAI to Design Repositories. The designers of a new product should consider the entire cyber-physical pathway for a design both at the outset of the project and in parallel to each step. The cyber-physical pathway includes all of the digital and physical outputs of the design and manufacturing process. It is vital for engineers and product managers to understand it. However, practices of individuals are only part of the solution, and they must direct their data and knowledge to the second area of DfAI application: the design repository (see Fig. 4). A design repository is any dataset that contains information regarding multiple product designs. Design conceptual, product description, material composition, and quality control information should be generated, made machine-readable, linked to other data through traceability, stored in a design repository, and curated into metadata descriptions of that design repository. Practical implementations that achieve high-quality design repositories will vary depending on the nature of the organization and the volume of its data. Some example guidelines could include well-documented and fully automatable APIs for data entry and retrieval, budgeting for human data validation, budgeting for the development of automated data validation, and research and development budget and pipeline for continuous improvements to existing and new data acquisition and validation systems. Additionally, the creation of dedicated roles that may focus on management and execution of technical design repository issues could increase the capability of organizations to enhance them over time, rather than relying on fitting such responsibilities within nonspecialized personnel's busy schedules.

Producing multiple forms of linked, machine-readable data allows those developers to rapidly produce labeled datasets for supervised learning or validation tasks. To actually achieve worthwhile results from these activities, organizations must invest in both specialized individuals to oversee these activities and training for all contributing individuals to uphold this goal at each smaller task. Additionally, business stakeholders in these opportunities must be convinced of their value through ROI calculations that estimate the potential benefits of being able to more inexpensively develop future AI or even to sell the higher quality data outright. Although the specific ways in which data quality and continuity are achieved are highly dependent on the particular industry, manufacturing processes, and products being considered, the general, initial DfAI heuristic is simple: the entire cyber-physical pathway of each engineered product should be understood, and gaps in data quality and continuity should be documented. After that heuristic is complete, follow-up DfAI heuristics should be applied to consider the ROIs of investing in enhanced data management techniques at each stage of the product design and manufacturing process, prioritize those potential changes, and then execute them in priority order.

3.4 Applying DfAI to Institutional Practice and Infrastructure. In addition to the design of physically engineered products, DfAI principles should also be applied to the practices, tools, and infrastructure that support the design and manufacturing overall. Human-in-the-loop AI can help operators and technicians with manual or semi-automatic manufacturing tasks. Thus, data surrounding the manufacturing tasks and the procedures that dictate them should be well-understood and then considered for DfAI-related issues. Similarly, the tools and machinery should also be considered for DfAI, ideally trending toward more complete

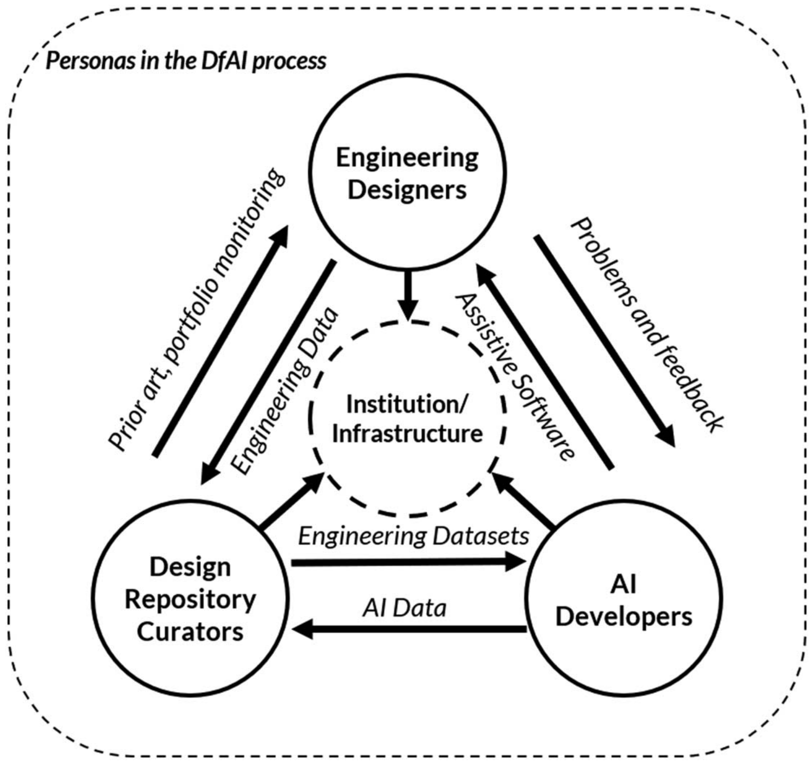

Fig. 5 Personas in the DfAI process and their communication and interaction relationships with each other and their central institution

and automated data-gathering through the adoption of IoT technologies. Furthermore, the largest scales of manufacturing infrastructure, factories, shipping, supply chain, distribution, and inventory, could also benefit from AI orchestration. How easily and effectively the data produced by these systems could be used for AI development should also be considered.

3.5 Applying DfAI to Artificial Intelligence Development Processes. Finally, DfAI principles should also be applied to the development of analytical tools and broader AI constructs that seek to improve the engineering design and manufacturing process. Generally, making improvements in this area means standardizing and enhancing the design process for AI. The industry must shift by treating the AI development process more like an engineered product design process by adopting DfAI principles, similarly to how other DfX techniques seek to streamline design in other ways.

Specifically, this DfAI application could be achieved in several ways. First, the user requirements and specifications of engineering design and manufacturing AI should be clearly understood. Essentially, "market research" into the gaps and challenges in a specific engineering design process should be clearly quantified and considered when determining whether an AI development process should be done and how it should be approached. Second, enhanced standardized techniques for describing the inputs, outputs, algorithms, and performance of AI tools should be developed and applied. The minimal documentation required by academic journals and existing business practices will not be sufficient to achieve compounding progress in the modern software landscape, which is rife with enormous and poorly documented data and software artifacts. Third, the design repositories used for the development, training, and evaluation of AI tools should be completely documented and disseminated when possible. This means sharing much more than just CAD files, but also hierarchically complex, high-dimensional labels, such as simulation results. Today, replicating or improving upon an engineering design deep learning study often means manually producing ones' own dataset. This laborious task must be improved through major collaboration efforts in the community and the development of next-generation design repository and interaction tools to support them. Finally, the results of the AI development process should be documented and fed back into the systems and tools associated with the other areas of DfAI application. We should not settle for simply using AI to enhance our current processes, but should use our growing knowledge to make those processes better suited for AI itself.

4 A Conceptual Breakdown of Personas in Design for Artificial Intelligence

Achieving long-term, future-state DfAI success requires the establishment of effective workflows both between and within specific business roles under the guidance of a supportive institution. Here, we refer to those business roles as personas. The three major personas of the DfAI process are (a) the engineering designers, (b) the design repository curator, and (c) the AI developer (see Fig. 5). Although some of these personas may be clearly identifiable roles at some institutions in the present day, others may be less clearly defined, less common, or entirely absent. Thus, we call for action to provide improved educational opportunities for individuals who may need to take on these roles.

The first persona participating in DfAI principles, engineering designers, are likely the most intuitive personas involved in DfAI (see Fig. 6). Generally, an engineering designer could include any worker responsible for the development of user requirements and specifications necessary for manufacturing a new product. This role could be a single person with a generalized skillset or be collectively fulfilled by a large team of specialists, depending on the size of the organization and the complexity of the specific manufacturing task. Although engineering designers are not the only personnel involved with product design and manufacture, they are specifically identified as key stakeholders in the DfAI personas since the conception of a product at the design stage is the beginning of its

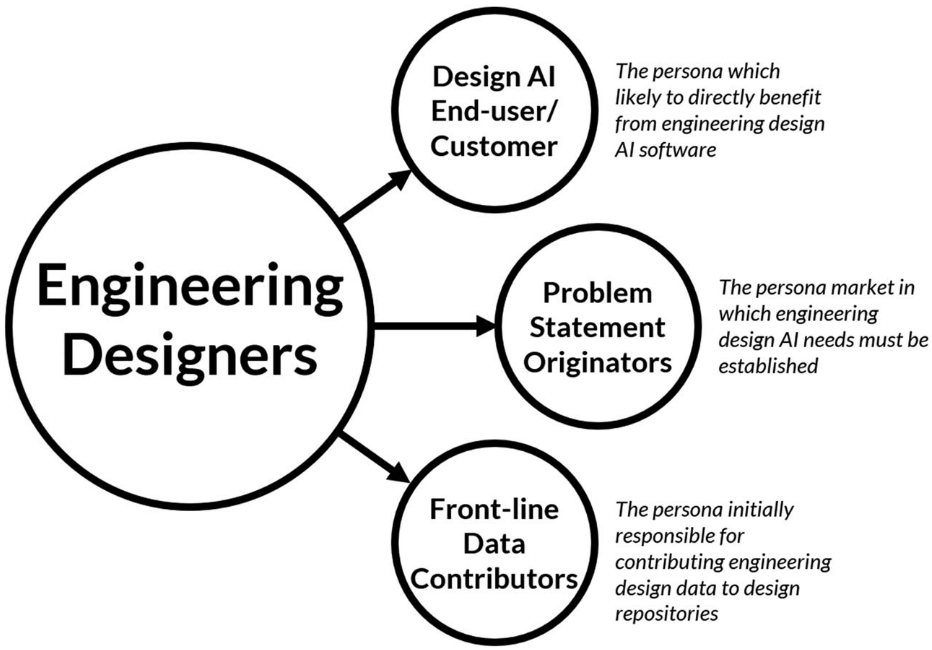

Fig. 6 The engineering designer persona in terms of typical roles and actions that comprise key participation activities in applications replated to DfAI that may benefit from DfAI principles

technical lifecycle. From this perspective, engineering designers are not at the end of the DfAI-principle application, but rather at the beginning. Ideally, they should have a high degree of communication with and cascade DfAI-related responsibilities to peripheral or downstream personnel that are key to the manufacturing process, such as manufacturing engineers, quality engineers, process engineers, industrial engineers technologists, manufacturing operators, factory managers, planners, and technicians. The precise roles and number of personnel in each of these adjacent engineering and manufacturing roles are organization-dependent, and standardization of such roles may be a beneficial topic of future work.

Engineering designers play many important roles in the broader DfAI. Some may be more obvious than others. For instance, engineering designers are the end-user of design AI applications. This role as the user situates them as an internal or external customer of design AI products. Even if effective design AI products are eventually produced and launched, their widespread use will depend on meeting the customer technical and user experience needs, which will be complex, varied, and continuously evolving with the ever-changing manufacturing technology landscape.

In line with this end-user role, engineering designers are the DfAI problem statement originators. This means that engineering designers must be able to clearly document, communicate, and justify the problems which are the highest priority to solve. AI developers may not understand the engineering problems as well as the actual designers completing day-to-day work.

Additionally, engineering designers are the originators of the engineering data which may benefit data-driven AI development. These data could take many forms, including product concepts, CAD files, quotes, test data, simulation data, prototype documentation, and countless other portions of the digital thread. Ensuring that engineering designers are trained, motivated, and supported to spend portions of their limited working time on documenting these data in a standardized and high-quality way is essential to the DfAI process. Generally, improving in this area means spending more time developing and executing procedures for engineering tasks and incrementally automating design tasks that are tedious or would otherwise cause the information to be lost.

The next DfAI persona, the design repository curator, is more abstract and perhaps less traditional than the engineering designer (see Fig. 7). Contemporary institutions are likely lacking a specialized individual or team responsible for maintaining design repositories that are intentionally designed for use as AI training datasets [13]. Broadly, the design repository curator is responsible for creating, maintaining, and extracting all data related to engineering design activities. Some near analogs exist. For instance, a database maintainer or system administrator resembles this role in terms of the technical data skillset required to generally interact with data. However, a design repository curator is differentiated from a generic database maintainer in that they must have greater engineering design and manufacturing knowledge to deliver design engineers with data management tools that will meet the current engineering design workflow demands and be extensible to future, AI-driven workflow demands [20]. Complete separation of data management and engineering design skillets creates a prohibitive wall to innovation and increases the expense of developing new systems.

The design repository curator cannot operate effectively without the creation of infrastructure that supports convenient access to the data originators, the engineering designers. Today, many institutions are skilled at creating design repositories that are effective for non-AI development purposes. For example, quality systems at regulated industries, such as medical or aerospace companies, are typically highly effective at storing data to meet the minimum legal requirements for those products. Creating effective infrastructure from a DfAI lens, however, means continuing to fulfill the existing needs and priorities of a business or organization while adding in DfAI requirements for that infrastructure early in design repository creation. From a practical standpoint, doing so could mean ensuring that data storage mechanisms store data in a convertible format, preserve machine readability at scale, maintain links between potential training data and labels, and are efficiently processable and sliceable as batches.

The final DfAI persona, the AI developer, ties the other personas together (see Fig. 8). The AI developer must obtain data from the design repositories and use that data to create design-processing-enhancing AI software constructs.

AI developers must be able to ideate, develop, market, and continuously improve AI software products that help design engineers. To do this, they must have interdisciplinary skills. These skills

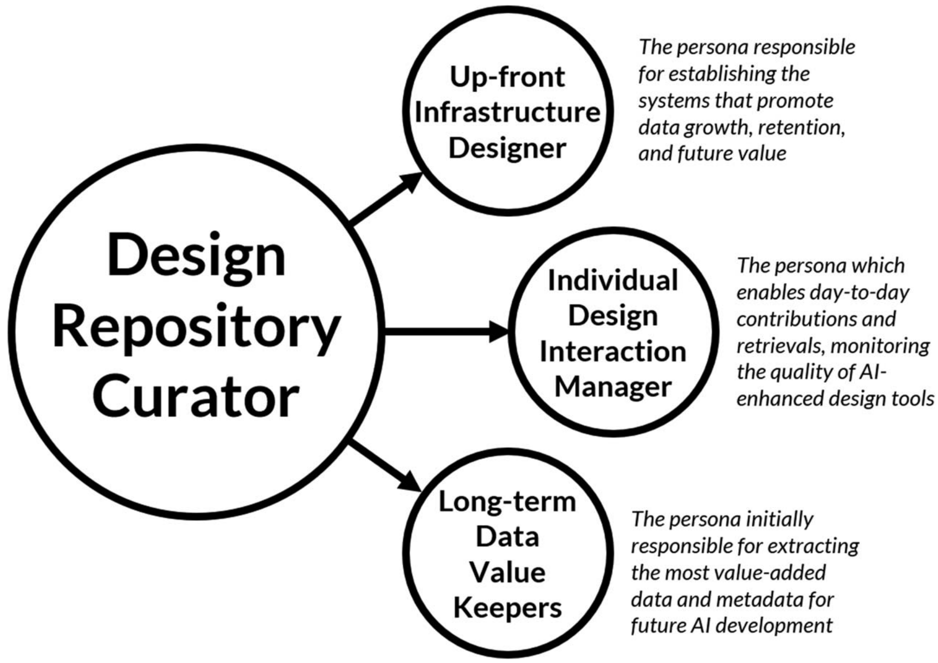

Fig. 7 The design repository curator persona in terms of typical roles and actions that comprise key participation activities in applications replated to DfAI that may benefit from DfAI principles

should overlap the fields of design and manufacturing engineering, computer science, data science, and AI development to some degree. This heterogeneity of knowledge would design AI developers both recognize areas in the engineering design space that work well and should not be substantially altered and also gaps in which transformative improvements may be made. The specific algorithms and technologies used to create design AI are the tools of the design AI developer and will vary depending on the application, resources, and development of future technology. The likelihood that numerous specific algorithms will be invented, become outdated, and be enhanced over time necessitates a combination of and a strong collaboration between generalist and specialist design AI developers.

In addition to understanding the problems and potential solutions in the design AI space, design AI developers must also interact skillfully and efficiently with design repositories and their curators [77–79]. Doing so successfully means retaining a broad knowledge of both engineering design data that currently exists in non-AI-enhanced engineering workflows and that which might exist under a more advanced, AI-driven workflow. For example, consider the transition from paper engineering drawing-driven

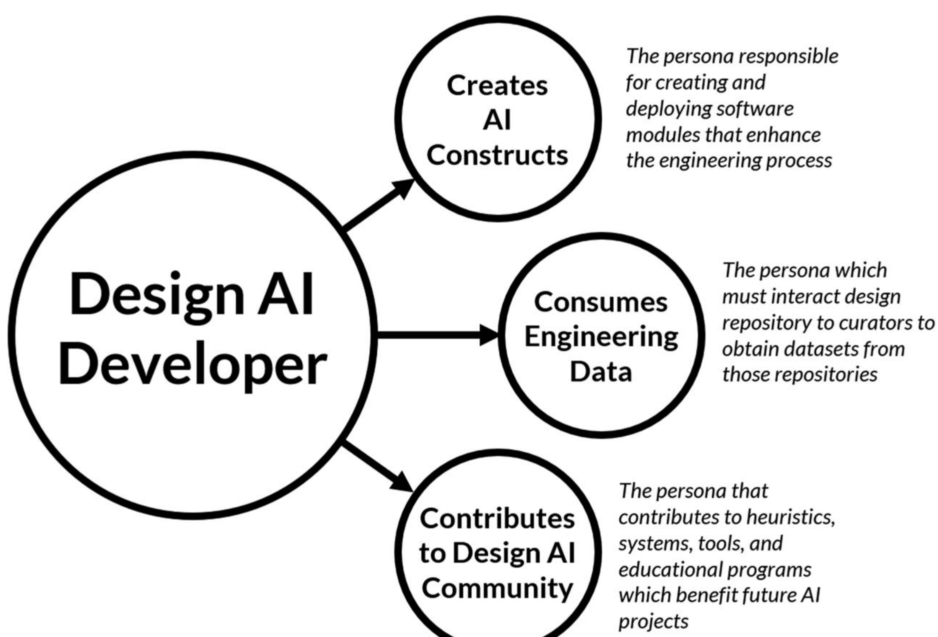

Fig. 8 The design AI developer persona in terms of typical roles and actions that comprise key participation activities in applications replated to DfAI that may benefit from DfAI principles

design to CAD-model-driven design [80]. This major shift in design technology produces exponential more machine-readable data, such as the 3D models themselves and simulation results. Future shifts will add even more data to the AI developer's toolkit, perhaps including automatically harvested data on the human user interface usage behavior that could be used to detect the designers' skill level and provide tailored feedback. Design AI developers being able to adapt and preempt future shifts in technology will help drive both the creation of that technology and the synergy with other personas, such as design repository curators that may need to store new forms of data.

Design AI developers also have a responsibility to a relatively new and growing community. Currently, the publication systems for presenting advancements in design AI rely on relatively old technology and lack standardization. Ideally, design AI developers will prioritize contribution to the standardization of terminology, methodology, results reporting, and quality of design AI. Further developing and publishing heuristics related to DfAI is an essential part of this process. In order to make faster progress as a community, design AI researchers must find ways to efficiently transfer knowledge through heuristics that are shared, extensible, and may be iteratively developed through collaborative and interdisciplinary research.

Finally, although not a single persona, the administration, management, and organization of the institutions and infrastructure under which the other personas work is also vitally important. Organizations are very capable of achieving ambitious and transformative goals when they are motivated to do so. This motivation is easier said than done. A portion of DfAI principles relates to building this motivation for business stakeholders, managers, departments, and institution administrators to fund and support advanced design repositories and design AI development projects. We propose that ideating and testing enhanced measures of return on investment of maintaining advanced design engineering data be increased. Understanding the timescales and benefits of applying DfAI principles economically will help them improve and proliferate. Creating design AI is not a short-term project, but rather a long-term collection of complex and interconnected projects and activities that extend well beyond the roles of most individuals or teams. DfAI should help clarify which efforts are likely to pay off in the long run.

5 Closing Remarks

DfAI stands to improve many areas of the holistic end-to-end design and manufacturing process, with stakeholders ranging from institutions who set procedures, designers who adhere to them, and future innovators who seek to use their learnings for the development of AI. To achieve optimal success in the challenging areas of data-driven design and AI development, design AI developers and design repository curators must not be an afterthought in the core operation of design and engineering institutions. A new specialty in DfAI must be grown with opportunities for the education of individuals, careers, and the growth of dedicated teams.

Like many fields, engineering design and manufacturing engineering are strongly geared toward short-term goals: launching the next project, getting the next grant, and publishing the next paper. Increasingly generalized manufacturing methods are enabling the manufacturing of increasingly optimized artifacts. Unless we augment our design engineers with a next-generation of CAD/CAM software based on more generalized AI and ML, our ability to design novel and useful artifacts will fall short of the potential of those new manufacturing techniques. The community must invest intellectual resources by advancing and applying the general principles of DfAI in the design repositories, design activities, and engineering software development activities that are conducted to efficiently and cost-effectively achieve the opportunities envisioned for AI-driven design.

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Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

No data, models, or code were generated or used for this paper.

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