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Expertise Modeling for Human-AI Collaboration in Design and Manufacturing: Scientific Foundations and Challenges

Abstract

Design and manufacturing firms have evolved over the last few decades with revolutionary technological advancements like computers, automation, and robotics transforming the design and manufacturing processes. In 2025, we are in the early stages of the next revolution with the advent of artificial intelligence and machine learning based tools. These tools are expected to transform the design and manufacturing processes in the next 15 years, along with these technologies' first-order and second-order effects on global operations, workforce, and innovation. In this context of new technologies ushering in a new era of rapid innovation, this essay discusses the profile of a successful high-tech global design and manufacturing firm in 2040. We identify the key challenges these firms are expected to face, focusing on the need for effective human-AI collaboration facilitated by modeling the expertise of humans and AI in the design and manufacturing process to predict their performance. We outline a research agenda—spanning expertise modeling, cost-performance aggregation, and dynamic task allocation—that forms the scientific foundation for scalable human-AI teams in design and manufacturing. Further, we discuss the broader impact of the proposed solution on the design and manufacturing industry and society as a whole.

1 Introduction

The world of 2040 will be defined by an unprecedented pace of technological advancement, particularly within artificial intelligence (AI) and machine learning (ML). These transformative technologies are set to reshape society and the global workforce, promising efficiency, productivity, and innovation gains. For design and manufacturing firms, integrating AI and ML will be instrumental in automating routine tasks, optimizing complex operations, and enhancing decision-making processes, paving the way for a new era of industrial capability.

Amidst this technological frenzy, a successful high-tech global design and manufacturing firm in 2040 will be characterized by several key attributes. Seamless integration of AI and ML technologies will be central to its success, facilitating decentralized and hyper-connected global operations. A commitment to sustainability and circular economy practices will help it stand out. Continuous and robust Research and Development (R&D) will fuel its innovative edge. However, these firms will also face the challenge of navigating complex regulatory frameworks and ethical standards related to AI, all while striving to maintain competitiveness in a rapidly evolving global market. Consequently, their workforce must be adaptable and flexible. A strong focus on human-AI collaboration will be essential to harnessing the full potential of AI and ML technologies along with the human workforce.

Even as AI systems excel in solving well-defined problems and become ubiquitous in nearly every facet of the design and manufacturing process, they are not a panacea. Many critical challenges are ill-defined, requiring nuanced human expertise and judgment. A significant portion of these will be "wicked problems", complex socio-technical challenges involving multiple stakeholders, where the very act of problem formulation evolves the understanding of the issue itself [4]. Therefore, this essay proposes that effective human-AI collaboration, facilitated by modeling the distinct yet complementary expertise of humans and AI systems, offers a powerful pathway to address these intricate challenges, combining the best of both humans and AI.

While significant progress has been made in AI and ML, substantial research is still imperative to develop the robust scientific foundations necessary for truly effective human-AI collaboration in design and manufacturing. This includes creating sophisticated models that capture the nuances of human and AI systems' expertise, tools for modeling and simulating these complex human-AI interactive processes, and designing incentive mechanisms for different human experts. Furthermore, dedicated research is needed to formulate frameworks for seamlessly integrating advanced AI models into existing design and manufacturing workflows.

The remainder of this essay is organized as follows. Section 2 discusses the profile of a successful high-tech global design and manufacturing enterprise in 2040. Section 3 describes the key challenges these firms are expected to face. Section 4 proposes a solution centered on expertise modeling for Human-AI collaboration. Section 5 elaborates on the scientific foundations necessary for effective human-AI collaboration in design and manufacturing processes. Section 6 discusses the broader impact of the proposed solution, and Section 7 concludes the essay, emphasizing the critical need for continued research and innovation in this vital area.

2 Design and Manufacturing Firms in 2040

In this section, we describe the profile of a successful high-tech global design and manufacturing enterprise in 2040. Figure 1 shows the key characteristics of a successful design and manufacturing firm in 2040. This section is organized along the three thrusts in Figure 1: technologies key to the success, workforce, and key differentiators.

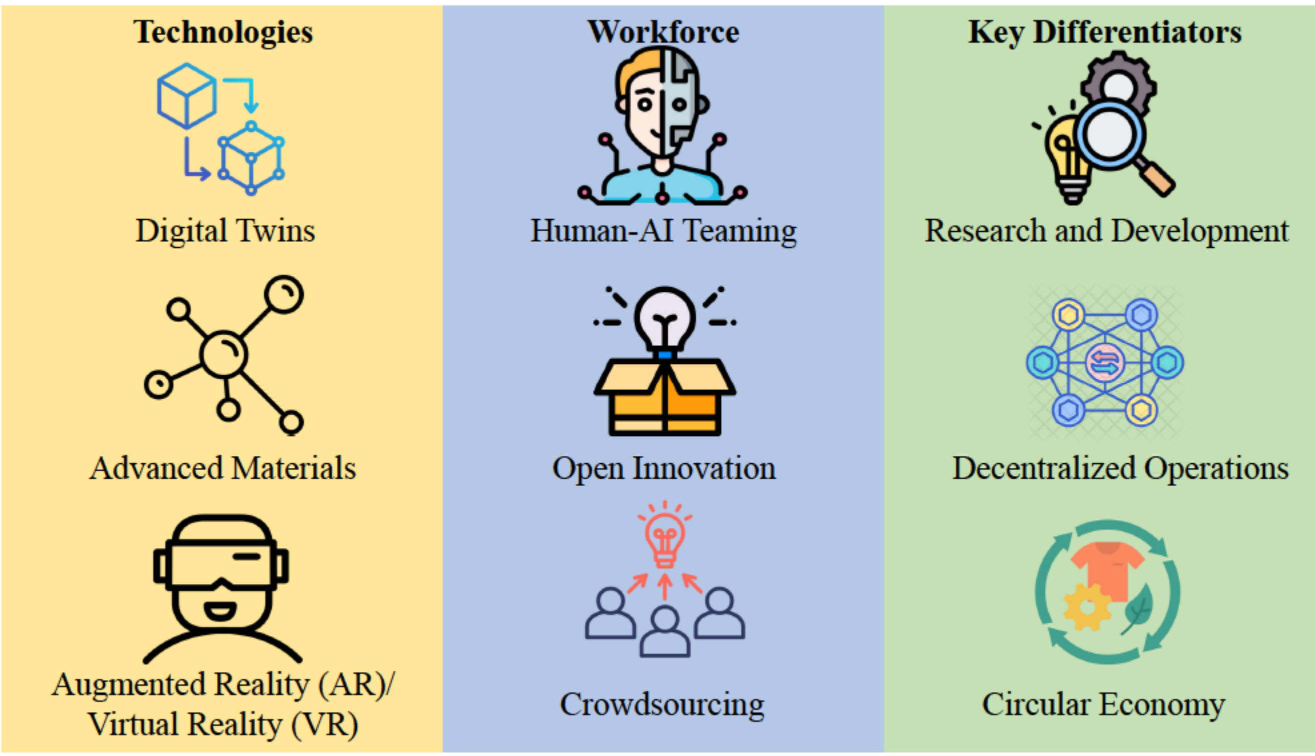

Figure 1: Key characteristics of a successful design and manufacturing firm in 2040.

2.1 Technologies Key to the Success of a Design and Manufacturing Firm in 2040

AI and ML-based systems have already started to play a significant role in design and manufacturing processes. The use of AI-based algorithms to generate design alternatives, optimize designs, and automate the design process have been documented in the literature [6, 21, 23]. Given the pace of the innovations, it is difficult to predict the future of design and manufacturing firms in 2030, let alone 2040. However, we can expect that AI and ML will be integrated into every aspect of the design and manufacturing process, from product design to production planning and quality control, and we will discuss some technologies that are expected to be core to the operations of design and manufacturing firms in 2040.

Digital twins will be a foundational technology in 2040, transforming how physical products, processes, and operations are conceptualized, implemented, and managed [17, 12]. Digital twins will enable firms to simulate factory operations before the foundation stone is laid. These dynamic virtual representations will allow the comprehensive simulation and optimization of everything from product designs to factory layouts and complex production workflows. Digital twins can serve as the virtual counterparts to physical smart factories, enabling continuous monitoring, autonomous process adjustments, and enhanced product quality. Furthermore, the development and deployment of autonomous robots and machines will be linked with digital twin environments as these robots, equipped with their own AI and ML capabilities for learning and adaptation, can be designed, simulated, and managed within the digital twin, ensuring their seamless integration into manufacturing processes, thereby boosting both precision and overall automation.

Further, Augmented Reality (AR) and Virtual Reality (VR) will become integral for training, maintenance, and collaboration. These immersive technologies will offer practical training modules, allowing employees to learn and master complex skills in safe, simulated environments, reducing reliance on physical facilities and mitigating workplace hazards [14]. This extends to operations involving potentially dangerous materials or environments, where personnel can perform tasks remotely using AR/VR interfaces, ensuring their safety. Moreover, AR/VR will dismantle geographical barriers to teamwork, fostering seamless remote collaboration by enabling teams to interact and co-create within shared virtual spaces. This will lead to improved communication, heightened efficiency, and reduced travel expenditures. Aided by AR/VR, mass customization will shift from a novelty to a baseline customer expectation, with products like footwear and ergonomic accessories tailored to individual specifications. AR and VR will create the engaging and effective customer interface crucial for making mass customization a widespread reality, meeting the growing demand for products uniquely suited to individual preferences and needs.

Another key technological focus for design and manufacturing firms will be the strategic adoption and development of advanced materials, particularly bio-based and sustainable ones. The ability to innovate and meet dynamic market and customer needs will increasingly depend on creating materials with unique, tailored properties. AI and machine learning algorithms are expected to revolutionize this domain by dramatically accelerating the discovery and design of novel materials [20]. These intelligent systems can rapidly generate and predict material candidates with specific desired characteristics, enabling designers to create innovative products and maintain a competitive edge in a rapidly evolving global landscape.

2.2 Workforce of a Design and Manufacturing Firm in 2040

The defining characteristic of the 2040 workforce in design and manufacturing will be extensive human-AI collaboration, enhancing productivity and innovation. Integrating AI based agents necessitates a paradigm shift in how work is conceptualized, demanding new skills and a workforce trained to partner effectively with AI systems, leveraging their analytical strengths while mitigating the limitations of AI systems. Establishing trust in AI through robust accountability and ethical frameworks prioritizing human concerns will be critical to the operations. Lifelong learning and adaptability will become standard as employees continuously evolve alongside AI capabilities. Rather than replacing humans, human skills will be augmented using AI, focusing on inherently human strengths like creativity, strategic intuition, emotional intelligence, and complex ethical decision-making, much like how robots assist surgeons.

By 2040, successful design and manufacturing enterprises would have thoroughly embedded open innovation practices as a primary engine for accelerating progress and enhancing competitiveness at a reduced cost compared to insular R&D models. This approach involves actively seeking and integrating external knowledge and capabilities from a diverse ecosystem, including universities, research labs, startups, suppliers, customers, and cross-industry partners. Firms will leverage novel platforms for idea exchange, engage in alliances, and external partnerships to solve complex challenges. In an era of rapid technological development and limited availability of domain experts, open innovation will be crucial for accessing specialized expertise needed to drive innovation.

A key operational focus for design and manufacturing firms in 2040 will be the strategic implementation of crowdsourcing to tap into the collective expertise, creativity, and problem-solving capabilities of a globally distributed and diverse range of contributors. Beyond traditional employment models, companies will leverage advanced digital platforms to engage global talent for specific tasks—from ideation and conceptual design challenges to complex engineering problem-solving, software development for manufacturing systems, and generating diverse user feedback for product validation. This approach will allow firms to access a vast pool of specialized skills on demand, gain varied perspectives crucial for breakthrough innovations, and significantly accelerate development cycles.

2.3 Key Differentiators for a Successful Design and Manufacturing Firm in 2040

Research and development (R&D) will be a key differentiator for design and manufacturing firms in 2040. The focus will be on developing new products and technologies that meet the changing needs of customers and the market. This will require a strong emphasis on innovation, collaboration, and agility in the R&D process. Rapid technological developments across various disciplines will find their way into design and manufacturing sooner or later. Advancements in computational sciences will also speed up innovations in other fields relevant to a manufacturing firm, like materials. New materials and polymers with unique properties can be predicted and simulated at unprecedented speeds, bringing revolutionary changes to the market. There will be tools that can simulate the entire product design process for given inputs. The possibilities are enormous, and anyone not adapting them to the design and manufacturing workflow will fall behind. This dynamic presents a particular urgency for US design and manufacturing firms. While the US has historically been a leader in global innovation, international competitors' rapid proliferation and adoption of advanced AI technologies pose a formidable challenge to this leadership. To navigate this intensely competitive global market, US firms must strategically invest in their own AI-driven R&D capabilities.

By 2040, sustainability and the principles of a circular economy will be key to any successful design and manufacturing firm, evolving from best practices to industry standard. Increasing global consumption, driven by an expanding worldwide middle class, coupled with the increasing scarcity of critical raw materials, highlights the urgency of this transformation. The focus will be on a commitment to minimizing waste streams, drastically reducing energy consumption throughout the value chain, and prioritizing the integration of sustainable, renewable, and bio-based materials from initial design conception through to end-of-life management. This necessitates a fundamental shift away from linear 'take-make-dispose' models towards a robust circular economy. In this paradigm, products will be intentionally designed for durability, ease of repair, straightforward reuse, efficient material recycling, and viable remanufacturing, ensuring that resources are kept in use for as long as possible, thereby closing loops and fostering long-term ecological and economic resilience.

By 2040, global design and manufacturing firms will operate through decentralized, hyper-connected structures, leveraging AI and ML for real-time collaboration and efficient decision-making across different locations. This interconnectedness, however, will necessitate navigating complex international AI regulations and ethical standards, demanding robust compliance, transparency, and risk management for probabilistic AI systems to ensure safety and accountability. Consequently, strategic partnerships with specialized systems engineering and AI security firms will become crucial, not only to safeguard the integrity of the design and manufacturing processes against the unpredictable nature of some AI algorithms but also to ensure the reliable and ethical performance of these critical technologies across the global enterprise.

3 Key Challenge: Need for Effective Human-AI Collaboration

While a design and manufacturing firm in 2040 will face a multitude of challenges, the one I believe to be the most critical is the need for effective human-AI collaboration facilitated by expertise modeling. As AI systems become more integrated into design and manufacturing processes, it is essential to ensure that humans and AI can work together effectively. This requires characterizing human expertise and decision-making processes, as well as understanding the strengths and limitations of AI models to enhance collaboration with AI systems. There will also be a spectrum of expertise within humans, ranging from enthusiasts within crowdsourcing to domain experts. Similarly, different AI models will be available for different tasks, making the choice difficult and modeling the expertise a necessity. The framework for human-AI collaboration will need to account for this variety.

AI-based algorithms excel in solving well-defined problems. But not all problems can be defined in terms of a loss or objective function to be maximized or minimized. Some problems are ill-structured/defined problems [22], as in the case of wicked problems [4]. Wicked problems are complex, multifaceted, difficult to define and solve. They often involve multiple stakeholders with conflicting interests and require a nuanced understanding of the social, cultural, and political context in which they exist. Examples of wicked problems include climate change, poverty, and healthcare reform. These problems are characterized by uncertainty, ambiguity, and a lack of clear solutions. AI is not a panacea for all problems. We need human expertise to deal with multiple stakeholders and conflicting interests. So, even though challenges like sustainability and circular economy will be key to a successful design and manufacturing firm in 2040, we argue that the most critical challenge is modeling the problem-solving and decision-making processes of humans and AI systems to facilitate effective human-AI collaboration. This is essential for ensuring that humans and AI can work together effectively to solve complex problems and make informed decisions while dealing with complex socio-technical challenges.

Humans are not perfect decision makers as they are prone to cognitive biases, errors, and limitations in their decision-making processes, and these limitations have been documented in the literature [15]. For example, humans may rely on heuristics or mental shortcuts that can lead to suboptimal decisions. Additionally, humans may struggle with information overload, leading to difficulty in processing and analyzing large amounts of data [10]. So, human-AI teams should set up in a way that AI systems can assist humans in overcoming these limitations. This requires carefully designing AI systems that can complement and enhance human decision-making.

Multiple taxonomies and models have been developed to describe the role of AI in the design process to facilitate human-AI teaming. Parasuraman et al. [19] propose that AI-based automation can be applied to four broad classes of functions: 1) information acquisition, 2) information analysis, 3) decision and action selection, and 4) action implementation. Terminologies have also been developed to describe the role of human and AI-based models in the control loop of an intended function. Paradigms for human-AI collaboration like human-in-the-loop (HITL) have been used in healthcare, autonomous weapons systems, robotics, etc., for decades [27, 26, 11]. Existing paradigms like HITL are helpful for guiding task assignments in scenarios where the role of humans and AI is clearly defined. With AI models becoming increasingly capable, it is no longer clear whether humans or AI should be better suited for a task, and the relative performance can also depend on the operational environment. In these scenarios, system designers need a way to assign tasks to humans or AI to maximize their unique strengths and minimize potential weaknesses.

4 Proposed Solution: Human-AI Collaboration Facilitated by Expertise Modeling

In this section, we propose how to use expertise modeling to predict the performance of humans and AI systems in design and manufacturing processes. Later in Section 5, we will discuss the scientific foundations necessary to support the proposed solution.

Figure 2 shows the algorithmic flowchart for evaluating and optimizing subproblem-solver combinations. The first step is to decompose the problem into subproblems. This can be done using various techniques, including functional decomposition, object-oriented decomposition, and domain-specific decomposition. Once the problem is decomposed into subproblems, the next step is to model the expertise of humans and AI systems. Once expertise is characterized, the expertise is used to estimate the performance of humans and AI systems. Later, the cost of the AI model/human is also calculated. The next step is to model the uncertainties in cost and performance. Once the uncertainties are modeled, the next step is to simulate the subproblem-solver combinations to estimate and cost and performance when AI and humans are assigned to solve different subproblems. Finally, the last step is to identify the optimal combination of subproblem-solver combinations.

Now let's discuss how some examples of dynamic human-AI teaming in design and manufacturing processes might look like. Here, dynamic human-AI teaming refers to the ability of humans and AI systems to work together in real-time, adapting to changing conditions and requirements. This type of collaboration is essential for addressing complex problems and making informed decisions in design and manufacturing processes. Consider part inspection in manufacturing. With computer vision-based models and robotics, the bulk of the inspection process can be automated. However, there will be instances where the AI model is not able to make a decision or makes wrong decisions for scenarios not part of the training datasets. In such cases, the human inspector can step in and make the decision. The human inspector can also provide feedback to the AI model to improve its performance.

Another example of dynamic human-AI teaming in the conceptual design phase can be the automation of 3D modeling and creating formal design representations from sketches and conceptual designs. Human designers are

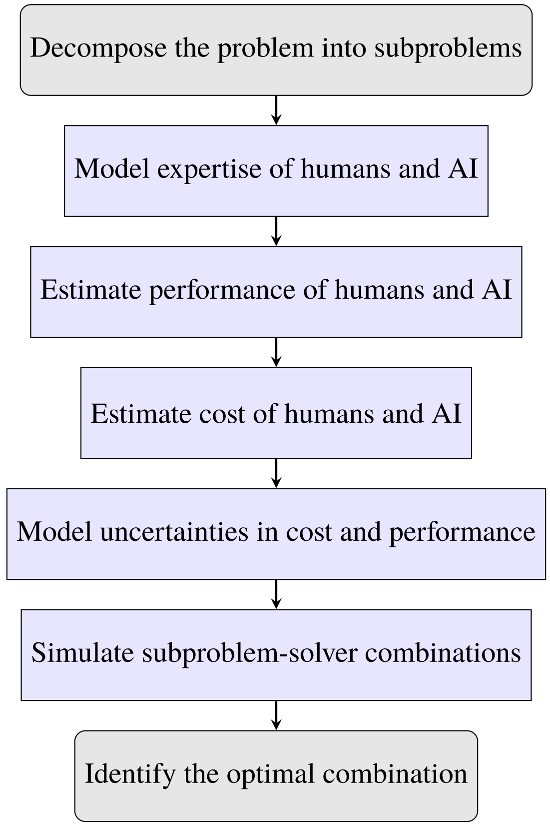

Figure 2: Algorithmic flowchart for evaluating and optimizing subproblem-solver combinations

creative and can generate novel ideas in the early stage of the design process. AI systems can assist human designers in this process by automating the creation of formal design representations from sketches and conceptual designs. Similarly, human designers can elicit boundary conditions and constraints from design requirements, and AI-based models can assist in shape/topology optimization based on the boundary conditions and constraints provided by the human designer. AI-based models can also be used for testing product concepts by using hallucinated LLM "personas", hence speeding up evaluation of ideas [3].

AI models can also assist humans in dealing with more complex challenges. While dealing with complex socio-technical challenges faced by a design and manufacturing firm, the humans will be negotiating with multiple stakeholders with conflicting interests. The AI models can assist humans in analyzing prior data and discussions and summarizing the key points. Similarly, the AI-based models can also simulate complex phenomena like climate change and its impact on the design and manufacturing process. The models can assist humans in making informed decisions by providing insights and recommendations based on the data, but the final decision will be made by humans.

5 Scientific Foundations for Effective Human-AI Collaboration

In this section, we will describe research questions worthy of investigation in the next 15 years to support the proposed solution to facilitate human-AI teaming for a successful design and manufacturing firm in 2040. The section is organized along the five research questions listed in Table 1.

5.1 RQ1: Modeling Expertise of Humans and AI

The current state of the art in the research related to expertise in engineering design focuses on classifying designers into two categories - experts and novices. Using different techniques like protocol studies and interviews,

	Research Question
RQ1	How to model the expertise of humans and AI and predict their performance?
RQ2	How to estimate the performance and cost of a system with humans and AI?
RQ3	How to engage with the variety of solvers available in 2040?
RQ4	How to decompose the design problem to leverage the strengths of humans and AI?
RQ5	How to allocate the tasks to humans and AI?

Table 1: List of Research Questions

researchers have tried to characterize the difference in the behavior between experts and novices. Ahmed et al. [1] studied how expert designers, aided by their experience, use a breadth-first approach for solving problems while novices resort to a depth-first approach. Christiaans et al. [7] studied how expertise affects the information acquisition behavior during design. Atman et al. describe a series of protocol studies on engineering students throughout their transition from first-year students to graduating seniors. Lloyd et al. [18] studied how different approaches used by designers were linked with the experience of designers. Alexiou et al. [2] performed a study using functional magnetic resonance imaging (fMRI) while solvers solved well-defined and ill-defined problem-solving tasks. Deng et al. [8] studied the difference in the performance of expert and novice solvers on a Computer-Aided Design modeling task. To summarize, the existing works in literature have used a range of techniques on people solving different problems to characterize the differences in their behavior and performance based on expertise. But beyond these empirical studies, a quantitative model for predicting performance based on expertise in design and manufacturing is missing.

We believe that a key research area will be to develop models of expertise of humans at multiple levels of abstraction. For crowdscourcing and mass broadcasting-based design, the performance of the best solution from the crowd should be modeled. This type of model will rely on game theory, design of contract structures, and incentive mechanisms to elicit the best solution from the crowd. The next level of abstraction will be the performance of an individual, i.e., modeling the performance of an expert in a domain. This type of model will rely on the characteristics of the problem and the expertise and predict the performance based on the characteristics of the problem and the expertise. Further to characterize the performance of an individual, we need to model the cognitive processes of the individual. This type of model can help us better understand the strengths and weaknesses of humans compared to AI systems.

5.2 RQ2: Aggregating Performance and Cost of Humans and AI

Consider a scenario where a human and an AI system are working together to complete a design or manufacturing task. The performance of the system will depend on the performance of both the human and the AI system, as well as the interactions between them. This requires a model that can predict the performance of the system based on the performance of the individual components (i.e., humans and AI) and their interactions. While the computer science research community has made significant progress in developing and benchmarking AI algorithms, there is a lack of models for predicting the performance of systems with both humans and AI [28]. This is a critical gap that needs to be addressed to facilitate effective human-AI collaboration. This is also an interdisciplinary research area that requires collaboration between computer science, engineering, and social sciences.

5.3 RQ3: Non-Traditional Contributors and Contracting Mechanisms

Bill Joy, co-founder of Sun Microsystems, famously said, "No matter who you are, most of the smartest people work for someone else" [16]. This statement highlights the importance of collaboration and the need to leverage the expertise of non-traditional contributors in design and manufacturing processes. So, a key research question will be when and where to utilize these contributors in the design process and how to structure the contracts and incentives to elicit the best solutions from them. Actively seeking and integrating knowledge and capabilities from a diverse external ecosystem, including universities, research labs, startups, suppliers etc. requires strategies to engage with these contributors. This can be facilitated by developing models for predicting the performance of a solving process with these external solvers, as well as tools for designing and implementing incentive mechanisms that can elicit the best solutions from solvers.

5.4 RQ4: Decomposing the Design Problem to Leverage the Strengths of Humans and AI

Another key challenge in allocating tasks to humans and AI is identifying how to decompose the design problem into subproblems that can be solved by different solvers. This requires an understanding of the expertise necessary to solve the problem and the strengths and limitations of different solvers. In the context of decomposing the design problem to enable external contributions, Solver-Aware System Architecting (SASA) [25] is a system architecting framework that has been developed to organize complex system design. The central hypothesis of SASA is that the system design outcomes can be improved significantly by intelligently combining decisions pertaining to technical problem decomposition, solver assignment (i.e., of experts, crowds, and specialists), and the design of the contractual incentive mechanisms. Szajnfarber et al. [25] demonstrate the effectiveness of SASA in a case study, a toy problem of golf as a surrogate model for a complex system design. The design process is represented as an effort to complete a golf course by simulating the strokes needed to traverse from tee to pin; and alternative solver types were represented by different stroke distributions, allowing for different solving paths to emerge (e.g., multiple short drives vs. a long drive and short approach) naturally. While SASA is a promising framework, further research is needed to develop tools for implementing system architecting frameworks like SASA in design and manufacturing processes.

5.5 RQ5: Heuristics for Allocating Tasks to Humans and AI

While having a model for predicting the performance of humans and AI systems is useful, it may not be practical to build such a model and use it for real-time decision-making, particularly in dynamic environments like design and manufacturing. In such cases, heuristics can be used to guide the decision-making process of allocating tasks between humans and AI. Heuristics are simple rules of thumb that can be used to make decisions quickly and efficiently, without the need for complex models or simulations. Identifying characteristics pertaining to the task/problem and the human/AI that lead to optimal performance can help with the task allocation. For example, if the task requires creativity and intuition, it may be better suited for a human. On the other hand, if the task requires processing large amounts of data or performing repetitive tasks, it may be better suited for an AI system.

Multiple works have explored the use of Reinforcement learning (RL) algorithms to develop heuristics for system design and optimization [13, 24, 9]. RL algorithms can learn from experience and adapt to changing environments, making them well-suited for dynamic human-AI collaboration scenarios. So an interesting research opportunity will be to identify generalizable heuristics for task allocation between humans and AI systems in design and manufacturing processes.

6 Broader Impact of the Proposed Solution

Implementing an expertise-based model for facilitating human-AI teaming will have a significant impact on society as a whole, catalyzing significant positive societal shifts extending far beyond the immediate design and manufacturing industry. Its core tenets of modeling expertise and human-AI teaming can potentially have an impact in three key areas: fostering a more inclusive and skilled workforce, elevating the nature of human work, and reshaping STEM education for future generations.

First, the proposed solution offers a powerful avenue for broadening workforce participation and addressing critical skill gaps, particularly within the US design and manufacturing sectors [5]. By leveraging advanced AR/VR technologies, integrated with expertise modeling, the framework can provide training, real-time assistance, and adaptive interfaces for people with disabilities to participate in manufacturing-related activities like welding [14]. This will empower individuals with disabilities, enabling them to engage meaningfully in complex design and manufacturing roles that might have previously been inaccessible. This taps into an underutilized talent pool to alleviate skill shortages but also promotes a more equitable and accessible future of work, aligning industrial advancement with social responsibility.

Second, the integration of AI models will redefine the landscape of human work by automating routine processes. Expertise modeling will enable the identification of tasks that can be effectively delegated to AI systems, empowering employees to dedicate their unique cognitive strengths, like creativity, critical judgment, complex strategic thinking, and interpersonal collaboration, to perform tasks that drive innovation. This can provide greater professional fulfillment to employees, who will feel more engaged and valued in their roles. Along with improving employee morale, this can also drive productivity and innovation within organizations.

Finally, the principles underlying this solution carry profound implications for transforming STEM education to meet the demands of a rapidly evolving technological world. Instead of a curriculum narrowly focused on specific tools and technologies that quickly become obsolete, the future of education must cultivate enduring skills in critical thinking, adaptive problem-solving, and lifelong learning. Understanding human expertise can also aid the development of tools to create tailored plans for the development of expertise. Education can then adapt to individual student goals, needs, paces, and learning styles, offering targeted support and supporting a deeper conceptual understanding of fundamental principles. This approach will equip students not just with current knowledge but with the cognitive agility required to thrive and innovate in the dynamic technological landscape of 2040 and beyond.

7 Conclusion

This essay started by describing the landscape awaiting design and manufacturing firms in 2040, identifying the core operational technologies and the critical challenges they will face. The central theme of the discussion is the need for effective human-AI collaboration, arguing that modeling the distinct expertise of both human and artificial intelligence within the design and manufacturing domain is paramount to addressing the "wicked problems" and intricate socio-technical challenges of the future. We have proposed a solution centered on this collaborative paradigm and emphasized the fundamental research questions that must be answered to build the necessary scientific foundations.

However, the scientific foundations to realize effective Human-AI Collaboration, while promising, are still in elementary stages. Bridging this gap necessitates a concerted, multidisciplinary endeavor, combining experts from computer science, engineering, psychology, and the social sciences. Such an ambitious undertaking demands robust, sustained collaboration between academia, industry, and governmental bodies to co-develop the essential frameworks, models, and ethical guidelines. Over the next fifteen years, strategic investment in this targeted research and development is critical to maintaining the dominance of the US as a predominant power in design and manufacturing. This commitment will be instrumental in developing the tools and techniques required for humans and AI to work synergistically, transforming design and manufacturing processes.

As discussed in Section 6, the successful implementation of the proposed solutions promises a profound and positive impact that extends beyond the design and manufacturing industry. By dedicating ourselves to addressing these research challenges today, we can unlock a future where technology augments human potential, creating sustainable, efficient, and groundbreaking processes that yield benefits for industry, the workforce, and society. The path forward requires vision, investment, and a shared commitment to pioneering the next frontier of collaborative intelligence.

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