FOCUS AND MODALITY: DEFINING A ROADMAP TO FUTURE AI-HUMAN TEAMING IN DESIGN

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ABSTRACT

The evolution of Artificial Intelligence (AI) and Machine Learning (ML) enables new ways to envision how computer tools will aid, work with, and even guide human teams. This paper explores this new paradigm of design by considering emerging variations of AI-Human collaboration: AI used as a design tool versus AI employed as a guide to human problem solvers, and AI agents which only react to their human counterparts versus AI agents which proactively identify and address needs. The different combinations can be mapped onto a 2×2 AI-Human Teaming Matrix which isolates and highlights these different AI capabilities in teaming. The paper introduces the matrix and its quadrants, illustrating these different AI agents and their application and impact, and then provides a road map to researching and developing effective AI team collaborators.

Keywords: Human-AI Teaming, Design for Artificial Intelligence, Machine learning, Teamwork, Artificial intelligence

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INTRODUCTION

Artificial intelligence (AI) has proven to be successful in many arenas that involve analyzing large volumes of data to provide insights that improve business decisions. In particular, in the area of design the promise is starting to bear fruit. A recent survey by McKinsey found that 24% of companies have AI-enhanced features in products and 21% used AI to optimized features (McKinsey Analytics, 2020). Moreover, 30% of the semiconductor industry already sees value in the use of AI and the rest are developing and evaluating options (McKinsey Analytics, 2020). Within manufacturing the AI market size exceeded over 1 billion USD in 2018 and is projected to reach 16 billion USD by 2025 (Global Market Insights). The impact in industry is being accompanied by a simultaneous increase in academic interest. For example, at Carnegie Mellon University a 2017 survey found that 84% of faculty said they work in the area of AI and Machine Learning (AI/ML) (College of Engineering, 2017). Within the Department of Mechanical Engineering, areas of AI application and active research include health, autonomous vehicles, materials discovery for energy, design and manufacturing, smart cities and society. This year, CMU also introduced the first MS degree in AI Engineering, as well as established the Human+AI Design Initiative.[1] However, these trends are not unique to Carnegie Mellon University, with many universities on a similar trajectory (Khanolkar *et al.*, 2021). AI/ML is clearly propagating across industry and academia alike.

The rising prevalence of AI clashes with the current practice of engineering design, which is largely a human activity executed in teams (Thomas O'Neill *et al.*, 2022; Williams *et al.*, 2022). The question we pose is this: *in what ways might AI/ML augment team-based engineering design?* The current work divides this question into two main considerations: (1) whether the AI is helping the team design the product itself (focusing on the problem) or whether the AI is guiding the team's problem-solving abilities (focus on the design process); and (2) whether the AI is reactive in that it is simply responding to requests for its input or proactive in that contributes to the solution based on its own volition. We refer to these dual considerations as *focus* and *mode*, respectively.

Engineers have used reactive AI assistance tools in both product design (Koch and Paris-Saclay, 2017) and concurrent-engineering design (Jin and Levit, 1996). In addition, AI assistance has been used at the concept generation (Camburn, Arlitt, *et al.*, 2020), concept evaluation (Camburn, He, *et al.*, 2020), prototyping (Dering *et al.*, 2018), and manufacturing (Williams *et al.*, 2019) stages,. Work has studied the impacts of AI assistance in aspects of engineering design, including decision-making, optimization, and computational tasks (Raina, Cagan, *et al.*, 2019; Rao *et al.*, 1999), and its effects on mental workload, effort, and frustration (Maier *et al.*, 2020, 2021). Bang et al. (2018) introduced DAPHNE as an intelligent cognitive assistant developed for providing support in system architecting, specifically for designing a constellation of satellites for Earth observation. However, little prior work has focused on proactive AI agents that augment team problem solving, especially in design.

Although there are many AI tools already being rapidly developed, another AI disruption is arriving that will again change the nature of how organizations will employ AI: the maturation of AI beyond just being a tool employed by humans. Two more advanced and proactive paradigms are emerging: (1) where AI will become a partner working alongside humans on a team (AI-as-Partner), and (2) where AI will take on the role of real-time guide for a team (AI-as-Guide). These new AI archetypes will not only accomplish the routine aspects of design but aid in and contribute to creative problem solving and collaborative team output. In this paper we explain how AI agents will work not just as tools but also as members of a team, and showcase when and how the AI-as-Guide and AI-as-Partner archetypes will best function, so that design organizations can identify and invest in the types of AIs that will have the most positive impact, and to motivate researchers to more deeply explore these modalities.

[1] https://engineering.cmu.edu/human-ai-design/

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AI-HUMAN TEAMING MATRIX

Intersecting these modalities (reactive versus proactive) and foci (problem focus versus process focus) generates the 2×2 AI-Human Teaming Matrix, the analysis of which results in a roadmap for research in, and eventually guidance on, when and how to employ specific types of AI. In considering these matrix dimensions, *mode* refers to whether the AI system is simply reactive (invoked by a user) or engages proactively with the organization (taking actions without specific user prompting). For example, Alexa or Siri *react* to queries or instructions. Although digital assistants may leverage data from other users to continuously improve in the background, tasks for a user are performed only when prompted by a user. Fully autonomous vehicles utilize *proactive* AI, conducting tasks such as braking or turning without user input.

The other dimension, *focus* describes the type of activities that the AI engages in, whether the AI is focused on a specific problem or whether it enables a process that can be applied across problem types. An AI that conduct specific tasks related to finite element analysis is inherently problem-focused: detecting whether a mesh is appropriate for a given geometry and load, and upon request suggesting improvements to a proposed mesh. An example of a process AI would be tracking and modifying the process of conversation, which could be employed to solve a variety of design problems.

These dimensions describe a 2×2 matrix of possible AI systems as shown in Figure 1. Although we present this matrix as discrete cells, AI agents can serve multiple modes. For example, a proactive agent can also be called upon by a human to serve as a tool, and may have varied capabilities based on its mode of use.

Focus \ Mode	Reactive	Proactive
Problem	AI-as-Tool	AI-as-Partner
Process	AI-as-Analytics	AI-as-Guide

Figure 1. The AI-Human Teaming Matrix: AI use within teams can focus on solving the problem (create the design) or improve the design process, and AI can be reactive in response to user queries or proactive in seeking to directly contribute to the problem or process.

We are already seeing reactive AIs deployed across many industries (e.g., mechanical engineering,[2] architecture,[3] and the design of space missions[4]). In this paradigm, the AI is invoked by a user to provide a narrowly-scoped and specific output – either providing some process analytics capability or used as a problem-solving tool. However, as AI becomes more advanced, and technologies like Natural Language Processing become more proficient, there is huge potential for AI to take on new roles within the organization. Specifically, AI has the potential to become a partner and teammate and even as a guide for the team. This shift requires AI to surpass its reactive existence as a tool, and to exist as a social agent within the structure of the organization.

[2] https://www.autodesk.com/solutions/generative-design
[3] https://www.aia.org/articles/178511-embracing-artificial-intelligence-in-archit
[4] https://www.boozallen.com/markets/space/artificial-intelligence-for-space-missions.html

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In the following sections we synthesize our research within the context of the AI-Human Teaming Matrix and use our work to provide examples of each of these paradigms and offer recommendations for when and how to take advantage of each. Each of these types (quadrants) provides unique value. Most important is to note not what the AI can do, but how it empowers a team to do things differently - more efficiently and more creatively.

AI-as-Analytics (lower left)

At its most basic implementation and interpretation, Machine Learning is a statistical assessment of data, enabled by fast processing and tuned algorithms. Thus, the most extensive use of such approaches has been for data mining, seeking new insights often buried within large data sets. Such ML agents available to teams empower decision making through refined accuracy and new interpretations of data, resulting in new insights and improved ideation for problem solutions. One example of ML data analysis within teams is to design teams themselves. For instance, in McComb, Cagan and Kotovsky (2017a), an AI agent was embedded with cognitive characteristics that emulate human problem solving, in particular the ability to design the configuration of a system. By then using the AI agent to synthetically generate a vast amount of data, team parameters such as team size or interaction frequency enable an ML assessment to determine the design of the teams - the selection of those parameters - given some problem complexity assessment. This is an unusual example of AI-as-Analytics, but such approaches are often common such as stock market performance (Maier, Menold, *et al.*, 2022), design evaluation (Song, McComb, *et al.*, 2022), or assessment of team communication (Ball and Lewis, 2018).

When organizing the workflow of a design team, when relevant data sources are available, insights from analytics should be actively made available to and leveraged by the team. Statistical analysis is not new. But a process to make not only the results available but interpolate, extrapolate and even interpret such results is provided by potential AI-as-Analytics applications, and opens up new and efficient advantages for the team to understand market trends, determine product features, and even provide insights into how to create the team itself.

AI-as-Tool (upper left)

If is often the case that the use of AI improves overall team performance towards key performance indicators. However, the introduction of AI tools can sometimes adjust behavioral aspects of the team as well. As one example, consider the example of team agility, which is how efficiently and effectively the team adapts to changes. Although necessary for complex problem-solving, such as design innovation, team agility is often difficult to achieve in practice. The evolution of AI affords unique opportunities for supporting team problem solving. While integrating assistive AI agents into human teams has been shown at times to improve team performance, it is still unclear if, how, and why AI affects team agility. Song et al. (2022) addressed these questions through a large-scale human experiment based on a multi-faceted design problem, comparing teams designing a solution with and without AI assistance. The results reveal that AI-assisted human teams enjoy improved coordination and communications, leading to better performance. At the same time, they are also able to better adapt to both evolving and abrupt team disruptions, devoting more effort to information handling and exploring the solution space more broadly. The AI takes care of a portion of tasks, saving a portion of team members' time and cognitive resources that then can be applied towards cognitive aspects of problem solving. In sum, working with AI enables human team members to think more and act less, meaning that they can think at a high level of reasoning to make more precise design changes.

Working with an AI-as-Tool shifts the human contribution in the team towards higher-value work, such as sense-making and information management (Song et al., 2021; Maier et al., 2021). Such tools are disrupting industry today, and will result in new types of CAD capabilities for design, analysis and manufacturing. The result is a widened toolbox for designers, resulting in greater efficiencies and more effective decision making. Designers should be trained to address these tasks efficiently using AI tools as an increasingly common part of their jobs.

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AI-as-Partner (lower right)

The potential for boosting team agility becomes more prominent under an AI-as-Partner paradigm. In studying how teams respond to change, we found the AI's role in change management becomes critical as the AI partner becomes a more proactive part of the team. In a recent experiment we (Xu *et al.*, 2023) sought to understand how having a proactive AI as a partner affects team performance and behavior in this way. In this experiment, we compared human-only teams to hybrid teams in which 2 of the 5 members were replaced with AI agents. The agents had capabilities to make a change to a design based on the current and evolving state of the design for specialized job functions on the team. In this case by replacing team members with AI partners, the number of human problem solvers in each specialized category was reduced, the question being how the capabilities of the resulting hybrid team changed. Midway through the experiments, teams experienced a shock in the market condition that significantly changed the problem statement and required the team to work on a version of the problem that the AI partners were not explicitly trained on.

Overall, teams perform similarly, achieving comparable profit across both problem-solving sessions. The similarity of their outcomes was surprising in that the AI agents were not trained to specifically solve or generalize to the second session problem and it was anticipated that the teams would therefore struggle. Yet because the human team members collaborated with and utilized the AI agents similarly to the way they work with other human team members, the AI+human teams performed comparably. After the shock, both team conditions show an increase in communication frequency. But the human designers on the AI agent teams need to work a bit more than they did prior to the shock in the condition upon which the AI was trained, increasing their communication with the AI agent, helping to overcome the increased difficulties - even though the AI partners are not trained in the second session problem, the human designers still reach out to their AI counterparts as part of their collaboration. This work indicates the promise of AI agents working as proactive partners to humans to solve challenging and open-ended problems.

We found that team communication is essential to success in collaborative human-AI teams. Collaborating with an AI-as-Partner further shifts the human contribution towards problem framing - the process of actively restating a problem to enable its solution by the AI partner. This is a critical skill that will enable human-AI partnerships to flourish in highly volatile environments. Training in the early stages of innovation thinking can help to support these skills. This matrix cell also starts to highlight how the design process and workflow and effort shift when incorporating the AI into the process.

A large benefit of the AI-as-Partner agent is the ability to shift resources within an organization, for duplication of human skills is no longer necessary. This may align with research on nominal teams, whereby team members solve the problem independently and select the best overall solution. Within the team, excess communication and effort to align solutions and processes among duplicated skills is inefficient (Gyory *et al.*, 2019; McComb *et al.*, 2017a, 2017b; Rietzschel *et al.*, 2006; Sio *et al.*, 2014). When an individual has such an AI agent as a partner without the additional social and communication overhead it may result in higher performance. As well, in resource or time critical situations, having one human able to solve design and other problems alone with an AI may result in superior decision making than if a group of humans with the same core skill sets must work together to achieve a common decision.

AI-as-Guide (upper right)

It may not always be necessary to engage an advanced AI agent directly in the problem-solving process. Rather, it may be more effective to focus the AI on guiding the overall process of the human team. Gyory et al., (2022) explored the automation of design process management to improve problem-solving behaviors and outcomes of teams. By process management we mean observing in real time the problem-solving process and serving as a guide to adjust team behavior to improve the process, overcoming teams getting stuck, going off course, or becoming inefficient. To accomplish this, we designed an experimental study and developed the architecture of an AI agent to manage the design process of engineering teams in real time, where the team was tasked with designing fleets of drones and the operation plans of delivering goods to different locations to maximize overall profit. This agent, which was trained on previous problem-solving behaviors of high- and low- performing teams, tracked features of teams' actions and communications during a complex design and decision-making task with multidisciplinary team members. When pre-defined human team behaviors deviated from the preferred state (based on natural language processing, design changes, and communication frequency), then based on the largest deviation, an intervention was presented to the appropriate portion of the team to suggest changes in how the team should interact. Although not required, these nudges were meant to help the team perform better. The human guides/managers and AI guides/managers each had access to the same real-time information, and same library of nudges that they could suggest to the team.

The AI process guide matched the capabilities of human process guides. These similarities held across several dimensions, including overall team performance, intervention strategy, as well as the perceived impact on team performance, process, and intervention efficacy. Overall, communication deficiencies and inefficiencies stood out as guiding measures to elicit interventions by both the human and AI process guides. This again highlights the criticality of effective communication management, particularly during a highly interconnected and interdisciplinary design problem such as the one presented in this work.

The AI-as-Guide effectively manages the process of the team, but human managers engage in a variety of other tasks. Therefore, by embracing the AI guide as more of a co-manager, human managers are freed to focus on other aspects such as mentorship, strategic vision, and problem insights. This is also a new potential organizational efficiency for teams. Not only has it been demonstrated that teams benefit greatly from a process manager (Gyory et al., 2019), but because AI-as-Guide can perform the management task in real time as effectively, new resources do not need to be allocated to a team. Rather than the burden of a human guide needing to attend to all team meetings, the team can turn on their AI-as-Guide agent to help their problem-solving progress.

PROCEED, BUT DO SO WITH CAUTION

While the promise offered by AI is tantalizing, there are also significant risks associated with its use. Although the four studies above highlight cases of AI that performed well when integrated within human teams, we have also shown that this is not always the case. In a study on the design of bridges, Zhang et al. (2020) first created a high-performance AI that was capable of designing bridges even more effectively than humans (Raina, McComb, and Cagan, 2019). Next, the researchers integrated this AI into a bridge design interface for human use and tested its impact. Surprisingly, designers using the AI performed worse than those who didn't! It turns out the better designers became lethargic, relying too much on the AI agent, and not as much on their own insights. Although this emerged in an AI-as-Tool paradigm, we can only expect that while the rewards are potentially greater in more proactive paradigms, the risk is greater as well.

When considering the use of AI there are a few considerations:

- ***Data is the new currency.*** Data is hard to get, but if you have it you can cull out new and meaningful insights. There are different ways to obtain the data you need to train on a situation: from prior studies and experience, synthetically by creating a digital twin and generating design solutions, by transferring data from other problems that may not be direct matches but that have some overlapping properties, and data augmentation especially for geometries that can be rotated, translated and stretched. Emerging studies highlight the ways in which data limits machine learning potential, while other studies highlight ways to minimize data usage by encoding expert knowledge (Maier, Soria Zurita, *et al.*, 2022) or physics (Li and McComb, 2022; Pierce *et al.*, 2021).

- ***Agents can be trained to mimic the reasoning of the people that generated the data***, enabling insights that align with problem solving. This mirrors the "digital twin" methodology that has been advanced in manufacturing and other fields (Jones *et al.*, 2019; Stump *et al.*, 2021; Tao

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et al., 2019). Such digital twins for problem solving activity are sources of uncovering behaviors in certain conditions, or extrapolating what impact certain conditions will have on problem solving activity or outcome. At the same time caution is needed to recognize that some analyses will depend on the individuals that were studied and this can lead to biases in outcome and their application.

- ***AI can act a specialist that comes in when needed.*** The AI does not have to always be watching and contributing, even in a pro-active situation. Instead, the capabilities can be used as needed by the team. Thus, the capabilities and interactions need to be inviting and meaningful, or else these AI agents will, like other technologies before them, be rejected by the user and no longer serve its intended value. This can enable the team to respond to changing demands of the design problem, appropriately increasing team size as needed.

- ***Humans get better with their experience, and so do AI agents.*** As with any coach, successive use of an AI can and should result in learning better group problem solving processes for future efficiencies. The data from any team problem solving, whether using the AI or not, can serve to augment and grow the data base from which the AI can be trained.

- ***AI adoption might be disruptive, but it doesn't have to be.*** We recognize that for many designers, especially those not trained in the area of AI, there is a need to begin reskilling these workers and managers to enable them to take advantage of future AI capabilities (Williams et al., 2022). Disruptive transitions can be smoothed by early adoption of components of the future technology. Considering an analogy of autonomous consumer vehicles, vehicles today provide nonverbal cues and instructions to drivers that could be worded as "A car is in your blind spot on your left", "Traffic congestion in 2 miles", and "brake now!!!". As consumers witness the abilities of these components and learn to trust them, the shift to autonomous driving lessens in magnitude. Similarly, components of AI-as-Partner and AI-as-Guide capabilities can be progressively employed in teams, enhancing near term results while equipping companies' teams for future success.

AI can stay on task, assess deep data and reach conclusions based on analyses in some precision. This capability advances the accuracy, quality and efficiency of problem solving. However, past research has emphasized the benefits of maintaining the human in the loop. This is an important lesson, as humanity has learned through several industrial revolutions, that a solution that beneficially combines humans with technology will almost always be better than technology alone. Although the capabilities of AI are increasing, the human is still broadly adaptable, creative, and able to translate across appropriate mental representations. The human can also evaluate the context of a problem and should have the expertise to assess that the solution direction is appropriate. Consider the use of an online map app where the user enters the wrong location or the app interprets it incorrectly. The user should assess that the goals of the directions are correct, or choose the route that addresses their overall needs.

As with any new capability, if the users on the team understand how it works, what its decisions are based on, and its limitations, the adaptation of the technology and the value of its application will increase. Companies must upskill their engineers to have a base level of capability in AI and ML if they wish to maintain any current competitive advantage.

CONCLUSION

This paper explores different archetypes of human-AI collaboration through type of focus (problem solving vs problem solving process) and mode (reactive vs proactive) through a 2×2 matrix we call the AI-Human Teaming Matrix. We emphasize the importance of focusing less on what the AI can do and more on how an AI empowers a team to be more productive and creative. Reflecting back across all quadrants in the matrix we found that the AI can save time and effort for human team members, giving those team members the ability to apply greater time and cognitive resources towards other aspects of the team and task. As the field of design continues to evolve in the Fourth Industrial Revolution, the role of AI as a teammate will emerge with new capabilities and impact. The awareness of AI being

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proactive vs reactive and the focus on designing a solution vs designing the design process itself indicates capabilities that AI agents will need as these technologies develop in research and industrial application environments.

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