6. Refocusing human–AI interaction through a teamwork lens

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Alongside the rapid development and progression of AI algorithms, parallel efforts have been made to apply AI algorithms to human-facing systems. Over the last few decades, computational systems have been mostly relegated to automating basic and repetitive tasks alongside humans, thus creating human–automation interaction (Lee & See, 2004). However, the last few years have seen major strides made in artificial intelligence (AI) allowing for more dynamic and complex problems to be solved. What separates the technologies is that automation is often task-oriented and lacks the flexibility to handle changes in the task it was designed for (known as brittleness), but AI has the capability to handle tasks with dynamic features and may even have the potential to handle multiple tasks in a dynamic environment, which also makes it more capable of working alongside humans in these environments (Wynne & Lyons, 2018). For example, implementations of automation would include using a robotic system to repeatedly place a specific object in a delivery bin, but an AI system would be able to receive various items and sort them into different delivery bins based on various features such as color, shape, and even function.

Thus, recent developments have sought to incorporate complex AI systems alongside humans to build more efficient workforces and collaboratively solve problems that would be too complex and dynamic to be automated (O'Neill et al., 2020; Woods et al., 1991). The result of this process is human–AI interaction, which refers to both the physical and digital interactions that humans have with technological systems that are infused and governed by AI algorithms (Amershi et al., 2019). Unfortunately, while the field of human–automation interaction served as a suitable starting point for human–AI interaction research, the rapid growth in the computational capabilities of AI has more distinctly separated the technology from its automation predecessor (Lyons et al., 2021; O'Neill et al., 2020). Subsequently, the field of human–AI interaction is outgrowing its foundation in human–automation interaction, and a new research perspective is required to continue the advancement of the domain.

The increased variety and complexity that has separated AI from automation has in turn impacted the complexity and variety in human–AI interaction research, making the field unfocused (Yang et al., 2020). The unfocused nature of human–AI interaction that currently exists demonstrates that the needs and requirements of the field may not be fully sustained by adapting human–automation interaction principles. Consequently, to allow the field to build off existing literature and focus on existing principles, a different research paradigm should be prioritized as a foundation for human–AI interaction over human–automation interaction. This chapter argues that teaming is the most relevant paradigm through which the field of human–AI interaction can be focused due to three factors: the prevalence of teamwork in the modern workforce; the widespread use of AI systems by modern teams; and the fact that AI systems are becoming more like teammates and less like automation tools.

Given that this is a handbook of virtual work, we wish to make the observation that human–AI interaction, by its very nature, is virtual. Because virtuality *is by definition* involving interaction through technology (Kirkman & Mathieu, 2005), and AI requires a technological medium through which human–AI interaction is possible, the current chapter on human–AI interaction offers a unique perspective on virtual work. Moreover, modern and future virtual work will naturally involve a degree of human–AI interaction, such as through team task recommender systems (discussed later). Thus, the unique perspective provided by this chapter, which views human–AI interaction from a teaming perspective, will only become more relevant as the integration of AI and in turn the degree of virtuality present in teams that use AI will only increase as the technology continues to advance.

The following chapter is split into three overarching sections that outline the currently unfocused state of human–AI interaction and present teaming as a perspective that can be used by researchers to refocus the domain. Section 1 details the currently broad and unfocused state of human–AI interaction as well as the domain's current attempts to consolidate research efforts. Section 1 additionally provides five different examples of real-world human–AI interaction sub-domains and discusses their differences and impacts on modern teams. Section 2 details a solution to help refocus human–AI interaction, that is, viewing and conducting human–AI interaction research through a teamwork lens. More specifically, Section 2 outlines how the concept of teaming meets the requirements of human–AI interaction, provides unique research opportunities for human–AI interaction, and discusses current research in teaming-oriented human–AI interaction. Section 3 provides specific recommendations for research objectives and the teaming principles that will help complete the aforementioned objectives. Additionally, Section 3 takes the opportunity to provide recommendations for regulations and standardizations and discusses some open-ended questions regarding the current state of human–AI interaction research.

HUMAN–AI INTERACTION AND WHERE TO FIND IT

While the initial operationalization of human–AI interaction was a simple iteration of human–automation interaction where AI was trained to handle basic tasks efficiently, recent research efforts have shifted the design of AI towards something known as human-centered AI. The research, development, and implementation of human-centered AI looks to shift AI from being a task-oriented technology to being a technology that holistically considers their entire environment, which includes the task, the humans they work with, and their impacts on society. This shift towards human-centered AI has mostly been in response to public perceptions towards AI that highlight the potential negatives of the technology if it is not designed with humans in mind. Consequently, this shift in the perception surrounding AI research also further separates it from human–automation interaction as automation is often more heavily oriented towards task specific requirements, which makes the domain limited in its ability to handle the requirements of human-centered AI. Thus, this section highlights these requirements through two main contributions: (1) a detailing of the current state of human-centered AI and the public perceptions that led to a shift towards that perspective, and (2) a discussion of various applications of human-centered human–AI interaction that demonstrate the variety and breadth of the field.

Public Perceptions on AI and Responses to Those Perceptions

Trending perceptions about AI

Due to the broader integration of AI technology into society in recent years, many researchers have taken a step back to examine the current challenges facing the human factors comprising human–AI systems. While research communities often see AI as a promising technology that is much more flexible and adaptable than its automation predecessor, societal perceptions often concentrate on the potential negatives of the technology. For instance, media outlets often emphasize the adverse outcomes of AI without balancing that coverage with the positive potential of the technology (Brennen, 2018). Moreover, these common perceptions boil over into other forms of media and representation that impact peoples' perceptions of AI. Examples of this media include popular film and TV series such as *The Terminator*, *Blade Runner*, *Ex Machina*, and even *Westworld*. While these depictions of AI appear highly fictional, especially to researchers, the concerns they raise can be valid, and they can often inspire negative perceptions of AI technology in society (Cave et al., 2018). Fortunately, these concerns and negative perceptions have since inspired new research centered around addressing the deficiencies and challenges facing the roles and implications of AI systems in society.

Responding to society's concerns with human-centered AI

Due to societal concerns, recent research efforts to improve human–AI interaction and societal perceptions of AI technology have led to an emphasis on a concept known as human-centered AI. Human-centered AI shifts the focus towards making AI systems responsible and capable actors within society, which includes improving their compatibility with humans alongside its technological capabilities (Xu, 2019). For instance, bias of AI systems has become highly talked about recently due to its clear and identified impact, and researchers have begun not only outlining its effects on society but also proposing solutions to prevent biased AI systems from impacting society (Ntoutsi et al., 2020). Other popular topics of research include the design and implementation of explainable AI systems, which seeks to remove the common concern around questionable black-box algorithms (Abdul et al., 2018). Additionally, work is being done to examine the holistic experience humans have with the systems as opposed to their initial reactions, which is key to understanding how traditionally social concepts and perceptions may impact system acceptance and use in the long-term (Knijnenburg et al., 2012). Efforts to build more human-centered AI systems are not limited to the above examples; however, the variety of the above examples demonstrate the current breadth of human-centered human–AI interaction research and having a consolidated research foundation is critical to ensuring that all of these concerns are addressed not only individually but holistically as well.

Attempts at consolidating human-centered AI research

Additionally, internal work is still being done to explicitly refocus and consolidate human–AI interaction research to provide more convenient lists for researchers and practitioners to follow when designing AI systems. A recent landmark publication in human–AI interaction consolidated various efforts to provide researchers with a holistic list of essential design considerations outlined by practitioners and researchers. These considerations were derived from modern AI systems and include, but are not limited to, adherence to social norms, mitigation of bias, clearly defined capabilities, and constant transparency (Amershi et al., 2019). Each recommendation was derived from literature in specific sub-domains of human–AI interaction, and each looks to research and optimize specific AI technologies for use by humans.

Unfortunately, while providing researchers and practitioners with eighteen helpful guidelines, this work also demonstrates the almost unmanageable complexity of human–AI interaction. Additionally, while some of these guidelines have a foundation that can be derived from human–automation research, many of them are unique to human–AI interaction and may be hard to design for without a foundation derived from previous research. Thus, while the guidelines outlined by this work and others are critical human–AI interaction, the operationalization of each of these guidelines for every system built is a daunting task that most likely will not be accomplished. Moreover, this task becomes more complicated when one accounts for the rapid pace that the field of AI is developing at, which necessitates rapid acceleration in the field of human–AI interaction, meaning this list will need to change constantly.

Seeing Human–AI Interaction in the Wild

Now that the current state of human-centered human–AI interaction has been outlined, it is important to discuss various implementations of human–AI interaction, and in doing so, the breadth of the field can be demonstrated while also highlighting common goals that are shared between different sub-domains. First, AI-enabled recommender systems will be discussed, which are applications that filter large amounts of data to provide users with a small selection that is more manageable. Second, AI-enabled management systems will be addressed, which refers to systems that utilize AI technology to coordinate and assign teams' resources and personnel so humans can focus on other, less data centric tasks. Third, virtual agents will be highlighted, which represent a sub-domain in human–AI interaction that often looks to use AI to make effective social interactions with humans through virtual characters. Fourth, AI-enabled robots, which utilize AI algorithms to physically interact with humans and other objects, will be reviewed. Finally, self-driving vehicles, which are automobiles that are controlled either partially or completely by computational AI algorithms, will be analyzed. These five sub-domains also represent different manifestations and roles of AI technology that differ widely between each other.

AI-enabled recommender systems

One of the most common utilizations of human–AI interaction is in the sub-domain of recommender systems. Recommender systems often use AI and machine learning algorithms to filter vast arrays of options down to smaller, more manageable selections that humans can choose from (Resnick & Varian, 1997). These systems are often incorporated in contexts ranging from media content platforms (i.e., YouTube or Netflix) to e-commerce sites (i.e., Amazon or eBay). Such systems can be critical in helping teams make fast and accurate decisions by removing options that do not merit human consideration (Wu et al., 2020). Interactions with these systems are often more minor as humans generally interact with the data provided by the system rather than directly interacting with the systems itself. While more interactive recommender systems have been created, they often utilize other interaction techniques, such as virtual agents, to facilitate human interaction.

AI-enabled management systems

Virtual management systems often take more generalized roles and provide basic assistive duties, such as scheduling, information retrieval, or resource management for teams or individuals, and they have seen their role increase significantly in the past decade due to the rise in popularity of smart home assistants and scheduling management systems (Perez Garcia et al., 2018). Like recommender systems, virtual management systems are critical in modern society as they provide a way for teams and individuals to offload simplistic tasks that computers are more capable of handling efficiently. For instance, healthcare AI systems are frequently required to adapt on the fly to the dynamic availability of healthcare professionals and the wants and needs of patients (Yu et al., 2018). While management systems are required to be highly in-tune with the teams they service they often minimize the amount of direct interaction humans have with them. These considerations result in systems remarkably different from other AI systems. Their degree of autonomy needs to be more significant to minimize the need for human intervention, allowing humans to focus on other essential tasks that AI cannot handle, thus resulting in minimal but critical instances of human–AI interaction.

AI-enabled virtual agents

Virtual agents often provide the greatest interaction for humans; however, the actual interaction and conversation are often seen as the most critical aspect of their design. Typical representations of virtual agents include video game characters or agents that handle humans' interactions with AI-enabled management systems. However, the goals of these agents often center not around their technical abilities but around their ability to interact with humans positively. For instance, anthropomorphism, including voice selection, graphical representation, and natural language ability of virtual agents, become critical factors in determining the content and quality of interactions humans have with these assistants (Rafailidis & Manolopoulos, 2019). Interactions with these agents are often more prolonged and social, but these systems become more practical when implemented as an interaction modality for a more complex technology.

AI-enabled robotic systems

AI-enabled robotics refers to using AI models to complete necessary robotic functions, such as "learning, planning, reasoning, problem solving, knowledge representation, and computer vision" (Murphy, 2019). What separates robotic systems from other examples of human–AI interaction is that the tasks they look to complete and their interactions with humans often occur in a physical space and require the manipulation of physical objects. Popular examples may range from home robotics, such as automated appliances (i.e., Roombas), to complex manufacturing systems, such as vehicle assembly systems. The usage of these systems is critical to modern teams as they can alleviate the physical stress and requirements of specific workloads while also fully enabling individuals to complete tasks not typically possible. Unfortunately, their emphasis on physical environments and physical safety can often make it more difficult to bridge research from other, more digital sub-domains within human–AI interaction (Khandelwal et al., 2017).

AI-enabled self-driving vehicles

Finally, a rapidly growing instance of human–AI interaction is self-driving vehicles, where AI systems can either partially or entirely operate a vehicle. This technology can help revolutionize modern society by providing individuals incapable of driving a means of transportation while also providing a safer and more convenient environment for humans. Specifically for modern workforces, the advent of autonomous vehicles will allow individuals to utilize their cars as mobile offices that allow them to work during their commute, thus reducing overall downtime. Additionally, entire fleets for delivery and transportation have the potential to become autonomous. Interactions with these systems can differ greatly based on the level of autonomy the AI systems has, with low levels needing interactions extremely similar to normal vehicles and high levels of autonomy requiring extremely simplistic interactions often done through apps. Like general robotics systems, the physical safety of self-driving vehicles is often researched; however, larger-scale scheduling problems also become a concern due to the potential multitude of vehicles that can exist simultaneously (Badue et al., 2021).

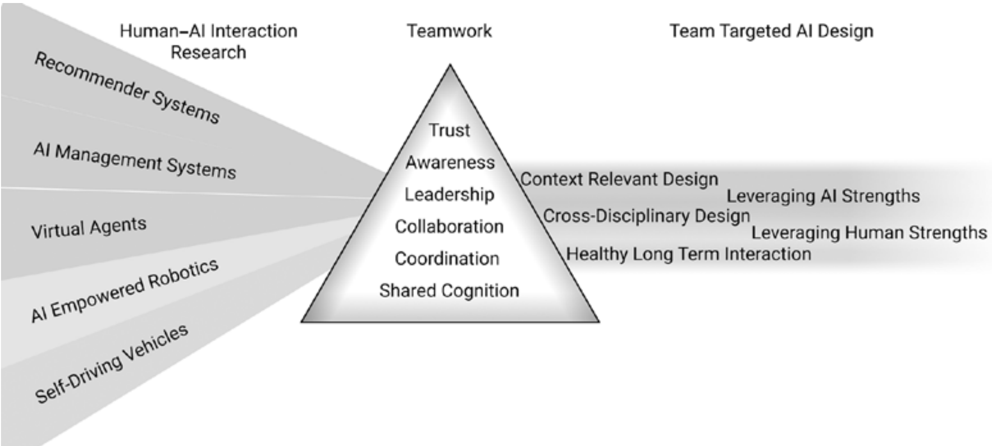
The five sub-domains outlined above in addition to the prior discussion on human–AI interaction's recent expansion create a picture of a research domain that is currently unmanageable for individual researchers to fully comprehend, especially when using a perspective solely derived from human–automation interaction. The above domains illustrate various roles and responsibilities created for AI systems, many of which are dynamic in nature and execution. Thus, a new approach to human–AI interaction is needed that meets the needs of human–AI interaction research, provides a common starting point for research to relate to, and helps bolster and ground the results of researchers in the community.

USING A TEAMING PERSPECTIVE TO REFOCUS HUMAN–AI INTERACTION

To help focus the field of human–AI interaction, this chapter proposes the use of a teamwork perspective where AI is a team member as opposed to a tool for automation, which has multiple benefits to the field of human–AI interaction. First, the field of teaming has decades of research with topics including the use of technology by teams, teammate perceptions and their impacts on teaming, and even the ability for humans to team with non-humans (Salas et al., 2005). Using this past literature will greatly benefit the field of human–AI interaction as many new and popular research concepts can be bolstered through highly similar and more researched concepts within teaming. For instance, the popular research topic of awareness in human–AI interaction would heavily benefit from a strong foundation in team cognition, which is a topic in teaming with decades of research demonstrating its measurement and benefit to teams.

Second, teaming provides a host of unique research topics that have yet to be fully explored in human–AI interaction but would provide a needed foundation for future, critical research. For instance, the concept of leadership in human–AI interaction, which is currently understudied in human–AI interaction would be effectively "jump started" using teaming literature, thus increasing the pace at which critical research can be conducted and verified (Flathmann, Schelble, & McNeese, 2021; Larson & DeChurch, 2020).

Finally, the examples of human–AI interaction highlighted above all have real-world applications within teaming, with manufacturing teams heavily utilizing robotics systems (Cherubini et al., 2016), healthcare teams becoming reliant on virtual management systems (Sezgin et al., 2020), and analytics teams utilizing recommender systems to increase productivity (Damiani et al., 2015), just to name a few examples. Thus, the teamwork lens also provides an explicit path towards integrating human–AI interaction research into real-world systems and the teams that will inevitably use them. The above justifications for the use of a teamwork lens when conducting human–AI interaction research (represented in Figure 6.1) will be further elaborated on below with specific examples on teaming concepts that could be highly relevant to human–AI interaction.



Source: Author's own.

Figure 6.1 *Graphical metaphor representing the use of teamwork as a focusing mechanism for human–AI interaction*

Teaming is a Standard for Human–AI Interaction

As mentioned above, when viewed as a standard for interaction, teaming can become holistically inclusive of the requirements and considerations outlined by human–AI interaction research. Moreover, AI supported teamwork, a sub-domain of both human–AI interaction and teamwork, necessitates a stronger adherence to human–AI interaction design considerations as the impacts of agent design and their interactions with humans are observably apparent through teamwork. For example, trust, a critical component of human–AI interaction (Glikson & Woolley, 2020), has been heavily researched within the field of teamwork (Costa, 2003). Fortunately, the existence of a robust research foundation around trust made it much easier to develop and validate the importance of trust in AI supported teams (McNeese et al., 2019). This finding is but one of many examples of teamwork research having a firm and historical foundation that new research is finding important to human–AI interaction. Unfortunately, without a teaming perspective, human–AI interaction would lack a historic and studied foundation that allows modern research to build on historical findings. While lacking this foundation would not prevent human–AI interaction research from being conducted, it will ultimately hinder the pace at which this research can occur as the prior research foundation from which experiments and hypotheses can be derived has not yet been fully established. Utilizing a teaming lens provides that foundation and experimental history, allowing for a natural starting point for researchers and practitioners to hypothesize how AI's design and development may impact humans through interaction.

Additionally, it is essential to note that the utilization of teaming as a scoping mechanism does not require the evolution of AI platforms to a level that is comparable to humans. Using a teaming perspective allows the collaboration and coordination of multiple different entities, regardless of their ecology. Historically, teaming has not been a phenomenon exclusive to humans, as animals have been shown to possess the ability to form and operate within teams of varying complexity (Anderson & Franks, 2001). Moreover, teaming provides a means of removing the barriers between these ecological differences, with humans and animals having teamed up for centuries. Research has even shown that the model of human–animal teams is a robust and comprehensive example for human–robot interaction as language and interaction barriers must be overcome in similar ways (Phillips et al., 2016). Thus, the variety of sub-domains within human–AI interaction can not only be accounted for by teamwork, but their unique strengths can be leveraged through teaming.

As a final note, the ability for teaming to bridge ecological barriers also extends to its ability to bridge technological barriers. As mentioned above, the concept of teamwork is already familiar to recommender systems, virtual agents, virtual management systems, self-driving vehicles, and robotics research. Thus, bridging the gaps between these domains and allowing cross-collaboration can be more easily facilitated through the shared commonality of teamwork. The key to this collaboration is understanding the unique roles humans and AI's can take to create interactions that are more than the sum of their parts. When viewed and implemented through a teamwork lens, human–AI interaction can ultimately create meaningful interaction regardless of the entities of the team, the team's environment, or goals.

Unique Affordances Provided by a Teamwork Perspective

Tying human–AI interaction concepts to more robust teaming concepts

Beyond meeting the requirements for human–AI interaction, adopting a teamwork perspective also provides unique affordances that will advance the field of human–AI interaction. These affordances are supported by the extensive amount of literature focused on studying traditional human–human teamwork. The affordances offered by the existing human–human literature give human–AI interaction researchers an advantage not offered to virtually any other field of research. Specifically, human–AI interaction can benefit by leveraging the well-known tools, concepts, and strategies from human–human teams to enhance things like cohesion between the human and the AI (Mou & Xu, 2017), levels of effective shared understanding between the two (Schelble et al., 2022), and even bias mitigation (Flathmann, Schelble, Zhang et al., 2021). Human–AI interaction can uniquely benefit from using the foundation developed by human–human teaming for several reasons, specifically, that teams are widespread in our society, existing in a wide variety of different environments and situational contexts. This diversity in application and theory makes adapting the traditional human–human teaming research to human–AI interaction far more manageable than starting from scratch.

Human–human teaming is ubiquitous across the various contexts of the workforce, which means it exists in nearly every application and domain that AI may one day play a role. This ubiquity gives researchers a significant head start in researching and improving human–AI interaction in settings like healthcare and entertainment while also anticipating the various roles AI may one day play in our society. Using the healthcare setting as an example, human–

human teaming researchers have discovered several concepts, guidelines, and tools specific to improving teaming in healthcare (Weller et al., 2014). These improvements benefit not only the teams themselves but tangential outcomes like medical device design and training programs, all of which are tied to the teams' overall goal of patient outcome.

Developing valuable insights in human–AI interaction can be advanced by adopting various concepts of team dynamics from human–human teaming literature. By its very nature, human–AI interaction is research into the dynamic relationship between the human and the AI they are engaging with to complete a task or query. As such, the teamwork perspective has a great deal to offer in the way of valuable concepts, frameworks, and instruments. For example, several concepts within human–AI interaction would benefit from being framed through teaming concepts like team cognition and awareness. Human–human teaming has been developing the concept of team cognition for decades (Orasanu, 1992), which embodies the idea that individuals within a team have shared knowledge that is organized and distributed amongst themselves (Cannon-Bowers et al., 1993). This concept and even its measurement tools can easily be adapted and applied to essentially any human–AI interaction; however, more importantly, it provides a validated and practical framework to improve the shared understanding and effectiveness of human–AI interactions. Alternatively, awareness provides an example more deeply rooted in design principles but has long been of significant importance to both practice and theory. Awareness describes how individuals within a collaborative environment know what others are doing, why they are doing it, and how this relates to their activities (Dourish & Bellotti, 1992; Gross, 2013). Given how important explainable AI and transparency have become in the various guidelines to human–AI interaction, the teaming concept of awareness represents decades of work that can be quickly and easily adapted to frame better human–AI interactions.

Transitioning difficult concepts from teaming

Expanding human-centered AI design to meet the requirements of teaming necessitates unique design considerations for AI agents that need to be further developed and researched. Certain teaming concepts can enhance multiple aspects of human–AI interaction like usability, trust, and efficiency. Unfortunately, these concepts may not be as easily transferred to human–AI interaction contexts. Such concepts require a better understanding of the unique dynamics between humans and AI, especially in teaming. These gaps have begun to be addressed by the literature, but a great deal of work remains. This challenge is exacerbated by the breadth of the current work in human–AI interaction as many sub-domains within the field are closely related to these two specific concepts like AI-managed agents, while others are far more distant, like recommender systems. It is worthwhile to conduct this future research and place human–AI interaction into the lens of teaming so the disparate contexts within the field can begin to work from the same models and theories, reaping more benefits from one another's work.

For instance, leadership is a monumental construct within the teaming literature with several models, theories, and empirical work (e.g., Morgeson et al., 2010); however, these concepts do not directly port to human–AI interaction because of the unique role AI takes in the relationship of human–AI interaction. Thus, while leadership dynamics have clear ramifications for human–AI interaction in systems where humans interact with an AI they perceive as subordinate or vice versa, additional steps must be taken before human–human leadership principles can be applied to human–AI interaction. As another example, influence describes the effect that one users' experiences, perceptions, and actions have on other team members in any capacity, but generally on their perceptions, actions, and effectiveness (Gruenfeld et al., 2000). This concept deals directly with interpersonal dynamics in teaming and has significant implications for human–AI interactions, but again, unfortunately, there is a dearth of literature analyzing influence between humans and AI. Though AI research is still in its relative infancy, that is no reason not to look towards the future and address these challenging concepts, advance the field, and ensure we are genuinely prepared to implement applied AI for human interaction.

Current human–AI interaction work viewed through a teaming lens

The teaming community has begun to recognize the importance of integrating existing teaming concepts with AI teammates, producing valuable research for human–AI interaction design (O'Neill et al., 2020). This research can be seen as a stepping stone to producing research more applicable to applied human–AI interaction. For example, initial conceptual models have been developed for leadership in AI-supported teams (Flathmann, Schelble, & McNeese, 2021), human perceptions of the ideal AI teammate (Zhang et al., 2021), and human–AI cooperation (Schelble et al., 2021). While team cognition is not as distinct from human–AI interaction as leadership and awareness, it has also received attention to determine how the concept in humans is affected by AI (Schelble et al., 2022). Applying the findings from this research into design applications for human–AI interaction is the next step in reframing human–AI interaction research and requires heavy collaboration between practitioners and researchers.

Shaping and designing AI to promote teaming

Once a strong connection between teaming and human–AI research communities is established, efforts can be made to deploy teaming principles into real-world human–AI systems rapidly. This connection is critical as reducing the lag time between the establishment of frontier research and considering that research in real-world system design is critical to improving user experience and overall perceptions of AI systems. This deployment will revolve around creating and implementing design recommendations for AI systems that specifically target teamwork functions in human–AI interaction. Beneficially, the field of human–AI interaction also places a heavy emphasis on design recommendations for real-world systems. This benefit ensures that the research community is not uprooted and forced to incorporate the practice of developing design recommendations, and instead, the existing recommendations only need to adopt a teaming mindset.

Early design recommendations will need to focus on the actual individual behaviors of AI systems and how their design impacts and considers teaming principles. These recommendations will generally target the task-level functionality AI systems have with the teams that interact with them. For example, design recommendations may center around the inclusion of critical human factors, such as awareness or acceptance, and how AI systems should consider these factors alongside technical performance when deciding on what action to take. Currently, some preliminary work is being done in this area through a teaming perspective to examine the balancing of an AI's technical capabilities and its compatibility with human collaborators (Bansal et al., 2019). However, this work does not represent the majority of human–AI interaction work, and a greater number of researchers and studies are needed to create a wealth of design recommendations for AI practitioners.

Second, design recommendations need to be researched and made for the mediums and modalities humans use as support technologies for human–AI interaction. While AI systems are often seen as standalone agents with their own personal interaction mediums, future systems would benefit from tighter integration with other teaming processes and technologies. For instance, groupware used for team collaboration provides a highly opportunistic entry point for virtual agents to interact with humans. The interlinking of groupware and AI systems would allow for a more natural integration of AI systems into teaming processes as teams, especially virtual teams, would already be comfortable interacting through the digital medium. Additionally, reducing the number of and simplifying these interaction modalities would reduce the overall complexity and overhead of implementing human–AI interaction into teaming environments, which would help overall acceptance and usage of the technology. Work has already begun in this area, with research efforts targeting the changes that need to be made to modern groupware systems to facilitate AI better by utilizing its unique strengths to improve the overall groupware experience (Flathmann et al., 2020). This work is an example of how a teaming perspective on human–AI interaction improves the contributions of individual actors and has the potential to use AI as a separate supportive technology for human–AI interaction.

Finally, work needs to be done on the actual evaluation of AI systems' impacts and acceptance in real-world teaming environments. While design recommendations are helpful for implementation, feedback from actual users is critical in the development of AI systems for human–AI interaction. Thus, if a teaming perspective is taken into consideration, the final stage of integrating that perspective would be to elicit feedback from real-world teams on their experiences, preferences, and needs of human–AI interaction. Fortunately, leveraging human–human teaming literature also provides a substantially stronger foundation to work from, giving human–AI interaction researchers valuable measurement tools that have already been developed and validated, requiring only minor adjustments for their specific use cases. This advantage can be exemplified by the premise of studying trust in human–AI interactions. For instance, feedback regarding humans' levels of trust with AI systems can be more easily measured using existing teaming measures, such as organizational trust (Mayer et al., 1995), team trust (Jarvenpaa et al., 1998), team member trustworthiness (Jarvenpaa et al., 1998), the propensity to trust (Jarvenpaa et al., 1998), and cognition-based trust (McAllister, 1995). This feedback from users and real-world measurements would then be directly looped back into the research, design, and production of AI systems to be used by teams.

Using the three methods described above for using a teamwork lens to conduct research will result in human–AI interaction transforming into human–AI teaming research. The goal is for AI systems to become more than a simple tool and rather top function as a teammate by having a greater level of autonomy, a specific role, and a constant presence on their assigned team (O'Neill et al., 2020). Conducting human–AI teaming research merits the ability for researchers to create active AI systems that holistically consider their individual task, the current state of their assigned team, and other environmental considerations. This approach ensures that interactions between humans and AI systems are not only human-centered but that the interactions themselves do not exist in a vacuum that is not applicable to other research environments or the real world. Conducting human–AI teaming research allows researchers to ensure the requirements of human–AI interaction are met while also going a step further to provide AI systems with the unique strengths inherited from being a teammate rather than a tool.

REDEFINING HUMAN–AI INTERACTION AND ITS RESEARCH TRAJECTORY

With an understanding of what human–AI interaction has the potential to look like through a teaming lens, it is vital to understand how this mindset shift should be realized in the coming years. Unfortunately, the current state of human–AI interaction is ultimately due to a lack of standardization in the community. While that standardization was initially forwent to encourage human–AI interaction research to keep pace with computational AI research, the lack of standardization has ultimately led to an unfocused and fragmented research domain. While attempts have been made to consolidate those fragmented research efforts, those attempts have only further highlighted the unmanageable state of human–AI interaction research that ultimately hinders its consideration in real-world AI systems. This chapter ultimately proposed the transition from human–automation interaction to teaming as the best lens to view human–AI interaction through as it provides a solid research foundation in previous literature and a means of directly linking human–AI interaction in research environments to real-world environments. However, while the presentation of this alternative domain demonstrates its applicability and utility to human–AI interaction, it is still necessary to explicitly outline the actions that need to be taken in the coming years to solidify the contributions of teaming to human–AI interaction and vice versa. Thus, this section will outline the immediate goals for the next decade for human–AI interaction research when taking a teaming perspective.

Additionally, the section will recommend standardizations and regulations for the human–AI interaction community derived from teaming, which will be critical to maintaining a focused nature in the human–AI interaction community. Finally, this section will close with a discussion of possible points of consideration and research questions that future human–AI interaction and human-centered research will be able to answer when looking through a teamwork lens. Ultimately, while the above contributions are crucial to demonstrating how human–AI interaction can be better focused and consolidated through teaming, the remaining discussion details the immediate action items that need attention to advance human–AI interaction in research and real-world contexts in concert.

Specifying Important Research Objectives and Relevant Teaming Literature

With human–AI interaction being viewed through a teaming lens, the coming decade presents a tremendous opportunity for meaningful advancement in understanding the relationship between humans and AI. As AI becomes more ingrained in our society through several of the technologies discussed in the current chapter, like self-driving vehicles, robotics, and virtual agents, the opportunity and necessity to make these advancements are necessary. It is essential to address these challenges in human–AI interaction to accomplish what human–computer interaction has done for decades: develop better design guidelines and solve design problems *before* deploying emerging technologies. What is more is that these challenges must be met at an unprecedented pace given the rapid technological advancements being made in AI, which is made even more difficult given the time-consuming nature of human subjects research. Many researchers have begun to help make these strides through human–AI teaming (O'Neill et al., 2020), tackling challenging topics such as awareness (Dubey et al., 2020), perceptions (Musick et al., 2021), trust (McNeese et al., 2021), coordination (Musick et al., 2021), and practical integration (Flathmann et al., 2019; Schelble et al., 2020). This collection of AI-supported

Table 6.1 *Examples of related literature to help frame multiple goals in different human–AI interaction contexts*

Research Objectives	***Human–AI Interaction Context***	***Relevant Teaming Literature***
Design transparent AI systems that are explainable by the end-user	Self-Driving Vehicles, Recommender Systems, Virtual Agents, AI-Enabled Robotics, Management Systems	Designing for Awareness in Collaborative Teaming Technology (Dourish & Bellotti, 1992; Gross, 2013)
Determine the degree of anthropomorphism that is most compatible with human interaction	Virtual Agents, Management Systems, AI-Enabled Robotics	Anthropomorphism in Human–AI Teaming (Fraune, 2020; Ososky et al., 2013)
Develop evidence-based training programs and protocols to improve safety, efficiency, and performance	AI-Enabled Robotics, Management Systems	Team Training Development Guidelines (Burgess et al., 2014; Shuffler et al., 2018; Swezey & Salas, 1992)
Combat and mitigate to the highest degree possible bias in AI systems and their human users	Virtual Agents, Recommender Systems	Causal Mechanisms of Bias in Teaming (Ashworth & Heyndels, 2007; FitzGerald & Hurst, 2017)
Produce AI systems and interfaces that reduce automation bias and user complacency to improve effectiveness and safety	Self-Driving Vehicles, AI-Enabled Robotics, Management Systems	Complacency in Human–AI Teaming and Healthcare Teaming (Grissinger, 2019; Wright, 2015)

Source: Author's own.

teaming literature is an excellent example of how many different topics are being targeted, but each builds and contributes to the others through the common thread of teamwork (Table 6.1). The existing AI-supported teaming research has revealed several exciting findings relating directly to interaction and design, highlighting how using teaming metrics in human–AI interaction research allows data from real-world subjects to be collected and interlink theory with application. For example, design plays an essential role in developing awareness of the AI for human users (Mercado et al., 2016). Specifically, these trust factors were improved by conveying the AI's confidence level through an icon's level of transparency (Mercado et al., 2016). A finding improving trust is vital as many other human–AI teaming studies have revealed several indications that humans hold a particular bias against working with an AI teammate (Demir et al., 2018; Walliser et al., 2017), especially when the number of AI teammates outnumbers them (Musick et al., 2021). Finally, there are several unexplored areas in AI-supported teamwork that would massively benefit human–AI interaction as a whole that require additional research. These topics include a need for more field studies, a focus on team cognition and influence, and achieving higher collective performance by AI-supported teams.

Standardizing and Regulating Human–AI Interaction to Ensure Human-Centeredness

In addition to understanding the next research steps facing human–AI interaction, it is also important to outline some needed standardization and regulation currently void in the domain. While the goal of this chapter is not to fully outline all needed regulations in the human–AI

Table 6.2 Example regulations or standards for human–AI interaction and teaming research and practice provide solid foundations

Human–AI Interaction Context	***Standardization & Regulation***	***Example in Teaming***
Self-Driving Vehicles	Regulation Regarding the Safety Standards and Liability of Non-Human Operated Vehicles	Occupational Safety and Health Administration (Wiseman, 1995)
Recommender Systems	Regulation of the Level of Interference in Recommendations from External Sources	American Bar Association Model Rules of Professional Conduct (American Bar Association, & Association), 2020)
Virtual Agents	Standardizations that Limit and Monitor the Communication of Disinformation to End-Users	Deception in Collaborative Virtual Teams (Twyman et al., 2020)
AI-Enabled Robotics	Standardization of Training Practices with Robotic Systems	Team Training Guidelines (Burgess et al., 2014; Swezey & Salas, 1992)
Management Systems	Regulation on the Communication of Protected and Sensitive Data to Different Human Operators	Health Insurance Portability and Accountability Act (Chan & Lee, 2020)

Source: Author's own.

interaction space, it is still worth demonstrating how teaming standardization and regulation can be used to directly inform the human–AI field, thus improving the quality and pace of creating human–AI regulations and standards. Additionally, there is currently a large void of government regulation that consistently leads to questions regarding liability when dealing with the consequences of AI systems. Some domains have begun including this regulation, such as management systems and newly created data privacy laws (Goldfarb & Tucker, 2011); however, sub-domains such as self-driving vehicles are harmed by a lack of needed regulation (Brodsky, 2016). Table 6.2 provides an example of how teaming research can help inform regulations or standardizations for each of the discussed sub-domains in human–AI interaction. Table 2 is not meant to be the final word; however, we offer it as a starting point.

Important Considerations and Closing Thoughts on Human–AI Interaction

We believe that it is vital to take a step back and evaluate the current trajectory of human–AI interaction and ask critical questions regarding how that trajectory and the goals of the domain need to change. This chapter ultimately provides this evaluation by posing questions regarding human–AI interaction and providing light discussion from a teamwork perspective. Ultimately, it is up to the community to decide the answers to these and other questions; however, the goal of presenting them is to ensure teams, which are predominant in the environments being targeted by human–AI interaction, are critically considered in the research domain when moving forward.

If teaming is not exclusive to humans, does AI need to be made in humanity's likeness? A large portion of computational AI research and human–AI interaction research currently seeks to artificially replicate human performance levels and human intelligence. While this is a noble effort, it is important to consider if this is the correct approach to building AI systems, especially when interacting with humans through teaming. Earlier, this chapter discussed how teaming provides a means of viewing interaction and collaboration without requiring humans for that interaction. Ultimately, human–animal teams do not seek to replace humans with animals but utilize the unique strengths of humans in concert with the unique strengths of animals to create effective teams. The same should be valid for human–AI interaction, and this is clear when taking a teaming perspective. Teaming allows AI systems to exist as their own entity and not as an inferior form of humans, which inevitably leads to unrealistic expectations of the AI and an overall negative experience for the user. AI systems excel at data processing, scheduling, and other computation-heavy tasks, often difficult for humans. On the other hand, humans are social beings that work best in social roles and environments. Thus, chasing the dream of AI becoming a replicant of humans ignores the strengths of both parties. The research community will have to determine if humans should remain the finish line for AI advancement moving forward.

Is it possible, and is it desirable for Human–AI interaction to maintain pace with AI research? A large portion of this chapter discusses how the pace of human–AI research can suffer from fragmentation and cause it to lag behind computational AI research. While this chapter removes those hindrances by using a teamwork lens, it is important to ask if human–AI interaction research should maintain pace with computational AI research. Traditionally, safety regulations and concerns regarding human subjects research provide a hurdle that slows the research community and is also integral to its ethicality. Unfortunately, real-world systems are often tested on humans without the same care and attention to ensure industry-led research maintains pace with its own computational AI research efforts. Ultimately, maintaining this pace in this way can harm the research in the long term, especially in the way of the acceptance and trust humans have for systems tested this way. Thus, the research community must standardize AI technology and the process of human–AI interaction research to ensure the safety and comfort of humans. Unfortunately, this decision may slow down the pace of research and cause it to lag behind computational AI research, but the potential harm caused by unsafe human–AI research is grand. Thus, the community will need to answer this question and determine how the integration of AI systems should be researched while still ensuring that research is timely and safe.

In conclusion, while great work has and is being done in the field of human–AI interaction, its unfocused nature prevents the domain from reaching its full potential. Not only does this fragmentation slow down overall research but it also hinders the ability for researchers to connect their work to others in the domain, which is one of the most important goals in conducting research. The teaming perspective provides research in human–AI interaction with the opportunity to build from a solid foundation created from decades of research and also provide a critical point of commonality between research work. Moving forward, utilizing a teaming perspective when conducting research will not only accomplish important research goals in human–AI interaction, but it will also help AIs integration into society and also ensure the goals of human–AI interaction are optimal for both the technology and the humans using it.

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