Human-Machine Teaming: What Skills do the Humans Need?

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ABSTRACT

Over the last few decades, technology has become increasingly intelligent. Technology is no longer a passive tool that supports a single human in their work, but an active teammate that collaborates and learns as a critical entity of the team. To date, human-machine (H-M) teaming research has primarily focused on the machines – how to design them, what their capabilities are, and how they can "learn." This conceptual paper takes the opposite view, focusing on the importance of selecting and training *humans* to be effective H-M teammates. To that end, this paper will address two questions: What unique skills do humans need to work well with machines as teammates, and how are those skills different from those required for effective human-human interactions? The challenges that H-M teams face drive the identification of the human skills. For example, humans are fundamentally biased to anthropomorphize machines and expect them to act like other humans (Proudfoot, 2011). Consequently, humans expect to understand and predict how and why machines are making their decisions. When machines do not act in accordance with human expectations, trust and coordination between humans and machines quickly break down (Mueller, Hoffman, Clancey, Emrey, & Klein, 2019). To mitigate this effect, we build machines with explainable AI to provide humans with insight into their decision making (Mueller et al., 2019). We can also improve H-M teaming by selecting humans who have individual traits such as openness to new experiences, tolerance for ambiguity, and high propensity to trust. Humans can be trained on perspective taking skills to understand how machines make decisions (Galinsky, Ku, & Wang, 2005). In addition, identifying the skills humans need to work with machines, this paper will make suggestions for how to train humans and machines together for effective H-M team performance (Nikolaidis & Shah, 2013).

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INTRODUCTION

Over the last few decades, technology has become more intelligent, working with humans in diverse ways. Technology is moving beyond the role of a passive tool supporting the work of a human; instead, technology is frequently engaging and interacting with humans as an active and vital team member. Human and machine interactions have rapidly progressed from actions like word processing to machines acting as physical and cognitive aids to augment human tasks. Consider Amazon warehouse workers who have machines help them find stock and ship out packages; or self-driving cars who make our commutes safer and more efficient by taking in and applying information about traffic patterns, obstacles, and lane lines. These smart machines and artificial intelligence (AI) can also help support humans in jobs with complex cognitive requirements. Some AI can serve as cognitive aids, supporting humans on tasks that require deep thinking. For example, AI can help analysts at work by sifting through data to find what is most important for decision making. Like a human team member, AI can anticipate human needs and learn preferences for what information humans want and when.

Smart machines and AI are changing the fundamental nature of how we view team membership and how those members work together to achieve team goals. Traditionally we have thought of teamwork as relationships between humans. In human teams, we think about coordinating work between team members, ensuring complementary expertise, building trust and cohesion, and making sure personalities don't clash. Now, humans are working with machines, making teaming different, if not more complicated. To fully realize the benefits that AI can have on organizational effectiveness, efficiency, and other outcomes, it is critical to ensure that both the human and machine team members have the knowledge, skills, abilities, and other attributes (KSAOs) necessary for effective team performance. These KSAOs should not only help both human and machine team members complete their independent tasks, but also help the collective function effectively as a team.

Research on human-machine (H-M) teams and artificial intelligence (AI) is traditionally housed within the computer science literature or other similar domains. That research has primarily focused on the machine – how to design machines, what their capabilities are, and how they can "learn." Substantial effort has been spent on designing machines to work well with humans. For example, making sure the machine can explain itself so the human can trust its's recommendations (Mueller et al., 2019). However, it is also important to think about designing humans to work with machines. The purpose of this paper is to present ideas on how to best "engineer" the humans to work well in H-M teams. To do so, we begin by summarizing what is known about composing effective human teams and apply that logic to propose necessary considerations when designing H-M teams. We will discuss how H-M teams are different from, and similar to, human only teams. As well as which competencies are important to consider in humans working with machines.

HUMAN TEAM PERFORMANCE

Traditional human teams have been defined as "a distinguishable set of two or more people who interact, dynamically, interdependently, and adaptively toward a common and valued goal/objective/mission, who have been assigned specific roles or functions to perform, and who have a limited life-span of membership" (Salas et al., 2006, p. 4). As depicted in Figure 1, team performance is dependent on the states and processes of the team. Motivational states include constructs like cohesion and trust. They influence how motivated team members are to work together well as a team. Shared cognitive states includes things like shared mental models, which influence whether the team members know how to work together as a team. Processes refer to how team members behave together as a team (coordination, planning, backing each other up; Marks, Mathieu, and Zaccaro, 2001). Team performance is also a function of the individual member KSAOs.

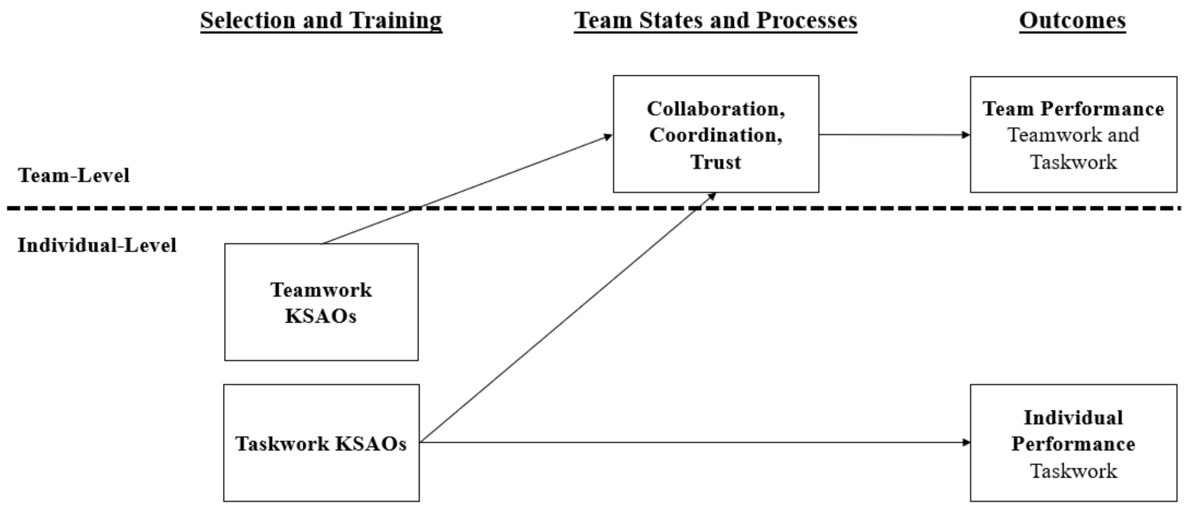

Figure 1. Individual and Team Competencies Impacting H-M Team Performance

ENGINEERING HUMAN TEAMS

The current paper focuses on the selection and training of human KSAOs as the critical interventions by which you can "engineer" the humans on H-M teams. As depicted in Figure 1, the way by which you engineer, or compose, the individual members of the team (through training or selection) has an impact on team performance. In traditional human teams, team composition refers to the overall mix of characteristics among people in a team, including the combination of knowledge, skills, abilities, resources, motivations, and communication styles of the team members. However, before we train and select, we need to understand what individual characteristics are most important.

Two questions are critical when considering the individual level KSAOs to select or train for. First, are the skills required for the task represented in the team members? Second, will the proposed team members work well together? These questions get at two aspects of teams, teamwork and taskwork (Eccles and Tanenbaum, 2004; Entin and Serfaty, 1999; Salas et al., 1992). *Taskwork* involves executing the technical components of the task; *teamwork* involves the application of non-technical skills in order to integrate individual team member contributions for overall team performance (Kluge, 2014). Team members must develop shared attitudes and behaviors that ensure team functioning, those is done through the integration of taskwork and teamwork. Many team designs fulfill the first requirement (do the members have the right skills and abilities to do the team mission) but not the second (will the members of the team work together well).

Teamwork and Taskwork KSAOs

There are four categories of KSAOs to think about when engineering a team: (1) generic taskwork KSAOs, (2) specific taskwork KSAOs, (3) generic teamwork KSAOs, and (4) specific teamwork KSAOs (defined below). These categories of KSAOs have been widely reported as contributing to team effectiveness (e.g. Cannon-Bowers, Tannenbaum, Salas, and Volpe, 1995; Fiore, 2008).

Taskwork KSAOs are the characteristics team members need to complete the task. *Generic task work KSAOs* are the individual capabilities which enhance one's ability to act effectively in broadly defined performance task domains. Consider the example of an Army squad. When staffing any squad, there are a set of basic KSAOs that all team members require (e.g., land navigation, marksmanship, physical fitness). These KSAOs are considered generic because they need to be held by most if not all of the members of a given team. *Specific task work KSAOs* refer to task capabilities necessary to effectively complete all of the performance requirements for a particular task or project. This could be specific knowledge, skills, expertise, or experience. These competencies are dictated by the mission requirements. Different team members may have different levels of different KSAOs, but the team as a whole should possess all required KSAOs. Consider the infantry squad example. In this case, some Soldier's may require expertise on specific weapons but that may not be necessary for all squad members. Thus, unlike generic KSAOs, heterogeneity of variance can be one of the preferred selection team engineering criteria for specific task KSAOs.

Teamwork KSAOs are those characteristics which enable the team to work together well. *Generic teamwork KSAOs* refer to the capabilities shared equally among all team members to work effectively in any generic team environment-regardless of the task (Cannon-Bowers et al., 1995). These knowledge and skills reflect requirements for collaboration and integrated action on team tasks. They are transportable across all teams on which members might work. Further, these are skills that all team members should have. Examples of generic teamwork KSAOs include preference for teamwork (collectivistic orientation; Eby & Dobbins, 1997), agreeableness (Newman and Wright, 1999), extraversion (Barrick et al., 1998), team regulation (Stevens and Campion, 1994), communication skills (listening and speaking), collaborative problem-solving skills. Teams whose members possess these KSAOs have been shown to have high social cohesion (Barrick et al., 1998, higher levels of interpersonal process and team cooperation (Eby and Dobbins, 1997) and more effective team processes (Porter et al., 2003).

Specific teamwork skills refer to the mix of attitudes, personality and values that would optimize teamwork effectiveness and group cohesion among a particular set of individuals working within particular contexts. Klimoski and Jones (1995) note that, "Creating the right mix can also mean controlling for those factors that count for interpersonal compatibility. Thus, establishing team requirements, in this case, would involve the issue of just what personality, style, or values congruence would be necessary" (p. 312). Cannon-Bowers et al. (1995) suggest that these KSAOs refer to knowledge of specific team members and their preferences and characteristics, and team cohesion, which we interpret as the strength of the unique bonds or connections among individuals. Examples of specific teamwork KSAOs, held by individual team members, include conflict management skills, team synergy facilitation skills, openness to experience (LePine, 2003), and coordination skills (Morgeson et al., 2005). Such skills have been shown to impact both the cognitive and motivational states of the team (Molleman et al., 2004).

It is useful to consider this framework as we identify what KSAOs humans should be trained on, or selected for, to work well across a variety of H-M teams. Our basic premise is that many of the taskwork and teamwork skills humans need for human teams will be very similar but not identical to what is needed in H-M teams.

ENGINEERING HUMAN-MACHINE TEAMS

The definition of traditional human teams can be modified to replace the term "people" with "actors" or "entities," the same definition can be applied to H-M teams. Thus, H-M teams *exist when one or more human(s) works interdependently with one or more machine(s) toward a common goal.* H-M teams and interactions can be thought of more generally as H-M Systems. Machines sometimes provide directions. Other times, humans and machines make decisions together. Sometimes multiple humans work with one machine. Sometimes they work with many machines.

This overarching definition of H-M teams can be used as an umbrella term for all of the names that have been used to describe such teams including, but not limited to: human-machine, human-robot, human-computer, computer-human, human-AI, human-agent, agent-robot, human-system, and man-machine (e.g., Drury et al., 2003; Onken, 2003; Schurr et al., 2019; Yanco & Drury, 2004). Each of these names comes before a variety of stems including "team," "coordination," "interaction," and "collaboration." Many models from several disciplines have been used to classify different types of both human-human and H-M teams.

For the purpose of this paper, we focus on the characteristics of H-M teams that will most substantially drive the teamwork KSAOs required of humans to interact with machine teammates effectively. We do not anticipate identifying all the taskwork and teamwork skills humans needed, but rather identify a few to consider.

Challenge 1: Humans are Fundamentally Biased to Assume that Machines Will and Should Act Human.

One challenge for H-M teamwork is humans are fundamentally biased to expect machines to act like humans (Proudfoot, 2011). Humans naturally utilize heuristics to assigning attributes to, and explain why, people do the things they do. These assumptions and mental models of other humans are built on fairly robust and accurate data. Unfortunately, humans tend to apply these same heuristics and mental models to their machine teammates, making inaccurate assumptions about what machines will do, and why. When humans fail to understand and predict machine actions, H-M coordination breaks down. For example, when in a self-driving car, humans continue to pay attention to the road and are constantly assessing whether they agree with the car's decisions. Self-driving cars are programmed to stay in the middle of a lane on a highway unless there is a specific obstacle. However, a human may notice that it is a windy day and that the truck next to them is wavering in its lane. In this case, if the human were driving, they would want to change lanes in case the truck causes a problem. However, the car may not be showing any signs of awareness of the truck. The human, frustrated and assuming that the car is not considering the potential danger of the truck, may decide to fight against the automation of the self-driving car and override its choices. This could potentially add to the danger of the situation if they failed to detect another obstacle that the car was taking into account.

Some suggest that technologists should be designing explainable AI that acts as human as possible, to help avoid the challenge of humans not being able to understand machines. While explainable AI could help in the self-driving car situation, by providing the human with an explanation of why it is making certain decisions (Koo et al., 2015), technology is often purposefully designed to not act human. Machines are intentionally created to be more efficient and effective at certain actions than humans are capable of being. Therefore, this solution would severely limit the performance potential of AI. Another solution for this challenge would be simply to teach humans to stop expecting technology to act like them. This is easier said than done. Humans are programmed to expect a human response from anything we are interacting with. However, machines and AI will continually surprise us, which can cause frustrations and H-M teamwork challenges ranging from lack of coordination to depleted trust.

That leaves us to identify the skills which could help humans overcome this bias. To do so, we can pull from the literature on training diverse human teams to work together. Interactions between humans and machines can be a lot like interactions between humans from different cultures. Cross-cultural teams face challenges when attempting to communicate with different languages, and people from each culture often have different expectations for the interaction (Adair, Okumura, & Brett, 2001). Given this analogy of working across cultures, many skills associated with cross-cultural coordination may also apply to H-M systems. For example, humans should be trained to engage in perspective taking, a skill one uses to actively attempt to understand the situation from the others' point of view (Galinsky, Ku, & Wang, 2005). Perspective taking skills help shape human cognitive processes to strengthen social interactions among diverse teammates (Galinksy et al., 2005). In addition to helping limit biases teammates have about one another, perspective taking strategies also encourage team members to be patient, help each other, and attempt to mimic each other's behavior to interact more easily.

Selecting for specific personality traits, which are not trainable, is another way to address the fundamental biases for machines to act human (Driskell, Goodwin, Salas, & O'Shea, 2006; Lepine, Hanson, Borman, & Motowidlo, 2000; Morgeson, Reider, & Campion, 2005). *Agreeableness* (the extent to which someone is cooperative and works to assist others), *conscientiousness* (one's level of thoughtfulness and attention to detail), and *openness to experiences* (one's willingness to embrace change and try new things) are three of the five "big-five" personality traits that are typically referred to in the psychology literature as predictive of important behaviors and outcomes in the workplace (Park et al., 2015). Humans that are high in agreeableness may be willing to accept AI suggestions and decisions without fully understanding how the AI is coming to such conclusions. Humans that are conscientious are likely to be more considerate of how AI works and be motivated to develop an accurate understanding of AI that will help reduce the bias that the AI will act human. Finally, humans who are open to new experiences may be willing to accept AI that they do not have experience working with.

Unlike humans, whose traits are relatively stable over time, and who learn at a stable pace, machines are constantly updating and changing. AI continues to learn and be trained on data. Sometimes the updates will be incremental and relatively unnoticeable to human teammates. At other times the AI may have more radical updates, making it completely different for humans to interact with. Sometimes radical updates can happen regularly, on a day to day or hour by hour basis. While humans often have the option to select "update later" when interacting with some technology like Smartphones and laptops, humans working intensively with machines may not always have that option. They may not always know what exactly was updated or why. This can add to the frustrations developed when humans expect machines to act human. Therefore, in addition to openness to experience, traits such as adaptability, tolerance for ambiguity, cognitive flexibility, and propensity to trust will be especially helpful when AI updates without warning (Charbonnier-Voirin & Roussel, 2012; Dennis & Vander Wal 2010; Gill, Boies, Finegan, & McNally, 2005; Herman, Stevens, Bird, Mendenhall, & Oddou, 2010). In particular, tolerance for ambiguity has been identified as an important teamwork skill in cross-cultural teams. Humans with these traits are likely to be more patient and willing to learn how to interact with the new AI updates. Additionally, they will be more skillful at quickly picking up on the differences (and why they matter) and apply that knowledge to update their team interaction models to better coordination with AI teammates (Mohammed, Klimoski, & Rentsch, 2000).

Challenge 2: Varying Levels of Machine Autonomy

Machines involved in H-M teams vary on their level of autonomy. Yanco and Drury (2004) have a framework to define levels of automation, ranging from fully controlled to fully autonomous. Those levels are based on how much decision power a machine has, as well as the extent to which the machine needs to interact with a human(s) before selecting an action. At lower levels of automation, machines do not make any decisions without a teammate or they may offer exhaustive lists of all possible options for a human to choose from. At more moderate levels of automation, machines may offer a shorter list of optimized suggestions and decision alternatives (Pfaff, Klein, Drury, Moon, & Liu, 2013). At highest levels of automation, machines will decide everything and take action without approval from a human; these machines may notify humans of the actions they are going to take, but they also may not.

Consider email as an example. Historically email has had low to no automation. Someone sends you a message and you receive it, with some alerts and the ability sort, organize, and search. Recently, lower to moderate levels of autonomy have been introduced. As a user writes an email, the system can now make suggestions for your next few words, grammar, and spelling. The system can also assess, using the body of the text, whether the user meant to send an attachment. If no attachment is provided, the system can provide the user with a warning they are about to send a message without an attachment. These are all helpful actions, but it is important to note that the email system is providing the user with options; it is not making these decisions for them. Email is an example where full automation could be problematic. Imagine if your email used a natural language processing model to match the language in the body of your email with the title of your documents, and then decided to attach a document without notifying you!

Now consider a machine that scores higher on the automation scale, an automatic transmission car. Imagine if your car asked you every time it wanted to switch gears. The car's new automatic ability to switch gears would not be any more useful than when the car was manual. That said, the advancement of automatic shifting took a long time for people to adopt. The same adoption challenges will be prevalent as cars transition to being more automated to the extent that they are self-driving. Self-driving cars have been designed to work well with humans. For example, designers learned that when a self-driving car sends messages to a driver about *what* it is doing (e.g., braking), was not helpful to the human driver and actually led to a decrease in the overall driving performance; however when the car produces messages about *why* it engages in certain activities (e.g., notifying the driver of an obstacle), the H-M team improves its performance (Koo et al., 2015).

While machines should continue to be designed to interact well with humans, the human element is still important. If the automation is designed well, eventually the human will learn to trust the machine and let it do the job it was designed for. However, there are a variety of individual KSAOs that are likely to facilitate the human using automation to the highest potential. For example, a propensity to trust and openness to new experiences were important characteristics for early adopters of automatic transmission (Gill, Boies, Finegan, & McNally, 2005). When humans are able to trust automation, and also make critical decisions about whether technology is acting as intended, they are better at collaborating with machine teammates (Basu & Singhal, 2016). Additionally, tolerance for ambiguity and cognitive flexibility are important skills for humans to be able to work with machines at high levels of autonomy. By selecting for these traits in humans, human teammates that believe that ambiguous situations are controllable will be able to work effectively with machines under conditions of uncertainty (Dennis et al., 2010; Herman et al., 2010).

Table 1 presents a summary of KSAOs that may be important characteristics of individuals working in H-M teams. These are driven by the challenges of (1) human bias that machines will act human and (2) working with machines at varying levels of autonomy. The table provides a definition of each KSAO as well as the extent to which that KSAO can be influenced through training or selection. Some of the KSAOs are traits or characteristics which are more stable in nature and difficult to address through training.

Table 1. Generic Teamwork KSAOs for Humans Working in H-M Teams

KSAO	Definition	Select or Train	Reference
Perspective taking	Understands and considers situations from another's point of view	Train, Select	Galinksy et al., 2005
Agreeableness	Cooperative; works to assist others	Select	Park et al., 2015
Conscientiousness	Thoughtfulness and attention to detail	Select	Park et al., 2015
Openness to experience	Willingness to embrace and try new things	Select	Park et al., 2015
Adaptability	Ability to change strategies when situation shifts	Train, Select	Charbonnier-Voirin & Roussel, 2012
Tolerance for ambiguity	Tendency to enjoy uncertain situations	Train, Select	Herman et al., 2010
Cognitive flexibility	Belief that ambiguous situations are controllable	Train, Select	Dennis et al., 2010
Propensity to trust	General willingness to believe others are competent and have good intentions	Train, Select	Gill et al., 2005

Challenge 3: Function Allocation Between Humans and Machines

Another challenge often faced by H-M teams is caused by poor function allocation between human and machine teammates. The foundational purpose of forming a H-M team, as opposed to a human-only or machine-only team, is to produce outcomes that require both human and machine skills. This is the same rationale for forming diverse cross-functional human teams. For example, interdisciplinary science teams are formed to study complex research questions that require diverse perspectives, expertise, and resources (Uzzi, Mukherjee, Stringer, & Jones, 2013). For human teams, tasks should be allocated depending on which teammate has the best expertise to complete them. For example, you may want an engineer to develop a testbed to conduct research, and a social scientist to develop the experimental design to test research questions. Similarly, functions between humans and machines should be split based on what they are good at.

Task/Function Allocation. Hoc (2000) notes that machines are better than humans at complex calculations and managing large amounts of data, whereas humans are more skilled at responding to unexpected situations. The division of labor between humans and machines needs to be considered at both the task and the function level. The allocation of work between humans and machines may not always be as simple as dividing tasks between an engineer and a psychologist. Therefore, humans and machines may overlap in the roles/functions they perform as well as the specific tasks they need to complete (Hoc, 2000).

Automation allocation. Poor function allocation can also arise when machines with low automation are given too much responsibility, or when machines with high automation are not given enough responsibility. To avoid this challenge, humans need a strong understanding of what the machines they work with are (and are not) capable of. This allows humans to make decisions of how tasks should be separated and how H-M interactions should be organized. Traits that help humans with automation allocation include conscientiousness and attention to detail, adaptability to learning new things or to the machine changing its levels of automation as it learns over time, and their willingness to engage in team backup behaviors with both their human and machine teammates (Martinez et al., 2015).

Teamwork interaction patterns. In addition to dividing up taskwork effectively, teamwork processes can be equally important for H-M teaming success. For example, poor function allocation can arise when ineffective decisions are made about whether machines should augment or supplement human tasks. The National Science & Technology Council (2019) suggest that there are three ways the humans and AI can interact with one another: alongside, when needed, and as a replacement. When AI performs *alongside* a human, it works directly with human teammates by aiding with things such as information retrieval, advice giving, or to help coordinate tasks. When AI performs alongside humans, it is especially crucial to consider solutions to the other challenges discussed in this paper (i.e., bias expecting machines to act like human and the level of autonomy of the machine). Teamwork skills will be most important when H-M teams perform alongside one another.

When AI performs *when needed*, it can step in and provide suggestions and solutions to help humans make decisions, while otherwise working in the background (National Science & Technology Council, 2019). In such situations, the task flow and division of function allocation will be important for human team members to be trained on. Humans will also need to remain adaptable to changing their patterns of work when AI offers new suggestions to be considered. Finally, when AI performs as a *replacement,* or instead of, a human by taking a set of tasks away from the human completely. This is likely to occur when a machine can complete a task independently without input of a human (e.g., a car shifting gears). In sum, when allocating functions in an H-M team (a) whether humans or machines are best at each sub-task and (b) whether and how humans and machines need to collaborate through a workflow both need to be considered. Thus, engineering H-M teams is dependent on both designing teamwork processes that will optimize H-M interactions and selecting and training humans to be able to engage in such interactions, based on their abilities to complete the tasks and functions they are allocated and their ability to engage in effective teamwork behaviors.

In order for humans to effectively collaborate with machines either (a) under situations of poor function allocation or (b) when determining how the team should interact, human team members will need more specific teamwork skills. Compared to the *generic* teamwork KSAOs reviewed under the first two challenges, the teamwork KSAOs needed to respond to the challenge of function allocation and interdependent are more *specific* to the focal team. First, humans must be able to build strong team interaction mental models (i.e., the cognitive understanding of who should be doing what on the team and how and when humans and machines should be working together), as long as a transactive memory of which humans and which machines hold specific knowledge, resources, and capabilities (Mohammed et al., 2000). Table 2 presents three important categories of knowledge that will be specific to each unique H-M team a human is part of.

Table 2. Specific Teamwork KSAOs for Humans Working in H-M Teams

KSAO	**Definition**	**Select or Train**	**Reference**
Team mental models	Team interaction models of which teammates should work together how and when; transactive memory of how knowledge, capabilities, and resources are distributed across the team	Train	Mohammed et al., 2010
Role clarity	Clear understanding of the responsibilities and behaviors associated with each role and teammate	Train	Beauchamp et al., 2002
Communication for norm alignment	Agreement/knowledge upon the methods by which teammates will collaborate	Train	Henderson et al., 2016

Importance of Team Training

Although many of the individual KSAOs in Tables 1 and 2 can be addressed via individual level training, we cannot underestimate the importance of team training. Particularly for the KSAOs noted in Table 2. Team training occurs when members of a team are trained *together,* often within the context of a given mission. There are a number of benefits to training outcomes when training occurs within the team context. Liang, Moreland, and Argote (1995) found that individuals trained within their respective teams exhibited greater skill transference and team performance compared to those ad hoc teams trained as individuals on their specific task. Similarly, training focused on team interactions specifically positively affected the development of team mental models, and in turn, team communication and performance (Marks, Zaccaro, & Mathieu, 2000). The advantages of team training over individual training result from additional team interactions, or even support from team leaders and team processes, like climate (Smith-Jentsch, Salas, & Brannick, 2001).

Just as in human-human teams, many of the KSAOs needed for effective H-M systems can be developed by allowing humans and machines to train and work together. This will let them learn how to interact, communicate, and predict each other's actions. The more time humans have to work with machines, the more they will be able to learn about machine behaviors, allowing them to anticipate and predict how the machines will act. With this knowledge, humans can learn to manipulate, influence, and even negotiate with, machines. Machines may even begin to learn from their human counterparts.

DISCUSSION

While H-M teams may not currently be as pervasive as human teams, the use of H-M teams is growing exponentially. Practitioners should consider selection and training methods to prepare for the future. This paper proposes that when engineering H-M teams, we must focus on more than designing machines who work well with humans. We also need to select and training humans to work with machines. The basic premise of this paper is that a portion of our understanding, and decades of research on effective human teams can apply to the needs of H-M teams. This paper identified generic and specific teamwork KSAOs, required for human teammates, that are likely to influence performance of H-M teams. The selection of KSAOs was informed by what is required for human teams as well as two specific challenges found in H-M teams. The benefits of identifying these skills is twofold. First, that means existing measures of KSAOs including perspective taking, personality, openness to experience, adaptability, tolerance for ambiguity, cognitive flexibility, propensity to trust can be used to select humans to work on H-M teams. Second, existing trainings used for effective human teaming, including cross-cultural teaming (e.g., perspective taking, trust building, co-learning) can be adapted to training for H-M teams. Finally, we should not overlook the power of team training for both human as well as H-M teams.

Future Research

Ultimately this paper hypothesizes that the individual human KSAOs identified will lead to more effective H-M team performance. Although the hypotheses are informed by solid research and an understanding of H-M team challenges, research could quantitatively validate those assertions. Do H-M teams perform better if the humans have these KSAOs? A research study could focus on answering that question.

Many other questions remain for future research. For example, how might team composition affect the training and competencies required for human H-M teammates? Is the ratio of humans to machines important (Yanco & Drury, 2004)? Second, if there are multiple machines on a team, how does the diversity of the machines across many variables to include automation and purpose affect team interactions? What skill are needed for humans who are interacting with multiple machines simultaneously, and how do those machines learn to interact with each other? Another important item to think about is whether there is a continuum of what does or does not qualify a group of humans and machines as a H-M team. For example, a machine intended to aid in training may work interdependently with a human to assist with a shared goal of human learning. However, we do not typically think of human instructors and human trainees to be part of a team, despite working together toward a shared goal. Finally, as technology continues to develop, it will become less obvious where the human ends and where a machine begins, particularly as "machines" less often become physical objects and are instead manifested as intangible artificial intelligence. Future considerations of H-M teams should account for this problem and determine whether such a distinction actually matters.

Conclusion

Although different, human-machine teams parallel human-human teams in many ways. We can look to decades of research on human teams to identify training and selection strategies, particularly for the humans in the teams. This paper is once small step toward informing future competency models and training solutions that are specifically tailored to H-M teams.

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