There's no "I" in HAT: Identifying Appropriate Skills for Human Agent Teaming of Varying Levels of Autonomy and Embodiment

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ABSTRACT

As the intelligence in autonomous systems expand, so too have their roles. These complex systems, and the intelligent agents of which they are comprised, serve more independent and interactive roles with humans than tools of the past. In order to ensure humans can effectively interact with this technology in human agent teams (HAT) there is a need to understand how the varying levels of autonomy and types of agent embodiment influence this interaction. The recent technological advancements in autonomous systems blur previous delineations between distinct types of agents based on their embodiment (e.g., physical—or tangible such as warehouse robots, virtual—or digital based agents such as a virtual assistant; and embedded—or invisible agents that operate without any embodiment such as a global positioning system (GPS) assistant; Glikson & Woolley, 2020). Autonomous systems may also exhibit multiple embodiments; for example, Unmanned Aerial Systems (UAS), which are physical, are also shown virtually on control stations, and exhibit embodied capabilities including object detection and mission planning. This paper will focus on what is needed to effectively train humans and manage HATs, including identifying the skills that humans need to work with agents across varying levels of autonomy. The paper will map out a framework for taskwork and teamwork skills by drawing on interdisciplinary research from the fields of research on human-human team (HHT) composition, selection, and training with research on HATs to address which skills are needed for which types of agents. These concepts will be discussed across emerging advanced agents that break the modern mold of singular embodiment and pose unique challenges, such as UAS that are controlled from thousands of miles away, or autonomous passenger vehicles that require human trust. Issues with current frameworks and guidance for performing a HAT task analysis are presented.

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INTRODUCTION

Military operations are becoming increasingly unmanned and automated, requiring optimization for human-agent dynamics (Gangl, Lettl, & Schulte, 2013; OSD, 2017). Artificially intelligence (AI) agents that can act independently of a human, are becoming more commonplace in a variety of applications, including smart home devices, manufacturing and assembly, shipping and delivery, autonomous vehicles and drones, and weapon systems. With the vast expansion of autonomous systems, safe and effective integration of AI into human operations is key. Although there have been many advancements in HAT, effective team dynamics is still an area of needed improvement (Walliser et al., 2019). Many issues prevent effective HAT, including biases that humans place on agents, under or overtrust and expectations of agents, predictability, reliability, and task allocation (Dubrow & Orvis, 2019; Glikson & Woolley, 2018; Roff & Danks, 2018). However, as agents become more complex, newer issues also emerge. For example, remote operations are challenging for operators to maintain situation awareness (SA) as they become out of the loop due to the lack of sensory information on which they normally rely (Endsley & Jones, 2004). Remote missile drones introduce additional issues extending into moral dilemmas, in which military personnel actions and decisions may differ when working with highly autonomous agents from remote locations, as they may not be fully aware of the impact that their actions have in the real world (Coeckelbergh, 2013). Finally, in the case of automated weapon systems (AWSs), which are extremely complex machines with varieties of autonomy at play, humans may incorrectly perceive their predictability or reliability (Roff & Danks, 2018). However, there are no current mechanisms within AWSs that exhibit the strong predictability required in complex and changing military environments. These new dynamics of varying autonomy and distributed operations may present new challenges that require specific skills of the agent and human that may not be represented in general frameworks. Considering the implications of these emerging areas of automated agents in the military, it is important to ensure effective and safe teaming between human and agent.

Current Space of Automation and Teaming Frameworks

The focus of HAT has shifted from a technology-centered approach to a human-centered approach in order to address issues in HAT collaboration and effectiveness (Glikson & Woolley, 2018). AI, the underlying technological component of an agent, represents an advanced spectrum of technologies that are capable of completing tasks within the environment, gathering information from outside environments, interpreting the information, generating results and evaluating the results of the AI's own actions. AI can take a variety of embodiment forms, but the three main forms outlined by Gilkson & Wooley (2018) include: (a) a physical robot, in which the agent is tangible and the human can touch and visually see its actions; (b) virtual agents carrying out tasks on a screen or within a virtual environment; and (c) embedded AI, in which the AI is submerged inside of another tool or a computer, which can carry out tasks that may be unbeknownst to the human. These classifications help to determine how the human member of a HAT team will interact with the AI teammate (or agent) and is an essential framework for understanding trust and reliability among different autonomous systems and HAT. (Gilkson & Wooley, 2018). Agents or robots are often classified by their primary function or their physicality (physical, virtual, or embedded). In the early 2000s and even 2010s technology could easily be seen in this categorical view: Roombas (a physical agent) which can vacuum your home; Clippy (a virtual agent) who helps you write documents; and Google Maps (an embedded agent) who can give you directions to your destination are all easily placed into categories. Even though Glikson and Woolley (2020) noted that agents may exist in multiple categories, agents with multiple embodiments are quickly becoming the norm. Therefore, it is critical that the complexities of novel agents with many functionalities are considered. In the civilian space, consider Amazon Alexa who has a physical space in one's home, but has a virtual voice for whom she is broadly recognized, and has many background capabilities. However, are the knowledge, skills, abilities, and other attributes (KSAOs) the same for someone using Clippy, which will simply change the format of a document as opposed to Amazon Alexa who could unlock your front door smart lock, call your family members, or make purchases for you? Likely not. Humans may trust a car to drive them from point a to point b but not trust its ability to dynamically respond to nearby traffic and choose a different route to get to the destination (e.g,. its ability to perform physical actions versus decision making actions). Therefore, the physical abilities and embedded abilities of an agent may be trusted differently. Agents are being developed with increasingly higher autonomy and responsibilities, however, agents now come in all shapes and sizes. In the military space, early drones were piloted and operated by soldiers as scouts for information gathering purposes. For example, a combat drone is physically present in the world and generally remotely piloted and may have embedded functionalities or subtasks including navigation, object detection, fuel management, and more. Drones now and in the near future can be operated from remote locations and tasked with a range of activities from supply delivery, missile strikes, and counter drone operations (Guitton, 2021; U.S. Air Force, 2016). Human teammates may trust a combat drone's ability to fly and avoid obstacles, but may not trust the combat drone to identify enemy assets and fire missiles without approval. There can also be overtrust in an autonomous system, which in military settings can lead to loss of life (e.g., 2003 Patriot missile incident; Scharre, 2019). On the other hand, lack of trust can lead to disuse, putting extra workload on the human and requiring too much monitoring of the agent. Thus, the ultimate goal is *calibrated trust* in HAT in which humans put an appropriate level of trust in the agent based on the capabilities and limitations of the agent's functionality (de Visser et al., 2020). Additionally, it is possible that as agents become more complex, that humans misunderstand the capabilities of agents (e.g., mistake lane keeping automation in vehicles for automatic driving; Mirnig et al., 2016). Therefore, a framework that requires the agent, as a whole, to fall into one of these categories, may not be appropriate with emerging agent types.

Other models include the level of autonomy (LOA) framework. LOA is defined as the range of design options implemented in a system to enhance self-sufficiency and self-directedness; ranging from manual operations that require humans to complete all functions, to fully autonomous operations, in which the system is able to perform the task in its entirety, requiring no assistance (Johnson et al., 2011). The different levels of autonomy are outlined more specifically in Sheridan and Verplank's (1978) LOA structured model. For example, automation levels may include when the computer or automated teammate either allows the human to veto any actions before any automatic executions, or the computer necessarily informs the human before executing any automated actions (Sheridan & Verplank, 1978). Understanding the best LOA in HAT missions may lead to improved mission performance, overall mission effectiveness, and ease of communication in HAT. However, LOA is contingent on the autonomous capability and the task of interest. For example, a self-driving car is autonomous in the sense that the vehicle can follow a road. However, it is only considered semi-autonomous once the car must also avoid traffic and fails to do so. Although these different levels are separated by an extra task, the makeup of the autonomy and the approach to communicate its status to the operator drastically changes; requiring new forms of coordination, interdependence, and communication design (Johnson et al., 2011). As LOAs fluctuate throughout a mission, designers typically overlook how humans may adapt to changes in different LOAs and how to implement higher LOAs effectively (Johnson et el., 2011). Depending on the type of automation and the complexity of the situation, each agent type will require different needs for teamwork, taskwork, and KSAOs. Additionally, considerations based on the type of agent or location of the agent and the needed teamwork requirements based on co-located, distributed, or entirely virtual agents are needed. Based on these stipulations, a simplistic framework or approach for KSAOs with clean categories is simply not feasible or inclusive of all possible scenarios. The following sections will discuss a more fluid framework that considers a broad range of how automation can be instantiated in HAT as well as guidance for identifying HAT KSAOs based on agent responsibility and team complexity. Finally, steps for conducting a task analysis specifically for HATs are presented.

HAT FRAMEWORK FOR SUPPORTING COMPLEX TEAMS

HAT's work most effectively and efficiently when both the HAT members have the KSAOs required for successful team performance (Dubrow & Orvis, 2019). Selective team composition is required to provide an overall mix of the essential KSAOs needed to create a productive and effective team. It is important to establish the LOA an agent teammate possesses, so the human can understand *why* it is acting the way it is (Dubrow & Orvis, 2019). This can be a difficult task, as current agents are now capable of shifting their automation level during a task, requiring the human to adapt, which can hinder HAT performance. AI and agent teammates are continuously being updated, advanced, changed and trained in a relatively short period of time, while humans learn at a more stable pace (Dubrow & Orvis, 2019). These updates, some incremental and some comprehensive, can create difficulties in interaction between teammates (e.g., the human may not know what was updated or why). However, traits such as openness to experience, adaptability, tolerance for ambiguity, cognitive flexibility, and propensity to trust can be extremely beneficial when an agent teammate updates without forewarning (Nikolaidis, Hsu &Srinivasa, 2017; Dubrow & Orvis, 2019). Humans with such traits are likely to act in a more patient manner, and be more willing to learn about new AI programs and updates (Dubrow & Orvis, 2019).

The answers to what skills the human and robots need and the effective teamwork dynamic will be highly dependent on the number of functionalities of the agent and the riskiness of the task associated with them. For example, as discussed by Stuck, Holthausen, and Walker (2021), a home-care robot can be trusted to water plants, collect mail, and place calls as needed. However, tasks such as shaving, regardless if it is a human or robot performing the task, is likely to stir some distrust from the one being shaved due to the inherent risk associated. It should be noted that miscalibrations between the perceived trustworthiness and actual trustworthiness of an agent again can lead to the under trust and overtrust in these situations (de Visser et al., 2020). Therefore, mediating factors for HAT will always need consideration. As HAT use expands in military settings, what should be considered when the warfighter's life is in the agent's "hands"? What will be required of the human in HAT for appropriate trust and teamwork as the agents become responsible for riskier tasks? How can individuals be selected or trained for HAT? What skills and knowledge must they possess to work effectively with each type of agent embodiment—and those with a variety of embodiments?

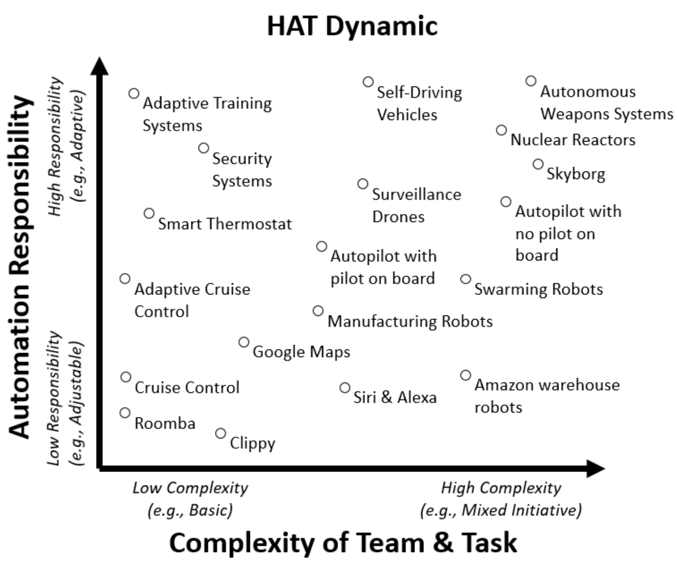

Figure 1. Examples of Agent Types based on Responsibility and Complexity

This paper aims to provide a framework as guidance to begin developing more effective team-style interactions and dynamics between humans and agents. The needed KSAOs and task allocation is discussed both for the human and agent design. The discussion applies the teamwork and taskwork dichotomy that is commonly used in human-human teams (HHT) to delineate KSAOs which promote effective member interactions (i.e., teamwork) from KSAOs which promote effective performance of the team (i.e., taskwork). The framework presented here builds upon previous concepts by removing the limitations of categorization. It acknowledges that an agent can possess many embodiments and have various functionalities that cover the full range of the autonomy gamut. HATs can be characterized by: (1) how much *responsibility*, or the amount of task delegated to the agent and the subsequent risk of delegating the tasks to the agent and (2) the *complexity*, or the challenges associated with the HAT dynamic due to the nature of the team and task such as distributed locations, high information and workload, or multiple agents working with one human. Therefore, the current framework aims to present continuums that can be leveraged to understand the baseline needs of HAT as well as key KSAOs required as automated agents become responsible for more and riskier tasks and as the HAT dynamic becomes more complex (see Figure 1).

TEAMWORK NEEDS

The teamwork track of team effectiveness is concerned with how team members work together, and is focused on how social interactions within a team relate to the team's functioning (Cannon-Bowers & Bowers, 2011). This may involve activities such as assigning roles, communication tactics, and various types of interpersonal interactions (e.g., conflict, decision-making), as well as key thoughts, feelings, and attitudes (e.g., trust, shared mental models) that the members have toward each other and the team as a whole (Cannon-Bowers & Bowers, 2011). Facilitating teamwork activities in HATs will thus require individual KSAOs, which improve these kinds of team member interactions. Research on effective teamwork skills in HHT has identified several individual team-generic KSAOs that may also be transferable to humans working in HATs (Liu et al., 2017). Because the teamwork track of team effectiveness focuses on interaction, a universal concept to any group, there are specific individual-level KSAOS which are likely to facilitate effective interactions in any team because they broadly concern the individual's attitudes, behaviors, and cognitions about working with others (not necessarily humans). In addition to identifying these KSAOs, it is also important to highlight contextual features which may strengthen the contributions of a KSAO to team effectiveness or make the KSAO particularly vital to team effectiveness (Mathieu et al., 2008). Below, each of the relevant teamwork-related knowledge, skill/ability, and other characteristics gleaned from the HHT literature is described. Special consideration is also noted to highlight when certain combinations of agent-teaming complexity and LOA may strengthen a KSAO's impact or when a KSAO may be particularly important to facilitating teamwork (see Table 1 for a summary of the identified teamwork KSAOs and the conditions in which they may be strengthened).

Table 1. Teamwork Needs

HAT Dynamic	**Human needs...**	**Agent needs to...**
All HATs	Knowledge of teamwork (Hirschfeld et al., 2006) Preference for teamwork (Stark et al., 2007) Understanding of agent capabilities (Mirnig et al., 2016) Knowledge of team roles (Mumford et al., 2008) Self-efficacy in managing agents (Parasuraman & Riley, 1997) Tasks that require reasoning, judgement, and flexible decision making (de Winter & Dodou, 2014)	Be transparent (Boring et al., 2019; Shaefer, Hill, & Jentsch, 2019) Provide explanations (Shaefer, Hill, & Jentsch, 2019) Be tasked with information processing, repetitive tasks, and responding to alarms (de Winter & Dodou, 2014) Utilize anthropomorphic appearances and behaviors (Glikson & Woolley, 2020; Zhao & Malle, 2020)
With Higher Automation Responsibility	Adaptability (Salas et al., 2007) Involvement in development of agent (Roff & Danks, 2018) Calibrated trust (de Visser et al., 2020; Mirnig et al., 2016) Perspective taking (Zhao & Malle 2020)	Have a trusted representative (Roff & Danks, 2018) Be observable (Christoffersen & Woods, 2002) Be able to negotiate team goals (Klein et al., 2004)
With Higher Team & Task Complexity	To monitor performance (Marks & Panzer, 2004) Openness to experience (Homan et al., 2008) To overcome biases placed on agents (Dubrow & Orvis, 2019)	Be incorporated from the start of training (Roff & Danks, 2018) Be directable (Christoffersen & Woods, 2002) Be predictable (Klein et al., 2004)

Knowledge

Regarding knowledge, two attributes have been linked to team effectiveness that broadly speak to an individual's understanding of how to productively work with others. First, being knowledgeable about teamwork itself is associated with team effectiveness (Hirschfeld et al., 2006). Individuals who understand that teams are inherently dependent on the connection between its members are more apt to actually enact these behaviors (Stevens & Campion, 1999). This knowledge may be particularly important for HATs in which the team's tasks are complex or its human and agent team members are physically distanced (i.e., remotely interacting). In such settings, the intricacies of interdependent work make member-to-member collaboration essential for completing tasks. The agent in these instances needs to be observable, or allow its information, status, and actions to be easily understood by the human teammate (Christoffersen & Woods, 2002). Second, understanding the roles within one's specific teams has also been associated with team performance (Mumford et al., 2008). That is, team members who know how their team operates are more likely to contribute to effective team functions. Clear transparency is essential to incur appropriate trust during HAT (Schaefer, Hill & Jentsch, 2019). Providing inadequate amounts of information can create ambiguity amongst an agent's intended actions, and can also lead to complacency. Transparency of the agent's tasks, and providing reasoning for the agent's processes and decision making leads to a shared understanding and mental model among teammates. If transparency among teammates does not occur it can lead to poor trust during HAT (Shaefer, Hill & Jentsche, 2019). This knowledge may be particularly important for human team members in HATs with highly autonomous agents and HATs with agents responsible for completing risky tasks. As agents become more complex, and can adapt to more situations, they may innately become less predictable causing confusion for the human operator (Klein et al., 2004). In these cases, to create a deeper sense of trust among HAT would be to close the loop between all involved in developing the agent. Each person will receive a degree of knowledge about the different aspects of the agent to generate a shared understanding of the agent from the early stages of development (Roff & Danks, 2018). Automated agents now have a multitude of functions as well as multiple subtasks—requiring a fundamental understanding of each subtask and the agent's limitations in each to ensure appropriate and calibrated trust in the agent (Mirnig et al., 2016). Otherwise, humans may place too much trust in the agent that exceeds its capabilities, ultimately leading to the agent not meeting human expectations, thereby damaging trust and task success (Mirnig et al., 2016). Early and continuous exposure to automated agents can aid in gradually building an operator's trust, as it allows for more time for trust building experiences and helps the operator to better understand the agent's actions (Roff & Danks, 2018). This could be achieved by introducing agents into basic training or any early training procedures. In such teams where agents carry more responsibility and self-sufficiency, knowledge of their advanced assignments will be even more essential for effective teamwork by a human team member.

Skills and Abilities

Regarding skills and abilities, three attributes stand out that demonstrate an individual's aptitude for working with others. First, performance monitoring refers to an individual's ability to accurately review and evaluate the work that another team member does, then take the appropriate action to improve future performance (Marks & Panzer, 2004). Accuracy and appropriateness are central to this skill. One must be able to correctly identify when another's work does not meet expectations, and they must be able to do this at the appropriate frequency as over-monitoring uses resources that the individual could be using towards another task, while under-monitoring could be associated with worse task performance (Marks & Panzer, 2004). This skill is particularly important to consider when agents in a HAT are more autonomous or tasked with riskier responsibilities. In such circumstances, human team members always bear the legal responsibility of any outcome that occurs. Appropriately and accurately monitoring the work that an autonomous agent does on risky tasks is important for preventing a range of negative outcomes. Under-monitoring or incorrectly monitoring an agent's work may lead to mistakes being enacted with undesirable consequences, whereas over-monitoring an agent's work consumes a person's resources that could be spent on other productive endeavors. Given the importance of monitoring in these situations, it is likely that good performance monitoring skills will be essential for performance in these teams. Second, an individual's adaptability is an important ability for conducive teamwork as it relates to how well a person can adjust to changing task demands (Burke et al., 2006). An individual with high adaptability is able to effectively redistribute their own resources and help accommodate changes to other team member's tasks. For the agent, it must also be adaptable, or otherwise known as directable. A directable agent can allow the human to delegate tasks or subtasks to the agent whenever novel situations arise (Christoffersen & Woods, 2002). Another skill needed of the agent is goal negotiation as the agent becomes more responsible for actions. Without being able to convey potential goals in the face of novel situations, agents will be unable to effectively coordinate with their human teammates (Klein et al., 2004). This effect is likely amplified in HATs with complex tasks or physical distance between HAT members, as adaptation will be even more important to react to the multiple risks that may occur when remotely conducting intricate, dynamic tasks. Lastly, an individual's team management skills are directly related to teamwork, as it refers to a person's capacity to plan the team's workflow (Burke et al., 2006). Individuals with high team management skills are able to directly facilitate teamwork by setting goals, coordinating team member involvement with tasks, and scheduling deadlines. From this, human operators that exhibit team management skills would be better equipped to perform in adjustable autonomous systems. Since human operators delegate tasks to automation in adjustable autonomy, using skills related to teamwork will serve as leverage to perform at higher levels of mission effectiveness (Toquam et al., 1997).

Other Key Attributes

Regarding other characteristics for the human in KSAOs, three types of individual attributes relate to team effectiveness. First, an individual's preference for teamwork is an attitude which describes a person's appreciation for being part of a team (Stark et al., 2007). This attitude may be more important in HATs that are high on task complexity and distance. When HAT members are separated to conduct difficult, intricate tasks together, teamwork behaviors become vital in order to successfully perform team tasks. Having a higher preference for teamwork is more important for humans in HATs within these circumstances as they are more likely to engage in these vital teamwork behaviors. Second, although research on personality has found many links between each of the Big Five traits—also known as extraversion, agreeableness, openness, conscientiousness, and neuroticism—and team performance (Liu et al., 2017), openness to experience may be particularly relevant to HATs. Beyond HHT findings which positively associate openness to experience and team creativity (Homan et al., 2008), individuals with high levels of openness to experience may be more receptive to teaming with technology during their first time in a HAT and thus continue teaming behaviors in HATs. Openness to experience would be even more important in HATs with higher levels of agent autonomy or agent task risk, as the human team member would be more willing to let the agent do its task without immediately overriding it or rejecting its input. For example, for Automated Weapon Systems (AWS) deep trust could be achieved by taking advantage of "transitive trust" (Roff & Danks, 2018, p.12) or trusting a third party because a member of the organization does. Creating managers or agent representatives, who are already trusted, to act as an extension of the agent can facilitate transitive trust, which can lead to a deeper trust with the agent. In a study by Chen and Barnes, Roboleader was created to serve as a human operator's assistant, who can delegate commands to a group of robots with lower capabilities (Chen & Barnes, 2012). Rather than the human operator managing each individual robot, Roboleader allows a single entity to control lower-level robots and communicate to the human operator. When Roboleader was perfectly reliable, results revealed that task times were reduced resulting in high efficiency levels. Using a manager, like Roboleader, could be an effective method for controlling multiple agents (Barnes et al., 2013). Lastly, self-efficacy has been found to positively relate to the team performance (Richter et al., 2012). Self-efficacy is often specified, and refers to an individual's belief that they are able to carry out a particular task or succeed in solving a certain problem (Bandura, 1997). Within HATs, this may be particularly relevant to teamwork—individuals who do not believe in their ability to interact with an agent may be more likely to misuse the agent or under-monitor its work (Parasuraman & Riley, 1997).

Regarding other characteristics for the agent in KSAOs, by observing the challenges currently faced with HAT, the key other characteristics can be identified. One such challenge with HAT is that humans are inherently biased to presume that their agent teammate will and should act human (Dubrow & Orvis, 2019). These assumptions are then also applied to their agent teammates, leading to inaccurate predictions of the agent's actions, which interrupts HAT coordination. In HHTs, these mental models and biases are, generally, an accurate way to predict or anticipate the expected outcomes of their teammates' actions. However, when these biases are applied to agent teammates, they are more often than not an inaccurate assumption about what the agent will do, causing the coordination between the agent teammates to degrade (Dubrow & Orvis 2019; Quinn, Pak, de Visser, 2017). To counteract this issue, technologists suggest that AI should be designed to act as human as possible, to allow these mental models to remain applicable (Zhao & Malle, 2020). This concept, however, severely hinders the potential performance capabilities of the AI. In order to mitigate this challenge, it is crucial to identify skills that could aid humans in overcoming their biases (Dubrow & Orvis, 2019). In cases of poor trust, strategies can be implemented during HAT to repair trust (de Visser, Pak, & Shaw 2018). Active trust repair is critical in dealing with errors among HAT. This includes apologies, denials, and explanations provided by the agent to mitigate deteriorating trust due to an error (de Visser, Pak, & Shaw 2018). Additionally, observing diverse team training provides some context on which skills may aid humans the most in overcoming biases. Interactions between agent teammates are very similar to cross-cultural teammates in regards to the challenges they face. Human teammates of differing cultures often have divergent mental models, assumptions, and expectations of their teammate counterparts and the same can be applied to HATs. Skills associated with cross-cultural competence may also pertain to HAT teams. Training humans in perspective taking (a skill someone utilizes in which a person is actively and willingly trying to understand a situation from the other teammates perspective or point of view) is a training mechanism that has been effective in improving cross-cultural competency (Miranda, 2002), and could be employed when training humans to work with agent teammates. The process of perspective taking limits biases teammates have about one another, and encourages members of the team to remain patient, be more open to helping, and even facilitates behavior mimicking, which allows the teammates to interact more deftly. Perspective taking is also more likely to occur, naturally and similarly to perspective taking with humans, if the agent teammates carry some form of human attributes, or human likeness (Zhao & Malle 2020). Anthropomorphism, or looking and acting human, may also assist with trust in agents (de Visser et al., 2016; Glikson & Woolley, 2020). Table 1 provides a summary of the baseline teamwork skills for the human and agent along with needed skills as automation responsibility and team and task complexity increase.

TASKWORK NEEDS

In HAT, one of the largest challenges is function allocation, or which tasks to give the human and which tasks to give the agent. The concept of HABA-MABA (Human Are Better At/Machines Are Better At) characterizes the strengths and weaknesses of agents and humans, which currently plays a central role in modern automation research within HAT (de Winter & Dodou, 2014). As contemporary society develops more technological advancements, the HABA-MABA list is evolving due to automation increasingly becoming more sophisticated and capable of performing tasks that were previously performed more effectively by humans. Agents are now better at performing precise and repetitive processes such as pattern recognition, data processing, responding to alarms, and maintaining productive control in high workload situations (de Winter & Dodou, 2014). On the other hand, humans are generally better at improvising, reasoning inductively, and exercising judgement (de Winter & Dodou, 2014). Furthermore, autonomous systems are able to function for longer periods of time, with greater efficiency and precision-unlike humans who are greatly impacted by excessive physical and mental workloads. In aircraft maintenance, where constant oversight of autonomous elements is needed, complacency is common due to redundant procedures. Although mechanics are equipped with the knowledge and experience to correctly perform maintenance procedures, familiarity and fatigue may occur overnight in critical elements, resulting in potential accidents (Tolleson, 2007).

In allocating tasks within HAT, any tasks humans are not able to perform at optimal level, should be delegated to the autonomous system (Boring et al., 2019). Furthermore, in circumstances where operators must perform a process under unsafe conditions, autonomous systems should perform instead. Although agents are capable of performing a wide array of processes, human engagement remains essential for HAT. Human capabilities provide better discretion when responding to unexpected events, conducting decision making, and maintaining the overall vision for success (Boring et al., 2019). Therefore, it is critical for human engagement and supervision to be present in HAT in the event the human must override automation during an unexpected event.

Automation Styles

As higher autonomy levels become more commonplace, it is critical for humans and agents to exhibit the necessary awareness and understanding amongst each other to ensure mission success (Schaefer et al., 2019). To further understand automation, human agents must differentiate between control automation and information automation. Control automation is the most recognized form of automation, in which the autonomous system governs the functions necessary to complete a specific task, whereas information automation allows the system to collect information on behalf of the human (Boring et al., 2019). As HAT operations require autonomous systems to complete more elaborate tasks, the functionalities of control and information automation inherently become more complex. Although information automation can function independently, it can complete the full spectrum of human activities when paired with control automation, allowing autonomous systems to complete a task without any human assistance. After selecting the appropriate amount of control and information automation necessary, the LOA may be established. In HAT, determining LOA is necessary for the efficiency and effectiveness of a mission, since LOA determines the interaction style between the agent and human operator (Johnson et al., 2011). For example, autonomous control systems in nuclear reactors demonstrate minimal computerized controls due to the severity of risk in the event of an accident. However, systematic approaches towards nuclear reactors present the need for autonomous controls with basic functions. Reflection of previous literature suggests that autonomous systems are better at performing repetitive tasks that require precision, whereas humans are more capable of executing tasks regarding recognition or decision making (Boring et al., 2019). Therefore, human oversight is implemented to ensure safety and immediate interaction in case something goes wrong. If a nuclear reactor was fully autonomous, where humans provided minimal oversight, the chances of humans engaging with the autonomous system in the event of an accident would be less likely due to the decrease in human supervision. From this, distinguishing the appropriate LOA and interaction style for the task type is essential to the dynamic of HAT. Glikson and Woolley (2020) present a framework of AI types which can be used as a basis for the form of the agent (physical, virtual, or embedded). It is also important to consider the way that the agent and the human *interact* with one another. Four main automation interaction styles exist currently in the HAT space: basic, adaptive, adjustable, and mixed initiative.

Basic automation is the most common interaction style, in which an autonomous system can go from being completely manual to fully automated; with no additional features in between. For example, a car can go from operating in a fully autonomous condition, in which no human input is needed, to switching into a fully manual mode of operation, where the human agent must fully operate the vehicle with no autonomous assistance. Due to the simplistic nature of switching from fully autonomous to fully manual in the basic automation style, in the event that the autonomy fails, the human operator may take over at any time. Although simplistic, this dynamic may potentially lead to delays in the human operator detecting problems with the autonomy. This phenomenon known as “Operator Out of the Loop" is a common drawback to basic automation due to the reduction of engagement between the autonomous system and operator when the automation is engaged (Kaber & Endsley, 2004). As a result, situational awareness exhibited by the operator is subsequently reduced, resulting in high potential of decreased mission effectiveness (Stanton, 2009).

Adaptive automation is dynamic and flexible in nature; and is a style in which the controls of functions shift between humans and agents depending on the situational demands of the environment (Inagki, 2003). For instance, when a human agent is experiencing levels of high workload, the autonomy will adapt by delegating and completing tasks automatically to alleviate workload. In this interaction style, the computer technology has complete authority over the operation, regardless of whether the human agent wants to override procedures (Miller et al., 2000). As the autonomous agent completes and assigns tasks, both control and information automation are implemented during adaptive automation. Although the use of information automation typically reduces the workload and situational awareness for the human operator, increased utilization of information automation may demonstrate lack of transparency between the agent and operator (Boring et al., 2019). For instance, when the agent is required to filter information, the human operator may potentially exhibit low levels of trust or high levels of overreliance. Since the operator is only following the tasks assigned, how and why decisions are taking place may not be fully understood by the human agent. Furthermore, the computing complexity of adaptive allocation demonstrates difficulties since the criteria followed during the adaptive autonomy condition must determine how and when functions are performed, and to whom functions must be assigned. As a result, the complex and highly-demanding functionalities that adaptive autonomy presents requires more development time and cost to produce (Klein et. al. 2004, Boring et al., 2019).

Adjustable automation is more human centered, as the human operator is required to reconfigure and allocate tasks to the automation. Studies have revealed that adjustable automation exhibits better HAT compared to basic automation because of its inherent flexibility and team-like structure (Valero-Gomez et al., 2011). Due to the dynamic nature of this interaction style, it is common for human operators to exhibit higher levels of workload—as they may find the task delegation time consuming and complex (Chen & Barnes, 2014). Unlike adaptive automation, the human operator takes initiative over any form of information automation, and delegates tasks for the agent to accomplish control automation procedures—which can lead to better situation awareness as the human stays in control (Chen & Barnes, 2014.

Mixed initiative automation is another type of interaction style, which entails collaborative decision making between the human operator and autonomous system (Chen & Barnes, 2014). For instance, during a mission task, the agent asks and informs the human to complete certain processes, the human operator reviews agent information and authorizes actions. Although automation serves a subordinate role in the mixed initiative condition, both operators must consistently share and communicate to each other to ensure proper human-system collaboration. In 2004, NASA developed a Mixed-initiative Activity Planning Generator (MAPGEN) which used mixed initiative autonomy to compute the optimal plan of action to conduct a Mars space mission (Bresina & Morris, 2007). By using constraint reasoning amongst physical constraints and priorities inputted by human agents, MAPGEN provided flexibility for operators to visualize different scenarios and the constraint specifications for each one (Chen & Barnes, 2014). Research suggests that mixed initiative dynamics are more effective than basic or full autonomy dynamics as humans hold final decision authority and the dynamic keeps humans informed of agent actions (Barnes et al., 2013). Table 2 provides a summary of the baseline taskwork skills for the human and agent along with needed skills as automation responsibility increases as well as team and task complexity.

Table 2. Taskwork Needs

HAT Dynamic	Human needs...	Agent needs to...
All HATs	To understand, predict, and adapt from agents' perceptions of the environment (Mirnig et al., 2016)	Perceive elements in the environment (Mirnig et al., 2016) Focus on information automation (Boring et al., 2019)
With Higher Automation Responsibility	Team management skills (Burke et al., 2006) Monitoring based on calibrated trust (de Visser et al., 2020)	Ensure human stays in the loop (Kaber & Endsley, 2004) Focus on control automation (Boring et al., 2019)
With Higher Team & Task Complexity	To be tasked with recognition and decision making (Boring et al., 2019)	Support the human in predicting and adapting to a situation (Mirnig et al., 2016) Be given precision-based repetitive tasks (Boring et al., 2019) Provide an agent manager in multi-agent teaming (Barnes et al., 2013)

Identifying Appropriate Task Allocation

The appropriate automation style will highly depend on the nature of the task and the natural skills of human and agent. In the automotive domain, current automation such as lane keeping automation focuses on tasking the automation with perception tasks (Mirnig et al., 2016). Automated vehicles perform well at this task compared to humans whereas humans are tasked with understanding, predicting, and adapting to the situation (Mirnig et al., 2016). For each domain, one must ask: "Will we have agents work as needed to assist the human? Or are we working towards agents as replacements to humans (Dubrow & Orvis, 2020)? What is the best way to support the human in both?" Tasks are allocated to teammates based on their differing KSAOs, which is what creates an effective team. As discussed by Dubrow & Orvis (2020), HAT tasks and automation allocation can be complex and difficult leading to human and agent roles overlapping. This can also occur when agents of differing levels of automation are either given too much responsibility or not enough. Poor function allocation can also arise when inadequate conclusions are made about whether the agent teammate should either supplement or augment the human's responsibility. Another way to address fundamental biases humans place upon their agent teammates, as well as to counteract for varying automation levels in HAT teammates is to establish role identity for each teammate early on and select a human teammate that has specific and beneficial personality traits, which may not be trainable. Given the wide range of HATs and the various work they engage in, it is unfeasible to provide a universal answer to the appropriate skills and tasks for humans and agents. However, there are widely applicable methods for uncovering the answers to these questions for any given team. Team task analysis is one such method by which these questions may be answered. Taken from research on HHTs, team task analysis (TTA) is a tool that systematically examines both individual and interdependent tasks that a team must do in order to identify the KSAOs necessary for the person(s) responsible for completing that task (Liu et al., 2017). One of the key features of TTA is that it specifically highlights and connects task interdependencies to member characteristics and KSAOs. Applied to HATs, TTA can be used to help allocate tasks and assign roles based on agent team member characteristics (e.g., automation styles) and human team member characteristics (e.g., KSAOs). Using recommendations from Burke (2004), Table 3 provides steps for conducting a TTA for HATs.

Table 3. Steps to HAT task analysis derived from Burke (2004)

Step	**Description**	**Relevant Citations**
1. Requirements analysis	Describe the specific tasks enacted by any member within a HAT.	
2. Identify human-agent tasking	Create separate lists for tasks done by human versus agent team members	Morgeson & Dierdorff (2011)
3. Create teamwork taxonomy	List all teamwork behaviors that each member must enact to help other team members.	Arthur et al., (2012)
4. Coordination Analysis	Identify task interdependencies and decide human-agent interaction styles (basic, adjustable, adaptive, mixed initiative).	Cannon-Bowers & Bowers (2011)
5. Determine critical tasks	Conduct task importance studies to prioritize essential tasks for training/selection. Consider the level of task complexity, teaming complexity, and agent's responsibility when evaluating task importance.	Bowers et al., (1993)
6. Identify KSAOs from critical tasks	Identify human KSAOs and agent characteristics that are required to perform critical tasks well.	Goldstein & Ford (2002)
7. Link KSAOs to team-tasks	Connect the KSAOs back to the team's tasks and goals. Train/select for critical human KSAOs. Restructure human-agent interaction or role requirements if needed (consider HABA MABA to align roles with human or agent tasking).	

CONCLUSION

This paper aimed to discuss the current space of HAT and the challenges associated with defining KSAOs for the space as a whole. Current frameworks and the limitations within them were presented. A fluid framework that presents the complexities of modern HAT as a continuum was developed based on the complexity of the team and the responsibilities of the agent. Current guidance that can be assumed for all HATs along with necessary additional skills as task complexity and agent responsibility increase are presented. As agents become more advanced, the nature of the HAT dynamic will continue to evolve and additional considerations will be needed. The framework presented here is by no means comprehensive but aims to provide a starting point for those creating new HAT in military settings and beyond. Agents will continue to shift from tool to teammate. By utilizing HHT research and human factors design research, designers of HATs can begin to find ways to leverage the capabilities of both human and agent to their fullest potentials.

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