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# NOTICES

## Disclaimers

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**14. ABSTRACT**

With ever-more intelligent technological capabilities and particularly the increasing availability, modes, and transmissibility of information that can reshape our understanding of the global context and human action within it, opportunities exist for advancing the mechanisms that we employ to train personnel and perform complex team operations. We propose that future mechanisms can be developed to enhance military team performance, for heterogeneous human-intelligent technology teams through technologies that focus on enhancing teamwork, or team states and processes, through individualized information, processing, and behavior for each team member. We discuss the potential capabilities of these future mechanisms, articulate why we believe these capabilities can be developed, and outline the critical scientific questions that must be addressed to enable this future vision.

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## Contents

# 1. Introduction

The recent acceleration in the emergence and widespread application of artificial intelligence and machine learning (AI/ML) is leading to a fundamental revolution in the way that society functions on all levels across the globe. Whether in wrist-borne sleep and activity monitors, online shopping carts, "smart" mobile devices, or even in our vehicles, AI/ML-enabled intelligent agents are quickly becoming ubiquitous and, as such, fundamental to life experience in the developed world. Public debates have emerged regarding the alternately fortuitous and disastrous potential of advances in such technologies, which are envisioned to enable monitoring and interpretation of the life patterns, precise prediction of the behaviors of individuals and groups, and even performance optimization through explicitly influencing brain states (Yuste et al. 2017). With ever-more intelligent technological capabilities and particularly the increasing availability, modes, and transmissibility of information that can reshape our understanding of the global context and human action within it, we are expectedly rethinking the mechanisms that we employ to train personnel and perform complex team operations.

We propose that future mechanisms can be developed to enhance team performance—specifically, military team performance—for heterogeneous human-intelligent technology teams through technologies that focus on enhancing teamwork, or team states and processes, through individualized information, processing, and behavior for each team member (Mait et al. 2017). We discuss the potential capabilities of these future mechanisms, articulate why we believe these capabilities can be developed, and outline an initial suggestion of the critical scientific questions that must be addressed to enable this future vision.

As the vision for Internet of Things promises a world of interconnected devices that anticipate our needs, we can expect future military teams to be equipped with an array of intelligent and networked agents that anticipate the needs of the team and make decisions both independently and in coordination with their human teammates. This will differ fundamentally from the human-centered team concepts on which military doctrine and organizational psychology are built. At present, military teams train and operate with a host of advanced technology (e.g., night vision technology, smart weapon technology), but at their core, the technology endows human team members with greater individual capabilities and does not effectively change the dynamics of human teamwork. Merely increasing individual member capabilities may not enhance the short- and long-term emergent properties of teamwork that are critical to team performance. This issue will become increasingly critical for future teams that are expected to require close cooperation, coordination, and communication between dynamic assemblages of human and agent (e.g., robots, intelligent assistants, and intelligent sensors) teammates, particularly when the teams are not trained together. Further, both Soldiers and intelligent agents (both envisioned to have varied levels of training, experience, and operational capabilities) will likely be required to adapt to new styles of work and interactions over the courses of their deployment that induce novel challenges that the teams must overcome. In envisioning this future of human–agent teaming, we hold 3 critical assumptions.

1) First, human capabilities and human team members within the future operating environment will continue to be necessary. The specific capabilities required of humans will change from what they are today, but technology will not replace humans completely.

2) Second, the roles of humans and the nature of the interactions they have with autonomy will change. The concept of technology being a tool for humans will be superseded by technology as mentored actors in the environment, teammates with unique non-human skills, and technology that augments fundamental human capabilities.

3) Third, the training required for humans and groups to be effective will change dramatically. Training will have to enable humans and teams to handle the dynamic and rapid evolution of technology, as well as the shift in critical analysis and action from humans to intelligent technology.

Advancements across many different domains are considered critical to this future human–agent teaming vision. Piekarski et al. (2016) document many of the challenges from an intelligent systems perspective, including control of large, distributed autonomous teams with varying levels of autonomy and intelligence; combining autonomous agents, sensors, and tactical super-computing to establish distributed networked intelligent systems; and methods for heterogeneous teams to carry out tasks under dynamic and varying conditions. Similarly, Suri et al. (2016) describe research challenges related to fundamental understanding of how to learn and devise complex models of the Internet of Battlefield Things, including goals, networks, information, and analytics that enable intelligent command and control, and battlefield services. In 2017, the US Army Research Laboratory began 2 large-scale collaborative research programs to address these challenges.

Neither of these current efforts focuses directly on optimizing solutions to enhance human strengths and mitigate human weaknesses, nor do they directly address development of the inherent teamwork (states and processes) between humans and autonomous agents that is extremely critical to this future vision. Here, we open discussion about one promising approach to addressing the larger problem of coordination and cooperation in human–agent teams—individualized and adaptive technologies that promote effective teamwork in teams of humans and intelligent agents. This report posits a number of critical capabilities necessary to realize the future human–agent teaming vision. Within this discussion, several reoccurring topics are critical to discuss upfront, including teamwork and individualized, adaptive technologies.

## 1.1 What Do We Mean by Teamwork?

Many researchers have argued that team performance is a multilevel process that includes both individual taskwork performance processes and individual- and team-level teamwork processes (Kozlowski and Klein 2000; Salas et al. 2007). Marks et al. (2001) provided definitions of taskwork and teamwork to distinguish the 2, suggesting that "taskwork represents what it is that teams are doing, whereas teamwork describes how they are doing it with each other" (p. 357). When we refer to human–agent teaming and human–agent teamwork, we are focused on the team-level states and processes that influence performance and effectiveness (e.g., cohesion, shared mental models, shared situation awareness, coordination, and communication), rather than individual taskwork.

## 1.2 What Do We Mean by Technology Agent?

To this point, it may be unclear what we mean when we use technology, agent, intelligent agent, and teammate. We consider the team to be composed of human team members as well as distributed sensors, robots, UAVs, autonomous vehicles, intelligent assistants, and other advanced technologies that can perform taskwork as part of the larger team, while we reserve the term technology for those devices, software, protocols, and other interventions that target the members of the team with the goal of improving team processes. It is entirely possible that a technology will also be a team member, which we refer to as an agent. We use the term technology when referring to its role as assisting in team performance as opposed to satisfying its role in the team (i.e., completing its assigned taskwork).

## 1.3 Technologies of the Future Should be Individualized and Adaptive

Military technologies and doctrine prioritize the interchangeability of operators. Although this leads to robust performance, assumptions about average operator capabilities limit system capabilities and also likely constrain high-performing individuals from using the full extent of their own and the system's capabilities. Future technologies need to be adaptive and individualized, accounting for individual's capabilities and limitations in real-time to achieve greater performance. In allowing individual agents to behave in manners that are consistent with their own strengths rather than imposing uniform behaviors, individual performance should be dramatically improved. Shifting to this paradigm also enables technological solutions to target particular individual capabilities and performance that improve team-level properties and performance.

Within this context, we focus here on science and technology to enable the interactions and interdependencies between heterogeneous members of human–agent teams, and specifically, on influencing individual team members with the goal of enhancing emergent team properties contributing to effective performance, and limiting emergent team properties contributing to less effective performance. The report posits 3 broad, intertwined areas that frame the technical and scientific challenges: 1) Individualized, Adaptive Technologies for Teamwork, which focuses on technologies that can adapt to individuals to optimize systems of interdependent agents for the purposes of enhancing overall team performance; 2) Adaptive Implementation, which focuses on the adaptive application of individualized technologies based on the dynamics of task and environmental context and team members (e.g., state, knowledge, skills, abilities); and 3) Training for Mutual Adaptation and Complex Teaming, which focuses both on how training must change for humans and agents to team in highly adaptive, highly intelligent technology contexts, as well as how individualized technologies can support on-the-job training.

## 2. Individualized, Adaptive Technologies for Teamwork

Emerging capabilities in science and engineering are enabling a future of adaptive and individualized systems that account for variability in an individual's capabilities and limitations in real-time to achieve greater individual performance. This individualized, adaptive approach is critical because it incorporates the ability to improve individual performance by enabling greater variability in behavior. However, if we want to realize the full human–agent teaming vision, it will not be sufficient that technology improves the performance of one human or agent. When considering team performance, it is well understood that team outcomes are not simply a sum or an average of the parts. Instead, emergent properties are the result of the interaction of the components of the system, which cannot be reduced to or described wholly in terms of the elementary components of the system considered in isolation. Teams are able to synergistically combine the attributes of team members to produce outcomes beyond the capacity of any one member or of the pooled output of all members. Similarly, ineffective processes and states of the team often emerge leading to team failures, regardless of the individual performance of each team member (Salas et al. 2009).

Considering the failures in human teams, breakdowns are commonly due to problems with team states and processes—insufficient communications, misunderstanding of team goals, undefined team responsibilities or lack of shared mental models, and conflict, as examples (Kohn et al. 2000; Salas et al. 2007). Team-focused training and development literature suggests that the best human teams can overcome external demands (e.g., distributed environments, lack of resources, time pressures) and some individual performance problems through a focus on effective team processes, such that they may not always perform the best on every task, but they will outperform teams lacking effective processes over time (Weaver et al. 2014). However, teams composed of humans, intelligent software agents, embodied agents, and networked sensors add complexity to the concept of emergent properties that may not be completely comprehended today. Considering cognitive and behavioral processes such as decision making and coordination, humans and agents will be working in disparate dimensions (time, space, world views, representations, mental models, etc.), yet need to seamlessly synchronize for collective action. For example, intelligent agents will process information, reason, and make decisions at scales beyond that of humans in both time and magnitude; and yet, we will want to include humans in the decision-making loop for many, if not most, decisions. Similarly, intelligent agents will learn and adapt far more rapidly than their human counterparts, but may possess less flexibility and range in what they can learn. How will we capitalize on the individual advantages of both humans and agents, and simultaneously enhance the performance of the collective group?

Not only will we need methods to bridge diverse capabilities, processes, and beliefs, but much of what we know about critical states and processes in human teams may not be applicable. The very notion of a shared mental model among humans and intelligent agents begs significant scientific and philosophical questions. Shared understanding of team responsibilities and goals among humans and intelligent agents, as it is practiced in human teams, assumes intelligent agents with human-like intelligence; however, non-human teammates will likely span the spectrum of machine intelligence—from passive sensors with only the ability to sense and communicate to advanced machine learning algorithms that can adapt and learn in real-time. Breakthroughs in representation learning and explainability should facilitate human understanding of machine reasoning, but are shared mental models like those targeted in human teams the right approach to human–agent teaming? The very nature of these emergent properties is fundamentally different than our conceptualization today, and assuming that human–agent team cohesion, coordination, and collective performance will develop in ways similar to human teams without concerted scientific focus and effort is naive. So, what are the critical states and processes for effective performance in human–agent teams, and how do we use individualized and adaptive technologies to elicit these emergent team processes in human–agent teams?

## 2.1 Capabilities

To effectively perform in these complex human–agent teams, we suggest the need for technologies that can adapt to individual team members (both humans and agents), as well as the emergent properties and constraints of the group over time, to optimize the system of interdependent agents. Here, we propose a few examples of future capabilities that we believe will be critical for enhanced human–agent teaming in the future operating environment previously described. With the overarching goal of overcoming limitations and enhancing strengths of individual humans and agents to optimize team-level states, processes, and performance, we expect capabilities in the following areas to be critical to enable this future vision:

### 2.1.1 Individualized Technologies to Enhance Coordination and Shared Understanding in Distributed Environments

While the emergent processes relating to coordination and shared understanding in human–agent teams may unfold much differently than with human–agent dyads, human-only teams, and agent-only teams, capabilities enhancing coordination and shared understanding in distributed environments, or environments where all team members are not collocated, will be critical. The focus here is not on the technologies that can physically communicate across distributed networks, but instead on individualized, adaptive technologies that couple advanced sensing techniques with state-of-the-art machine learning approaches to enhance capabilities for teams of humans and agents to come together, cognitively and behaviorally, to anticipate each other's decisions and actions, and perform interdependent, collective tasks in synchrony.

### 2.1.2 Technologies Targeting Cohesion and Swift Action with New, Diverse, and Rotating Teammates

An advantage of human–agent teams is the ability to bring together diverse expertise and capabilities particularly targeted for performance on a specific mission. However, rapid reconfiguration of teams does not come without a price, or an effect on team processes, both initially and over time (Bell and Outland 2017). Compounding this known problem, human–agent teams are inherently diverse at a deep level, and these differences between humans and agents have the potential to drastically mutate over time in human–agent teams (with agent adaptation and learning). Therefore, capabilities are needed to facilitate swift development of cohesive action in diverse human–agent teams that include new, rotating, and evolving team members. To improve interoperation, we propose these technologies need to enable humans and machines to compensate dynamically for shortcomings of other members through individualized, adaptive mechanisms. For example, each team member may have individualized agents responsible for quickly getting them up to speed on team members, roles and responsibilities, strengths and weaknesses, and predicted actions throughout the mission, in relation to their own role, knowledge structure, biases, strengths, and current state.

### 2.1.3 Individualized Approaches to Developing Agile Group Performance and Team Efficacy with Human and Agent Degradation and Loss

Not only is swift action important when teams are rapidly reconfigured, but agile performance is critical amid unexpected changes, including both human and agent degradation and loss. Degradation and loss of both humans and agents has strong repercussions on the perceived efficacy and the collective performance of the human–agent team. However, humans and agents may experience degradation and loss in much different ways, including affectively and behaviorally, which can subsequently impact the cohesion of the group. For example, maintaining and demanding a pure task focus after an injury could be viewed negatively by human team members and cause friction within the group. Individualized technologies that can quickly detect the degradation or loss of an agent, monitor affective, behavioral, and cognitive changes due to loss, and subsequently reallocate roles and responsibilities across the team that appropriately account for the variation in team member states are critical. As an example, individualized technologies may detect affective changes in team members and work with task allocation technologies to adjust roles and responsibilities within the group to provide opportunities for understanding and coping with loss when needed, but simultaneously maintain functioning.

### 2.1.4 Technologies to Minimize Process Loss with Continual Individual Development, Ever-Increasing Complexity of Action, and Prediction of Future Behaviors

Human–agent teams, as envisioned in the future, will be capable of performing within environments of ever-increasing complexity, both internally and externally, that are almost inconceivable today. To facilitate effective performance within these realms of complexity, individualized, adaptive technologies are needed to minimize the process losses (e.g., communication, coordination, backup behaviors) we currently see with complexity in teams. Where appropriate, these technologies would target effectiveness in terms of both quality and efficiency within the states and processes that are critical in human–agent teams.

## 2.2 Why Do We Think This Can Happen?

With the prevalence of advanced technologies in society, we can easily envision a future of adaptive and individualized systems that function with an individual's capabilities and limitations to achieve greater human-system performance. This individualized human-technology approach is expected to enable greater variety in human behavior, while having the ability to maintain consistent, robust outcomes when viewing the human-technology behavior as a system. However, when considering multiple agents and multiple humans, much work still needs to be done to fully realize the envisioned future of human–agent teaming. Here we draw on key findings from research into individualization technologies, human teams, intelligent agent teams, and mixed agent teams to identify a foundation for future research questions on how individualized technologies can enhance human–agent teamwork.

### 2.2.1 Individualization

Recently, we have seen unparalleled advancements in sensor and analysis technologies that provide new insights into different facets of human psychology, physiology, behavior, and performance. For example, advances in neuroscientific tools have revealed fascinating discoveries on how differences in brain structure and function are associated with precise human behaviors (Telesford et al. 2016; Garcia et al. 2017). Advances in social and environmental sensing tools have provided unprecedented insights into patterns of gross human social behaviors (Kalia et al. 2017), while advances in biochemical or fluid sensing (i.e., blood, sweat, and tears) are providing unique insights into the continuous dynamics of internal human states and traits. More generally, advances in wearable devices have enabled the tracking of a wide range of factors including activity, sleep patterns, and various physiological parameters (Bonato 2010). These advances can be coupled with novel computational methods to infer motivations, predict behavior, and reason about the environment and the agents acting in it.

### 2.2.2 Human Teams

Research on human teams started out very disparate; however, a growing consensus amongst experts in the field suggests the importance of a core set of team inputs, as well as attitudinal, behavioral, and cognitive emergent states and processes that impact performance-related outcomes (Marks et al. 2001; Ilgen et al. 2005; Salas et al. 2005; Burke et al. 2006; Salas et al. 2009). Team cognitive processes and states relate to shared cognitive activities such as shared situation awareness, shared mental models, transactive memory, and macrocognition (Cooke et al. 2007), while affective/motivational team processes and states include concepts such as team cohesion, collective efficacy, and intragroup conflict. Behavioral processes and states represent what teams actually do, or their actions, to produce team performance outcomes, such as communicate, coordinate, and adapt (Kozlowski et al. 2015). From this work, emerges a core set of actionable properties of teams that can be targeted for performance enhancements. However, questions remain regarding how these states and processes translate in human–agent teams.

Additionally, there is a growing body of literature on team composition and team assembly, which examines the influence of individual factors, relational and multimodal networks, and ecosystems of teams on group outcomes such as satisfaction and performance. While much work has linked semistable, individual compositional elements of teams (e.g., personality, cognitive ability and styles, demographics, knowledge and ability) to group-level processes and outcomes (see Cooke 2015 for review), less is known regarding the influence of individual characteristics in dynamic, long-term team contexts, where individual attributes may vary within the group and within individuals over time. Harnessing this within-group and within-individual variability in a team context requires a careful methodological approach to avoid risking loss of data richness when aggregating attribute data across individuals over time and across groups. Currently, little is known about how dynamic individual variability contributes to team performance, primarily because measuring continuously variable individual attributes is difficult and incorporating these variable attributes into models of group interaction dynamics has been methodologically infeasible until very recently (Schecter and Contractor 2016). In addition to recent advances in networked-based models that enable examination of more complex dynamics, incorporating individual variability into group-based performance measurements, dynamic measurement of team emergent properties and group performance has also advanced. Kozlowski et al. (2015) provided a research paradigm for examining the multilevel dynamics of emergence using computational modeling, simulation, and experimentation approaches. Simultaneously, many researchers have been making great progress in developing continuous, unobtrusive measures of these dynamic team processes, using sensor- and systems-based data (e.g., Olguın et al. 2009; Baard et al. 2012; Rosen et al. 2012; Kozlowski et al. 2013; Orvis et al. 2013; Duchon et al. 2014). While research examining the relationships between individual dynamics and team outcomes in relation to group composition and assembly remains scarce, these recent advancements in computational approaches and measurement of individual and team dynamics provide an opportunity to develop individualized approaches targeting team states, processes, and performance over time.

### 2.2.3 Intelligent-Agent Teams

As opposed to the human-only teams research, which looks across this broad set of states and processes to enhance team performance, research on intelligent-agent teamwork tends to focus on coordination in teams of intelligent agents posed as problems of task allocation (Gerkey and Matarić 2004). Given some fixed team task and a team of individual agents with specified capabilities, how can the taskwork be optimally distributed? In human-only teams, this relates to division of labor, role clarity, and explicit coordination (Van de Ven et al. 1976; Kogut and Zander 1996). Although a difficult computational problem, both exact and heuristic methods already exist to solve these problems. Another potentially more difficult aspect of coordination in intelligent-agent teams is the ability to develop strategies and policies for teamwork in real-time to respond to the unique environment and team makeup instead of relying on preplanned or rule-based strategies (Stone et al. 2010). However, recent breakthroughs in deep reinforcement learning have led to the ability to learn complex cooperative behaviors in multiagent systems in an end-to-end framework (Foerster et al. 2016; Sukhbaatar et al. 2016). In addition, significant advances in terms of distributed optimization have laid the theoretical groundwork for distributed cooperation in teams of intelligent agents (Nedic et al. 2010). For evidence of the rate of improvement in teams of intelligent agents, the RoboCup competition provides one such example of cooperation of fully autonomous systems in a complex environment.

### 2.2.4 Mixed-Agent Teams

The question of how to merge advances in human team-focused research with advances in the research on intelligent agent teaming remains a challenge for enhancing teamwork in human–agent teams; however, considerable research has explored coordination in mixed-agent teams. The extant literature has most commonly offered substitution-based function allocation to balance exclusive control or decision authority between humans and autonomous systems (Sheridan 2000; Dekker and Woods 2002). Some function allocation concepts have considered task type and the level of autonomy (Parasuraman et al. 2000) alongside typical "man-is-better-at"-"machine-is-better-at" roles (Fitts 1951). Such function allocation concepts have been instantiated in a number of different control frameworks, the most widely recognized of which is supervisory control (Sheridan 1992), which can be implemented in a variety of ways ranging from autonomous waypoint navigation to shared control schemes in which both the human and the autonomous system provide control inputs with different relative contributions (e.g., Crandall and Goodrich 2002).

## 2.3 Scientific Questions

While there is growing evidence that we can employ individualized approaches to enhance human–agent teamwork in the complex environments envisioned in the future, there are limited examples of true human-autonomy teams involving multiple humans and multiple intelligent agents. Additionally, much of the current research using individualized technologies focuses on optimizing individual performance within the team without consideration for overall team emergent properties and performance. In the following, we propose some of the core scientific questions addressing interactions between humans and agents that are critical to the future of human–agent teaming.

1) Shared mental models underlie the effective communication and coordination of human teams, and similar concepts have emerged in multiagent systems both organically and by inspiration from human teaming. In complex teams of the future, will it be necessary to maintain a shared mental model amongst teams of humans and intelligent agents? If so, how do we operationalize "shared" mental models in these complex teams? How will human–agent teams develop and manage these shared mental models of the problem, environment, and other team to facilitate communication and rapid mission planning and adaptation?

2) Effective teams capitalize on a rich knowledge of each other's strengths, weaknesses, and patterned behavior to inform role assignment. In a future human–agent teaming scenario in which intelligent agents can instantly download new behavior models, no coherent team may exist for longer than a single mission or sub-goal. Is it possible to rapidly achieve the effect of rapport with new team members (e.g., anticipate their actions or recognize their strengths and weaknesses)? What aspects of rapport-building and trust are most critical in these evolving teams, and how do we develop these in both humans and agents?

3) A rich body of literature connects particular teamwork processes such as communication, shared mental models, and coordination with effective team performance in human teams. Will models of the critical emergent team processes generalize to human–agent teams? Will the same emergent team processes be critical in human–agent teams, or will other novel team processes emerge? How will such properties be validated and measured?

4) Future human–agent teams must contend with variability in the most general sense. Human team members possess diverse capabilities and personalities, each of which is subject to significant variability. In addition, intelligent agents will manifest as unmanned ground and aerial vehicles, networked knowledge bases, and personal assistants, constantly learning and adapting. How do we incorporate complex human and agent variability into closed-loop systems targeted toward team-level performance? What novel approaches are critical to using individualized technologies for the purposes of optimizing the human–agent team? How do these approaches use variability over multiple timescales enable the optimization of team performance immediately (e.g., single task) and over long periods of time (multiple missions, life cycle of team)?

# 3. Implementation

Underlying the individual capabilities and emergent team processes are complex interdependencies between individual and team states. This means that effective implementation of an individualized technology depends on an understanding of the downstream effects. Intervention at the individual level without regard for how it will interact with simultaneous individual interventions and the current states and processes of the team will not lead to improved team processes and performance. In the previous section, we focused on describing these future technologies that are individualized to overcome limitations and enhance strengths of individual humans and agents, but are focused on enhancing human–agent teamwork. Now, we focus on the capabilities needed to strategically apply and implement these technologies, taking advantage of knowledge about individual humans and agents, as well as emergent team properties. Here, we brainstorm critical capabilities needed to implement the mentioned technologies when appropriate or needed, including being intelligent enough to know when interaction may overburden the team or result in unexpected negative consequences across individual team members or amongst diverse, yet interdependent coordinating mechanisms within the team.

## 3.1 Capabilities

### 3.1.1 Real-time Monitoring of Individual and Team States and Processes

The first critical capability is the ability to assess and deliver technologies to enhance human–agent team performance to the right individuals at the right time, to enhance the performance of the group. This builds on current capabilities focused on continuous monitoring of individual states to optimally tailor augmentation technologies to the individual to enhance individual performance. Instead, however, this capability requires 1) aggregation of multiple data-types to provide valid measures of team states and processes, and 2) a systems-based perspective, continually monitoring all nodes within the human–agent team to determine the optimal intervention in real-time. This holistic assessment is then used to tailor delivery of technologies to enhance team states, processes, and performance in the most effective ways. Importantly, this could include tradeoffs in individual performance for the benefit of the collective, or varying interventions for particular individuals or subgroups to achieve desired states of the collective.

### 3.1.2 Adaptation During Complex Events in a Dynamic Environment

In addition to understanding the individual and team dynamics to deliver at the point of need, effective implementation of these future technologies requires understanding of and adaptation to the external dynamics critical to the context of the team and mission. Examples of these external dynamics that must be monitored and incorporated into implementation of future technologies include environmental factors, sociocultural influences and shifts, changes in mission goals, and perhaps changing goals of higher-level and adjacent teams. When considering technologies to enhance the effectiveness of a human–agent team, a systems-based approach to affecting this performance must include adaptation from the environment during all phases of planning and action.

### 3.1.3 Synergizing Cognitive, Affective, and Behavioral Processes

Another critical capability in regards to implementation of individualized, adaptive technologies to enhance human–agent teaming includes the capability to synergize between different types of processes and states within the team. Team states and processes are correlated, so understanding, measuring, and accounting for the dynamic interplay between different types of emergent group properties is important. For example, one can imagine times when providing more information (enhancing shared situational awareness) could result in delays in collective action, as human team members take time to process new information. Considering the directly enables human-technology designs (dyadic) pairs and subgroups of the team, and understanding critical elements of emergence (e.g., distribution of team situation awareness, or coordination among pairs versus entire group), approaches to optimally balance across subgroups may be beneficial as well. For example, when information and action demands are high, "cognitive" processing may be offloaded to a subgroup of intelligent agents for a period of time to allow for greater concentration on physical movement in a subgroup of human teammates. Thinking over slightly longer timescales, there might be times when teams should focus efforts on enhancing team affective states, such as cohesion, rather than jumping into specific cognitive and behavioral processes, such as decision making. Future technologies must consider tradeoffs amongst these states and processes to achieve optimal performance over the life-cycle of the team.

### 3.1.4 Coordination of Individualized, Adaptive Agents and Humans

The final capability needed to implement individualized, adaptive technologies to enhance human agent teaming is the ability to dynamically adapt control and decision authority between humans, autonomous systems, and consensus protocols in the face of dynamic team states, goals, and environmental context. Of particular importance is the fact that external factors, such as military doctrine, rules of engagement, or political implications, may often dictate when intelligent agents are allowed to make certain decisions. In situations where the intelligent agent is not permitted to make decisions, the team must be capable of shifting the balance of control for that decision to the appropriate human team member with minimal disruption to the remaining team functions. Enabling these shifts in control could involve tradeoffs where the immediate team performance is sacrificed to satisfy top level constraints, such as military doctrine and enable long-term mission success. As complex coordination mechanisms develop, considering transformation of such top level constraints will be critical, as well, particularly with emerging advances in consensus decision making in heterogeneous teams.

## 3.2 Why Do We Think This Can Happen?

We are presently witnessing the diffusion of intelligent technologies into every facet of modern life. Digital personal assistants, such as Google Home and Alexa, leverage a suite of internet-based sources to provide users access to information and entertainment through a natural language interface. Phones, watches and other wearable devices can provide detailed insights into behavior, and physiology during everyday activities. Self-driving cars appear to be on the verge of wide spread use. For enhanced human–agent teaming, we must combine the capability for real-time sensing and prediction of the states of individual team members—as well as the whole team—with scientific advancements in understanding the interdependencies in individual and team states and processes in human–agent teams to deploy precise technological interventions. Here we draw on key findings from research into artificial intelligence/machine learning and adaptive control architectures to identify a foundation for future research questions to adaptively apply individualized technologies to enhance human–agent teamwork.

### 3.2.1 Artificial Intelligence and Machine Learning

The ongoing revolution in machine learning and artificial intelligence, precipitated by deep learning, points to a future with the capability to individualize technology at the point of need and adapt during dynamic and complex events (LeCun et al. 2015). The highly publicized successes of deep learning span visual perception (Krizhevsky et al. 2012), speech recognition (Hinton et al. 2012), and sequential decision-making (Mnih et al. 2015; Silver et al. 2016), but machine learning technologies can more broadly recognize facial expressions (Ranjan et al. 2018), generate natural language descriptions of visual input (Socher 2014), and allow intelligent agents to learn the preferences of humans (Warnell et al. 2017). These latter modalities offer a vision for how machine learning can be used to interface with humans and even other intelligent agents in a teaming scenario. Simultaneously, industry-led efforts are underway to make deep learning-enabled devices deployable in the real-world through embedded hardware and cloud computing. Taken together, many of the scientific capabilities required for real-time inference of motivations and behavior prediction exist today. However, there is much work to do in developing the predictive algorithms for individual, team, and external (e.g., societal, organization) states and behaviors. With each layer, complexity and uncertainty make accuracy and timeliness of these predictions more challenging.

### 3.2.2 Control Architectures for Continuously Adapting Human–Agent Teams

Another critical area for realizing this individualized human-technology approach to enhance human–agent teaming is embedding the capability to infer motivations, predicting behavior and reason about the environment into a closed-loop system that can initiate individualized interventions at the right time to improve team performance by leveraging the strengths, and offsetting the limitations of each agent, whether human or autonomous. For instance, it has long been understood that, though autonomy can execute predictable, well-defined procedures with superior speed and reliability, humans are far superior at tasks that require inductive reasoning and adaptation to novel and/or changing information (Fitts 1951; Sheridan 2000; Cummings 2014). As a result, system integrators have developed a wide range of approaches to supplement autonomy with human inputs to increase resilient and robust performance within complex, dynamic, and uncertain environments. Adaptive schemes have been developed to enable active management of the balance of inputs from human and autonomous agents through user selection (Crandall and Goodrich 2001), based on cost-benefit estimates of the performance of the agents (Sellner et al. 2006), or by enabling the autonomy to periodically query the operator for assistance (Fong et al. 2003a, 2003b). Unfortunately, the majority of these approaches have only succeeded in limited and controlled contexts, and have not been widely adopted for real-world use. However, with relatively few exceptions, most approaches have treated the human as the apex of the command hierarchy (Billings 1991; Sheridan 1992; Fong et al. 2003a; Abbink et al. 2012) rather than as a fully collaborative agent (Woods and Branlat 2010). We join those who have argued that adherence to this premise has limited how well human inputs have been integrated with autonomous systems (Woods 1985; Woods and Branlat 2010; Cummings and Clare 2015).

We argue that the failure of traditional systems-level design approaches is due, at least in part, to failing to fully account for the dynamic strengths and vulnerabilities the individual agents. More recent efforts have pursued human-automation interactions that capture a more authentic essence of natural teaming behavior (Woods and Branlat 2010; Lyons 2013; Chen and Barnes 2014). In our own work, we recently proposed the Privileged Sensing Framework, an evolved approach that treats the human as a special class of sensor rather than as the absolute command arbiter (Marathe et al. 2017). This approach is based on the concept of appropriately "privileging" information during the process of integration, by bestowing advantages, special rights, or immunities based on the characteristics of each individual agent, the task context, and/or the performance goals. One recent study has demonstrated that this approach to enable natural teaming behavior has enabled a team of humans and intelligent agents to work together to efficiently label targets of interest in large image datasets (Bohannon et al. 2016). Building on this example to include broader application spaces and more dynamic intelligent agents will require continued research in a variety of areas.

## 3.3 Scientific Questions

Implementing individualized technologies to enhance teamwork in human–agent teams requires: a) precise observation or inference of individual and team states, processes, and performance over time, b) understanding of dynamic events in the operational environment and within the hierarchical and lateral structure of the teams, and c) the ability to seamlessly and synchronously allow for adaptation while maintaining effective collaboration, coordination, and dynamic control amongst humans and agents. While much progress is being made in these areas, we suggest that addressing the following scientific questions is critical to realizing this future vision for human–agent teaming:

1) The ability to deliver interventions to modify behavior of the appropriate team member at the appropriate time will be critical for enabling effective human–agent teams. What type of interventions are likely to be most effective at enhancing team performance? How will the need to enhance performance of each individual agent be balanced against the need to improve performance of the team? What types of situations warrant sacrificing the performance of an individual team member for the good of

the team? What types of situations or tasks warrant sacrificing team performance to enhance individual performance?

2) What methods are needed to sense shifts in environmental and sociocultural influences, changes in mission goals, and determine relevance to the team mission? As dynamic events unfold, the availability of information is often sparse, and the reliability of information available is often unknown. What mechanisms must be in place to account for and adapt to the fluid nature of information availability and reliability in these dynamic situations? How can human–agent teams be designed to adapt to these events effectively, given the expected changes in information reliability?

3) To enhance human–agent team performance, technologies must be capable of balancing among different types of states and processes within the team. On one level, there are questions regarding balancing individual and team variability, such as: How can advanced measurement technologies be used to infer individual and team states and behaviors, incorporating variability in humans and agents over time? How can advanced measurement methodologies and modeling techniques be employed to understand dynamics in team processes over multiple timescales? On another level, there are questions regarding the balancing the skills and tasking of individual team members on multiple timescales: How can technologies assist in the dynamic allocation of tasks to individual team members to appropriately balance the variability in both physical and cognitive skills and capacity across the team to maximize team performance? How can technologies be used to manage team activities to enhance effective states such as cohesion? Given all of these competing needs, how can technologies effectively balance all of these needs to achieve optimal performance over the life-cycle of the team?

## 4. Training for Mutual Adaptation and Complex Teaming

The development and implementation of the future human–agent teaming vision, including the individualized technologies for enhanced human–agent teaming previously described, generates both the potential and need for a training revolution. Individualized and adaptive designs have the potential to reduce aspects of current training requirements and enable novel training focused on the technological complexity and pervasiveness expected to dominate the next generation of warfare. This approach directly enables human-technology designs (dyadic), as well as heterogeneous human–agent organizational designs (team and organizational), that maximize the potential capabilities that future technologies offer rather than restricting capability to ensure maximal interchangeability of operators. We envision advancements in science and engineering focused on individualized, adaptive technologies for enhancing teamwork to lead to novel capabilities revolutionizing the way we train both individuals and teams for superior group performance. We also anticipate that this shifting focus toward a more mainstream and pervasive incorporation of intelligent and adaptive technologies into organizations will precipitate a shift in critical knowledge, skills, and abilities across jobs. Further, we expect this work will push research on shared mental models, such as transactive memory systems (Wegner 1986; Palazzolo 2017), to develop fully integrated hybrid human–agent teams that require training in new ways for augmented conceptualizations of who knows what on the team.

At the individual level, we can expect many key tasks that are traditionally trained to be completely automated or conducted in conjunction with agent-based technology, or aided by robots, sensors, and software. This creates a need for STEM-related competencies for designing, manipulating, and troubleshooting software and hardware technologies on the job—a need we already see shifting K–12 curriculums. In addition to thinking about what cognitive capacities are added to teams, maintenance of certain information sources and knowledge domains may no longer be required. For example, with the addition of smartphones, most people have stopped remembering phone numbers. Technological advancements also drives questions regarding what unique and important capabilities humans can add to the teams of the future, impacting individual training content, design, and delivery. We suggest that humans will always be critical to higher-order decision-making, complex coordination, human-centric civil engagements, etc., but the individualized, adaptive capabilities expected in the future could dramatically change elements of these roles, the information and resources available at the point of need to enact these roles, and the modes and methods regarding how training is delivered in a team context.

## 4.1 Capabilities

While individual and team taskwork and the critical individual knowledge, skills, and abilities to complete these tasks are expected to transform, to prepare for the future of human–agent teaming, our conceptualization of training for teams and the teamwork competencies critical for enhanced team performance needs to dramatically evolve. Aligned with the focus of this paper on a future teaming concept, we brainstorm several capabilities related to training, development, and continuous learning for teams that may be necessary to help prepare for this future.

### 4.1.1 Training Teamwork Competencies in Human–Agent Teams

While human teammates are responsible for different taskwork in future human–agent teams, this will only increase the importance of key teamwork competencies. For example, communication will need to be generalized to build shared understanding and commitment to team goals among humans and intelligent agents. Convergence on shared goals may need to be iterative and not top-down in a scenario in which human team members cannot process the same amount of information at the same timescales as intelligent agents, yet require involvement in the decision-making process. Understanding the critical competencies for human–agent teamwork and advanced methods to train these competencies in humans, agents, and together as a team will be critical to this future vision.

### 4.1.2 Preparing for and Incorporating Mutual Adaptation

Variability, evolution, complexity, and adaptation are critical factors prevalent in human–agent teams of the future. In human teams alone, the variability in human states and behaviors over time, as well as external factors, critically impact team outcomes (Kozlowski et al. 2013). This creates a necessity for team members to continually adapt. In the military, unit-focused training is typically designed to eliminate this variability. Targeted toward consistent performance across a sufficient range of scenarios, repeated successful execution of a team task during diverse training scenarios is hoped to maximize the probability of successful execution (or minimize the probability of failure) in unforeseen environments and conditions of the future. However, this approach may not be successful in the complex environments of the future, where on-the-fly decision-making, changes in tactics, and novel organizational forms may be critical to success. Capable of contributing to this advantage, agents can learn and adapt at a pace much faster than that of humans and in manners that human team members may not be able to predict and understand. Yet, with agents as viable team members, humans must fluidly adapt to the potential changing team dynamics as the agent evolves. Capabilities to ensure predictability of learning and symbiotic adaptation between humans and agents that enhance group processes and leads to superior team performance are critical.

### 4.1.3 Training for Diverse, Rotating, and Evolving Team Members

With the future human agent teaming vision comes the idea of greater diversity and change in team members and team membership. Specifically, envisioned advantages to these complex teams include the ability to bring together the exact skills and abilities required for a particular mission. Therefore, capabilities are needed for quickly bringing together diverse teams of humans and agents to perform effectively as a group. For example, with long-term, continuous knowledge of existing team members' preferences, states, and behaviors, an individualized, adaptive agent may be responsible for working with team members to quickly assimilate the individual to the group, efficiently understanding new/changing roles and responsibilities of team members, and promoting heightened shared understanding of the task and situation across the team. Augmented and virtual reality may offer on-the-fly training to a team to quickly rehearse a mission, with continuous monitoring of cognitive states and communication to provide individualized, adaptive instruction when a team member seems have misunderstanding or is out of sync with the group.

### 4.1.4 Continuous Learning Using Individualized, Adaptive Agents for Enhanced Human–Agent Team Performance

Related to the capabilities already described is a truly radical transformation in training that necessitates preparation—advanced capabilities to provide continuous training of both taskwork and teamwork skills throughout missions and over time to facilitate dynamic, agile, and adaptive behaviors and superior performance by the team. The concept of a learning organization has been discussed in the literature for decades (Senge 1990), purporting the importance of continuous learning of members and continuous transformation. These concepts are incorporated in military training concepts as well (e.g., Department of the Army 2017). With individualized, adaptive technologies, intelligent tutoring systems, virtual and augmented reality, and continuously evolving teams, we can conceive of a truly revolutionized capability for continuous learning that can be incorporated into future human–agent teaming concepts.

## 4.2 Why Do We Think This Can Happen?

### 4.2.1 Individualized Instruction

We can see instantiation of the start of this revolution for training already occurring in many domains. In education, evidence-based instructional strategies, curriculums, and training tools trend toward individualized and adaptive methodologies to capitalize on individual student strengths and weaknesses. For example, universal design for learning is centered on applying individualized technology to facilitate learning, addressing the disconnect between an increasingly diverse student population and "one-size-fits-all" curriculums (Rose and Meyer 2002). Similarly, flipping the classroom attempts to make coursework more compatible with varied learning styles by providing a variety of tools (often technology-based) to gain first exposure to material outside of class, using class time to assimilate knowledge through interaction-based methods such as problemsolving, discussion, or debates. Numerous studies have demonstrated significant learning gains using this approach (Hake 1998; Mazur 2009; Deslauriers et al. 2011).

The application of individualized, adaptive instructional methodologies using agent-based technology has also been demonstrated (VanLehn 2011). Intelligent Tutoring Systems (ITS) monitor individual user interactions and states, and use artificial intelligence tools to assess trainee performance adaptively, applying pedagogical interventions to support learning (Goldberg et al. 2012). The concept of intelligent tutoring systems for teams has also been established (Sottilare et al. 2017), with scientific gaps identified (Goodwin et al. 2015) and establishment of research efforts focused on advancements needed for team-based ITS. Advancements in both individual and team-focused ITS, coupled with advancements in continuous measurement and understanding of human states and behaviors, create a critical path forward for a training revolution that incorporates individualized, adaptive instruction. While much of the focus now is on individual learners and individual development, initial work has begun to consider the use of individualized instruction for enhancing teamwork.

### 4.2.2 Team-focused Training

As research on individualized, adaptive instruction progresses, a body of work on team-focused training provides some recommendations for training humans to work better in teams. Coherent and overlapping of theories and models of team effectiveness have emerged in the literature, which define a critical set of team states and processes for enhanced performance and effectiveness in complex, dynamic groups (Marks et al. 2001; Ilgen et al. 2005; Salas et al. 2005; Burke et al. 2006). Additionally, teamwork competencies have been defined (Cannon-Bowers et al. 1995; Cannon-Bowers and Salas 1997; Salas et al. 2009) and training programs have been built around these competencies (e.g., Shuffler et al. 2010). Much of the team-based training literature focuses on getting teams up to speed, ready to perform together quickly (e.g., Horn 2014), which is critical to the future notion of more diverse, rotating team members. The effectiveness of training for teamwork has been reliably demonstrated for both teamwork behaviors and overall team performance (see McEwan et al. 2017 for review), with the most effective team training programs focused on teamwork as opposed to taskwork (Salas et al. 2008). However, this work has primarily been focused on human teams or use of technology as a tool (rather than a teammate) and generally does not conceptualize of agents as team members who facilitate continuous team learning, enhanced processes, and adaptation.

### 4.2.3 Realistic Training Environments

Finally, research findings in training design, coupled with recent advancements in technologies, have led to a focus on realistic training environments, on-the-job training, and training at the point of need within industry, academia, and the military. In a summary of the literature on realistic training environments, Grossman and Salas (2011) conclude that conducting training and practice in realistic training environments, or environments that resemble the workplace, increases the likelihood that trained competencies will transfer to knowledge and performance on the job. McEwan et al. (2017) reported similar findings with use of realistic training environments and simulations for team performance. Recent technological advancements, including the proliferation and cost-effectiveness of virtual and augmented reality systems, coupled with artificial intelligence for enhanced experience and customization, create the potential for large-scale implementation of this on-the-fly training in realistic settings, thereby adding to the potential for a revolution in training.

## 4.3 Scientific Questions

While a foundation exists to consider training for the complex, evolving nature of human–agent teaming envisioned in the future, the literature on training has placed very little focus on this precise need. Education and training fields are beginning to focus on the use of individualized, adaptive technologies; however, emphasis is not placed on considering these technologies as teammates and how that might change the content and delivery of training. Team science is advancing training for enhanced teamwork, but the idea of humans and agents as team members does not seem to be a critical element this work. Many research questions must be addressed to begin to prepare for this future. Some examples include:

1) As we move forward, we must understand the human and agent competencies critical for human–agent teamwork. What are the core competencies unique to: a) human–agent teams, b) humans working in human–agent teams, and c) autonomous agents working in human–agent teams? After identifying and defining these competencies, we must explore how to best develop these critical teamwork competencies, through individual and/or team-focused training. How do we synchronize training and development amongst diverse members, including humans and autonomous teammates?

2) Envisioning the future, we expect agents capable of learning and adapting at high speeds, and humans that must fluidly adapt with these team members. How do we prepare humans to work with evolving agents? How do we prepare agents to understand and evolve symbiotically with humans? What

technologies can be developed to enhance this mutual adaptation in human–agent teams?

3) Human–agent teams are expected to be characterized by diversity, and rotating and evolving team membership. What are the critical features of individualized, adaptive training technologies to enhance teamwork in these diverse and evolving teams? What future capabilities are critical for quickly bringing together diverse teams of humans and agents to perform effectively as a group? In what ways can embedding intelligent agent trainers in teams reduce the efficiency costs and increase the productivity benefits associated with diverse and dynamic team membership?

4) Finally, the future we are considering opens potential for novel training capabilities to continually enhance the collective intelligence of the group. Can we use principles of individualized instruction and human–agent teamwork to develop evolving systems of humans and agents with ever-increasing intelligence and capabilities, capable of more complex performance over time?

## 5. Conclusion

In this paper, we proposed that future technologies focusing on enhancing teamwork, or team states and processes, through individualized information, processing, and behavior are critical to enabling and enhancing human–agent teaming. We focused on the critical science and technology to enable the interactions and interdependencies between heterogeneous members of human–agent teams, and specifically, on influencing individual team members with the goal of enhancing the emergent team properties that lead to effective performance, while minimizing negative effects. We discussed the potential capabilities expected through advancements in individualized, adaptive technologies, implementation, and training focused on emergent processes of groups; and articulated why we believe these capabilities can be developed. Finally, we provided initial suggestions of some of the critical scientific questions that must be addressed to enable this future vision and expect discussions, additional questions, and novel conceptualizations of capabilities to continue developing from here. We see this paper as providing a foundation to continue to grow our knowledge and capabilities in an essential area of research for the military, human–agent teaming. By addressing these critical research gaps, through scientific discoveries and innovations, we expect to enable a future vision of human–agent teams that have the capabilities that far surpass current Soldier teams, including: greater team resilience with robust, adaptive performance; faster, dynamic reconfiguration to match capabilities to mission requirements; faster, more informed team decision making; and reduced risk to Soldiers.

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## List of Symbols, Abbreviations, and Acronyms

| | |
|---|---|
| AI/ML | artificial intelligence and machine learning |
| Dyadic | directly enables human-technology designs |
| ITS | Intelligent Tutoring Systems |

1 (PDF) DEFENSE TECHNICAL
INFORMATION CTR
DTIC OCA

2 (PDF) DIR ARL
IMAL HRA
RECORDS MGMT
RDRL DCL
TECH LIB

1 (PDF) GOVT PRINTG OFC
A MALHOTRA

1 (PDF) ARL
RDRL HRB B
T DAVIS
BLDG 5400 RM C242
REDSTONE ARSENAL AL
35898-7290

8 (PDF) ARL
SFC PAUL RAY SMITH CENTER
RDRL HRO COL H BUHL
RDRL HRF J CHEN
RDRL HRA I MARTINEZ
RDRL HRR R SOTTILARE
RDRL HRA C A RODRIGUEZ
RDRL HRA B G GOODWIN
RDRL HRA A C METEVIER
RDRL HRA D B PETTIT
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1 (PDF) USA ARMY G1
DAPE HSI B KNAPP
300 ARMY PENTAGON
RM 2C489
WASHINGTON DC 20310-0300

1 (PDF) USAF 711 HPW
711 HPW/RH K GEISS
2698 G ST BLDG 190
WRIGHT PATTERSON AFB OH
45433-7604

1 (PDF) USN ONR
ONR CODE 341 J TANGNEY
875 N RANDOLPH STREET
BLDG 87
ARLINGTON VA 22203-1986

1 (PDF) USA NSRDEC
RDNS D D TAMILIO
10 GENERAL GREENE AVE
NATICK MA 01760-2642

1 (PDF) OSD OUSD ATL
HPT&B B PETRO
4800 MARK CENTER DRIVE
SUITE 17E08
ALEXANDRIA VA 22350

ABERDEEN PROVING GROUND

11 (PDF) ARL
RDRL HR
J LOCKETT
P FRANASZCZUK
K MCDOWELL
K OIE
RDRL HRB
D HEADLEY
RDRL HRB C
J GRYNOVICKI
RDRL HRB D
C PAULILLO
RDRL HRF A
A DECOSTANZA
RDRL HRF B
A EVANS
RDRL HRF C
J GASTON
RDRL HRF D
A MARATHE