CHAPTER SEVEN

Agents as Collaborating Team Members

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Network-centric warfare has emerged as a key defense doctrine in response to a new geopolitical reality of having to respond to multiple, distributed incidents or threats, with an ill-defined or rapidly changing enemy. Transformational teams are a key element of the network-centric doctrine (Navy 2004; U.S. Army 2006). Such teams are characterized as having an ad-hoc, agile membership with rotating, heterogeneous members who have distributed, asynchronous relationships. Another key characteristic of the future combat environment is the pervasiveness of massive amounts of information, enabled by large numbers of field-deployed sensors, satellite-based images, network connectivity and enhanced communication channels. Given the abundance of information, geographic and cultural diversity of team members, and the dynamic nature of the team and its tasks, transformational team members need ways to augment their decision-making, shared understanding development, and intelligence analysis capabilities.

Software agents and autonomous systems offer the possibility of enhancing these capabilities because of their ability to plan and adapt appropriately in new contexts, learn, move as needed, and work cooperatively with people and other agents (Campbell et al. 2000; Cohen and Levesque 1991; Deshmukh et al. 2001; Middelkoop and Deshmukh 1999; Tambe et al. 1999). A common example of a simple software agent is the Microsoft Office
assistant. This agent can observe how you utilize a Microsoft product and provide suggestions for more effective use.

In this chapter, we focus specifically on augmenting the cognitive capabilities of teams. We approach augmentation from a cognitive perspective, because the increased information processing requirements and dynamic nature of tasks test the limits of human capabilities. Past research has shown that for individuals such limitations can be reduced through augmentation (Schmorrow and McBride 2004; Schmorrow, Stanney, Wilson, and Young 2005). Moreover, cognitive augmentation may enhance macrocognitive processes that are essential drivers of team collaboration and overall performance. Macrocognitive processes, as discussed in the first chapter of this book (Warner, Letsky, and Wroblewski, this volume), include a range of internal and external cognitive activities from visualizing complex information to developing individual knowledge that is interoperable across team members to developing a set of alternative solutions. As we will discuss, agents can help team members with their macrocognitive processing by creating visualizations of high dimensional data, maintaining a knowledge repository, and simulating options under consideration. The augmentation possibilities are virtually endless, but the current state of knowledge regarding human-agent interaction in a team domain is underdeveloped. Thus, our purpose here is to suggest a research agenda for determining optimal configurations of human-agent teams.

The chapter begins with a review of the agent augmentation literature, highlighting the limited examination of team-level human-agent collaboration, the limited use of agents as first class team members, and the lack of research on augmenting macrocognitive processes. We then introduce a conceptual framework for designing and managing effective
human-agent teams, including (1) their socio-technical structure, (2) the team-level augmentation strategies and corresponding characteristics of agents that may be most effective for human-agent collaboration, and (3) the collaboration performance monitoring required to dynamically aid the cognitive processes of teams and their members. Next, we present examples of the types of agents that could be created. In doing so, we highlight several combinations of augmentation strategies and agent characteristics that could assist teams completing different types of collaboration tasks and delineate how these agents enhance various macrocognitive processes. We conclude by discussing our framework’s contribution to the study of human-agent teams.

Agent-based cognitive augmentation

Cognitive augmentation through agents refers to supporting human information processing by means of a computer-based system that has sensing capabilities to monitor the human and its environment and an “understanding” of how and when to augment the cognitive capabilities of a human. The concept of computer-assisted, cognitive augmentation dates back to the 1960s when Licklider (1960) and Engelbart (1963) envisioned a human-computer symbiosis. They proposed to extend the capabilities of the human brain by computers to achieve a system with superior information processing capabilities. This visionary concept inspired research in human factors engineering (Schmorrow, Stanney, Wilson, and Young 2005) and computer science, particularly in the area of artificial intelligence (Wooldridge and Jennings 1995) where agents represent the building blocks for augmentation.
Agents, in this context, are defined as autonomous software units that combine inherent knowledge and goals with information about the environment and take action to support other agents or humans (Bradshaw 1997; Negroponte 1997). Middleton (2002) classifies four broad types of agent support systems: (1) character-based agents, which are designed after real-world characters, such as a police dog, and can provide an intuitive interaction right from the start, (2) social agents, which acquire their information by interacting with other agents and fusing their information, (3) learning agents, which either monitor the human, ask for feedback or are directly re-programmed by the user, and (4) agents with a user model, which is either behavioral or knowledge-based. The categories are non-exclusive and a particular agent can be a combination of these four categories.

In our review, we focus on the research that includes a human component in conjunction with an agent or system of agents. Much has been written about multi-agent systems that we do not review, but may be of interest as background information, including an introduction to multi-agent systems (Weiss 1999), a comprehensive survey of the theory and practice of agent systems (Wooldridge and Jennings 1995), practical and industrial application examples of such systems (Parunak 1998), and design guidelines for agent systems (Middelkoop and Deshmukh 1999).

*Individual Human Augmentation*

To provide humans with the appropriate cognitive augmentation, agents have to know the human’s current cognitive state by assessing, for example, workload or comprehension level (Dorneich, Ververs, Mathan, and Whitlow 2005). Through neural measures (e.g., EEG), behavioral measures (e.g., reaction time) and physiological measures (e.g., heart rate) a proxy for the cognitive state can be determined. For a comprehensive list of
measures see Bruemmer, Marble, and Dudenhoeffer (2002) and Lyons (2002). One of the challenges in an augmentation system is to translate the human’s actual cognitive state into augmentation requirements. To that end, Plano and Blasch (2003) distinguish between task analysis and cognitive task analysis. Task analysis interprets the physical activities of the user interacting with the system, whereas the cognitive task analysis uses a mental model of the operator to interpret the user’s action and infer the user’s thoughts. Thus, cognitive task analysis assists in determining the expected cognitive load for a given task. This expected load, when compared to actual cognitive load, identifies when and how much augmentation is needed.

Once the augmentation needs are established, agents can appropriately augment the human’s information processing capabilities. The goal is to achieve cognitive congeniality (Kirsh 1996) and not to overload the human. Agents can reduce cognitive load by performing functions such as (1) presenting task-relevant information to optimize sensory processing, (2) sequencing and pacing tasks to minimize cognitive load, and (3) delegating tasks to reduce number and cost of mental computations (Schmorrow, Stanney, Wilson, and Young 2005).

Cognitive augmentation of individual humans can be employed in many different general application domains. Schmorrow, Stanney, Wilson, and Young (2005) consider operational, educational and clinical domains. In the operational domain, a wide variety of types of agents and tasks have been examined. For example, Plano and Blash (2003) created a data-fusion system that provides humans with the right information at the right time to enhance their performance on search tasks. Moreover, through their target tracking interface design, which includes displaying information and audio warning, humans can
better filter the information provided by the agents. In the education domain, agents can play an integral part in scenario-based training systems. For instance, route planning agents (Payne, Lenox, Hahn, Sycara, and Lewis 2000) and information retrieval/lookup agents (Harper, Gertner, and Van Guilder 2004) may be used to vary the training exercises based on decisions made by the trainees. In the clinical domain, patients with attention-deficit hyperactivity disorder (ADHD) can be helped by agents that reinforce good paying-attention behavior (Schmorrow et al. 2005). A fourth domain for consideration is the military domain where significant advances in human-agent collaboration have been made. Honeywell’s human-agent cognitive system provides an illustrative example (Dorneich, Ververs, Mathan, and Whitlow 2005). This system supports soldiers in fast decision-making situations. Agents monitor the state of humans through sensors and determine the human’s engagement, arousal stress and comprehension level. Agents can proactively take actions to mitigate cognitive overloads.

Agents have to be designed that can decide how and to what degree to augment the human. Moreover, they have to be able to decide when and who to augment. Logically, tasks should be assigned to humans and agents based on which entity can best perform the task in question. For instance, agents may be better suited to evaluating different options and searching for an optimal solution because they can systematically search through a solution space whereas humans jump around and are guided by their prior knowledge, experience and intuition (Burstein and McDermott 1996). Thus, agents may be the best entity to conduct such evaluation functions.
**Human-Agent Teams**

Research in cognitive augmentation has focused mostly on individual augmentation and on multi-agent teams. Furthermore, to our knowledge, none has focused directly on supporting macrocognition in teams. Burstein and McDermott (1996) have compiled a list of challenges in artificial intelligence, and the necessary research projects corresponding to those challenges, to enable human-agent collaborations. Their list addresses aspects of specialization, information, and communication, but it does not articulate a difference in team vs. individual human-agent augmentation. Alternatively, Xu and Volz (2003) present a shared mental model for multi-agent systems, but neglect to consider the human role in the developed system. This theme is common in multi-agent system research as numerous examples of these systems exist that consider teamwork without introducing a human component (e.g., Junes et al. 1999; Tambe 1997; Tidhar, Heinze, and Selvestrel 1999). For example, STEAM - Shell for TEAMwork (Tambe 1997) builds on the *joint intensions* concept (Cohen and Levesque 1991; Levesque, Cohen, and Nunes 1990) and hierarchical *Shared-Plans* model (Grosz and Kraus 1996) to provide an environment to deploy multi-agent collaborating teams.

A limited amount of research has focused on human-agent collaboration. For example, Payne, Lenox, Hahn, Sycara, and Lewis (2000) devised agents that support time-critical team planning tasks. In their application, three military commanders have to lead their platoons such that all platoons meet at one point at a specified time. Both humans and agents can initiate communication, monitor their respective performance, and execute tasks. Sycara and Lewis (2004) provide a second example. They report on two experiments that demonstrate how agents may be useful in assisting their human counterparts’ planning and
communication activities, particularly selecting and directing communication. Furthermore, they ascertain that humans find agents more useful when they have been designed with the humans’ needs (vs. the agents’ capabilities) in mind. A third, and final, example is the research of Siebra and Tate (2005) examining how human teams use agent assistants during the planning process. In this work, they describe an integrated, constrained-based framework for collaborative activity-oriented planning, where customized agents can be deployed at any decision level to handle activity planning tasks. In addition to these specific examples, several human-agent systems have been advanced that facilitate collaboration such as Brahms (Clancey, Sachs, Sierhuis, and van Hoof 1998), KAoS (Bradshaw, Feltovich et al. 2004), and Collaboration Management Agent (Allen and Ferguson 2002). These systems’ specific features are summarized in Bradshaw, Acquisti et al. (2004).

The majority of agents that have been developed for interaction with humans play a subordinate role and make team contributions only under direct human supervision (Burstein, Mulvehill, and Deutsch 1999). In order to expand the role of agents in mixed teams, agents must be able to understand and predict human behavior (Bruemmer, Marble, and Dudenhoeffer 2002). In other words, they need leadership capabilities, autonomy, and proactivity. Incorporating these types of agent characteristics are among the greatest challenges facing the field, but are essential for effective human-agent systems (Dickinson 1998). As mentioned, agents have typically been subordinate. Their role, however, can span a spectrum from subordinate to equal team-player to leader (Bruemmer, Marble, and Dudenhoeffer 2002; Sheridan 2006). To determine appropriately which leadership characteristics along this spectrum they should employ to best support the human entities
on the team, agents must have autonomy. Moreover, depending on the situation within the team, agents may have to shift roles dynamically. To facilitate such behavior, Scerri, Pynadath, and Tambe (2002) developed an adjustable autonomy model that determines an optimal transfer-of-control strategy. Agent proactivity, another necessary characteristic for effective human-agent collaboration, has received attention recently. Yen and colleagues (2001) devised CAST (Collaborative Agents for Simulating Teamwork), which anticipates information needs based on a shared mental model in multi-agent teams. The CAST model has been extended to include the dynamic nature of anticipated information needs (Fan, Wang, Sun, Yen, and Volz 2006). Also during this period, Fan, Yen, and Volz (2005) developed a framework for proactive information delivery. This framework combines their conceptualization of information needs with axioms for helpful behavior in large teams to produce a model for agent teams that provide information proactively.

To this point, we have focused on the agent side of the human-agent team. One essential element from the human perspective is trust. Some researchers go as far as seeing trust as one of the greatest challenges for the adoption of autonomous agents (e.g., Bruemmer, Marble, and Dudenhoeffer 2002; Middleton 2002). Humans must accept agents as team players in order for the human-agent team to become a reality. Indeed, the human must be able to rely on the information presented by the agent so that the agent’s contribution can be used as extended sensory information (Plano and Blasch 2003). Robust agent designs and systematic research directed at understanding how best to augment human team behavior are two critical elements needed to help overcome distrust. As the reliability and usability of agents increase, we can anticipate that levels of trust in agent team members should increase accordingly.
This review highlights the need for systematic research on human-agent collaboration that focuses on how to embed agents in teams as fully functional team members. The extant research we have just described provides integral pieces necessary for accomplishing this objective. Several critical gaps, however, must be addressed. First, the research has not focused on designing agents that can function as team members by supporting critical processes such as macrocognitive processes. Second, no design methodology exists for ascertaining optimal human-agent team configurations. Third, research on tracking team progress and dynamically changing agent support based on that progress is needed.

**Designing effective human-agent teams**

To address the gaps identified in the literature review, we present a conceptual framework for designing effective human-agent teams (see Figure 7.1). Three salient features of this framework deserve mention. First, the framework considers human-agent teams as socio-technical systems (STS), where humans, agents, and the environment are intrinsic resources that can be used to accomplish a complex task (Emery and Trist 1960). Second, the framework is driven by a focus on using agent team members to augment the capabilities of the team as a whole. Third, the components necessary to facilitate enhanced team performance through human-agent team processes are embedded in a collaboration environment that is continuously monitored. This environment constitutes elements such as the collaboration situation parameters (i.e., time pressure, information and knowledge uncertainty, quantity/dynamics of information (Letsky, Warner, and Salas, this volume)), the team’s task, and the human composition of the team (i.e., diversity, co-location), etc.
An extensive team literature exists that describes the human dimension of our system. We, therefore, focus on the human-agent interactions in the system by outlining the research needed to help us understand (1) the cognitive and coordination mechanisms used by human-agent teams, composed of rotating, heterogeneous members (humans and software agents) who have distributed, asynchronous relationships, as they collaborate to make decisions, develop a shared understanding, and/or conduct intelligence analysis and (2) ways in which these mechanisms can be augmented dynamically. Once completed, this research will advance a theory of human-agent reconfigurable collaboration and a set of team augmentation guidelines. To further articulate the research agenda, we highlight the basic research required in the following three areas: (1) socio-technical team structure, (2) reconfigurable team augmentation, and (3) collaboration performance monitoring.

*Socio-Technical Team Structure*

Basic research is needed to determine how to design and optimize a human-agent STS. STS structure is a function of the assignment given to the team, environmental/domain considerations and the characteristics of the players in the system (both humans and agents). The challenge facing scholars is identifying how these inputs can be transformed into an optimal team structure and a set of recommended processing strategies. Thus, the overall goal of this research area is to develop a set of models and guidelines that can be used to rapidly design network-centric transformational teams of humans and agents for specific tasks.

One possible way to accomplish this goal is to develop models of the human-agent STS by exploiting the extant literature on economic models of teams (Levchuck, Yu,
Levchuk, and Pattipati 2004; Marschak and Radner 1972; Mesarovic, Mako, and Takahara 1970; Rusmevichientong and Van Roy 2003; Schneeweiss 2003). The STS team structure problem can be formulated as an expected utility maximization problem, where the STS structure and coordination rules are decision variables; task coordination and performance requirements represent the constraints; and utility is a function of the efficiency of processing the collaborative task and associated costs (information, delay and decision). Cognitive task analysis can be used to determine the task structure, cognitive requirements of tasks and coordination necessary to perform the tasks. The resulting model should describe the functional representation needed to staff the human side of the team. Moreover, it should identify where agents can most effectively assist their human counterparts. We envision the STS structure to have agents at different levels: (1) supporting the team as a whole, (2) providing support for sub-groups of humans, and (3) helping individual team members perform their tasks.

To identify the appropriate processing strategies for mixed-initiative systems, the work by Levchuck and colleagues (2003) can be used to formulate strategies for mission monitoring, information processing and command processing. Their model can be enhanced, for example, by developing multi-scale decision-making techniques that can cope with, not only organizational, but also geographical or temporal scales needed to model network-centric human-agent teams (Krothapalli and Deshmukh 1999) and by incorporating a corresponding economic incentive scheme for the human-agent interaction that accounts for both rationality and bounded rationality issues (Kahneman 1994; Simon 1997).
**Reconfigurable Team Augmentation**

We now address the issues related to developing a fundamental understanding of what type of augmentation will most enhance team cognition and collaboration in a manner that improves overall team performance. Several types of augmentation actions have been postulated for mixed-initiative systems, ranging from augmented sensors, to individuals, to teams and organizations (Schmorrow and Krause 2004). Herein, we focus on team-level augmentation.

The agents have to decide which action to take based on the state of the system, their own policy demands, costs of the actions, anticipated impact on performance, and activities of other agents. Typical agent assistance could be in the form of augmented capacity, knowledge sharing or task reallocation. Augmented capacity refers to enhancing human decision-maker’s capacity to communicate, observe/scan, or complete cognitive/motor task processing. Knowledge sharing encompasses many activities such as knowledge/information transfer among STS members that facilitates knowledge interoperability and enables and ensures shared team understanding. Task reallocation refers to realigning task assignments among members to level the workload. We envision that assistance will dynamically change based on workload changes; thereby requiring reconfigurable agents. This research should result in guidelines for supporting key cognitive processes with agents, thereby enhancing team collaboration and, ultimately, performance.

The type of augmentation support that an agent can provide depends on the agent’s characteristics. Several dimensions of agent characteristics have been discussed in the literature, such as autonomy, social ability by means of agent-communication language, and
proactiveness (Wooldridge and Jennings 1995). These characteristics determine the capabilities the agents bring to the team. In this section, we focus on six characteristics that are relevant for incorporating agents in mixed-initiative teams, where both software agents and humans collaborate to improve the overall team performance.

**AUTONOMY: Fixed/Adjustable** Autonomy is a fundamental characteristic of an agent that relates to its ability to exhibit goal-directed behavior, where the goals are inherent to the agent itself and not prescribed by outside entities (Bradshaw 1997). A software agent that does not have any autonomy may not be much different than a computer program that is executed by the user when needed. However, by incorporating the ability to pursue its own goals within the constraints placed on its actions, the computer programs start to interact in a more meaningful and richer manner with humans. Hence, by definition agents have some degree of autonomy (Franklin and Grasser 1996). The level of autonomy that an agent has may be fixed throughout its lifetime or may be adjustable based on the needs of the situation. One can view adjustable autonomy as a mechanism to appropriately trade off authority and responsibility between various team members (human or agent) during the execution of a task. Automatic adjustments of autonomy can be made either by the agents themselves or by the humans on the team. Agent initiated adjustments in autonomy might typically be required when the current configuration of human-agent team members has led to, or is likely to lead to, failure and when no set of competent, authorized humans are available to make adjustments themselves (Barber and Martin 1999). The mechanisms for adjusting autonomy can be coarse-grained, such as mode setting, or fine-grained, based on specific policies that provide guidelines for limiting agent actions under specific situations.
**REACTIVITY: Reactive/Proactive** The level of reactivity assigned to the agents determines how the agents initiate an augmentation action or are triggered to make a decision. We can consider agents along a continuum of reactive to proactive response capabilities. Purely reactive agents respond to the current state of the entity they are supporting or on external stimuli, such as a request for assistance from humans or change in environmental variables. Agent reactive capabilities can be based on inputs from the human team members or sensors that provide information about the current state of individual or collaboration activity. Proactivity refers the agent’s ability to take initiatives, make conscious decisions, and take positive actions to achieve chosen goals (Fan, Yen and Volz 2005). The proactive capabilities of agents can be based on predictive models of team task performance that the agents use to decide on appropriate type and level of augmentation (Georgeff and Lansky 1987). These predictive models allow the agents to anticipate when individual team members may be expected to exceed their cognitive capacity threshold or communication capabilities or if a task needs to be reassigned to an agent.

**PLANNING HORIZON: Myopic/Look-Ahead** The agent decision-making planning horizon can be myopic, where an optimal augmentation action is chosen considering only the current state of the system, or look-ahead, where the optimal decision policy is chosen based on implications along the entire task horizon. Single-stage optimal-action selection models may be used by agents to determine the optimal augmentation actions and level in the myopic planning horizon case. In the look-ahead planning models, the agent decision policies can be formulated as Markov Decision Processes (MDP) (Puterman 1994). The reward function of the MDP depends on the efficiency of the overall task completion and the cost of augmentation, and may be additive over the task horizon. The optimal
augmentation policy, which belongs to a set of actions representing all possible augmentation choices, minimizes the objective’s expected value over the entire task horizon. Given the computational complexity of MDP formulations, approximations and heuristic approaches are often necessary to allow these look-ahead models to be implemented for agent augmentation with real-time performance requirements.

**LEARNING: Enabled/Not enabled**    
Agent decision policies can be stationary, where in they do not vary over time, or non-stationary, where the optimal augmentation policies evolve over time based on observations of the system. The evolution of decision policies based on observations can also be referred to as learning. In the situation when the decision policies are stationary, we can argue that the agent does not learn from its experience. The evolution of optimal augmentation strategies occurs due to two non-exclusive reasons: (1) the agents could learn about the impact of their past augmentation actions and adjust their strategies accordingly and (2) agents in a loosely-coupled system could anticipate other agents’ and humans’ actions while formulating their own optimal strategies. Different learning strategies for agent augmentation policies can be used, ranging from smoothing functions to reinforcement and Q learning methods (Barto and Mahadevan 2003; Greenwald, Shenker and Freidman 2001) that will allow the agents to infer causal relationships between their actions and team performance. A key concern in learning models is the robustness of the resulting strategies.

**POSITION IN TEAM HIERARCHY: Leader/Follower**    
In mixed initiative teams, agents can function at various levels of the team hierarchy (Burstein and McDermott 1996). Typically, one envisions agents in the follower role. However, agents can play the role of a team leader when the task to be performed is too complex for a single human being to
manage or when the leader of the team is unavailable. Agents can move between these roles based on the state of the team and the task they are performing.

**LEVEL OF SUPPORT: Team/Individual**  
This aspect refers to the entity that is augmented or supported by the agents. The agents may support individual team members or the team itself. In augmenting individuals, agents can function as personal assistants or monitor the team member’s cognitive state. Team-level augmentation support can be provided in terms of enhancing the ability of the group to complete the task in an efficient manner. For example, a team-level support agent can assist in sharing of appropriate knowledge among team members to enable planning tasks. Team-level agents can also monitor overall collaboration activity to decide when augmentation is needed.

**Collaboration Performance Monitoring**

Research activity is needed here to develop a fundamental understanding of *when* and *who* among the team would benefit from augmented capabilities. We suggest designing a monitoring and diagnostic system based on individual- and team-level metrics that will indicate when the human decision-maker needs assistance and what types of assistance would be most beneficial for ongoing team processing and overall team performance. Thus, the overall goal of this research activity should focus on creating a collaboration performance monitoring system that can be embedded into the computational architecture. This real-time system needs the ability to facilitate dynamically adaptive augmentation based on the collaboration environment’s status.

Several appropriate metrics, including indicators such as biometrics and role overload assessment have been developed to determine when individuals can benefit from assistance (see for example, Schmorrow and Kruse 2004). Research is needed to establish the
appropriate team-level metrics. Herein we discuss potential process and outcome measures that may be useful. We begin with examples of direct and surrogate measures of cognitive processes. Mental model convergence can be used as a direct measure of cognitive processes by ascertaining how much shared understanding exists among team members. Using short surveys and calculating a team convergence score and individual member contributions to that score (see for example, McComb and Vozdolsaka 2007), we can highlight who on the team has dissimilar views. Surrogate measures of team-level cognition can also be examined, such as conflict and resource mapping. Conflict among team members may be beneficial or detrimental, depending on the type and amount of conflict transpiring (Jehn and Mannix, 2001). Limited amounts of task and process conflict allow teams to exchange ideas and be creative. Any interpersonal conflict and high amounts of task and process conflict debilitate a team’s ability to work on their assignment, thereby adding to the cognitive load associated with teamwork. Resource mapping onto the task demands will identify areas where expertise is appropriately (or inappropriately) assigned to tasks (Blackburn, Furst, and Rosen 2003). If the expertise is not assigned effectively, the cognitive demands placed on the team to accomplish the task will be greater than if the appropriate personnel were assigned. We focused our examples on assessing cognitive processes, but a performance monitoring tool could be expanded to include a myriad of team process variables as well (e.g., coordination mechanisms).

While process measures may provide the best opportunities to identify when the team needs support and/or redirection, outcome measures can also assist with this endeavor. Blackburn and colleagues (2003) identified several outcome measures that organizations routinely use to assess the output of the team. They are quality (e.g., the ability of the
proposed solution to meet mission objectives), quantity (e.g., the amount of membership turnover), creativity (e.g., the number of novel concepts generated), cost (e.g., the additional monies necessary to implement changes in mission scope), and timeliness of deliverables (e.g., the progress to schedule). Performance assessment may also be focused on perceptions, such as satisfaction with the team and degree of cohesion among team members. Ensuring satisfaction and cohesion will enhance the teams’ abilities to collaborate effectively on the current project and on future endeavors (Hackman and Oldham 1980). These outcome measures should be incorporated into the ongoing monitoring of the team so that any necessary midcourse corrections can be implemented to curtail underperformance when it is identified.

Augmenting team macrocognitive processes

Macrocognitive processes are one of the primary means by which transformational teams complete their objectives. Human capacity for these processes is inherently limited. Thus, introducing agents as fully-functioning team members may increase a team’s cognitive capacity. In Figure 7.2, we provide examples of agent support that may enhance macrocognitive processes. Our examples depict a wide array of agents that showcase the three augmentation strategies (i.e., augmented capacity, task reallocation, and knowledge sharing) and embody different combinations of agent characteristics (i.e., reactivity, autonomy, planning horizon, learning, level, and hierarchical position). Moreover, we focus on aiding human team members working on three types of collaboration tasks: (1) team
decision-making/course of action selection, (2) development of shared understanding, and (3) intelligence analysis (team data processing).

[Insert Figure 7.2 about here]

These example agents represent a spectrum of complexity. For instance, one of the least complex agents is the agent assisting in simulating outcomes of options available to human decision-makers. This agent’s role on the team would be performing what-if analyses to ascertain the probable results of various options being considered by the human members of the team. It augments capacity because it can execute several instances of simulations simultaneously and keep track of the solutions, which would be infeasible for humans. This particular agent is unsophisticated in that it completes a specific task when it is put into service by a human team member. In other words, it is a follower that is reactive, does not have any autonomy, focuses only on the task given (i.e., it is myopic), and cannot learn as it simulates. This particular agent could be more sophisticated if, for example, it was programmed with learning capabilities. These capabilities may, perhaps, allow it to learn what strategies are best suited for the extant scenario and to use this information to tailor its simulation parameters.

At the other end of the spectrum, an agent designed to enable and enforce the explicit, agreed upon protocols governing interactions is highly sophisticated. This agent needs to monitor interactions among multiple team members over a period of time to determine if the team members are interacting in an appropriate and meaningful manner. In order to achieve the task of enabling interaction, the agent needs to facilitate knowledge interoperability among team members. As the shared understanding among team members increases, and their corresponding mental models converge, the nature of interactions
among them will change. Monitoring and enabling protocols, especially when the content of the interactions is changing over time, requires the agents to be proactive and to look ahead in terms of the expected actions by team members. The agent needs to learn about the team members’ common knowledge and shared understanding by observing the interactions among them over time. Furthermore, the agent needs to assume leadership role in governing the flow of information at the team level.

Our purpose in presenting these examples of agent support is to demonstrate how various agent designs, from simple to complex, can augment macrocognition across collaboration task types. This set of nine agents, presented in Figure 7.2, is by no means an exhaustive list of potential agents that can be introduced into transformational teams. Rather, they exemplify the myriad of ways in which agents can augment macrocognitive processes and illustrate the range of sophistication that can be designed into these agent team members.

**Benefits of Agents As Team Members**

The basis of the approach we have presented is that agents can function as team players and achieve parity with their human counterparts for task planning and execution in transformational teams. Our focus has been on demonstrating how macrocognitive processes can be augmented (see Figure 7.2). Two additional benefits may result from the incorporation of agents into teams. First, these agents may enhance the team’s overall performance. These enhancements may be as seemingly simple as utilizing an agent to manage a team’s dynamic schedule, thereby helping the team to meet its timing goals. Also, an agent team member may uncover unexpected connections through data mining
that may help the team to create unique alternative solutions that would not have been fathomable without the agent’s results.

The second benefit is that agents may provide essential elements necessary for team self-management, as we will demonstrate via the example agents already described in Figure 7.2. Hackman (2002) identified five team design/structure elements necessary for effective self-management. The first element is to be a real team. Real teams have an articulated task, clear boundaries, explicit authority, and stability. Agents functioning as knowledge repositories can help improve stability by keeping information/knowledge available even when team membership changes, which may enhance a team’s ability to be a real team.

Second, a compelling direction energizes the team, orients their attention/action and engages members’ talents appropriately. Agents can help keep the team energized by tracking their forward progress and reporting their goal achievement. Also, they can keep the human team members oriented on their task by creating visualizations of high dimensional data, thereby keeping them focused on the big picture instead of lost in details that may be cognitively difficult to organize. The third element is enabling structure, which includes a clear work design, established norms and appropriate staffing. Agents enforcing the explicit, agreed upon protocols governing interactions, not only exist as part of the enabling structure, they extend it to include monitoring human team member behavior to ensure that the norms are respected and followed.

Fourth, supportive contexts have team reward systems, up-to-date information, educational opportunities, and adequate resources. By using agent team members to keep information updated in the collaboration space, all team members have access to current
conditions. Finally, *expert coaches* help members focus their efforts equitably, devise appropriate performance strategies, and align individual skills/knowledge with requisite work. Agents monitoring the cognitive load of the human team members can ensure that individual team members do not exceed their maximum cognitive loads. In cases where an individual is approaching her/his maximum, the agent can reallocate the task(s) to other qualified team members with available cognitive capacity.

**Conclusions**

Augmenting human cognitive capabilities is not a new phenomenon. Indeed, an example of a commonly seen natural augmentation is a police dog supporting a human partner (Bruemmer, Marble, and Dudenhoefler 2002). The dog augments the human’s cognitive capabilities through sniffing. The dog complements its human partner and together they are better at finding drugs and following tracks. The dog also augments the human’s physical capabilities through its ability to reach human-inaccessible areas and confront potential threats. Artificial augmentation is also becoming more common place. For instance, robots are routinely used by first responders to enter burning buildings, examine potential bombs, explore unfamiliar terrain, or conduct any other function that may be life-threatening to humans. As our acceptance of these assistants grows and our understanding of how best to assist increases, we envision a day when agents become fully functional members of self-managing teams.

To realize our vision, systematic research is needed to answer questions such as:

- What agent characteristics are most appropriate for various types of augmentation?
• Are different augmentation approaches and agent configurations needed for different collaboration tasks?
• How does the collaboration environment (e.g., distributed vs. co-located) in which the team is embedded impact the effectiveness of augmented support?
• How does embedding agents as team players impact team processes and performance?
• Do agents enhance a team’s ability to self-manage?

In this chapter, we presented a framework to guide the basic research needed to answer these types of questions. This framework was constructed by organizing and extending the extant literature on human-agent interaction and approaching augmentation from a team cognition perspective. Salient features of this framework are integrating agents as key members of socio-technical teams, emphasizing team-level augmentation, and incorporating processes to identify and enable different augmentation actions based on the collaboration environment’s current state. This holistic view of human-agent collaboration makes our framework a novel approach to this increasingly important body of knowledge.

As the network-centric doctrine gets widely deployed in defense and other sectors of society, use of mixed-initiative teams comprised of humans and agents is going to be a critical factor in ensuring successful completion of complex tasks. The framework presented in this paper provides a foundation for designing and researching such human-agent teams, in which agents play a critical role in augmenting the cognitive capabilities of teams.
Figure 7.1 Conceptual framework for designing effective human-agent teams
### Agent Characteristics:
- **Autonomy:** A= Adjustable, FX=Fixed
- **Reactivity:** R=Reactive, P=Proactive
- **Planning Horizon:** MY=Myopic, LA=Look Ahead
- **Learning:** LE=Enabled, LNE=Not Enabled
- **Hierarchical Position:** L=Leader, F=Follower
- **Level:** T=Team Level, I=Individual Level

<table>
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<tr>
<th>Team Task Types</th>
<th>Examples of Agent Support</th>
<th>Macrocognitive Processes</th>
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</table>
| **Team Decision Making/ Course of Action Selection** | Simulating options under consideration  
Augmentation Type: Augmented Capacity  
Agent Characteristics: FX, R, MY, LNE, F, T/I | ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] |
| | Preparing/updating a dynamic schedule  
Augmentation Type: Task Reallocation  
Agent Characteristics: A, P, LA, LE, F, T | ![Checkmark Icon] |
| | Notifying all team members when goals are achieved  
Augmentation Type: Knowledge Sharing  
Agent Characteristics: FX, R, MY, LNE, F, T | ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] |
| **Development of Shared Understanding** | Creating visualizations of high dimensional data  
Augmentation Type: Augmented Capacity  
Agent Characteristics: A, P, MY, LE, F, T | ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] |
| | Maintaining knowledge repository  
Augmentation Type: Task Reallocation  
Agent Characteristics: FX, R, MY, LNE, F, T/I | ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] |
| | Enforcing explicit, agreed upon protocols governing interactions  
Augmentation Type: Knowledge Sharing  
Agent Characteristics: A, P, LA, LE, L, T | ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] |
| **Intelligence Analysis (Team Data Processing)** | Mining intelligence data from distributed sources to identify correlations  
Augmentation Type: Augmented Capacity  
Agent Characteristics: A, P, MY, LE, L/F, T/I | ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] |
| | Monitoring cognitive states and (re)negotiating responsibility for pre-selected activities  
Augmentation Type: Task Reallocation  
Agent Characteristics: A, P, LA, LE, L, T/I | ![Checkmark Icon] ![Checkmark Icon] |
| | Maintaining up-to-date information in the collaboration space  
Augmentation Type: Knowledge Sharing  
Agent Characteristics: FX, R, LA, LNE, L, T | ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] ![Checkmark Icon] |

Figure 7.2 Examples of agent support
References


Schneeweiss, C. (2003), *Distributed decision making*, 2nd ed. (Heidelberg: Springer).


