Human–Agent Teaming for Multirobot Control: A Review of Human Factors Issues

Jessie Y. C. Chen and Michael J. Barnes

***Abstract*—The human factors literature on intelligent systems was reviewed in relation to the following: efficient human supervision of multiple robots, appropriate human trust in the automated systems, maintenance of human operator's situation awareness, individual differences in human–agent (H-A) interaction, and retention of human decision authority. A number of approaches—from flexible automation to autonomous agents—were reviewed, and their advantages and disadvantages were discussed. In addition, two key human performance issues (trust and situation awareness) related to H–A teaming for multirobot control and some promising user interface design solutions to address these issues were discussed. Some major individual differences factors (operator spatial ability, attentional control ability, and gaming experience) were identified that may impact H-A teaming in the context of robotics control.**

***Index Terms*—Automation, human–agent (H-A) teaming, human factors, human–robot interaction, individual differences, intelligent agent, situation awareness, trust, user interface design.**

I. Introduction

ROBOTIC systems have been increasingly used for various tasks, including transportation safety, search and rescue, space exploration, and military operations [1]–[3]. In the U.S. military, there is a trend to implement robotic systems that can perform some of the functions on the battlefield currently conducted by soldiers (e.g., casualty extraction, explosive detection and disposals, reconnaissance and surveillance, supply transportation, building clearing, and firefighting, etc.) [1], [4]–[7]. The same trend is manifesting itself in the civilian sector with the advent of the Google driverless car, autonomous farm equipment, and unmanned commercial aircraft [8]. The inexorable trend toward greater societal reliance on unmanned systems begs the question of control. Based on numerous real-world experiences in robotics operations during emergencies (e.g., World Trade Center, Hurricane Katrina, and Utah Mine disaster), Murphy and Burke [3] suggest that, with current technology, every robot should be controlled by at least two humans to avoid safety complications. The ratio (i.e., required manpower) increases depending on the complexity of the environment and the degree of automaton. In order to maintain an economically feasible human–robot ratio, robotic systems are being developed with the increasing levels of autonomy and sophistication [9]–[11]. However, increases in autonomy may not overcome the human's span of apprehension limits—around 7 (+ or – 2)—related to monitoring multiple systems at the same time [12]–[14]. Research on human–automation interaction has also identified several human performance issues associated with increased autonomy: tunnel vision, degraded situation awareness (SA), misuse and disuse of automated systems, and complacency [9], [15], [16].

In recent years, several research efforts have developed intelligent software agents that can assist human operators in managing multiple robots in military tasking environments [17]–[19]. Indeed, a recent report on the Role of Autonomy in U.S. Department of Defense Systems recommended that "increased autonomy can enable humans to delegate those tasks that are more effectively done by a computer, including synchronizing activities between multiple unmanned systems, software agents and warfighters—thus freeing humans to focus on more complex decision making" [11, p. 1]. As systems become more intelligent and sophisticated, it has been increasingly possible for human operators to stay "*on* the loop" (i.e., supervisory control) rather than "*in* the loop" (i.e., active control) [20]. However, staying "on the loop" does not make operators' jobs easier; as Parasuraman and Manzey [21] noted, automation does not simply perform tasks for humans—it changes the nature of humans' tasks.

In this paper, we perform a review of the state-of-the-art agent technologies for multirobot control as well as the most critical human–agent (H-A) interaction/interface issues that need to be addressed in order for such systems to be effective. In Part I of this paper, we review a number of topics from flexible automation to autonomous agents and point out the advantages and disadvantages of these approaches. In particular, we address the advantages of mixed-initiative models to leverage both human and agent decision strengths. To illustrate one such approach, we discuss our own research for a specific hybrid approach (RoboLeader) and present some of our major findings. In Part II, we discuss in detail two key human performance issues (trust and SA) related to H-A teaming for multirobot control as well as some major individual differences factors (operator spatial ability, attentional control ability, and gaming experience) that may impact H-A teaming in the context of robotics control. In Part III, we examine some promising user interface design solutions to address those human performance issues discussed in Part II and also summarize some design guidelines based on our own and reviewed research. Our review is based on the literature on human interaction with automated and autonomous

Manuscript received April 17, 2013; revised September 19, 2013 and November 18, 2013; accepted November 18, 2013. Date of publication January 2, 2014; date of current version January 16, 2014. This work was supported by the U.S. Department of Army under the Army Technology Objective of Safe Operations for Unmanned Reconnaissance in Complex Environments. This paper was recommended by Associate Editor A. M. Howard.

J. Y. C. Chen is with the U.S. Army Research Laboratory—Human Research and Engineering Directorate, Orlando, FL 32826 USA (e-mail: jessie.chen@us.army.mil).

M. J. Barnes is with the U.S. Army Research Laboratory—Human Research & Engineering Directorate, AZ 85613 USA (e-mail: michael.j.barnes.civ@mail.mil).

Digital Object Identifier 10.1109/THMS.2013.2293535

systems. Some cited studies were not conducted in contexts of multirobot control, but the results were relevant and, therefore, were included. Due to the length limit, we do not cover issues related to the perceptual aspects of human–robot interaction (e.g., field-of-view, video quality, robot orientation and attitude, etc.) or cover topics that relate to control issues for individual robots. Interested readers may refer to detailed reviews by Chen, Haas, and Barnes [22] and Chen *et al*. [9]. In order to maintain our focus we have limited our discussion to essential points that develop an understanding of the human factors issues related to human–agent collaboration particularly where multiple systems are involved.

PART I—HUMAN–AGENT TEAMING FOR ROBOTICS CONTROL

II. Human–Agent Teaming for Robotics Control

Before we delve into the discussion of all the issues related to H-A teaming, a few notes on the terminology are in order. While there are numerous definitions of "agent" (including intelligent agent, software agent, etc.), it is commonly accepted that an agent should possess the following characteristics: autonomy, observation of the environment (through some forms of sensors), action upon an environment (through some forms of actuators), and direction of its activity toward achieving certain goals [23]. The complexity of these systems varies greatly and ranges from a simple "reflex agent" (e.g., a thermostat) to an agent that can learn and evolve. While robots are agents by definition, agents do not necessarily have physical embodiment. In the context of our current discussion, we will use the term "agent" to refer to a broader class of intelligent systems (with or without physical embodiment) that are consistent with the definition given previously. We will use the term robots when the physical embodiment component is important in the discussion.

A. Human–Agent Roles

Successful agent technologies take advantage of the differences between human and agent strengths, as human reasoning has very different characteristics than algorithmic reasoning [24], [25]. The roles assigned to each refer to the general functions performed by each partner such as overall supervision by the human and algorithmic optimization by the agent with the understanding that functions may be reassigned during emergencies [26], [27]. H-A teams seem to be particularly effective for open-ended missions in which not all events can be preprogrammed (e.g., most combat situations). Agents can perform specialized functions but authority resides with a human supervisor for safety and tactical reasons [1], whereas agent technology inevitably will become more proficient as both digital memory and optimization algorithms improve, certain functions will remain human in the foreseeable future because of the human's ability to understand patterns of behavior, human intentions, macro implications, and ethical responsibilities [28]–[30]. Thus for H-A teams, the agent is always the subordinate member, who can be given permission to act autonomously only under specified conditions (e.g., emergencies [31], [32]).

B. Human–Agent Communications

H-A teams assume a relationship that goes beyond a human controlling or supervising agents [32]. Teams are more than intelligent entities working on a common problem—teams coordinate (share knowledge and depend on each other's output) and collaborate (work together on common functions) [24] and share a common knowledge framework [33]. In order for H-A interactions to be as natural as human–human (H-H) interactions, research efforts have been focusing on ways to support natural language communications between humans and agents [34]. Effective natural language communications require not only disambiguating the syntax and semantics of the utterance but also its pragmatics relating to the tasking environment and the intention of the speaker [35], [36]. Even with relatively constrained environments, agents can be confused by ambiguous commands that humans could decipher easily [34], [37]. The additions of gestures, gaze-facilitated language processing, and better training protocols are enhancing the ability of humans and robots to engage in more natural two-way communications, but natural language processing (NLP) is still relatively unsophisticated compared with H-H dialogue [38]. Currently, they are approximations of NLP that are designed for specific environments suggesting that a limited dialogue with agents is possible. Command languages (CLs) are simple lookup tables that require exact wording for commanding robots (or robots replying) and whose lexicons are geared to specific populations. CLs have proven useful in robotic environments for discrete tasks such as menu selection [39]. Another approach is exemplified by the controlled natural language (CNL) architecture which has a formal logic-based computational structure but is more constrained than NLP in its lexicon and assumptions. The CNL is most useful for specialized environments; compared with CL, the CNL is capable of engaging in complex dialogues such as a call-for-fire mission based on realistic military scenarios [40].

C. Human–Agent Architectures

An important requisite for fluid agent–human communication is a common cognitive framework. This suggests that the underlying agent architecture should be compatible with, or perhaps even mimic, human cognition. For example, the beliefs, desires and intentions (BDI) architectural framework uses a mentalist metaphor emulating human thought and motivation but whose basic structure is based on the computational logic (see Section III-C 3 mixed-initiative systems) [41]. In contrast, cognitive architectures were originally designed to investigate human cognitive processes and have only recently been adapted as architectures for robotic intelligence [37]. For example ACT-R and SOAR were developed to emulate human cognitive processes through the use of production systems (if–then rules), neural nets, and learning algorithms [42]–[44]. There are various active research programs that use cognitive architectures to foster H-A (or human–robot) communication [37], [45]. A good example is a U.S. Air Force research project that has developed a software agent which acts as an artificial crew member communicating with human team members—via NLP protocols embedded within an ACT-R architecture [46]. These

TABLE I
INTELLIGENT SYSTEMS FOR MULTIROBOT CONTROL

Intelligent Systems & Key Refs	Potential Strengths	Potential Weakness
Teaming Agents [48]-[54]	Supporting optimal task-allocation planning and flexible plan-execution; allowing graceful plan-degradations; facilitating proactive information distribution.	Human-Agent team performance more sensitive to the changes of tasking complexities (i.e., degrading faster) than Human-Human teams.
Hierarchical Agents [12][55]-[57]	Greater flexibility in adjusting to task complexity (dividing task complexity between senior agents and specialized agents).	Communications among agents; difficulty in dealing with truly novel situations (algorithms too cumbersome when dealing with complex hierarchies).
Adaptive Automation [19][31] [58]-[66]	Balance between reducing workload for manual control and reducing SA loss for automated tasks; reducing the task management load; particularly useful in emergency situations.	Harmful effects associated with sudden changes in task state (triggered inappropriately); usurping delegation authority from the human.
Adjustable Automation [18][19][58] [67]-[71]	Human initiating adaptivity of the joint human-system task.	Increased workload associated with selecting appropriate autonomy levels, especially under emergency situations.
Mixed-Initiative Systems [58][59][64] [72]-[75]	Collaborative decision making between a human and an intelligent system. Mixed-initiative systems' ability to respond to developments in the tasking environment.	Communication mechanisms between the agents and the humans to express their intents; decision etiquette must be explicit to avoid confusion.

examples are still research projects and currently have limited utility for open-ended real-world situations.

III. Agents for Human–Robot Teaming

In artificial intelligence, an intelligent agent is typically defined as "an autonomous entity which observes and acts upon an environment and directs its activity toward achieving goals" [23, p. 34]. This definition covers a variety of possible uses for intelligent agents, from swarms with individual agents of limited intelligence that evince sophisticated behaviors holistically, to agents that respond to particular tasks in a manner that emulates human intelligence. The necessity for more powerful intelligent agents that can interact with human operators in increasingly sophisticated ways will require that current capabilities be augmented with techniques and technologies that facilitate effective H-A team interactions [24], [47]. This section will briefly review several types of agents that have been used in human–robot interaction (HRI) tasks, including the RoboLeader agent that was developed in our own laboratory. Table I presents a summary of the technologies discussed in this section as well as strengths and weaknesses of each approach.

A. Teaming Agents

In recent years, researchers have designed agents that support team behaviors [48], [49]. Korsah *et al.* [49], for example, presented a multirobot control system, called xBots, that could support optimal task-allocation planning and flexible execution of the plans as well as allow graceful degradations of the plans should failures or unexpected events happen. One key difference between the xBots system and other market-based approaches is that it optimizes the plans based on temporal constraints in the tasking environments. In order to facilitate natural interaction between humans and robots/agents, dialog management systems such as TeamTalk [50] have also been developed. The effectiveness of TeamTalk has been evaluated in a simulated environment that involved multiple robots for search and rescue tasks [51]. Other researchers found that the *type* of communication among agents and human teams impacted the overall H-A team performance [52]. For example, Harbers *et al.* [52] found that communication with agent team members concerning world knowledge of the tasking environment was not as effective as communicating the human's intent.

Other H-A teaming research and development efforts, while not directly applied to multirobot control domains, are potentially useful for developing intelligent agents that can function as teammates to the humans in multirobot tasking contexts. For example, Fan *et al.* [48] developed an agent, R-CAST, that uses the Collaborative Agents for Simulating Teamwork (CAST) model based on the Recognition-Primed Decisions (RPD) framework [53] to support the development of shared mental models and proactive information sharing between the human operators and the agent (see also [54]). In essence, the objective of the R-CAST agent is to facilitate the "collaborative-RPD" process between the human operator and the agent by reasoning and representing the "contextual needs of collaboration" in the following areas: decision process (establishing shared mental models between the human and the agent), recognition aspects (cues, goals, expectancy, and courses of action), and the inference mechanism. Fan *et al.* [48] conducted a human-in-the-loop simulation experiment and demonstrated that the H-A teams outperformed the H-H teams in complex military command-and-control decision-making tasks, regardless of the time pressure imposed on the teams. However, the H-A team performance was more affected by the changes of tasking complexities (i.e., degraded faster when tasks were more complex) than the H-H teams. The results of the Fan *et al.* study suggest that using collaboration models such as R-CAST to form H-A teams may lead to better performance, although the overall H-A team performance may be moderated by tasking complexities.

B. Hierarchical Agents

In complex tasking environments, individual agents usually lack flexibility and thus may be able to perform only very circumscribed problem sets. For more complex problems, hierarchical agent systems are being designed with agents that have specialized intelligence embedded within multilayer architectures [55]–[57]. The individual agents have specific tasks and a means of communicating with one another. The ability to divide task complexity between senior (more capable) agents and specialized (less capable) ones allows hierarchies to adjust to greater complexity and better adjust to change. Agent technologies with military importance have been demonstrated for a number of realistic applications. For example, hierarchical agents have been successfully used to control multiple UAVs to locate targets cooperatively during high fidelity simulations [56], [57]. Similar agent technology has been used for cooperative control of multiple UAVs during live demonstrations [55]. However, complex hierarchical systems have some potential disadvantages, such as cumbersome algorithms and inadequacy in truly novel situations. Furthermore, as more levels are involved and as more entities need to be controlled, communication among agents inevitably becomes more challenging [12], [57].

C. Flexible Automation

Flexible automation refers to systems that invoke various levels of automation depending on the operator's state, critical events in the environment, or algorithms related to specialized problem sets. The approaches differ in their workload requirements (amount of cognitive resources available for tasks) and allocation of decision authority [58]. Flexible automaton is a useful set of concepts for eliciting agents while minimizing workload, depending on the requirements of the specific tasks in which agents are being used. There are various definitions of the components of flexible automation [9], [12], [14], [19], [31], [58]–[61]. To simplify our discussion, we divide the decision space into three traditional areas of research depending on whether the decision to automate is made primarily by software, by the human, or both. The differences among types of flexible automation involve the role of the human in decision making—(1) adaptive systems assign tasks under specified conditions determined before the mission; (2) adjustable (also known as adaptable) automation requires humans to decide when to invoke automation during the mission; whereas (3) mixed-initiative systems entail joint actions and decision making (e.g., the planning process) throughout the mission [19], [31], [59].

1) Adaptive Automation: Adaptive systems are being developed to maintain a balance between reducing workload for manual control and reducing SA loss for automated tasks [60]. Adaptive automation is most effective for multitasking situations wherein a fully automated task may be neglected if the operator becomes complacent or allocates attentional resources to other tasks [61]. A trigger based on environmental or internal state indicators is used to allocate tasks to either automation or manual control. During low workload, the task is allocated to the human; during high workload conditions, the task is automated. The advantage of using adaptive automation, compared with full automation, lies in keeping the human engaged but not overwhelmed. For example, Parasuraman *et al*. [31], [61] investigated various types of automation for monitoring unmanned aerial and ground systems. The results showed superior SA and change detection for adaptive rather than static automation conditions, presumably because the adaptive trigger drew the operator into the monitoring task. Physiological measures (e.g., electroencephalography [EEG], functional magnetic resonance imaging, and heart rate) have been used successfully in a number of laboratory settings as triggers to different workload states as well as to improve UAV control performance [62], [63]. Operator error rates and task difficulty have also been used effectively as triggering mechanisms to improve secondary task performance, reduce mental workload, and improve SA for supervisory control of heterogeneous robotic platforms [31].

Adaptive systems help reduce the operator's task management load—the operator does not have the additional task of deciding when or what tasks to automate (as in the case of adjustable automation in [58]). More importantly, when there are safety issues and time constraints in tasks such as monitoring a missile in-flight, the operator may not have the luxury of giving permission before the automated systems are activated [64]. On the other hand, there are a number of technical and philosophical issues that are associated with adaptive systems [19]. If the trigger is less than perfect, then sudden changes in task state may be annoying or even dangerous. Furthermore, adaptive systems, by their very nature, usurp delegation authority from the human. Parasuraman *et al*. [61] and Steinhauser *et al*. [65] provided several design guidelines for implementing adaptive automation based on their own experimental results as well as reviews of empirical research on adaptive automation and aiding [9]. Finally, Feigh *et al*. [66] presented a systematic framework describing how (i.e., types of adaptations) and when (i.e., the trigger mechanisms) automated systems can adapt.

2) Adjustable Automation: In adjustable (or adaptable) automated systems, in contrast with adaptive automation, the adaptivity of the joint human-system task is initiated by the human (as opposed to the automated systems in the case of adaptive automation) [19], [58], [67], [68]. In a recent experiment on adjustable autonomy for multirobot control, Valero-Gomez *et al*. [69] tested the effectiveness of a flexible system and a system with a fixed level of autonomy in a simulated search-and-rescue tasking environment. The results showed that the flexible system (e.g., the operator could reconfigure the task during plan execution or take control of the robots) supported better human–robot team performance than did the inflexible system. Kidwell *et al*. [70] compared the effectiveness of an adjustable automated system with an adaptive system for a multirobot control task. They found that, while higher workload was associated with the adjustable system, participants' change detection was better with the adjustable system than with the adaptive system. Miller and Parasuraman [19] have developed an adjustable system (Playbook) wherein specified algorithms known as *plays* can be elicited by the operator to improve performance during high workload mission segments. The Playbook paradigm has been used successfully to simulate UAV flights and has been used in simulation and field testing of UAV automation for the U.S. Army [18]. In a recent experiment, Miller *et al*. [71] examined the effects of nonoptimal Playbook solutions on operator performance. The advantage of adjustable systems is that the decision authority is never usurped by the machine; the disadvantage is that in time-constrained and high workload environments, management of automation allocation decisions may be too time consuming or too complex to be practical.

3) Mixed-Initiative Systems: Mixed-initiative systems involve collaborative decision making between a human and an intelligent system much like the relationship between a human and a subordinate but autonomous assistant [59], [72], [73]. The U.S. Defense Science Board report on autonomy suggests that "instead of viewing autonomy as an intrinsic property of an unmanned vehicle in isolation, the design and operation of autonomous systems needs to be considered in terms of human-system collaboration" [11, pp. 1–2]. One of the major advantages of mixed-initiative systems is to mitigate the "brittleness" associated with systems that do not allow human input [74]. Clare [74] demonstrated that, by adding human input into the otherwise automated multirobot control environment, the overall system performance increased by 12%. An example of a mixed-initiative decision system is the NASA-developed Mixed-initiative Activity Plan GENerator (MAPGEN) to aid planners for the Mars space mission [75]. The MAPGEN used constraint reasoning to generate mission plans for the Mars mission based on priorities input by human planning experts considering science objectives as well as temporal and physical mission constraints. The MAPGEN allows the human planners flexibility in creating "what-if" scenarios and specification of constraints, resulting in a synergistic relationship between humans and MAPGEN. Another example showed the utility of a mixed-initiative system in the context of a simulated search-and-rescue task involving 200 robots searching a large wilderness area [73].

Tecuci *et al*. [59] point out that designing a mixed-initiative system requires consideration of seven issues: task parameters, control, shared awareness, communications, personalization, software architecture, and evaluation. This suggests that the system designers should not only consider the relative technical merits of the software agents and the human operators' capabilities but also the ability of both the agents and the humans to communicate their intents as well as the mixed-initiative system's ability to respond to developments in the tasking environment. The BDI framework has been used to develop mixed-initiative systems in various contexts, where agents' beliefs are updated based on their perception of the environment, communications with other agents/humans, and their inference mechanisms [41], [76], [77]. Once the agent's beliefs are updated and if new tasks are identified, the agent continues with goal-selection (Desires) and planning/execution (Intentions). In order for the agent to be optimally transparent to the human operator, its BDI need to be effectively conveyed to the human. As we will explain in later sections, system transparency is critical for operators to calibrate their trust in agents as well as to maintain adequate SA of the tasking environments. Part Three will review some useful user interface designs that can support these requirements.

It should be pointed out that mixed-initiative systems are inherently flexible and can integrate both adaptive and adjustable agents within a common framework [58]. During emergencies, an adaptive agent could act autonomously if a temporal deadline expires, whereas in the adjustable case, the human could instantiate a specialized agent (e.g., a play) based on suggestions from a mixed-initiative agent [64]. An example of a mixed-initiative system (RoboLeader) is discussed below. The purpose of the discussion is not only to review experimental results relevant to mixed-initiative systems but also to elucidate H-A design issues discovered during simulations in realistic military environments. More general research findings related to efficient H-A teams are discussed in the final sections of the paper.

D. RoboLeader

Future military and civilian environments (e.g., air traffic control) will require humans to supervise multiple autonomous systems. However, human attentional span is limited by working memory capacity; thus, H-A teams are an effective means of combining the algorithmic sophistication of agents with the meta-understanding of experienced humans. In particular, we argue that mixed-initiative models of agent control unite the advantages of adaptive agents that can respond rapidly to situation changes and adjustable agents that the human can elicit to solve complex problems [19], [31], [59]. Our posited agent should have general intelligence related to the mission domain, a repertoire of algorithmic solutions for specific problems, and be capable of supervising multiple systems while communicating with the human supervisor. We will discuss one of our research projects (RoboLeader) in order to motivate a discussion of the human factors issues involved in using an agent to supervise multiple intelligent systems.

RoboLeader was developed to investigate issues associated with controlling multiple robots in multitasking environments. Three assumptions were used to inform RoboLeader development: 1) *mixed-initiative interaction*—with humans having ultimate decision authority to ensure flexibility and safety as well as the incorporation of implicit goals that agents may not be aware of [30], [78], [79]; 2) *supervisory control* in nature—to ensure manageable workload and SA for controlling multiple robots in multitasking environments [9]; 3) *agent transparency*—to both the autonomous systems and the human (see discussion in Section IV) [80]. Instead of directly managing each individual robot, the human operator only manages one entity—RoboLeader. The operator can, therefore, better focus on other tasks requiring his/her attention. More specifically, RoboLeader can collect information from subordinate robots with limited autonomy (e.g., collision avoidance and self-guidance to reach target locations), making tactical decisions, and coordinating the robots by issuing commands, waypoints, or motion trajectories [81]. In typical mission situations, RoboLeader would recommend route revisions when encountering environmental events that require robots to be rerouted. The human operators, in turn, can accept the plan revisions or modify them as appropriate. RoboLeader, therefore, is a mixed-initiative system that consists of both human and machine decision-making components. It also possesses characteristics of hierarchical systems because it serves as the interface between the human supervisor and the less capable (in terms of decision authority) robots.

A series of human-in-the-loop simulation experiments have been conducted to investigate the control structure and interface requirements between the human supervisor and RoboLeader, with number of robots, task-load, target mobility, agent error type, and agent reliability level being manipulated systematically [17], [82]. Overall, RoboLeader was effective for enhancing the H-A team performance while reducing the operators' workload; however, effects of operator individual differences consistently impacted the operator performance. Across all three experiments, participants with higher spatial ability consistently outperformed those with lower spatial ability in tasks that required the most visual scanning, regardless of the availability of RoboLeader and other experimental manipulations. Participants with higher attention control ability and those who played video games frequently were able to multitask better than their counterparts. Frequent gamers also repeatedly exhibited better SA of the mission environments than did infrequent gamers. Further discussion on these individual differences issues will be presented in Section VI.

In general, the RoboLeader research suggests a synergy between humans and intelligent agents—but not an equivalency. The agents were ideal for circumscribed solutions and as means to reduce the operator's burden of multitasking. However, it is essential to maintain the human's ultimate decision authority without affecting the agents' awareness of the unfolding combat situation. The following sections will review some of the key human performance issues in H-A teaming as well as potential user interface design solutions to mitigate those issues. While there are numerous human performance issues that can be examined, due to the length limit, we focus on operator trust, SA, and individual differences. In these sections, we discuss research findings that cover a wide range of issues such as operator workload, multitasking and task switching requirements, imperfect automation, etc. However, issues such as training interventions, effects of stressors (psychological or environmental) on operator performance are not included.

PART II—HUMAN PERFORMANCE ISSUES IN HUMAN–AGENT TEAMING

IV. Trust in Automation

In mixed-initiative operations, the human operator's trust in the automated systems is a critical element of the H-A team performance. Trust issues are particularly germane to our focus on multisystems control by an intelligent agent because mistrust or over trust will propagate to the component systems. There have been numerous definitions of trust in the literature of organizational psychology, interpersonal relationships, and human–machine interactions, among other fields [80], [83]–[85]. In the context of H-A interaction, Lee and See's definition of trust, one of the most widely cited definition ("the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability"), seems most relevant as it captures the "appropriateness of trust, the influence of context, the goal-related characteristics of the agent, and the cognitive processes that govern the development and erosion of trust (p. 54)", all of which are critical to effective H-A teaming [80, p. 54].

Lee and See's [80] identification of antecedents for trust development in the context of human–automation interaction (i.e., purpose, process, and performance) provides a framework for discussion of system and environment-related factors that contribute to trust development. The *Purpose* factor deals with the degree to which the automation is being used according to the designer's intent. The *Process* factor deals with the question of whether the algorithm of the automated system is appropriate for a given tasking situation. The *Performance* factor deals with system reliability, predictability, and capability. Humans require user interfaces that capture the state of the system as a whole in order to interact appropriately with a supervisory agent. For example, the second RoboLeader experiment, comparing a false-alarm-prone agent to a miss-prone agent, indicated the efficacy of a central display of multirobot status for rapid error checking [17]. It should be pointed out that over-trust is as deleterious as under-trust. In other words, calibration is an important element of trust—appropriate trust implies that humans understand an agent's limits as well as its benefits [17], [86]. The following sections review the system and environment-related factors as well as human-related factors in H-A trust. Potential system-design principles derived from research findings are also reviewed.

A. *System and Environmental-Related Factors*

According to a meta-analysis on human trust in robotic systems [87], robot performance-related factors (e.g., reliability, false alarm rate, failure rate, etc.) were found to be better predictors of trust development than attribute-related factors (e.g., robot personality, anthropomorphism, etc.). Also important to trust development in the context of human-automation interaction is the system's level of transparency and observability available to the human operator [80], [88]. Besides the 3P's (purpose, process, and performance) of the automation, it has been reported that the operator's overall task-load (e.g., difficulty of the task or single task versus multitask) impacts the degree to which he/she relies (or over relies) on the automation [89], [90]. In a recent study, Manzey *et al.* [89] investigated performance consequences of automated aids (for fault identification and management) that are occasionally unreliable in a simulated multitasking supervisory control task. The results showed that while automation benefits both primary (fault diagnosis) and secondary task (response to communications) performance, a significant automation bias effect (complacency) was observed, even for those who had made an effort to verify the appropriateness of the aids' output. Additionally, Manzey *et al.* observed that the data seemed to suggest individual differences in susceptibility to automation bias effects. Section VI-A will discuss individual differences in attention control ability and their effects on human interaction with automation. Finally, according to McBride *et al.* [91], there appears to be an interaction between automation error type and task-load level. In their simulation experiment, McBride *et al.* found that participants were more prone to erroneous compliance with a false alarm-prone system when under heavy task load than when the task load was lighter. However, the same effect of task load (greater reliance on a miss-prone system when under heavy task load) was not observed for miss-prone conditions. Recently, Gao *et al*. [92] developed a computational model of real-time human–automation collaboration to control multiple robots based on system performance, operator trust, and operator cognitive workload. Empirical data showed that the model was able to predict operator performance within 2.3% [92].

A number of studies have examined the differences in people's perceived reliability of human aids versus automated aids [83], [93], [94] and human-like versus machine-like cognitive agents [95]. Although several factors may affect the perception (e.g., the context of the decision-making tasks, the operators' self-confidence in performing the tasks, the operators' monitoring strategies and expectations of performance of the systems, etc.), it was found that people tend to perceive the automation as being more capable and reliable than the human aids (when in fact the same information was provided to the participants) [93]. However, the caveat is that people are more sensitive to the automation's errors than to another human's errors; this relative sensitivity leads to a more rapid drop in trust in the automated aids once errors are detected [96]. Furthermore, de Visser [95] demonstrated that when a human-like cognitive agent appeared to be more cooperative rather than competitive, operator's trust in agent recommendations increased; however, no such differences were observed for a machine-like agent. Finally, Lyons and Stokes [97] investigated the effects of risk on human operators' reliance on decision aids coming from humans and automated systems. They found that, as the risk became greater, the human operators tended to rely more on the automation rather than the human aid.

The issues related to trust in autonomous systems span multiple levels and encompass social and ethical aspects. The HRI community is currently debating the locus of responsibility (human or robot) when a robot commits a harmful act under a human's command. Notably, Kahn *et al*. [98] showed that a robot may be perceived as unethical when it causes harm. Although safeguard measures have been proposed to prevent robots from committing unethical or dangerous acts [99], the legal implications have yet to be tested [8]. Finally, as intelligent systems become increasingly sophisticated and are capable of learning/evolving either based on their learning algorithms or access to information from other networks (e.g., cloud-based systems), it is imperative to examine the implications of these capabilities on operator trust in the systems. Since predictability is a critical aspect of trust development and maintenance, agent behaviors that change over time because of learning or new inputs from another network may prevent operators from properly calibrating appropriate trust. In summary, current research suggests that agent trust issues are influenced mostly by agent's performance, but agent–human interactions are complex—workload, risk, and perception of the agent's reliability all impact operator reliance [87].

B. Human-Related Factors

The previous section discussed agent factors and system contexts, considering the human part of the team is equally important. Research shows that operator's self-confidence (in his/her own ability to complete the task manually) is a critical factor in moderating the effect of trust (in automation) on system reliance [94], [100]–[102]. Lee and Moray [102] and Lewandowsky *et al*. [94] found that when self-confidence exceeded trust, operators tended to use manual control; when trust exceeded self-confidence, automation was used more. Chen and Terrence [100] showed that there is a strong interaction between type of automation errors (misses versus false alarms) and operators' self-assessed confidence in their attentional control, which will be discussed in the Section VI-A.

Past research shows that when humans work with automated systems as a team, they do not always trust their machine teammates properly—they may misuse (over-rely) or disuse (underrely) the system based on their perception of the automated systems [16]. A distinction important to disuse or misuse of automation is the difference between evaluation errors and intent errors. For *evaluation* errors, the operator misperceives the optimal solution and commits a calibration error. For *intent* errors, the operator is aware of the aid's superiority but still chooses to "disuse" automation in order to maintain control over the decision environment. For example, Beck *et al*. [103] reported that 84% of their participants chose to perform a target detection task manually although they were aware of the superiority of an automated target detection aid. Furthermore, research shows that the cognitive context of the decision-making process determines the tendency of the operator to disuse or misuse automated systems [93]. In a series of experiments, Dzindolet *et al*. [93] showed that by a simple change in decision order, *disuse* of an automated target recognition device changed to *misuse*. This suggests that locus of responsibility determines the context of the automation decision in that operators take more responsibility for making decisions versus automation (even when doing so is suboptimal) if they make the initial decision [93]. It has also been reported that both the cost of automation errors and the cost of verification affect humans' reliance on decision aids, as well as the effects are also moderated by age with younger adults being more appropriately responsive to cost factors including verification and error costs [104]. Finally, human operators' attitudes toward and trust in automated systems can also be influenced by their personalities (e.g., introversion versus extroversion) [105], [106], affective factors (e.g., moods and emotions) [107], and states of stress such as fatigue [108]–[111].

V. Human Operator's Situation Awareness of the Tasking Environment

One of the most critical factors for achieving effective supervisory control of multiple robots is maintaining adequate SA of the overall tasking environment as well as individual robots. In the context of H-A teaming for robotics control, it has been reported that human operators' SA of the tasking environment tends to degrade when the paths for the robots are automatically generated by path-planning agents [112]. Conversely, researchers have found situations where automation improved SA [113]–[115]. Overall, the literature seems to suggest that automation that "pulls the operator out of the loop" degrades SA (of the automated tasks), whereas automation that allows the operator to focus more on the mission environment improves SA—especially for nonautomated tasks [82], [116]. The conflicting findings are, to a large extent, related to the SA measures used in the studies (*direct* versus *indirect,* see [116] for a meta-analysis). Flexible automation discussed earlier allows the system designer to more precisely design the automated system with the operator's cognitive requirements in mind. For example, Kaber *et al*. [60] evaluated the effectiveness of adaptive automation (in the context of air traffic control) for supporting different stages of information processing (i.e., information acquisition, information analysis, decision making, and action implementation) [68]; they reported that automating the information *acquisition* part of the task was most beneficial for supporting SA (see also [117]). According to a recent meta-analysis, when automation moves from *information analysis* to *decision making,* negative impacts of automation on SA is especially pronounced [116].

The disadvantages of automation are manifest most clearly when automation is less than perfectly reliable [116]. Frequently, changes in the environment may require operators to modify their plans for the robots. Muthard and Wickens [118] evaluated the effects of automation on pilot's performance in plan monitoring and revision. They found that pilots only detected about 30% of the experimenter-induced changes, which should have resulted in flight plan revisions. Plan continuation errors were especially pronounced when there was an unreliable automation aid (compared with no aid). Mumaw *et al*. [119] showed an even more alarming inadequacy in monitoring performance. In their study, pilots only detected about 3% (1 of 32 total cases) of unexpected changes to the mode of an automation aid. Indeed, it has been well documented that operators are frequently unaware of mode changes when interacting with automation systems and, therefore, are confused about the systems' behaviors [120]. In fact, data show that even if changes in the environment are detected, operators may have difficulty interpreting the relevance of the changes and their effects on the existing plans [121]. The rest of this section will discuss the issues related to multitasking and task switching, both of which have significant impact on the operators' development and maintenance of SA.

A. Multitasking and Task Switching

In most future operational settings, humans will very likely be expected to perform other tasks concurrently while operating a robot (or multiple robots) [17]. While updates of information are needed, recent studies have also shown that interrupting a primary task (i.e., supervisory control of robots) with an intermittent task (e.g., communication messages) can have a negative impact on SA [122], [123]. Basic research on costs of task switching consistently shows that responses tend to be substantially slower and more error-prone after task switching [124]–[126]. This is important because simultaneous control of multiple robots will require the operator to switch attention/control among the vehicles from time to time [127]. Empirical evidence showed that when the task stimuli (e.g., spatial reasoning) or required responses are similar in competing tasks, operator's task performance can be degraded significantly because of switch costs [126]. In the context of multirobot control, task switching costs can be problematic since the information processing required for dealing with one robot may interfere with dealing with another robot, either due to the similarity in task stimuli (e.g., video streams from the robots) and/or similarity in required task responses (e.g., map-based tasking/planning and spatial processing).

Research has been conducted to investigate the effects of task switching on robotics operator performance and SA [61], [128], [129]. SA may also be affected perceptually as a result of the change blindness phenomenon, which is the inability to perceptually attend to a change in one's environment. Parasuraman *et al*. [61] examined change blindness in the context of a supervisory control task, in which participants were asked to monitor a UAV and an unmanned ground vehicle (UGV) video feed in a reconnaissance tasking environment. Parasuraman *et al*. found that change blindness occurred most frequently when a "distracter" was present, but also occurred while participants shifted their attention from the UAV monitoring task to the UGV monitoring task. These results also suggest that task switching during a robot supervisory task may incur change blindness, which by its very nature affects an operator's SA. In fact, empirical evidence showed that the cost of switching attention among robots could incur loss of SA and require as long as 12 s to regain SA [130].

According to Norman [131], interruptions incur the greatest cognitive costs during high workload phases such as planning (intention forming and action planning) and evaluation (outcome interpretation and assessment). Thus, interface designers should account for this so that primary tasks are only interrupted during emergency situations or during moments of low workload. There is some evidence that cost may be reduced if the participants have a chance to prepare for the switch or receive task switching cues [124]–[126], suggesting that alerts should be provided to the operator indicating the changes to the interface and the degree of importance of the changes [132]. Training interventions can also be developed to help operators acquire attention managment skills in dealing with multitasking requirements [133]. For example, Wilson *et al*. [133] demonstrated the utility of a gaze-training paradigm that was effective in enhancing participants' multitasking performance.

VI. Individual Differences Factors

Significant individual differences in cognitive task performance and interaction with automation have been repeatedly documented in the literature [17], [106], [134], [135]. Szalma [136] suggests that individual differences should be considered more frequently in user interface designs and training intervention developments. In fact, based on empirical data, it has been observed that effects due to individual differences in cognitive abilities can sometimes be even greater than effects due to interface design manipulations [137]. Manzey *et al*. [89] observed significant individual differences in susceptibility to automation bias effects in the multitasking environments they simulated, although the authors did not identify what individual differences factors contributed to the observed behaviors. Previous research has shown that some individuals show more performance decrements than others when multitasking and these decrements may be related to their poorer abilities to control and allocate attention [125], [138], [139]. These results suggest that individual differences in attentional control seem to play a critical role in determining an operator's overall multitasking performance. As mentioned before, research also shows that individual differences in spatial ability and gaming experience play important roles in determining operators' SA in multirobot tasking environments [17], [82]. The following section briefly reviews these individual differences factors that may impact the overall effectiveness of H-A teaming for multirobot control. The impacts of operators' personalities on their interaction with automated systems were briefly discussed in Section IV-B. Therefore, the current section will only focus on attentional control, spatial ability, and gaming experience.

A. *Attentional Control*

Attentional control is defined as one's ability to focus and shift attention in a flexible manner [140]. According to a recent U.S. Air Force's survey of subject matter experts on the performance of UAV operators [141], attentional control is one of the most important abilities that affect an operator's performance since the robotics control task is inherently multitasking (e.g., sensor manipulation, tracking, communication, etc.). Past research has shown that poor attention allocation was related to degraded human performance in multirobot control [130], [142]. Several studies have shown that there are individual differences in multitasking performance, and some people are less prone to performance degradation during multitasking conditions [125], [139]. There is an evidence that people with better attentional control can allocate their attention more flexibly and effectively, and attention-switching flexibility can predict performance of tasks ranging from flight training to driving [138], [140], [143], [144]. It has also been reported that working memory capacity may be a better predictor of multitasking performance than attention [145], [146], especially visuospatial working memory [147].

Several studies showed that operators with lower attentional control interacted differently with automated systems than those with higher attentional control—they tended to rely more heavily on automation, even when the reliability of those systems was low [17], [100], [148]. For example, it appears that for high attentional control participants, false-alarm-prone systems tend to be more detrimental than miss-prone alerts, due to *disuse* of automation (although this difference is moderated by the ease of verification of the alerts' validity, as shown in [17]). For low attentional control participants, conversely, miss-prone automation was more harmful than false-alarm-prone automation, due to *misuse* of (i.e., over-reliance on) automation. These findings have implications for designs of agents for multirobot control (e.g., agents could be developed that are sensitive to individual differences). More research should also investigate training interventions (e.g., attention management) and/or user interface designs (e.g., multimodal cueing displays, automation transparency, and visualization techniques) that can mitigate performance shortfalls of those with lower attentional control [9], [22], [133], [149].

B. *Spatial Ability*

Spatial ability has been found to be a significant factor in certain visual display domains [150], multitasking involving flight asset monitoring and management [151], navigation [137], [152], visual search tasks [17], [100], [153]–[157], and robotics task performance [158], [159]. U.S. Air Force scientists [141] and [160] interviewed 53 subject matter experts about abilities that were critical to effective performance of UAV control tasks in terms of piloting and sensor operations—spatial ability was identified as an important factor for both tasks. Rodes and Gugerty [137] showed that even though effective user interface designs compensate for low spatial ability in some spatial (UAV navigation) tasks, optimal task performance required both an effective interface and high spatial ability. Our previous research showed that individuals with higher spatial ability exhibited more effective visual scanning and target detection performance during HRI-related multitasking [17], [82], [100], [153]–[156]. Based on these findings, it seems reasonable to expect operators with higher spatial ability to perform better with agents in multirobot control tasking environments, especially if more spatial information processing is required from the human. Alternatively, training interventions that could enhance the spatial interpretations required to perform a mission task might also be of benefit [161]–[163].

C. *Gaming Experience*

According to Green and Bavelier [162] and Hubert-Wallander *et al.* [164], experienced action video game players, compared with infrequent/non-gamers, were found to perform significantly better on tasks that required visuospatial selective attention, multiple object tracking, rapid processing of visual information and imagery, and flexibility in attention allocation. Chen and Barnes [17] and Hambrick *et al.* [145] also demonstrated the relationship between video game experience and multitasking performance. These results are consistent with previous findings that visuospatial working memory is an important predictor of multitasking performance [147] and video game playing may improve individuals' visuospatial working memory and, in turn, their multitasking performance (see [162] for a discussion on the training effects of video game playing). Indeed, in a recent review on the effects of video gaming on spatial cognition, Spence and Feng [163] concluded that playing action games contributed to players' sensory, perceptual, and attentional abilities (e.g., contrast sensitivity, spatial resolution, attentional visual field, enumeration, multiobject tracking, and visuomotor coordination and speed). The beneficial effects of video game playing seem to be related to changes in brain functions and were observed for both basic and complex spatial task, and the improvements were found to be long lasting [163]. More importantly, the benefits of video game playing can potentially transfer to tasks that are not closely similar to the tasks in the games (i.e., "far transfer"), according to Spence and Feng. In fact, a

U.S. Air Force study [165] concluded that, based on interviews of UAV pilots, gamers' superior visual information processing skills may be able to translate into superior robotics management performance. Indeed, a recent U.S. Air Force study [166] found that frequent video gamers outperformed infrequent gamers on robotics (UAV) tasks and, in some cases, performed as well as experienced pilots.

Cummings *et al.* [167] found that frequent gamers collaborated more with an automated UAV replanning system (higher degree of consent) than did infrequent gamers. Consistent with this finding, Clare [74] found that while frequent gamers were faster in performing their multirobot control tasks when working with a planning agent, they tended to over-trust the agent than did infrequent gamers; however, proper priming (about agent performance/reliability) was effective in helping gamers more properly calibrate their trust. Finally, Chen and Barnes [17], [82] demonstrated that frequent gamers exhibited significantly better SA of the tasking environments than did infrequent gamers. Therefore, based on these findings, it is expected that frequent gamers may work better with agents in multirobot control tasking environments due to their superiority in visual attention allocation and visuospatial information processing. The implication of the individual differences findings summarized previously is that successful H-A systems and training must accommodate the individual differences of the potential user population. Military systems, in particular, must be designed for users with different strengths and weaknesses. The final part of this paper briefly summarizes user interface designs that have the potentials of supporting effective H-A team performance in the context of multirobot control. Because of the wealth of material discussed in the final sections, user interface design guidelines based on Part II and Part III are summarized in Table II with pointers to pertinent references and a brief description of their design implications.

PART III—USER INTERFACE DESIGN FOR HUMAN–AGENT TEAMING

VII. User Interface Design for Human–Agent Teaming for Multirobot Control

Mixed-initiative H-A interaction in highly dynamic multitasking environments inherently require the user interface to support the following: human understanding the agent's intent/behavior and the mission environment, optimal human attention of different aspects of the tasking environment, and ease and flexibility of human input. This section briefly summarizes how each of these can be accomplished via effective interface designs.

A. Human Understanding the Agent and the Tasking Environment

Proper uses of information visualization techniques can help operators make sense of information and thereby enhance their SA of their mission/tasking environments (for a review on human factors issues related to information visualization, see [168]). Lee and See [80] recommended that the capabilities and limitations of the automated systems be conveyed to the operator, when feasible, in order for the operator to develop appropriate trust and reliance. Lessons learned from a U.S. Naval Intelligent Autonomy program indicated that human operators sometimes questioned the accuracy and effectiveness of the output produced by intelligent systems such as those generating automated plans due to the operators' difficulties of understanding the rationales behind the output [78]. In a recent study, Van Dongen and van Maanen [169] found that participants' perceived understandability of a decision aid's reasoning process had a significant impact on their reliance on its recommendations.

Lee [170] proposed that, in order to increase automation transparency to the operator, system designers should make the system's 3P's (purpose, process, and performance) as well as the *history* of the 3P's visible to the operator. However, the presentation should be in a simplified form (e.g., integrated graphical displays), so the operator is not overwhelmed by the amount of information to process [171], [172]. Cummings *et al.* [72] suggested caution when using visualization tools for mixed-initiative multivariate path-planning tasks, especially when cost functions vary greatly in their sensitivity to changes in the variables of the plan. Operators' decision making may be prone to errors when dealing with more sensitive functions due to their difficulty in determining the true costs of different plan options. When appropriate, information about dynamic system confidence and context-related nature of automation reliability should be conveyed to the operator [173]–[176]. The effectiveness of ecological interface designs (EIDs) for H-A interaction has been investigated in several studies [177]–[180]. In these studies, EIDs have been used to portray (graphically) the following: capabilities and limitations of agent, intent of agent, and quality of plan revisions proposed by agent. These studies consistently found that EIDs were effective in supporting operators' understanding of agents' behavior as well as predictions of agents' future behaviors and, thereby, promoting proper operator trust calibration. Finally, Clare *et al.* [181] demonstrated that operators' SA (in a multirobot mission context) was significantly better when they were allowed to modify multiple objectives (e.g., area coverage, fuel efficiency, target tracking, etc) of the planning agent than when they could modify one or no objective.

Madhavan and Wiegmann [83] suggested, based on the research findings of Nass and Moon [182] on humans' social responses to computers, that techniques such as anthropomorphizing automation may help individuals better calibrate their trust in the systems. Specifically, the "humane" responses/characteristics exhibited by automation may reduce users' biases toward machines and facilitate their application of reciprocal behaviors or calibration of trust (although the effects may be moderated by factors such as users' ages, as demonstrated in [183]) [95]. However, Lee and See [80] cautioned that any anthropomorphizing of the automation should be carefully evaluated to ensure appropriate trust. Finally, Parasuraman and Miller [184] recommended that automation etiquette be considered when user interfaces are designed for automated systems. They found that poor etiquette (i.e., more interruptive and

TABLE II
USER INTERFACE DESIGN GUIDELINES ON HUMAN–AGENT TEAMING FOR MULTI-ROBOT CONTROL

Issues	Guidelines and Key References
Flexible human-agent interaction	- User interface should provide the operator with the flexibility to test different options and the user interfaces should enable flexible adjustments of weighting of constraints via a user-friendly mechanism (e.g., sliders, Schedule Comparison Tool). [80][167] [181][190] - The system should be able to adjust to operator workload and allow agents to act autonomously under specified conditions. [58][59] - Natural language communications vs. command language vs. controlled natural language: NLP is the most flexible but also the most brittle solution; controlled languages are useful for more constrained environments but also subject to ambiguity; command languages are the least ambiguous but also the least flexible solution. [34][35][39][42][43][194][195] - Any anthropomorphizing of the automation should be carefully evaluated to ensure appropriate trust. [80] - Automation etiquette should be considered when user interfaces are designed for automated systems. [184]
Maintaining operator's ultimate decision authority	- The mechanism for ensuring human authority needs to be embedded in the agent architecture (e.g., mixed-initiative systems). [72] - The user interface must support operator understanding of the agent's behavior and the mission environment as well as effective task resumption after interruptions. [177][187][188] - The operator should be able to query the automation, inspect raw information sources, and verify or negate the automated advice. [117] [190]
Support operator's multitasking performance	- Interruptions incur the greatest cognitive costs during high workload phases such as planning (intention forming and action planning) and evaluation (outcome interpretation and assessment). Thus, interface designers should account for this so that primary tasks are only interrupted during emergency situations or during moments of low workload. [131] - Switching among similar tasks (e.g., spatial processing) is more harmful than switching among dissimilar tasks. Additionally, the range of operator tasks should be reduced when possible to mitigate task switching costs. [12][130] - Task switching cost may be reduced if the participants have a chance to prepare for the switch or receive task switching cues, suggesting that alerts should be provided to the operator indicating the changes to the interface and the degree of importance of the changes. [124]-[126] [132] - In interruption-prone tasking environments, operators should have easy visual access to the primary task to facilitate task resumption after the interruptions. [185][188] - User interface should support operator's recovery of SA after task interruptions. St. John and Smallman suggest these principles: (1) automating change detection; (2) providing unobtrusive (yet noticeable) notification; (3) prioritizing the overview list; (4) providing access on demand for cluttered displays (p. 131). [187] - Scott et al. presented these design guidelines for interruption assistance interfaces: (1) enable user control of event replay; (2) provide visual summary of critical events but limit the summary only to goal-related events; and (3) clearly indicate relationships between past and current system state (p. 703). [186]
Automation transparency is essential	- Systems' 3P's (purpose, process, and performance) as well as the *history* of the 3P's be presented to the operator in a simplified form such as integrated graphical displays. [80] [170]-[172] - Agent's reasoning process should be conveyed to the operator in order for the operator to develop appropriate trust and reliance. [169] - Capabilities/limitations of the automated systems should be conveyed to the operator, when feasible, in order for the operator to develop appropriate trust and reliance. [80] - When appropriate, the operator should have access to the dynamic information about system's confidence level and context-related nature of automation reliability. [167][173]-[176]
Visualization and training techniques enhance human–agent collaboration	- Proper uses of information visualization techniques can help operators make sense of information and thereby enhance their SA of their mission/tasking environments. [168][177] [196] - Visualization displays should be carefully designed for multivariate planning tasks, especially when cost functions vary greatly in their sensitivity to changes in the variables of the plan. Operators' decision making may be prone to errors when dealing with more sensitive functions due to their difficulty in determining the true costs of different plan options. [72] - Employ visualization techniques (e.g., EID and augmented reality) to enhance operator SA and support operators' understanding of agents' behavior as well as predictions of agents' future behaviors and, thereby, promoting operator SA and proper trust calibration. EIDs have been used to portray (graphically) the following: capabilities and limitations of agent, intent of agent, and quality of plan revisions proposed by agent. [74][168]-[180] [196] - Operators should be trained to understand the system's 3P's (purpose, process, and performance). [80][197]
Human individual differences must be part of the human/agent design process	- Successful human-agent systems and training must accommodate the individual differences of the potential user population. This can be accomplished by interface design, selection, training, or even designing agents that are sensitive to individual differences among humans. [17][82][133][149] - Operator attentional control is one of the most important abilities that affect an operator's multi-robot control performance. Training interventions (e.g., attention management) and/or user interface designs (e.g., multimodal cueing displays, automation transparency) should be developed to mitigate performance shortfalls of those with lower attentional control. [9][17][22][100][133][141][148][149] - Operator spatial ability is critical to effective performance of robot control tasks. Operators with lower spatial ability should be supported by effective user interfaces (e.g., visualization techniques) and training regimens (e.g., interpretation of spatial information, development of spatial task strategies) for tasks that involve spatial information processing. [17][82][100] [137][141] [153][156][160]-[163] - Frequent video gamers tend to have better SA of the tasking environment and also tend to perform better on tasks that require visuospatial selective attention, multiple object tracking, rapid processing of visual information and imagery, and flexibility in attention allocation. However, user interface designs should take into account that gamers have been found to have a tendency to over-trust intelligent agents they work with; techniques such as priming about agent performance/reliability appears to be a promising way to mitigate gamers' miscalibration of trust. [17][74][145][162][175][198]

impatient) resulted in not only lower operator trust but also poorer operator task performance (automation malfunction diagnosis) compared with the good etiquette condition (agent more courteous and patient).

B. Attention Management and Recovery From Interruption

When controlling multiple robots at the same time, it is inevitable that the operator will focus on some aspects of the environment (e.g., one of the robots) before resuming his/her monitoring of all the robots. Techniques that facilitate task resumption have been proposed and tested in various tasking environments [185]–[187]. Some techniques focus on reminding the operator where he or she was before the interruption [185], while others present aids for the operator to quickly review what happened during the interruption [186], [187]. Ratwani and Trafton [188] recommended that in interruption-prone tasking environments, operators should have easy visual access to the primary task to facilitate task resumption after the interruptions. Ratwani *et al*. [185] demonstrated that simply by reducing the size (by about 75%) of the window for the interrupting task (i.e., reducing the occlusion of the primary task screen by the interrupting task window), participants were able to resume their primary task significantly faster. Eye tracking data also showed that participants were more accurate at returning to where they left off with the smaller interruption windows.

Other more sophisticated techniques to facilitate recovery from interruptions have also been developed. For example, St. John and Smallman [187] discussed the utility of an SA recovery tool (named Change History EXplicit [CHEX]) which displayed a textual event history list in a naval air warfare environment). St. John and Smallman suggest that four design principles be followed when developing SA maintenance and recovery tools: 1) automating change detection; 2) providing unobtrusive (yet noticeable) notification; 3) prioritizing the overview list; 4) providing access on demand for cluttered displays [187, p. 131]. Other researchers have proposed replay tools that can communicate recent significant events to the operators via video [186]. For example, Scott *et al*. [186] presented two types of replay tools—one replaying the events at 10× real-time speed and the other presenting bookmarks on the event timelines so the operator could view the replay by selecting the bookmarks. Results showed that both replay techniques were effective, especially when the tasking environment was challenging. Based on the results, the authors presented several recommended design guidelines for interruption assistance interfaces: 1) enable user control of event replay; 2) provide visual summary of critical events but limit the summary only to goal-related events; and 3) clearly indicate relationships between past and current system state [186, p. 703].

Dorneich *et al*. [123] took a different approach and developed a wearable adaptive system, the Communications Scheduler, which used physiological sensors (EEG and electrocardiogram) to detect operators' cognitive workload in a multitasking situation (including navigation, cognitive, monitoring, and maintaining SA). The Communications Scheduler decided whether to interrupt the user's current task based on the urgency of the situation, the operator's cognitive workload, and the system state. The interruption etiquette was designed based on H-H interactions. Empirical testing showed that the Communication Scheduler positively impacted participants' performance by rescheduling their priorities, resulting in only a temporary loss of SA for low priority messages.

C. Ease and Flexibility of Human Input

In mixed-initiative planning, it has been reported that operators may have difficulties at times when trying to specify mission parameters (e.g., goals and constraints) in the way required by the automated planning system [78]. In order to address such issues, Cummings *et al*. [189] designed an intelligent path-planning agent that was able to assist human operators with a simulated maritime navigation task while supporting flexible human interactions. The user interface of the planner agent was designed based on the objectives of promoting automation transparency and conveying environmental uncertainties while providing the participants with flexibility in specifying constraints for the solutions. In addition, a number of researchers found that in order to facilitate proper operator trust calibration, especially when systems cannot maintain perfect reliability, it is beneficial to provide the operator with the flexibility to test different options and the user interfaces should enable flexible adjustments of weighting of constraints via a user-friendly mechanism (e.g., sliders) [80], [181], [190]. The operator should also be able to query the automation, inspect raw information sources, and verify or negate the automated advice [117]. This remedy can potentially mitigate the "merging trust" phenomenon described in [191] where operator's trust in higher-reliability system was "pulled-down" by lower-reliability systems (i.e., system-wide trust calibration versus component-specific calibration). User interface design guidelines based on discussion in Part II and Part III are summarized in Table II.

VIII. Conclusion and Future Research

The objective of this paper was to identify important human factors issues related to H-A teams in the context of multirobot control. We reviewed a number of technical issues required for successful collaboration between humans and agents for supervision of multiple intelligent systems concluding as follows.

1) An agent that acts as an interface between human operators and intelligent systems is an efficient means of allowing operators to supervise multiple systems.
2) Effective H-A communication does not require open-ended NLP but will require an agent architecture that can infer, even at rudimentary level, the operator's intent.
3) Mixed-initiative architectures take advantage of the synergy between the more sophisticated world-view of an experienced human as well as the agent's logical precision and more rapid latencies.

Based on the literature and our own research, we developed user interface design guidelines for effective H-A synergy which are elucidated in Parts II and III as well as summarized in Table II. Many of these guidelines generalize to supervision of autonomous systems but others are more specific to supervising multiple systems using agent technology. Our more general conclusions are as follows.

1) Effective calibration of operator trust in autonomous systems is critical and can be achieved by system transparency, training, and an understanding of the limitations as well as the strengths of the agent technologies.
2) Transparency should encompass the current and futures states of multiple intelligent systems as well as the intent of the agent acting as an intermediate supervisor.
3) Switching among multiple subsystems requires human factors design augmentations to keep the operator current during multitasking or during concurrent changes among component systems.
4) Individual differences among human operators are an important factor in supervisory proficiency.

Improvements in agent technology and autonomy are increasing exponentially [192]. However, there are still important and difficult issues that need investigation. Free-form NLP is proving difficult to implement not only because of semantic ambiguity but also because of the pragmatics of context [34]. As the context changes, even the interpretation of a simple command changes. “Screen the backdoor” (the capstone scenario of a major U.S. Army robotics program) may be ambiguous depending on context; for example, if a robot views multiple structures, it may be uncertain which door to go to, which is a backdoor, or even if a low window is a door. Advances in computational logic will improve agent reasoning [41], but effective agent technology will requires bidirectional communications. Agents must be able ask questions as well as answer them. Research in this area does not have to be verbally based; gestures, schematics, graphics, and pictures may be useful communication media [9], [17], [82]. CLS will become more sophisticated as their ontologies allow multiple words or images to be mapped to meaningful actions especially if the mappings are specialized for specific populations [193]. Furthermore, controlled language architectures that are designed for more constrained environments could result in useful dialogues among agents as well as among agents and humans [194]. Bidirectional communications research is, by its very nature, multidisciplinary requiring research psychology, computer science, computational linguistics, etc.; however, like most complex research, it is best attacked in small chunks. Another important area that has yet to be extensively investigated is effective user interface design to promote shared mental model between the human operator and the automated systems. As agents become more intelligent, their “mental model” (theory of mind) of the human operator’s intent will become more sophisticated and accurate. More research is needed on how this (machine) understanding can be portrayed to the human so s/he can gauge the accuracy of this interpretation and, in turn, facilitate effective mixed-initiative interactions.

Finally, as pointed out by Parasuraman and Manzey [21], automation does not replace the human—it changes the nature of the human’s task. In his review of the seminal article on human-automation interaction by Parasuraman and Riley [16], Lee [15] concluded that “automation requires more, not less, attention to training, interface design, and interaction design”. There is no requirement for intellectual equality between humans and artificial agents; the important issue is to understand the factors necessary for partnership problem solving in truly complex real-world environments. Recent research programs such as the U.S. DoD Autonomy Research Pilot Initiative have started to investigate some of these H-A teaming issues that have to be addressed in order for H-A teams to perform effectively in the real world with all its complexities and unanticipated dynamics (see (http://www.defenseinnovationmarketplace.mil/ARPI.html).

The current review summarizes the most critical human factors issues and potential user interface design solutions to mitigate those issues. The design guidelines were derived from data of empirical studies, and admittedly, a lot of which were conducted in controlled laboratory settings. However, as an initial set of guidance, this review should be a useful document to those who wish to understand the human factors aspects of H-A teaming for multirobot control.

References

[1] M. J. Barnes and A. W. Evans, “Soldier-robot teams in future battlefields: An overview,” in *Human–Robot Interactions in Future Military Operations*, M. J. Barnes and F. Jentsch, Eds. Surrey, U.K.: Ashgate, 2010, pp. 9–29.

[2] K. Jones and E. Schmidlin, “Human–robot interaction: Toward usable personal service robots,” *Rev. Human Factors Ergonom.*, vol. 7, pp. 100–148, 2011.

[3] R. Murphy and J. Burke, “The safe human–robot ratio,” in *Human–Robot Interactions in Future Military Operations*, M. J. Barnes and F. Jentsch, Eds. Surrey, U.K.: Ashgate, 2010, pp. 31–51.

[4] L. Greenemeier. (2010). Robot pack mule to carry loads for G.I.s on the move. *Sci. Amer.* [Online]. Available: http://www.scientificamerican.com/article.cfm?id=boston-dynamics-ls3

[5] K. Osborn. (2011). Army building smarter robots. *Army AL&T Mag.* [Online]. Available: http://www.usaasc.info/alt_online/article.cfm?iID=1101&aid=07

[6] E. M. Purdy, “The increasing role of robots in national security,” *Defense AT&L*, vol. 5, pp. 26–29, May/Jun. 2008.

[7] P. W. Singer, “War of the machines,” *Sci. Amer.*, vol. 303, pp. 56–63, 2010.

[8] Morals and the machine. (Jun. 2012). *The Economist.* [Online]. Available: http://www.economist.com/node/21556234?fsrc=scn/tw/te/ar/moralsandthemachine

[9] J. Y. C. Chen, M. J. Barnes, and M. Harper-Sciarini, “Supervisory control of multiple robots: Human performance issues and user interface design,” *IEEE Trans. Syst., Man, Cybern. C, App. Rev.*, vol. 41, no. 4,, pp. 435–454, Jul. 2011.

[10] M. L. Cummings, S. Bruni, and P. J. Mitchell, “Human supervisory control challenges in network-centric operations,” *Rev. Human Factors Ergon.*, vol. 6, pp. 34–78, 2010.

[11] Defense Science Board, “The role of autonomy in DoD systems,” Under-secretary of Defense, Washington, DC, USA, 2012. [Online]. Available: http://www.acq.osd.mil/dsb/reports/AutonomyReport.pdf

[12] M. Lewis, H. Wang, S. Chien, P. Velagapudi, P. Scerri, and K. Sycara, “Choosing autonomy modes for multirobot search,” *Human Factors*, vol. 52, no. 2, pp. 225–233, Apr. 2010.

[13] G. Miller, “The magical number 7 plus or minus two: Some limits on our capacity for processing information,” *Psychol. Rev.*, vol. 63, no. 2, pp. 81–97, 1956.

[14] H. Wang, M. Lewis, P. Velagapudi, P. Scerri, and K. Sycara, “How search and its subtasks scale in N robots,” in *Proc. Int. Conf. Human–Robot Interaction*, 2009, pp. 141–147.

[15] J. D. Lee, “Review of a pivotal human factors article: Humans and automation: Use, misuse, disuse, abuse,” *Human Factors*, vol. 50, pp. 414–410, Jun. 2008.

[16] R. Parasuraman and V. Riley, “Humans and automation: Use, misuse, disuse, abuse,” *Human Factors*, vol. 39, pp. 230–253, Jun. 1997.

[17] J. Y. C. Chen and M. J. Barnes, "Supervisory control of multiple robots: Effects of imperfect automation and individual differences," *Human Factors*, vol. 54, pp. 157–174, Apr. 2012.

[18] L. Fern and R. J. Shively, "A comparison of varying levels of automation on the supervisory control of multiple UASs," in *Proc. AUVSI's Unmanned Syst. North Amer.*, 2009.

[19] C. Miller and R. Parasuraman, "Designing for flexible interaction between humans and automation: Delegation interfaces for supervisory control," *Human Factors*, vol. 49, pp. 57–75, Feb. 2007.

[20] M. Maybury, "Human-centered autonomy," presented at the Workshop Human-Mach. Trust for Robust Auton. Syst., Ocala, FL, USA, 31, Jan. 2012.

[21] R. Parasuraman and D. H. Manzey, "Complacency and bias in human use of automation: An attentional integration," *Human Factors*, vol. 52, pp. 381–410, 2010.

[22] J. Y. C. Chen, E. C. Haas, and M. J. Barnes, "Human performance issues and user interface design for teleoperated robots," *IEEE Trans. Syst. Man, Cybern. C, App. Rev.*, vol. 37, no. 6, pp. 1231–1245, Nov. 2007.

[23] S. J. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 3rd ed. Upper Saddle River, NJ, USA: Prentice-Hall, 2009.

[24] J. Bradshaw, P. Feltovich, and M. Johnson, "Human–agent interaction," in *Handbook of Human–Machine Interaction*, G. Boy, Ed. Farnham, U.K.: Ashgate, 2011, pp. 283–302.

[25] D. Kahneman and G. Klein, "Conditions for intuitive expertise: A failure to disagree," *Amer. Psychol.*, vol. 64, pp. 515–526, 2009.

[26] J. Scholtz, M. Theofanos, and B. Antonishek, "Theory and evaluation of human robot interactions," in *Proc. Int. Conf. Syst. Sci.*, 2002, pp. 125–143.

[27] M. A. Goodrich and A. C. Schultz, "Human–robot interaction: A survey," *Found. Trends Human—Comput. Interaction*, vol. 1, pp. 203–275, 2007.

[28] P. N. Johnson-Laird, "Mental models and human reasoning," *Proc. Nat. Acad. Sci.*, vol. 107, no. 43, pp. 18243–18250, 2010.

[29] G. Klein and A. Jarosz, "A naturalistic study of insight," *J. Cogn. Eng. Decision Making*, vol. 5, pp. 335–351, 2011.

[30] D. Woods, J. Tittle, M. Feil, and A. Roesler, "Envisioning human-robot coordination in future operations," *IEEE Trans. Syst., Man, Cybern. C, App. Rev.*, vol. 34, no. 2, pp. 210–218, May 2004.

[31] R. Parasuraman, M. Barnes, and K. Cosenzo, "Adaptive automation for human–robot teaming in future command and control systems," *Int. C2 J.*, vol. 1, pp. 43–68, 2007.

[32] I. Inagaki, "Smart collaboration between humans and machines based on mutual understanding," *Annu. Rev. Control*, vol. 32, pp. 253–261, 2008.

[33] N. Cooke, E. Salas, and J. Cannon-Bowers, "Measuring team knowledge," *Human Factors*, vol. 42, pp. 151–173, 2000.

[34] S. Tellex, T. Kollar, S. Dickerson, M. Walter, A. Banerjee, S. Teller, and N. Roy, "Approaching the symbol grounding problem with probabilistic graphical models," *AI Mag.*, vol. 32, pp. 64–76, 2011.

[35] D. Jurafsky and J. Martin, *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition*. Upper Saddle River, NJ, USA: Prentice-Hall, 2009.

[36] E. Santos, H. Nguyen, F. Yu, K. Kim, D. Li, J. Wilkinson, A. Olson, J. Russell, and B. Clark, "On intent-driven insider threat detection for intelligence analyses," *IEEE Tran. Syst., Man, Cybern. A, Syst. Humans*, vol. 42, pp. 331–347, 2012.

[37] D. N. Cassenti, T. D. Kelley, R. Yagoda, and E. Avery, "Improvements in robot navigation through operator speech preference," to be submitted.

[38] M. Camak and A. Thomaz, "Designing robot learners that ask good questions," in *Proc. Int. Conf. Human–Robot. Interaction*, 2012, pp. 17–24.

[39] E. Redden, C. Carstens, and R. Pettitt, "Intuitive speech based robotic control," Army Research Laboratory, Aberdeen Proving Ground, MD, USA, Rep. ARL-TR-5175, 2010.

[40] E. Nyberg, T. Mitamura, and W. Huijsen, "Controlled languages for authoring and translation," in *Computers and Translation: A Translator's Guide*, H. Somers, Ed. Amsterdam, The Netherlands: John Benjamins, 2003, pp. 245–282.

[41] A. Rao and M. Georgeff, "BDI agents: From theory to practice," in *Proc. Int. Conf. Multiagent Syst.*, 1995, pp. 312–319.

[42] J. G. Trafton, L. Hiatt, A. Harrison, F. Tamborello, S. Khemlani, and A. Schultz, "ACT-R/E: An embodied cognitive architecture for human–robot interaction," *J. Human–Robot Interaction*, vol. 2, pp. 30–55, 2013.

[43] J. Laird, N. Derbinsky, and J. Voigt, "Performance evaluation of declarative memory systems in soar," in *Proc. Behavior Representation Model. Sim. Conf.*, 2011, pp. 33–40.

[44] M. Scheutz and P. Schermerhorn, "Affective goal and task selection for social robots," in *Handbook of Research on Synthetic Emotions and Sociable Robotics: New Applications in Affective Computing and Artificial Intelligence*, J. Vallverdú and D. Casacuberta, Eds. Hershey, PA, USA: IGI Global, 2009, pp. 74–87.

[45] U. Kurup, C. Lebiere, and A. Stentz, "Integrating perception and cognition for AGI," in *Artificial General Intelligence 2011, LNAI 6830*, J. Schmidhuber, K. R. Thórisson, and M. Looks, Eds. Heidelberg, Germany: Springer-Verlag, 2011, pp. 102–111.

[46] J. Ball, C. Myers, A. Heiberg, N. Cooke, M. Matessa, M. Freiman, and S. Rodgers, "The synthetic teammate project," *Comput. Math. Org. Theory*, vol. 16, pp. 271–299, 2010.

[47] S. Green, M. Billinghurst, X. Chen, and J. Chase, "Human-robot collaboration: A literature review and augmented reality approach in design," *Int. J. Adv. Robot. Syst.*, vol. 5, pp. 1–18, 2008.

[48] X. Fan, M. McNeese, B. Sun, T. Hanratty, L. Allender, and J. Yen, "Human–agent collaboration for time stressed multi-context decision making," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 40, no. 2, pp. 306–320, Mar. 2011.

[49] G. Korsah, B. Kannan, B. Browning, A. Stentz, and M. Dias, "xBots: An approach to generating and executing optimal multi-robot plans with cross-schedule dependencies," in *Proc Int. Conf. Robot. Autom.*, 2012, pp. 115–122.

[50] I. Rudnicky, A. Pappu, P. Li, and M. Marge, "Instruction taking in the teamtalk system," in *Proc. AAAI Fall Symp.-Dialog with Robots*, 2010, pp. 173–174.

[51] M. Marge, A. Pappu, B. Frisch, T. Harris, and I. Rudnicky, "Exploring spoken dialog interaction in human-robot teams," in *Proc. Robots, Games, Res.: Success Stories USARSim IROS Workshop*, 2009, pp. 10–17.

[52] M. Harbers, C. Jonker, and B. Van Riemsdijk, "Enhancing team performance through effective communications," in *Proc. Annu. Human-Agent-Robot Teamwork Workshop*, 2012.

[53] G. Klein, "Naturalistic decision making," *Human Factors*, vol. 50, pp. 456–460, 2008.

[54] S. Nikolaidis and J. Shah, "Human-robot teaming using shared mental models," in *Proc. Annu. Human-Agent-Robot Teamwork Workshop*, 2012.

[55] S. Clauss, P. Aurich, S. Brggenwirth, V. Dobrokhodov, I. Kaminer, and A. Schulte, "Design and evaluation of a UAS combining cognitive automation and optimal control," in *Proc. AIAA Infotech Aerospace Conf.*, 2012.

[56] M. Hou, H. Zhou, M. Zhou, and G. Arrabito, "Optimizing operator-agent interaction in intelligent adaptive interface design: A conceptual framework," *IEEE Trans. Syst., Man, Cybern. C, App. Rev.*, vol. 41, no. 2, pp. 161–178, Mar. 2011.

[57] P. Scerri, T. von Gonten, G. Fudge, S. Owens, and K. Sycara, "Transitioning multiagent technology UAV applications," in *Proc. Annu. Conf. Auton. Agents Multiagent Syst.*, 2008, pp. 89–96.

[58] M. A. Goodrich, "On maximizing fan-out: Towards controlling multiple unmanned vehicles," in *Human–Robot Interactions in Future Military Operations*, M. J. Barnes and F. Jentsch, Eds. Surrey, U.K.: Ashgate, 2010, pp. 375–395.

[59] G. Tecuci, M. Boicu, and M. Cox, "Seven aspects of mixed-initiative reasoning," *AI Mag.*, vol. 28, pp. 11–18, 2007.

[60] D. Kaber, C. Perry, N. Segall, C. McClernon, and L. Prinzel, "Situation awareness implications of adaptive automation for information processing in an air traffic control-related task," *Int. J. Ind. Ergon.*, vol. 36, pp. 447–462, 2006.

[61] R. Parasuraman, K. Cosenzo, and E. de Visser, "Adaptive automation for human supervision of multiple uninhabited vehicles: Effects on change detection, situation awareness, and mental workload," *Mil. Psychol.*, vol. 21, pp. 270–297, 2009.

[62] L. Prinzel, G. Freeman, M. Scerbo, P. Mikulka, and A. Pope, "A closed-loop system of examining psychophysiological measures for adaptive automation," *Int. J. Aviation Psychol.*, vol. 10, pp. 393–410, 2000.

[63] G. Wilson and C. Russell, "Operator functional state classification using multiple psychophysiological features in an air traffic control task," *Human Factors*, vol. 45, pp. 381–389, 2003.

[64] M. J. Barnes and J. Grossman, "The intelligent assistant concept for electronic warfare systems," *Naval Warfare Center*, China Lake, CA, USA, Rep. TP 5585, 1985.

[65] N. Steinhauser, D. Pavlas, and P. Hancock, "Design principles for adaptive automation and aiding," *Ergon. Design*, vol. 17, pp. 6–10, 2009.

[66] K. Feigh, M. Dorneich, and C. Hayes, "Toward a characterization of adaptive systems: A framework for researchers and system designers," *Human Factors*, vol. 54, pp. 1008–1024, Dec. 2012.

[67] J. Langan-Fox, J. Canty, and M. Sankey, "Human-automation teams and adaptable control for future air traffic management," *Int. J. Ind. Ergon.*, vol. 39, pp. 894–903, 2009.

[68] R. Parasuraman, T. B. Sheridan, and C. D. Wickens, "A model for types and levels of human interaction with automation," *IEEE Trans. Syst., Man, Cybern A, Syst., Hum.*, vol. 30, no. 3, pp. 286–297, May 2000.

[69] A. Valero-Gomez, P. De La Puente, and M. Hernando, "Impact of two adjustable-autonomy models on the scalability of single-human/multiple-robot teams for exploration missions," *Human Factors*, vol. 53, pp. 703–716, 2011.

[70] B. Kidwell, G. Calhoun, H. Ruff, and R. Parasuraman, "Adaptable and adaptive automation for supervisory control of multiple autonomous vehicles," in *Proc. 56th Annu. HFES Meeting*, 2012, pp. 428–432.

[71] C. Miller *et al.*, "Delegating to automation: Performance, complacency and bias effects under non-optimal conditions," in *Proc. Human Factors Ergonom. Soc. Annu. Meeting*, 2011, pp. 2482–2486.

[72] M. L. Cummings, J. Marquez, and N. Roy, "Human-automated path planning optimization and decision support," *Int. J. Human–Comput. Stud.*, vol. 70, pp. 116–128, 2012.

[73] B. Hardin and M. Goodrich, "On using mixed-initiative control: A perspective for managing large-scale robotic teams," in *Proc. Int. Conf. Human–Robot Interaction*, 2009, pp. 165–172.

[74] A. S. Clare, "Modeling real-time human-automation collaborative scheduling of unmanned vehicles," Ph.D. dissertation, Dept. Aeronaut. and Astronaut., Massachusetts Inst. Technol., Cambridge, MA, 2013.

[75] J. Bresina and P. Morris, "Mixed-initiative planning in space mission operations," *AI Mag.*, vol. 28, pp. 75–88, 2007.

[76] G. Briggs and M. Scheutz, "Multi-modal belief updates in multi-robot human-robot dialogue interactions," in *Proc. AISB/IACAP Symp: Linguistic Cognitive Approaches Dialogue Agents*, 2012, pp. 67–72.

[77] G. Ferguson and J. Allen, "Mixed-initiative systems for collaborative problem solving," *AI Mag.*, vol. 28, pp. 23–32, 2007.

[78] M. Linegang, "Human-automation collaboration in dynamic mission planning: A challenge requiring an ecological approach," in *Proc. Human Factors Ergon. Soc. Annu. Meeting*, 2006, pp. 2482–2486.

[79] S. A. Guerlain, "Using the critiquing approach to cope with brittle expert systems," in *Proc. 39th Annu. HFES Meeting*, 1995, pp. 233–237.

[80] J. D. Lee and K. A. See, "Trust in technology: Designing for appropriate reliance," *Human Factors*, vol. 46, pp. 50–80, 2004.

[81] M. Snyder, Z. Qu, J. Y. C. Chen, and M. J. Barnes, "RoboLeader for reconnaissance by a team of robotic vehicles," in *Proc. Int. Symp. Collab. Tech. Syst.*, 2010, pp. 522–530.

[82] J. Y. C. Chen and M. J. Barnes, "Supervisory control of multiple robots in dynamic tasking environments," *Ergonomics*, vol. 55, pp. 2043–1058, Sep. 2012.

[83] P. Madhavan and D. Wiegmann, "Similarities and differences between human-human and human-automation trust: An integrative review," *Theoretical Issues Ergon. Sci.*, vol. 8, pp. 277–301, 2007.

[84] R. Mayer, J. Davis, and F. Schoorman, "An integrative model of organizational trust," *Academy Manage. Rev.*, vol. 20, pp. 709–734, 1995.

[85] J. Rempel, J. Holmes, and M. Zanna, "Trust in close relationships," *J. Personality Soc. Psychol.*, vol. 49, pp. 95–112, 1985.

[86] R. Hoffman, M. Johnson, J. Bradshaw, and A. Underbrink, "Trust in automation," *IEEE Intell. Syst.*, vol. 28, no. 1, pp. 84–88, Jan./ Feb. 2013.

[87] P. Hancock, D. Billings, K. Schaefer, J. Y. C. Chen, E. de Visser, and R. Parasuraman, "A meta-analysis of factors impacting trust in human–robot interaction," *Human Factors*, vol. 53, pp. 517–527, 2011.

[88] F. Verberne, J. Ham, and C. Midden, "Trust in smart systems: Sharing driving goals and giving information to increase trustworthiness and acceptability of smart systems in cars," *Human Factors*, vol. 54, pp. 799–810, 2012.

[89] D. Manzey, J. Reichenbach, and L. Onnasch, "Human performance consequences of automated decision aids: The impact of degree of automation and system experience," *J. Cogn. Eng. Decision Making*, vol. 6, pp. 57–87, 2012.

[90] R. Parasuraman, R. Molloy, and I. Singh, "Performance consequences of automation-induced 'complacency'," *Int. J. Aviation Psychol.*, vol. 3, pp. 1–23, 1993.

[91] S. McBride, W. Rogers, and A. D. Fisk, "Understanding the effect of workload on automation use for younger and older adults," *Human Factors*, vol. 53, pp. 672–686, 2011.

[92] F. Gao, A. Clare, J. Macbeth, and M. Cummings, "Modeling the impact of operator trust on performance in multiple robot control," in *Proc. AAAI Spring Symp.: Trust Auton. Syst.*, 2013.

[93] M. Dzindolet, L. Pierce, H. Beck, L. Dawe, and B. Anderson, "Predicting misuse and disuse of combat identification systems," *Mil. Psychol.*, vol. 13, pp. 147–164, 2001.

[94] S. Lewandowsky, M. Mundy, and G. Tan, "The dynamics of trust: Comparing humans to automation," *J. Exp. Psychol., Appl.*, vol. 6, no. 2, pp. 104–123, 2000.

[95] E. de Visser, F. Krueger, P. McKnight, S. Scheid, M. Smith, S. Chalk, and R. Parasuraman, "The world is not enough: Trust in cognitive agents," in *Proc. 56th Annu. HFES Meeting*, 2012, pp. 263–267.

[96] J. Jian, A. Bisantz, and C. Drury, "Foundations for an empirically determined scale of trust in automated systems," *Int. J. Cogn. Ergon.*, vol. 4, pp. 53–71, 2000.

[97] J. Lyons and C. Stokes, "Human-human reliance in the context of automation," *Human Factors*, vol. 54, pp. 112–121, 2012.

[98] P. Kahn *et al.*, "Do people hold a humanoid robot morally accountable for the harm it causes?," in *Proc. Int. Conf. Human–Robot Interaction*, 2012, pp. 33–40.

[99] R. Arkin and P. Ulam, "Overriding ethical constraints in lethal autonomous systems," Georgia Institute of Technology: Atlanta, GA, USA, Rep. GIT-MRL-12–01, 2012.

[100] J. Y. C. Chen and P. Terrence, "Effects of imperfect automation on concurrent performance of military and robotics tasks in a simulated multitasking environment," *Ergonomics*, vol. 52, pp. 907–920, 2009.

[101] P. de Vries, C. Midden, and D. Bouwhuis, "The effects of errors on system trust, self-confidence, and the allocation of control in route planning," *Int. J. Human-Comput. Stud.*, vol. 58, pp. 719–735, 2003.

[102] J. D. Lee and N. Moray, "Trust, self-confidence, and operators' adaptation to automation," *Int. J. Human-Comput. Stud.*, vol. 40, pp. 153–184, 1994.

[103] H. Beck, M. Dzindolet, and L. Pierce, "Automation usage decisions: Controlling intent and appraisal errors in a target detection task," *Human Factors*, vol. 49, pp. 429–437, 2007.

[104] N. Ezer, A. D. Fisk, and W. Rogers, "Age-related differences in reliance behaviour attributable to costs within a human-decision aid system," *Human Factors*, vol. 50, pp. 853–863, 2008.

[105] S. Merritt and D. Ilgen, "Not all trust is created equal: Dispositional and history-based trust in human–automation interaction," *Human Factors*, vol. 50, pp. 194–210, 2008.

[106] J. Szalma and G. Taylor, "Individual differences in response to automation: The five factor model of personality," *J. Exp. Psychol., Appl.*, vol. 17, pp. 71–96, 2011.

[107] S. Merritt, "Affective processes in human-automation interactions," *Human Factors*, vol. 53, pp. 356–370, 2011.

[108] V. Finomore, G. Matthews, T. Shaw, and J. Warm, "Predicting vigilance: A fresh look at an old problem," *Ergonomics*, vol. 41, pp. 791–808, 2009.

[109] C. Neubauer, G. Matthews, L. Langheim, and D. Saxby, "Fatigue and voluntary utilization of automation in simulated driving," *Human Factors*, vol. 54, pp. 734–746, 2012.

[110] J. Reichenbach, L. Onnasch, and D. Manzey, "Human performance consequences of automated decision aids in states of sleep loss," *Human Factors*, vol. 53, pp. 717–728, 2011.

[111] J. Warm, R. Parasuraman, and G. Matthews, "Vigilance requires hard mental work and is stressful," *Human Factors*, vol. 50, pp. 433–441, 2008.

[112] J. Marquez and M. L. Cummings, "Design and evaluation of path planning decision support for planetary surface exploration," *J. Aerosp. Comput., Info., Comm.*, vol. 5, pp. 57–71, 2008.

[113] L. Allender, "A cognitive engineering approach for human–robot interaction: Lessons from the examination of temporal latency," in *Human–Robot Interactions in Future Military Operations*, M. J. Barnes and F. Jentsch, Eds. Surrey, U.K.: Ashgate, 2010, pp. 315–334.

[114] S. Galster and R. Parasuraman, "The application of qualitative model of human interaction with automation in complex and dynamic combat fight task," in *Proc. Annu. Symp. Aviation Psychol.*, 2003, pp. 411–416.

[115] B. Lorenz, F. Di Nocera, S. Rottger, and R. Parasuraman, "Automated flight management in a simulated spaceflight micro-world," *Aviation, Space, Environ. Med.*, vol. 73, pp. 886–897, 2002.

[116] L. Onnasch, C. D. Wickens, H. Li, and D. Manzey, "Human performance consequences of stages and levels of automation: An integrated meta-analysis," *Human Factors*, in press.

[117] E. Rovira, K. McGarry, and R. Parasuraman, "Effects of imperfect automation on decision making in a simulated command and control task," *Human Factors*, vol. 49, pp. 76–87, 2007.

[118] E. Muthard and C. Wickens, "Factors that mediate flight plan monitoring and errors in plan revision: Planning under automated and high workload conditions," in *Proc. Int. Symp. Aviation Psychol.*, 2003, pp. 857–862.

[119] R. Mumaw, N. Sarter, and C. Wickens, "Analysis of pilots' monitoring and performance on an automated flight deck," in *Proc. Int. Symp. Aviation Psycho.*, 2001.

[120] N. B. Sarter and D. D. Woods, "'How in the world did we get into that mode?' Mode error and awareness in supervisory control," *Human Factors*, vol. 37, pp. 5–19, 1995.

[121] M. Endsley, "Toward a theory of situation awareness in dynamic systems," *Human Factors*, vol. 37, pp. 32–64, 1995.

[122] M. L. Cummings, "The need for command and control instant message adaptive interfaces: Lessons learned from tactical tomahawk human-in-the-loop simulations," *Cyber Psychol. Behavior*, vol. 7, pp. 653–661, 2004.

[123] M. Dorneich, P. Ververs, S. Mathan, S. Whitlow, and C. Hayes, "Considering etiquette in the design of an adaptive system," *J. Cog. Eng. Decision Making*, vol. 6, pp. 243–265, 2012.

[124] S. Monsell, "Task switching," *TRENDS Cogn. Sci.*, vol. 7, pp. 134–140, 2003.

[125] J. Rubinstein, D. Meyer, and J. Evans, "Executive control of cognitive processes in task switching," *J. Exp. Psychol., Human Perception Perf.*, vol. 27, pp. 763–797, 2001.

[126] A. Kiesel, M. Steinhauser, M. Wendt, M. Falkenstein, K. Jost, A. Philipp, and I. Koch, "Control and interference in task switching: A review," *Psychol. Bulletin*, vol. 136, no. 5, pp. 849–874, 2010.

[127] P. Squire and R. Parasuraman, "Effects of automation and task load on task switching during human supervision of multiple semi-autonomous robots in a dynamic environment," *Ergonomics*, vol. 53, pp. 951–961, 2010.

[128] J. Crandall, M. Goodrich, D. Olson, and C. Nielsen, "Validating human-robot systems in multi-tasking environments," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 35, no. 4, pp. 438–449, Jul. 2005.

[129] P. Squire, J. G. Trafton, and R. Parasuraman, "Human control of multiple unmanned vehicles: Effects of interface type on execution and task switching times," in *Proc. Conf. Human–Robot Interaction*, 2006, pp. 26–32.

[130] M. Goodrich, M. Quigley, and K. Cosenzo, "Task switching and multi-robot teams," in *Multi-Robot Systems: From Swarms to Intelligent Automata*, L. Parker, F. Schneider, and A. Schultz, Eds. Dordecht, The Netherlands: Springer, vol. 3, 2005, pp. 185–195.

[131] D. Norman, "Cognitive engineering," in *User Centered System Design: New Perspectives on Human-Computer Interaction*, D. Norman and S. Draper, Eds. Hillsdale, NJ, USA: Erlbaum, 1986, pp. 31–61.

[132] N. Sarter, R. Mumaw, and C. Wickens, "Pilots' monitoring strategies and performance on automated flight decks: An empirical study combining behavioral and eye-tracking data," *Human Factors*, vol. 49, pp. 347–357, 2007.

[133] M. Wilson, S. Vine, E. Bright, R. Masters, D. Defriend, and J. McGrath, "Gaze training enhances laparoscopic technical skill acquisition and multi-tasking performance: A randomized, controlled study," *Surg. Endoscopy*, vol. 25, pp. 3731–3739, 2011.

[134] R. Parasuraman and Y. Jiang, "Individual differences in cognition, affect, and performance: Behavioral neuroimaging, and molecular genetic approaches," *NeuroImage*, vol. 59, pp. 70–82, 2012.

[135] T. Shaw, G. Matthews, J. Warm, V. Finomore, L. Silverman, and P. Costa, "Individual differences in vigilance: Personality, ability and states of stress," *J. Res. Personality*, vol. 44, pp. 297–308, 2010.

[136] J. L. Szalma, "Individual differences in human-technology interaction: Incorporating variation in human characteristics into human factors and ergonomics research and design," *Theoretical Issues Ergon. Sci.*, vol. 10, pp. 381–397, 2009.

[137] W. Rodes and L. Gugerty, "Effects of electronic map displays and individual differences in ability on navigation performance," *Human Factors*, vol. 43, pp. 589–599, 2012.

[138] L. Feldman Barrett, M. Tugade, and R. Engle, "Individual differences in working memory capacity and dual-process theories of the mind," *Psych. Bulletin*, vol. 130, pp. 553–573, 2004.

[139] E. Schumacher, T. Seymour, J. Glass, D. Fencsik, E. Lauber, D. Kieras, and D. Meyer, "Virtually perfect time sharing in dual-task performance: Uncorking the central cognitive bottleneck," *Psychol. Sci.*, vol. 12, pp. 101–108, 2001.

[140] D. Derryberry and M. Reed, "Anxiety-related attentional biases and their regulation by attentional control," *J. Abnormal Psychol.*, vol. 111, pp. 225–236, 2002.

[141] W. Chappelle, K. McMillan, P. Novy, and K. McDonald, "Psychological profile of USAF unmanned aerial systems Predator & Reaper pilots," in *Proc. Aerosp. Med. Assoc. 81st Annu. Sci. Mtg.*, 2010, p. 339.

[142] J. Crandall and M. L. Cummings, "Attention allocation efficiency in human-UV teams," in *Proc. AIAA Infotech Aerospace Conf.*, 2007.

[143] M. Bleckley, F. Durso, J. Crutchfield, R. Engle, and M. Khanna, "Individual differences in working memory capacity predict visual attention allocation," *Psycho. Bulletin Rev.*, vol. 10, pp. 884–889, 2003.

[144] D. Kahneman, R. Ben-Ishai, and M. Lotan, "Relation of a test of attention to road accidents," *J. Appl. Psychol.*, vol. 58, pp. 113–115, 1973.

[145] D. Hambrick, F. Oswald, E. Darowski, T. Rench, and R. Brou, "Predictors of multitasking performance in a synthetic work paradigm," *Appl. Cogn. Psychol.*, vol. 24, pp. 1149–1167, 2010.

[146] M. Bühner, C. Konig, M. Pick, and S. Krumm, "Working memory dimensions as differential predictors of the speed and error aspect of multitasking performance," *Human Performance*, vol. 19, pp. 253–275, 2006.

[147] H. Logie, S. Trawley, and A. Law, "Multitasking: Multiple, domain-specific cognitive functions in a virtual environment," *Memory Cognition*, vol. 39, pp. 1561–1574, 2011.

[148] J. E. Thropp, "Individual differences using automation," Ph.D. dissertation, Dept. of Psychology, Univ of Central Florida, Orlando, FL, USA, 2006.

[149] P. Dux, M. Tombu, S. Harrison, B. Rogers, F. Tong, and R. Marois, "Training improves multitasking performance by increasing the speed of information processing in human prefrontal cortex," *Neuron*, vol. 63, pp. 127–138, 2009.

[150] K. Stanney and G. Salvendy, "Information visualization: Assisting low spatial individuals with information access tasks through the use of visual mediators," *Ergonomics*, vol. 38, pp. 1184–1198, 1995.

[151] B. Morgan *et al.*, "Individual differences in multitasking ability and adaptability," in *Proc. Human Factors Ergonom. Soc. Annu. Meeting*, 2011, pp. 919–923.

[152] C. Chen, M. Czerwinski, and R. Macredie, "Individual differences in virtual environments—Introduction and overview," *J. Soc. Inform. Sci.*, vol. 51, pp. 499–507, 2000.

[153] J. Y. C. Chen, "UAV-guided navigation for ground robot teleoperation in a military reconnaissance environment," *Ergonomics*, vol. 53, pp. 940–950, 2010.

[154] J. Y. C. Chen, P. Durlach, J. Sloan, and L. Bowens, "Human robot interaction in the context of simulated route reconnaissance missions," *Mil. Psychol.*, vol. 20, pp. 135–149, 2008.

[155] J. Y. C. Chen and C. T. Joyner, "Concurrent performance of gunner's and robotic operator's tasks in a multitasking environment," *Mil. Psychol.*, vol. 21, pp. 98–113, 2009.

[156] J. Y. C. Chen and P. Terrence, "Effects of tactile cueing on concurrent performance of military and robotics tasks in a simulated multitasking environment," *Ergonomics*, vol. 51, pp. 1137–1152, 2008.

[157] T. Fincannon, F. Jentsch, B. Sellers, and J. Keebler, "Beyong 'Spatial Ability': Examining the impact of multiple individual differences in a perception by proxy framework," in *Proc. Int. Conf. Human–Robot Interaction*, 2012, pp. 127–128.

[158] D. Cassenti, T. Kelley, J. Swoboda, and D. Patton, "The effects of communication style on robot navigation performance," in *Proc. Human Factors Ergon. Soc. Annu. Meeting*, 2009, pp. 359–363.

[159] C. E. Lathan and M. Tracey, "The effects of operator spatial perception and sensory feedback on human–robot teleoperation performance," *Presence: Teleoperators Virtual Environments*, vol. 11, pp. 368–377, 2002.

[160] W. Chappelle, P. Novy, B. Randall, and K. McDonald, "Critical psychological attributes of U.S. Air Force (USAF) predator & reaper sensor operators according to subject matter experts," in *Proc. Aerosp. Med. Assoc. Annu. Sci. Meeting*, 2010, p. 253.

[161] C. L. Baldwin and I. Reagan, "Individual differences in route-learning strategy and associated working memory resources," *Human Factors*, vol. 51, pp. 368–377, 2009.

[162] C. Green and D. Bavelier, "Enumeration versus multiple object tracking: The case of action video game players," *Cognition*, vol. 101, pp. 217–245, 2006.

[163] I. Spence and J. Feng, "Video games and spatial cognition," *Rev. Gen. Psychol.*, vol. 14, pp. 92–104, 2010.

[164] B. Hubert-Walllander, C. Green, and D. Bavelier. (2010). Stretching the limits of visual attention: The case of action video games. *WIREs Cognitive Sci.*, vol. 2. [Online]. Available: http://www.bcs.rochester.edu/people/daphne/VisionPDF/hubertwallander.pdf

[165] J. Triplett, "The effects of commercial video game playing: A comparison of skills and abilities for the Predator UAV," M.S. thesis, US Air Force—Air University, Maxwell Air Force Base, Alabama, USA, 2008.

[166] R. McKinley, L. McIntire, and M. Funke, "Operator selection for unmanned aerial vehicles: Comparing video game players and pilots," *Aviation, Space Env. Med.*, vol. 82, pp. 635–642, 2011.

[167] M. L. Cummings, A. Clare, and C. Hart, "The role of human-automation consensus in multiple unmanned vehicle scheduling," *Human Factors*, vol. 52, pp. 17–27, 2010.

[168] G. Robertson *et al.*, "Selected human factors issues in information visualization," *Rev. Human Factors Ergon.*, vol. 5, pp. 41–81, 2009.

[169] K. van Dongen and P. van Maanen, "A framework for explaining reliance on decision aids," *Int. J. Human–Comput. Stud.*, vol. 71, no. 4, pp. 410–424, 2013.

[170] J. D. Lee, "Trust, trustworthiness, and trustability," presented at the Workshop on Human-Mach. Trust Robust Auton. Syst., Ocala, FL, USA, 31, Jan. 2012.

[171] M. Cook and H. Smallman, "Human factors of the confirmation bias in intelligence analysis: Decision support from graphical evidence landscapes," *Human Factors*, vol. 50, pp. 745–754, 2008.

[172] H. Neyedli, J. Hollands, and G. Jamieson, "Beyond identity: Incorporating system reliability information into an automated combat identification system," *Human Factors*, vol. 53, pp. 338–355, 2011.

[173] N. Bagheri and G. Jamieson, "The impact of context-related reliability on automation failure detection and scanning behavior," in *Proc. IEEE Int. Conf. Syst., Man, Cybern.*, 2004, pp. 212–217.

[174] X. Dong and C. Hayes, "Uncertainty visualization: Helping decision makers become more aware of uncertainty and its implications," *J. Cog. Eng. Decision Making*, vol. 6, pp. 30–56, 2012.

[175] J. McGuirl and N. B. Sarter, "Supporting trust calibration and the effective use of decision aids by presenting dynamic system confidence information," *Human Factors*, vol. 48, pp. 656–665, 2006.

[176] Y. Seong and A. Bisantz, "The impact of cognitive feedback on judgment performance and trust with decision aids," *Int. J. Ind. Ergonom.*, vol. 38, pp. 608–625, 2008.

[177] M. L. Cummings and S. Bruni, "Human-automation collaboration in complex multivariate resource allocation decision support systems," *Int. J. Intell. Decision Technol.*, vol. 4, pp. 101–114, 2010.

[178] H. Furukawa, H. Nakatani, and T. Inagaki, "Intention-represented ecological interface design for supporting collaboration with automation: Situation awareness and control in inexperienced scenarios," in *Proc. Human Performance, Situation Awareness Autom. II*, 2004, vol. I, pp. 49–55.

[179] H. Furukawa and R. Parasuraman, "Supporting system-centered view of operators through ecological interface design: Two experiments on human-centered automation," in *Proc. Human Factors Ergon. Soc. Annu. Meeting*, 2003, pp. 567–571.

[180] B. D. Seppelt and J. D. Lee, "Making adaptive cruise control (ACC) limits visible," *Int. J. Human-Comput. Stud.*, vol. 65, pp. 192–205, 2007.

[181] A. Clare, M. Cummings, J. How, A. Whitten, and O. Toupet, "Operator objective function guidance for a real-time unmanned vehicle scheduling algorithm," *AIAA J. Aerosp. Comput., Inform. Commun.*, vol. 9, no. 4, pp. 161–173, 2012.

[182] C. Nass and Y. Moon, "Machines and mindlessness: Social responses to computers," *J. Soc. Issues*, vol. 56, pp. 81–103, 2000.

[183] R. Pak, N. Fink, M. Price, B. Bass, and L. Sturre, "Decision support aids with anthropomorphic characteristics influence trust and performance in younger and older adults," *Ergonomics*, vol. 55, pp. 1059–1072, 2012.

[184] R. Parasuraman and C. Miller, "Trust and etiquette in high-criticality automated systems," *Commun. ACM*, vol. 47, pp. 51–55, 2004.

[185] R. Ratwani, A. Andrews, M. McCurry, J. G. Trafton, and M. Peterson, "Using peripheral processing and spatial memory to facilitate task resumption," in *Proc. Human Factors Ergonom. Soc. Annu. Meeting*, 2007, pp. 244–248.

[186] S. Scott, S. Mercier, M. Cummings, and E. Wang, "Assisting interruption recovery in supervisory control of multiple UAVs," in *Proc. Human Factors Ergonom. Soc. Annu. Meeting*, 2006, pp. 699–703.

[187] M. St. John and H. Smallman, "Staying up to speed: Four design principles for maintaining and recovering situation awareness," *J. Cog. Eng. Decision Making*, vol. 2, pp. 118–139, 2008.

[188] R. Ratwani and J. G. Trafton, "An eye-movement analysis of the effect of interruption modality on primary task resumption," *Human Factors*, vol. 52, pp. 370–380, 2010.

[189] M. L. Cummings, M. Buchin, G. Carrigan, and B. Donmez, "Supporting intelligent and trustworthy maritime path planning decisions," *Int. J. Human–Comput. Stud.*, vol. 68, pp. 616–626, 2010.

[190] E. Roth, M. Hanson, C. Hopkins, V. Mancuso, and G. Zacharias, "Human in the loop evaluation of a mixed-initiative system for planning and control of multiple UAV teams," in *Proc. Human Factors Ergon. Soc. Annu. Meeting*, 2004, pp. 280–284.

[191] D. Keller and S. Rice, "System-wide versus component-specific trust using multiple aids," *J. Gen. Psychol.*, vol. 137, pp. 114–128, 2010.

[192] L. G. Weiss, "Autonomous robots in the fog of war," *IEEE Spectrum*, vol. 48, no. 8, pp. 30–57, Aug. 2011.

[193] S. Tellex, T. Kollar, S. Dickerson, M. Walter, A. Banerjee, S. Teller, and N. Roy, "Understanding natural language commands for robotic navigation and mobile manipulation," in *Proc. Nat. Conf. Artif. Intell.*, 2011.

[194] S. Poteet, P. Xue, A. Kao, D. Mott, D. Braines, and C. Giammanco, "Controlled english for effective communication during coalition operations," in *Proc. 18th ICCRTS C2 Underdeveloped, Degraded Denied Oper. Environments*, Alexandria, VA, USA, 2013.

[195] R. Pettitt, E. Redden, and C. Carstens, "Scalability of robotic controllers: An evaluation of controller options experiment III," U.S. Army Research Laboratory, Aberdeen Proving Ground, MD, USA, Rep. ARL-TR-5989, 2012.

[196] G. L. Calhoun and M. H. Draper, "Multi-sensory interfaces for remotely operated vehicles," in *Human Factors of Remotely Operated Vehicles*, N. Cooke, H. Pringle, H. Pedersen, and O. Connor, Eds. Oxford, U.K.: Elsevier, 2006, pp. 149–163.

[197] M. S. Young and N. A. Stanton, "What's skill got to do with it? Vehicle automation and driver mental workload," *Ergonomics*, vol. 50, pp. 1324–1339, 2007.

[198] J. Wright, J. Chen, S. Quinn, and M. Barnes, "The effects of level of autonomy on human-agent teaming for multi-robot control and local security maintenance," Tech. Rep. (ARL-TR-6724), U.S. Army Research Laboratory, Aberdeen Proving Ground, MD, USA, 2013.

Jessie Y. C. Chen received the B.A. degree in linguistics from National Tsing-Hua University, Hsinchu, Taiwan, in 1987, the M.A. degree in communication studies from the University of Michigan, Ann Arbor, MI, USA, in 1989, and the Ph.D. degree in applied experimental and human factors psychology from the University of Central Florida, Orlando, FL, USA, in 2000.

She is a Research Psychologist with U.S. Army Research Laboratory (ARL)—Human Research and Engineering Directorate at the field element in Orlando. Her research interests include human–robot interaction, human–vehicle interaction, human supervisory control, and individual differences.

Dr. Chen's received the U.S. Army Modeling and Simulation Award (Army-wide Individual Experimentation) in 2008 and the Best Paper Award for the Army Science Conference (Behavioral Sciences and Human Performance session) in 2010.

Michael J. Barnes received the B.A. degree in psychology fronm the University of Arizona, Tucson, AZ, USA, and the M.A. degree in engineering psychology from New Mexico State University, Las Cruces, NM, USA.

He is currently a Research Psychologist with the Human Research and Engineering Directorate, the U.S. Army Research Laboratory (ARL) Adelphi, MD, USA. In this capacity, he was the lead for the human–robotic interaction component of the program of Safe Operations for Unmanned systems for Reconnaissance in Complex Environments. Prior to ARL, he conducted human factors research for the U.S. Navy and served as an HF Manager for the General Electric Corporation. His research interests include HRI investigations of risk visualization, intelligence processes, and unmanned aerial vehicles crew systems.

Mr. Barnes has served on a number of NATO committees related to HRI and battlefield visualization. He has authored or coauthored more than 80 articles and edited a book *Human–Robot Interactions in Future Military Operations* (2010, Eds. Barnes & Jentsch).