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Human-Centered Command and Control of Future Autonomous Systems

**Topic**
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# Human-Centered Command and Control of Future Autonomous Systems


## Abstract

The DoD's envisioned role shift for humans from *operators* to future autonomous systems *supervisors* presents significant challenges for developing effective decision support. What decision support will supervisors need to effectively oversee autonomous systems? What will their task needs be and how can we support them with usable and useful supervisory human-machine interfaces (HMIs) and tools? Here, we inform the requirements and design of future decision support through a systematic cognitive engineering and analysis process. Structured interviews with 27 unmanned systems experts were carefully sequenced across four groups, with results and artifacts from one group informing the next interviews. Interviews focused on supervisory monitoring and intervention tasks and were designed to feed a user- and task-centered, scientifically-principled HMI design process to develop the decision support. The interviews informed this design process by populating three key design artifacts: (1) a model of current and future tasks, (2) their allocation across humans and automation, and (3) the necessary supporting human-automation exchanges. A framework for system designers to allocate tasks across humans and automation was extended to provide an objective basis for *subject matter experts* to contribute their expectations for future automation. The interview results show how today's task needs are not met by current HMIs and tools, and how persisting with them is unlikely to meet the future needs of more nuanced supervisory decision making. Our results inform the design of future supervisory HMIs that target and mitigate today's capability gaps and shed light on how to begin to achieve the DoD vision.


**Keywords**: supervisory control, autonomous systems, decision support, human-machine interface, user-centered design

## Introduction

### *The Evolving Role of the Human in Unmanned and Autonomous Systems*

The role of the human operator of autonomous systems is anticipated to undergo a significant transformation from today's single-vehicle, single-mission *operator* into tomorrow's multi-vehicle, multi-mission *manager* (DoD, 2009). Dramatic improvements and increases in autonomy are expected to enable this transformation (DoD, 2012). The DoD is investing heavily in researching and developing the autonomy **technologies** required to support the future vision. Here, we focus on the equally important but often neglected issue of supporting the future **human end-user** of these technologies who must supervise the autonomous systems and manage multiple concurrent missions.

Supporting the future human supervisor means anticipating and supporting their task needs as they change from monitoring vehicles and sensors today to monitoring mission-level goals, tasks, and status in the future (see **Figure 1**). Future users will *supervise* vehicle- and sensor-related *automation* for multiple vehicles and missions. Given that different tasks require different tools and displays (Larkin & Simon, 1987; St. John, Oonk, Smallman & Cowen, 2001), the shift to supervisory tasks will require careful selection and (re)design of tools and displays to support them. We have recently analyzed the tendency across work domains to inappropriately keep legacy displays and display "metaphors" even when they inadequately support users' tasks. We relate this tendency, in part, to flawed intuitions about the effectiveness of certain display formats (Smallman & Cook, 2013; Smallman & St. John, 2005). These issues only heighten the need to carefully address the new task requirements for autonomous systems, and to ensure that the display metaphors and tools developed align with these new task needs.

How can we understand and support these new task needs? Here, we report work on a task- and user-centered design (UCD) approach to supervisory decision support and human-machine interface (HMI) design for future autonomous system supervision. Such an approach is critical to ensuring that the system and automation are engineered around the needs of the user (Diaper & Stanton, 2004; Norman, 1986). We focus specifically on monitoring and problem intervention tasks during mission execution.

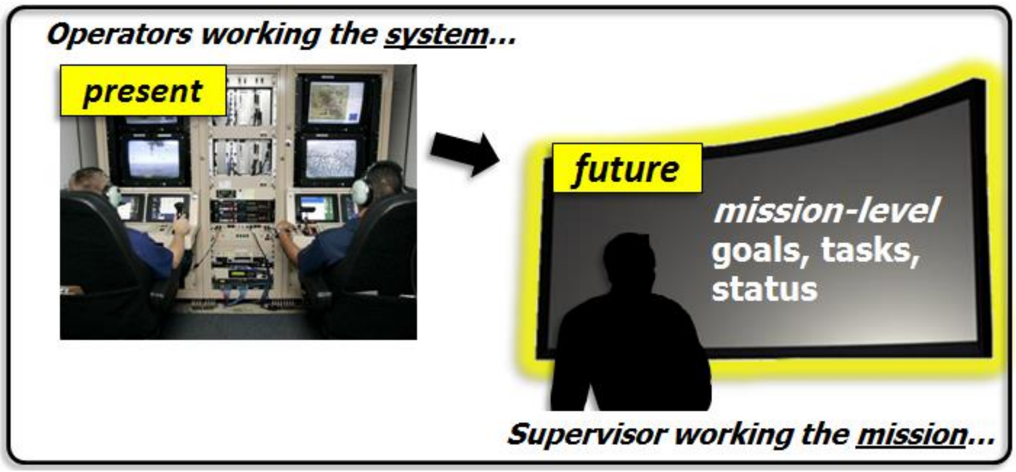


**Figure 1. DoD's envisioned role transformation from today's multi-operator, single-vehicle control to a future supervisor of highly automated and autonomous systems.**

*Tailored User-Centered Design (UCD) Approach*

UCD is an approach to human-computer interaction design that makes supporting the user and their needs the paramount goal of design (Norman, 1986). UCD approaches stem from Norman and Draper's book *User-Centered System Design* (1986), with design principles (Norman, 1988), "rules" (Shneiderman, 1987), and heuristics for usability engineering (Nielsen, 1993, 2000) all emerging and evolving over time. For example, the Ecological Interface Design approach borne from ecological psychology stresses engineering sophisticated domain understanding into tool design (Bennett & Flach, 2011; Vicente & Rasmussen, 1992). Other approaches stem from notions of *situated cognition* and focus on respecting the joint nature of engineered cognitive systems (Woods & Roth, 1988). Still others focus on applying a UCD philosophy within modern agile software development (e.g., Osga, 2006). In general, the UCD process begins with user requirements analysis and progresses through a series of iterative design prototyping and review spirals. Here, we were faced with several complex and unique domain challenges that shaped and tailored our specific UCD approach.

First, we are designing for a situation and a user population that does not yet exist. User task needs are not yet defined, and cannot be specified using traditional methods of analyzing existing work on existing systems performed by existing users. Additionally, future automation capabilities are still being defined and can only be estimated.

Second, the current team and role structure will need to be re-aligned to fit a single supervisor in the future[1]. The work performed by two or three humans today will be performed in the future by a single user and a suite of automation jointly managing multiple vehicles and missions (DoD, 2009). The use of automation is often referred to as a "double-edged sword" to denote its potential to reduce user workload and improve efficiency, but also to introduce challenges with situation awareness, automation reliance, and accountability (Bainbridge, 1983). If not carefully designed and integrated into users' tasks, automation's costs can quickly outweigh its benefits. A tempting solution to compensate for inherent human cognitive limitations is to introduce even *more* automation (e.g., *automated monitoring* of automation); however, this approach introduces yet *another* system that a user needs to monitor (Parasuraman & Riley, 1997), further complicating the situation. Despite the general guidance and lists of issues to consider for designing automation and associated HMIs, there is currently no "universal formula for automating systems" (OSD, 2012).

Third, design must occur within the constraints of system development. Large-scale military and industry system development tends to be centered more on technology and less on user needs, and generally aims to minimize change. Although the reasons for these tendencies may be just, the effects on user and system performance tend to be negative. A technology-centric focus has resulted in inadequate or even failed systems (e.g., Tvaryanas, 2012). The tendency to maintain legacy systems and minimize change has been a barrier to improvement; several of the human factors-related issues identified in analyses from almost a decade ago (e.g., Tvaryanas, 2004; Williams, 2004) linger in many of today's unmanned systems and HMIs. These issues impact several aspects of unmanned system operation and safety. Human causal factors have been implicated in the majority of unmanned aircraft system (UAS) mishaps from 1994-2003 (Tvaryanas, Thompson, & Constable, 2006). Although UAS accident rates have generally declined over the years, accident rates within the US Air Force are currently higher for the three largest UAS than for other aircraft categories[2] (Bloomberg, 2012). The fact that today's control systems and HMIs for unmanned vehicles are already straining to support effective *single vehicle operation* raises concerns for their ability to support *multiple* vehicle missions in the future. Causing further concern is the limited success of previous attempts to increase the number of vehicles per operator (e.g., Predator Multi-Aircraft Capability (MAC)).

We developed and employed a UCD process tailored to address these challenges and constraints in the development of future decision support, see **Figure 2**. This modified UCD process is unique in its flexibility, domain-grounding, *and* scientifically-principled approach. It leverages the unique expertise and recognizes the limitations of each stakeholder (e.g., subject matter experts (SMEs), human factors scientists/designers), and assigns stakeholders roles accordingly. For example, SME feedback was focused on expectations for future automation based on extensive experience with unmanned vehicles, rather than subjective preferences for display designs, given the limits in SME intuition about displays revealed by our recent Naïve Realism research in metacognition and visual displays (Smallman & Cook, 2011). The role of the human factors scientists and designers was to apply expertise in cognitive science, human-automation allocation, and relevant work domains to develop concepts to meet future supervisory work domain and task needs. **Figure 2** shows the general steps of UCD (middle), and how we tailored it to apply cognitive science (top) and domain expertise (bottom) at key points throughout the process to support user abilities and future user task needs.

[1] The future vision will undoubtedly involve *multiple* human supervisors interacting and collaborating. Our specific focus in the current work is on the general transformation of the human role from *operator* to *supervisor*.
[2] The combined accident rate of the Air Force's three largest UAS (9.31 per 100,000 hours of flight for Global Hawk, Predator, and Reaper) is currently the highest rate for any aircraft category, and more than three times as high as the fleet-wide average of 3.03 per 100,000 hours of flight (Bloomberg, 2012).

In this paper, we focus on the first three UCD steps (shown in color in Figure 2) and how they provide a principled basis for the design of systems, automation, and HMIs for the future autonomous systems supervisor. These three steps were to (1) define the key tasks in unmanned system operation and supervision, (2) specify the allocation of those tasks to humans and automation currently and for the future, and (3) specify the necessary information exchanges between humans and automation for effective supervision.

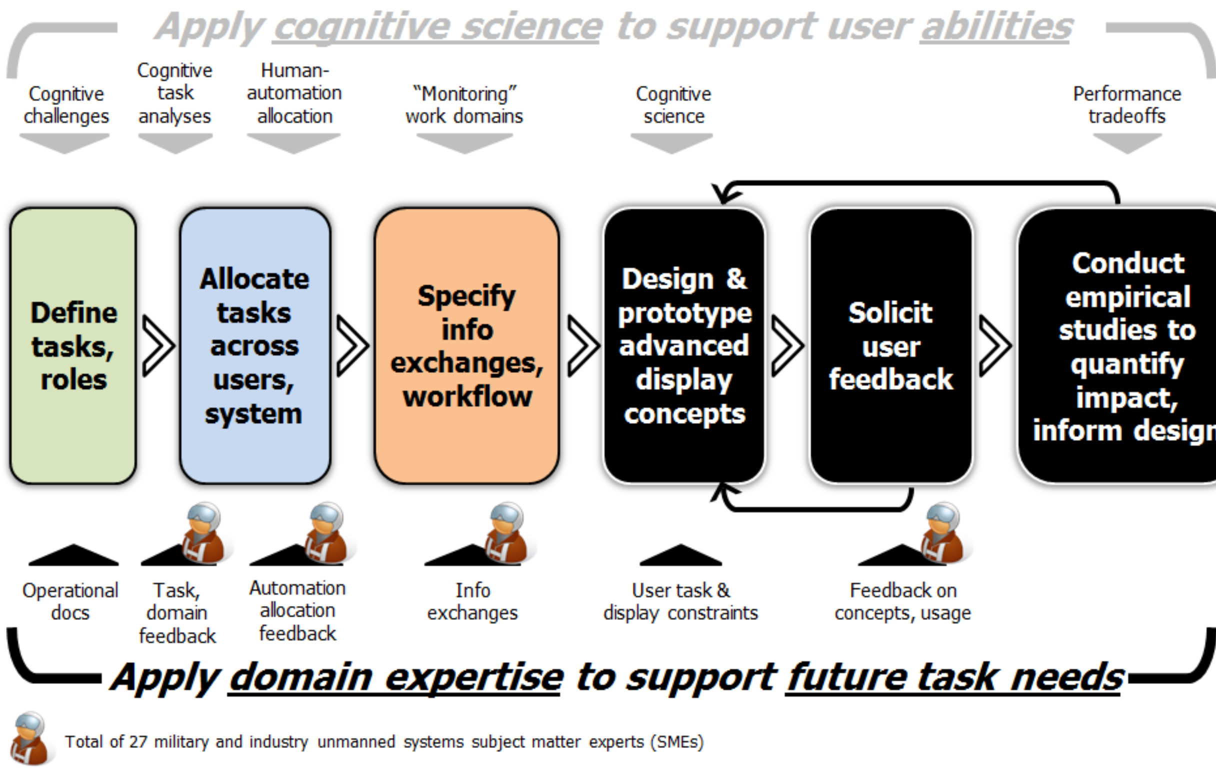


**Figure 2. Highlights of user-centered design (UCD) process tailored for this effort.**

This approach addressed each of the challenges mentioned above. First, by carefully specifying the core tasks involved in unmanned systems operation and supervision, we provide *a basis for defining future user task needs*. Given the same core work performed currently will still need to be completed in the future, what will change is *how* the work gets accomplished. Therefore, we harnessed expertise from *current* SMEs with experience in vehicle, sensor, and mission commander unmanned vehicle roles to help define the task needs of *future* users.

Second, with a human-centered automation philosophy of humans and automation working cooperatively to achieve common objectives (Billings, 1996), we used a rational and principled method for task and function allocation to humans and automation, *in support of the role re-alignment needed in the future*. There are varied techniques and models of human-automation allocation with different strengths and weaknesses (e.g., automating as much as possible defines the role of the human by what is left over from the automation rather than the strengths of the human). We developed and employed novel techniques to enable SMEs to contribute their domain, task, and technology expertise to inform human-automation allocation. Additionally, we developed and used novel methods to define effective information exchanges between humans and automation (Klein, Woods, Bradshaw, Hoffman, & Feltovich, 2004).

Third, the user- and task-centered nature of our approach *appropriately directs the focus onto immutable needs of the user*, and not the technology or the idiosyncrasies of a particular platform. Since future systems will grow out of existing systems, it is crucial to understand which aspects of today's systems and HMIs are viable for the future, and which should be re-evaluated. Here, today's systems were assessed against users' task needs to begin to assess which unmanned vehicle "display metaphors" and features remain viable and which should be abandoned. Although the capabilities of future autonomous vehicles will improve vastly, the same cannot be said for the capabilities of future human supervisors. Those supervisors will possess the same perceptual and cognitive processing faculties as today's unmanned vehicle operators. They will have the same attentional limitations and bottlenecks (Simons & Rensink, 2005) and limited memory capacity that requires context and association in order to function (Anderson, 1983), and exhibit the same serial, slow goal-directed problem solving behaviors (Newell & Simon, 1972). A key element of our UCD process is matching the design of the tools and HMIs to the abilities of humans through the careful application of scientific concepts and lessons learned in other application domains.

The unmanned vehicle and systems domain is vast and complex. There are many research efforts currently underway tackling different aspects of achieving the future DoD vision for autonomy. We scoped our cognitive engineering efforts to focus on tasks related to monitoring and problem detection, given that those tasks are the most complex aspects of supervisory control (Sheridan, 2006), and that future users will become monitors of automation and situations, responsible for keeping automation in check and compensating for automation's limitations.

Interviews with unmanned vehicle experts were sequenced across multiple SME groups and sites, with interview stages designated for each SME group for efficiency. Given the time limitations of the SMEs, the interviews were carefully designed and prepared to maximize SME feedback and minimize intrusion. Novel approaches were developed and employed to provide an objective basis for SMEs to share their expectations for future automation and to facilitate translating the task analysis results to actual design.

Prior work has described various aspects of current unmanned aerial vehicle (UAV) practice by user role (Cooke, Rivera, Shope, & Caukwell, 1999; Gugerty, 2004; Nehme, Crandall, & Cummings, 2007) and begun to analyze aspects of control of groups of vehicles (e.g., Cummings, Bruni, Mercier, & Mitchell, 2007; Drury & Scott, 2008; Nehme, Scott, Cummings, & Furusho, 2006; Scott & Cummings, 2006). However, there have not been detailed prescriptive task models created that address the issue of how to aggregate and rationalize those roles for the future supervisor and how to incorporate SME expectations of future roles and automation. Our approach is unique in creating this prescriptive model through capturing current user expectations for future automation and its integration, through a novel staged and sequential UCD approach. The design artifacts resulting from this work inform initial prototype concepts reported elsewhere (see Smallman & Cook, 2013).

## Materials, Method, and Results

### *Cognitive Engineering and Analysis Approach and Process*

Within our tailored UCD process, we conducted a staged *task analysis* to define the task needs for *future* autonomous system supervision through interviews with *present-day* unmanned vehicle domain experts. There are many approaches to conducting task analysis, a multitude of methods for conducting it, and a variety of outcomes, design artifacts, and products resulting from it (see Diaper & Stanton, 2004, for a review). The selection of which approach and method to use depends on several factors, including the goals of the analysis, the design artifacts needed, and the stakeholders involved in the process. The approach used in this effort synthesized elements from multiple methods to achieve the goals of the analysis and design.

The task analysis was conducted using the following staged interview approach with a broad, representative sample of unmanned systems SMEs, sequenced over time and across different military and commercial industry sites, to produce specific design artifacts. It focused on the three steps shown in color in **Figure 2**. A key design artifact produced was a taxonomy of roles and tasks for unmanned system operation and supervision. **Figure 3** shows a thumbnail sketch of which parts of the role-task taxonomy each stage focused on.

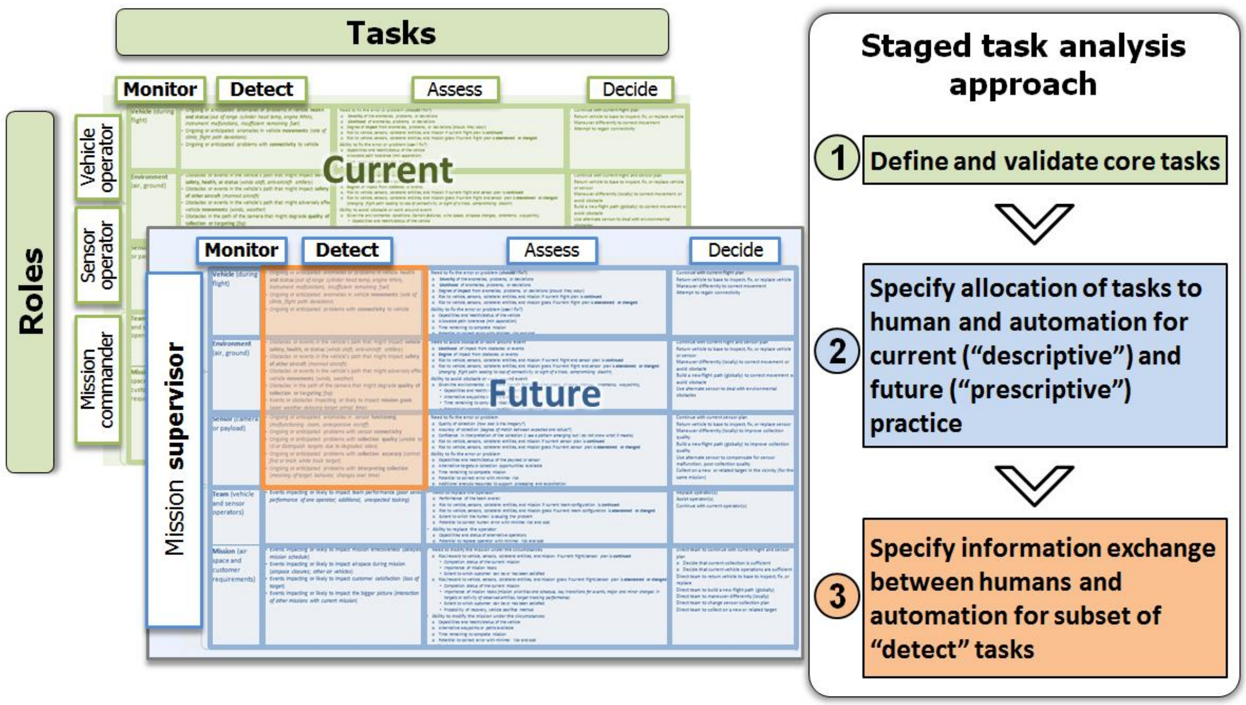


**Figure 3. Overview of staged interview process.**

**Stage 1: Define core tasks involved in unmanned vehicle / system operation and supervision**

- **Process**: Generated role-task matrix for core unmanned system user roles and tasks performed during mission execution. Reviewed and revised role-task matrix with unmanned vehicle SMEs.
- **Rationale**: Center interventions around users' tasks. Scope design effort around core tasks performed during mission execution.
- **SMEs**: One unmanned maritime domain SME and five SMEs from a military controlled testing venue for unmanned vehicles.
- ***Design artifact**: role-task matrix* (**Figure 5**).

**Stage 2: Specify current (*descriptive*) allocation of tasks to humans and automation, and propose future (*prescriptive*) allocation**

- **Process**: Specified current and proposed future allocation of tasks in Stage 1 role-task matrix to humans and automation through SME involvement. Used innovative approach to involve SMEs in task allocation, expanding on approach developed for system designers (Parasuraman, Sheridan, & Wickens, 2000).

- **Rationale**: Define starting point to build from to achieve future vision. Understand extent of gap to bridge between today and future. Inform task allocation based on strengths/limits of humans and automation and user task needs. Inform algorithm development.
- **SMEs**: 13 SMEs from a leading commercial provider of high-performance UAS.
- ***Design artifact****: role-task matrix with descriptive and prescriptive task allocation* (Figure 5).

**Stage 3: Specify information exchange between humans and automation for subset of detection tasks**

- **Process**: Generated key information inputs and outputs for human-automation information exchanges for a subset of detection tasks from Stage 2 prescriptive role-task matrix. Reviewed and revised key information inputs and outputs with unmanned systems SMEs. Employed novel procedure to involve SMEs in design-critical decisions for information *access* and level of *detail*.
- **Rationale**: Support user information exchanges with automation. Facilitate user trust and insight into automation. Facilitate mapping from results to design.
- **SMEs**: Eight SMEs from a major US Air Force UAS training facility.
- ***Design artifact****: information inputs and outputs for human-automation exchanges.*

| Date | Site | Rate & Rank or Civilian | Unmanned Vehicle Role | | | | DOD UAS Group | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | 1 | | 2 | | 3 | | 4 | | 5 | |
| | | | Vehicle | Sensor | MC | Consult | Exp | Yrs | Exp | Yrs | Exp | Yrs | Exp | Yrs | Exp | Yrs |
| April | Navy exercise | O-5 (CDR) Ret | | | | x | | | | | | | | | | |
| May | Military test venue | Capt / 06 | x | x | x | | Expt | 14 | Expt | 14 | | | | | Expt | 10 |
| May | Military test venue | Civilian | x | x | | | | | | | Expt | 7 | | | | |
| May | Military test venue | Civilian | x | x | x | | | | Expt | 2 | Expt | 5 | | | | |
| May | Military test venue | Civilian | x | x | x | | | | | | | 7 | | | | |
| May | Military test venue | Civilian | x | | x | | | | | | Expt | 6 | | | | |
| June | Industry UAS | Stan / Eval Instructional Auditor | x | x | x | | | | Expt | 4 | | | | | | |
| June | Industry UAS | Operations Action Center | x | x | | | | | Int | 3 | | | | | | |
| June | Industry UAS | O2 (former service) / FSR | x | x | | | | | Int | 2 | | | | | | |
| June | Industry UAS | E5 (former) / Field Service rep | x | x | | | | | Expt | 3.5 | | | | | | |
| June | Industry UAS | E6 / Fire Servie Trainer | x | x | x | | | | Int | 4 | | | | | | |
| June | Industry UAS | E7 (Ret) / Pilot Instructor | x | x | x | | | | Expt | 3.5 | | | | | Expt | 4 |
| June | Industry UAS | UAS Instructor / Operator | x | x | | | | | Expt | 2.25 | | | | | | |
| June | Industry UAS | Airline Pilot / Training Program Mgr | x | x | | | | | Expt | 5 | | | | | | |
| June | Industry UAS | O-4 (Ret) / Director of Mission Support | x | x | x | | | | Int | 1 | Expt | 2 | | | | |
| June | Industry UAS | Operator Training Mgr | x | x | x | | | | | | Expt | 7 | | | | |
| June | Industry UAS | O-4 / Advanced Operations Training | x | x | x | | | | Expt | 3 | | | | | Int | 2 |
| June | Industry UAS | Pilot Instructor | x | | | | | | Expt | 3 | | | | | | |
| June | Industry UAS | UAS Pilot Instructor | x | | | | | | Expt | 1.25 | | | | | | |
| July | AF training | O-4 / Maj | x | | | | | | | | | | | | Expt | 3.5 |
| July | AF training | O-4 / Maj | x | | | | | | | | | | | | Expt | 5 |
| July | AF training | Maj | x | | x | | | | | | | | Expt | 2 | Expt | 2.75 |
| July | AF training | Maj | x | | | | | | | | | | Expt | 4.92 | | |
| July | AF training | TSgt | | x | | | | | | | | | Int | 1.33 | Expt | 3.17 |
| July | AF training | TSgt | | x | | | | | | | | | | | Expt | 11 |
| July | AF training | TSgt | | x | | | | | | | | | Expt | 2 | Expt | 2 |
| July | AF training | SSgt | | x | | | | | | | | | Expt | 3 | Expt | 5 |
| Tota | 27 | | 22 | 19 | 11 | 1 | Avg 14.0 | | 3.7 | | 5.7 | | 2.7 | | 4.8 | |

27 military and civilian unmanned systems experts experienced in vehicle control, sensor control, and mission command on a range of unmanned vehicle platforms (DoD UAS Group 1-5) for missions ranging from operational tests through theater operations.

**Figure 4. Summary of SME participant characteristics.**

*Participants*

A total of 27 domain experts from four unmanned systems-related groups were interviewed over four months in 2012. Different types of unmanned vehicle SMEs were selected to yield a sampling of users with experience across vehicles, mission types, and team configurations, in both the military and industry. Details of participant characteristics are summarized in Figure 4.

Sites

SMEs from four groups were recruited: 1) a Fleet Forces Command-sponsored annual Navy exercise, 2) a military controlled testing venue for unmanned vehicles, 3) a leading commercial UAS provider, and 4) a major US Air Force UAS training facility. Across sites, the SMEs were universally motivated and interested in improving the operation and safety of unmanned and future autonomous systems and having the opportunity to impact design and development.

Platforms

SMEs had experience with unmanned maritime craft and unmanned aerial systems, including an array of DoD Group 1 – 5 UAS; platforms included *Sea Fox, Mako, TigerShark, Arrow, Aerosonde, ScanEagle, Predator (MQ-1),* and *Reaper (MQ-9).*

Experience

Twenty-six of the SMEs were experienced in one or more of the roles of *vehicle operator*, *sensor operator*, and *mission commander*. In total, 22 had experience as vehicle operator, 19 as sensor operator, and 11 as mission commander. One additional SME with expertise in unmanned maritime vehicles, CONOPS, and Navy fleet exercise-based testing also participated. All SMEs reported their experience level as intermediate or expert, with a range of 1-14 years of experience across platforms.

*Materials and Method – General*

The interviews and site visits were designed and scoped to support the three task analysis stages described earlier and shown in **Figure 3**. With the exception of some minor variations due to scheduling and availability, the same general interview procedure was used across all sites. We approached and made formal requests to several unmanned vehicle sites and groups with potential SMEs with a range of experience. Since all SME participation was voluntary and un-paid, several measures were taken to minimize the time burden to the SMEs and their daily routines while maximizing the feedback gained from the SMEs during the interviews.

Each interview session consisted of two scientist interviewers and one or two SMEs. The SMEs were informed of the institutional review board (IRB) approval of the study and the voluntary nature of their participation at the start of the session. Care was taken to explain the purpose of the effort, the criticality of SME involvement in the design process, and the potential benefits and payoffs for users. The goal of designing automation as a peer or assistant to, rather than a replacement of, human performance was stressed. After obtaining informed consent, general information about each SME's background and experience with unmanned vehicles was collected. Each set of materials was tailored to each task analysis stage. The interview materials served to structure and direct the interview discussions and provide the context necessary for soliciting the SME knowledge and expertise needed (Cooke, 1999). The interviews were highly interactive, with SMEs reviewing, commenting on, and helping to refine the interview materials, providing elaborating examples when necessary.

Site visits also included tours of the facilities and ground control stations (GCS), observations of live training exercises, hands-on access to UAS simulators and HMIs, and viewing the unmanned vehicles on the flight line and parked in hangars. SMEs and key personnel were thanked for their participation at the end of the interview sessions and site visits. Some SMEs who offered to provide additional feedback and clarification were contacted with follow-up questions.

*Materials, Method, and Results – Stage 1*
*Defining Core Tasks in Unmanned Vehicle Operation and Supervision during Mission Execution*

The goal of the first task analysis stage was to codify and analyze the core tasks of unmanned vehicle operation, capturing the general cognitive and perceptual challenges in monitoring and assessing information during mission execution (vs. system-specific control tasks). The scope of the task analysis was on **monitoring and assessment tasks**. Planning, takeoff, platform-specific control, landing, and recovery-related tasks were *outside* the scope of interest.

Stage 1 materials were drafted prior to the interviews to maximize the efficiency, focus, and value of the time-limited interviews with SMEs. These materials consisted of a set of draft tasks, organized by roles in a “role-task matrix” (Spillers, 2004). The draft role-task matrix was informed by a review of previous task analyses in the unmanned systems and related domains, and relevant operational doctrine and concepts of operations (e.g., Cook & Smallman, 2010; Fleet Forces Command, 2008; Gugerty, 2004; Nehme, Crandall, & Cummings, 2007; OSD, 2012; Sibley & Coyne, 2012). Generally, roles are collections of tasks to perform a specific function. Decomposition into roles and tasks is a standard technique with useful application to both software development and HMI design within a UCD approach (e.g., Osga, 2006). Organizing tasks by roles has several advantages: Roles allow tasks to be clustered into meaningful chunks as a basis for assignment, provide a means to map work onto any team configuration (current or future, human and automation), and suggest ways to organize HMIs that support users taking distinct roles (Smallman, Cook, Beer, & Lacson, 2009).

A single individual can perform one or more roles. Each role for current unmanned vehicle operation—*vehicle operator*, *sensor/payload operator*, and *mission commander*—is often assumed by a single individual, though one person takes on more than one role in some team configurations (e.g., one person serving as vehicle *and* sensor operator). The future supervisor and supporting automation will be expected to take on the multiple roles currently assumed today by multiple individuals.

**Figure 5** shows the content of the core role-task matrix. Current (and future) roles are specified in rows. Task groups of *monitor*, *detect*, *assess*, and *decide* are shown in columns. Specific tasks are listed in each cell created by the intersection of *role* rows and *task group* columns. Task group columns are ordered roughly in the sequence they are performed; for example, ***monitor*** the vehicle to ***detect*** anomalies or problems, and ***assess*** the ability or need to fix the problem, to help ***decide*** which course of action to pursue. Within a role row, similar tasks are grouped together (e.g., the vehicle operator tasks include monitoring the ***vehicle***, and the ***environment***). Each task phrase is constructed by combining the column header with the bulleted task beneath (e.g., **Detect** ongoing or anticipated anomalies or problems with vehicle health and status…”). These task groups align roughly with a classic four-stage view of information processing (Parasuraman et al., 2000) and this decomposition allows us to develop targeted support for these tasks, and anticipate where weaknesses will arise.

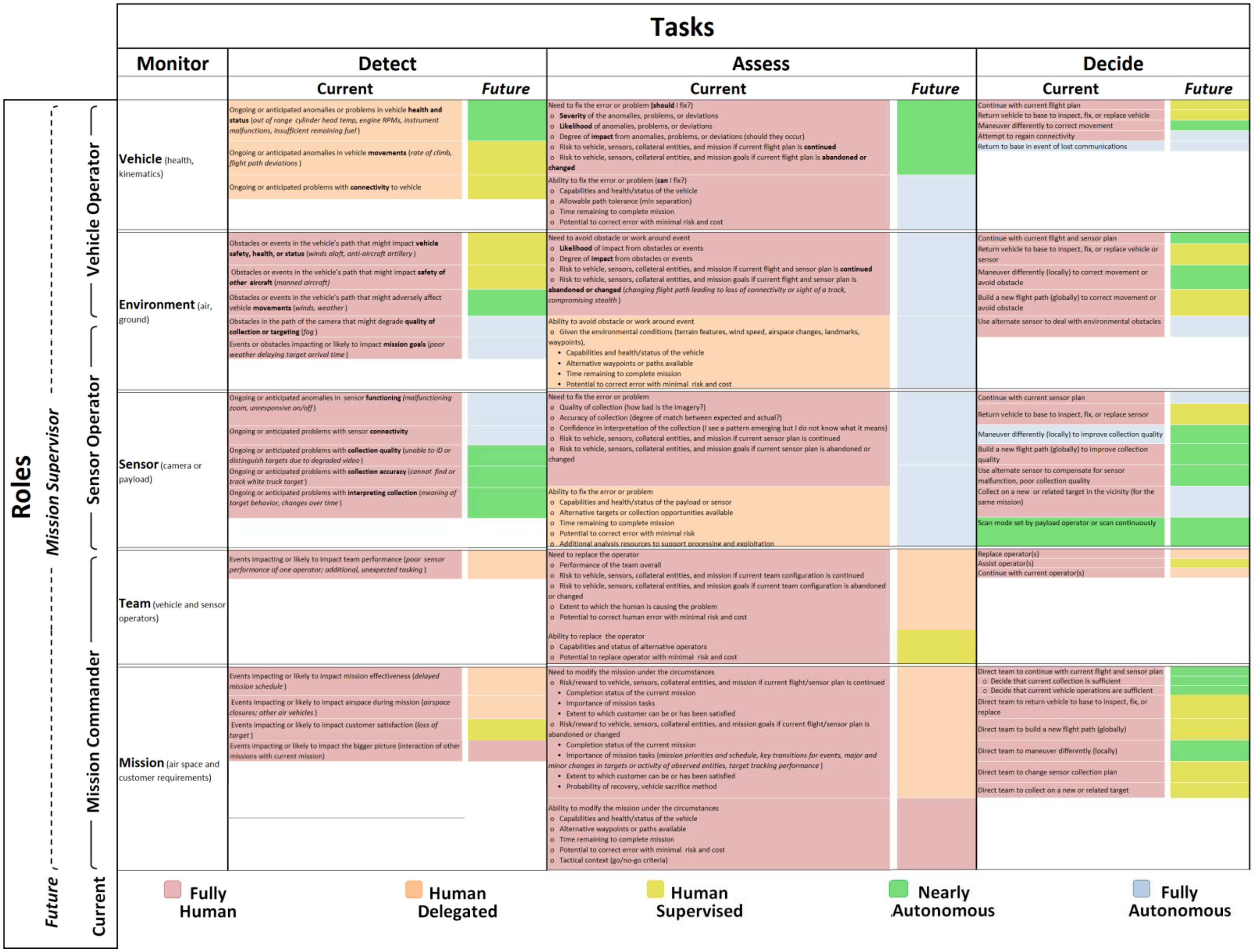


Figure 5. Stage 1 role-task matrix, with Stage 2 descriptive (current) and prescriptive (future) task allocation.

To reflect the core goals of unmanned systems operation and the satisficing rather than optimizing goal that often currently prevails, tasks were focused on *detecting and responding to problems or changes* ("detect ongoing or anticipated problems with collection quality") rather than just *generally monitoring situations* ("monitor collection quality"). This focus on detecting and responding to problems or changes has been validated throughout the SME interviews: although operators do monitor (collection) quality, their *goal* is to ensure it stays above a particular level, and any deviations from this are indicators that (collection) quality is or will become sub-standard. Additionally, this focus on detecting *ongoing or anticipated* problems reflects the goals of operators to both monitor proactively and to respond to changes that arise.

The tasks were deliberately general, high level, and phrased in terms of achieving a particular goal (avoiding limitations due to platform specificity). For example, "Detect ongoing or anticipated anomalies or problems in vehicle health and status" is general enough to pertain to detecting out-of-range indicator values caused by malfunctions or environmental conditions for any number of different unmanned platforms. Operators today are responsible for detecting these anomalies or problems by directly monitoring the vehicle indicator values (engine oil level, temperature, pressure, RPMs, etc). Future users are likely to off-load some of that data monitoring to automation, and instead focus their efforts on ensuring the automated monitors themselves are in check.

The draft role-task matrix was initially created with sticky notes on butcher paper to keep it agile and flexible as we reviewed and refined it with SMEs, and to deliberately convey to the SMEs how open it was to their feedback and rearrangement. Information used or needed for the tasks was listed at the bottom in the draft version. The draft role-task matrix went through two reviews and revisions, first with the unmanned maritime vehicle SME by telecon, and second with five SMEs from the military controlled testing venue. Feedback consisted of additions, deletions, modifications, and clarifications in content, wording, and task placement. Following these sessions, the role-task matrix was revised and translated into a digital format (**Figure 5**). This revised role-task matrix was used as the basis for the descriptive and prescriptive task models, described next. **Figure 5** shows both the role-task matrix and the color-coded results of the SME allocation of tasks to humans and automation from Stage 2.

*Materials and Method – Stage 2*
*Descriptive (Current) and Prescriptive (Future) Allocation of Tasks to Humans and Automation*

The goals of Stage 2 were to (1) specify the allocation of tasks to humans and automation in current practice (*descriptive*) and (2) propose a task allocation scheme for future practice (*prescriptive*). The role-task matrix developed in Stage 1 was used as the basis for the descriptive and prescriptive assignments. A group of 13 SMEs from a leading commercial UAS provider contributed input for the descriptive and prescriptive task assignments.

A vocabulary and systematic yet simple method was needed for SMEs to communicate and classify the descriptive and prescriptive allocation of tasks to automation and humans. For this, a simple rating scale was developed, leveraging from existing automation scales from the supervisory control literature and operational documentation (e.g., DoD, 2011; Parasuraman et al., 2000; Sheridan & Verplank, 1978).

For simplicity, this scale consisted of five task allocation categories ranging from *fully human* to *fully autonomous*. Each category specified the roles of *both* the human *and* the automation, describing their relative functions, authority, and relationship. This conveyed the importance of the *joint* human-automation relationship in creating a joint cognitive system (Woods & Hollnagel, 2006). This approach was intended to avoid the shortfalls of other methods that have focused disproportionally on the automation and technology, conceptualized of autonomy as simple delegation of a complete task to a computer, or treated automation as operating at discrete and rigid levels (DoD, 2012).

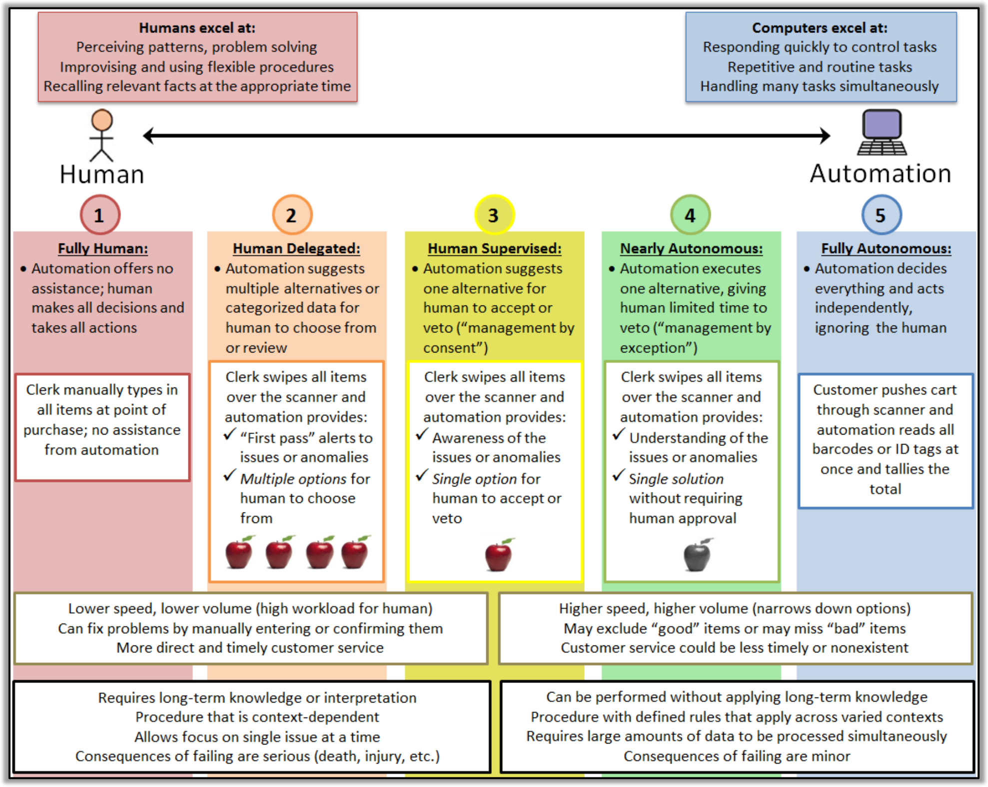


**Figure 6. Task allocation scale and categories for Stage 2.**

The task allocation procedure was introduced incrementally to SMEs by covering the concepts in Figure 6 from top to bottom. First, some basic examples of the relative strengths of humans and automation were described, inspired by Fitts' classic list (1951). Next, the task allocation scale and the description of each category were reviewed. To make the categories meaningful to all SMEs, they were grounded in the increasingly popular automated grocery store checkout systems. Associated examples of futuristic automation assisting with scanning and tallying groceries were mapped to the categories. Generic tradeoffs in speed, accuracy, and customer service listed beneath the grocery store example in Figure 6 were discussed. The everyday example was used to encourage the SMEs to learn the task allocation concept rather than focus on specific details of unmanned vehicle technologies and capabilities.

Next, to help the SMEs begin to think about the task allocation concept in terms of unmanned vehicle tasks, a vehicle operator task was mapped to the task allocation categories. The example task was "detect ongoing or anticipated anomalies or problems with vehicle health and status" and the specific example mapping was as follows:

- User monitors vehicle health and status and is responsible for detecting all out of range values or problems (*1 – Fully human*)

For 2 – 5, "detection" automation helps to monitor the health and status of the vehicle and:

- alerts the user to all out of range values; user must review all alerts and decide which ones warrant attention and which to dismiss (*2 – Human delegated*)

- alerts the user to a subset of out of range values, for the user to review and approve or dismiss (similar to "management by consent") (*3 – Human supervised*)
- decides on the subset of out of range values of concern; the user can dismiss alerts within a given time period (similar to "management by exception") (*4 – Nearly autonomous*)
- decides on the subset of out of range values of concern; the user has no ability to review or dismiss (*5 – Fully autonomous*)

The essence of this allocation activity was indicating how a task could be performed by users and automation to varying degrees. For example, *detecting* anomalies can be done completely by a user or can be assisted to varying degrees by some *detection* automation that the user reviews, approves, rejects, or takes no part in. Similarly, *assessing* whether an anomaly can and should be fixed can be done completely by a user, or can be assisted by some *assessment* automation that the user reviews, approves, rejects, or takes no part in.

To perform the descriptive and prescriptive task allocation, SMEs were provided with large printouts of the core role-task matrix from Stage 1 (the text only in **Figure 5**), and used colored highlighters matching the colors of the allocation categories in **Figure 6** to simply allocate tasks to the categories.

For the *descriptive* allocation, SMEs approximated the *current* allocation of tasks to humans and automation. For the *prescriptive* allocation, SMEs were asked to indicate the *ideal* allocation of tasks to the future autonomous system supervisor and future automation. SMEs were asked to assume a future vision (approximately 20 years in the future) in which a single person will manage multiple unmanned vehicles across multiple missions, with dramatically improved and expanded automation enabling this multi-vehicle and multi-mission capability. The user's job will be to manage this improved automation that will take on aspects of the functions that are currently handled primarily by humans. Concrete examples of tasks for which some automation is available or under development today were provided to help SMEs envision the types of tasks that automation might be available to support in the future. Examples included route re-planning, change detection, anomaly detection, collision and terrain avoidance, target tracking, and vehicle coordination.

It was further explained that SMEs should think of the prescriptive task allocation as being flexible and adaptive as opposed to rigid (Rouse, 1988; Scerbo, 1996), which will be especially important in the dynamic and unpredictable environments of the future. We explained that even with this improved automation, a human supervisor will always be critical: events will unfold and issues will arise that will be beyond the scope of what even the best automation will be able to handle, and will require the monitoring, intervention, and judgment that only a human can provide. We reminded SMEs of the human-centered approach of this research, advocating that future automation assists rather than replaces human performance (Wickens & Hollands, 2000). We acknowledged the challenges of imagining this future vision with all of the assumed advancements in automation.

To aid in assigning the prescriptive task allocation categories, we provided SMEs with a set of criteria to use as an objective basis and a rationale for future automation allocation. The criteria (summarized at the bottom of **Figure 6**) were:

- **Knowledge / experience**: Task does/does not require application of long term knowledge
- **Context sensitivity**: Task entails a procedure with context-dependent/independent rules

- **Workload / processing capacity**: Task allows focus on single issue at a time vs. requires parallel processing of large data sets and multiple issues
- **Consequences**: Consequences of failing are serious (death, injury) vs. minor

These criteria are related to the evaluative criteria for automation design developed by Parasuraman et al., (2000). Our methodology provided a novel way of adapting these criteria, intended for use by system designers, to harness domain expertise and input from *unmanned vehicle SMEs* to inform future task allocation tailored to the unique requirements and nuances of the autonomous systems domain. SMEs assigned prescriptive task allocation categories using the colored highlighters, and used the assignment criteria above as a basis for their categorizations. The criteria were not strictly tied to the allocation categories, but helped guide the direction of the SME assignments to categories.

For both the descriptive and prescriptive allocation activities, responses were discussed as a group. Results color-coded by SME responses are presented in **Figure 5**.

*Stage 2: Results*

The color coding of the descriptive and prescriptive role-task matrix reveals key patterns and differences across the two models. For the descriptive role-task matrix, SMEs classified the vast majority of current-day tasks as *fully human* (predominance of red color coding in the "current" columns of **Figure 5**). For the vehicle operator and sensor operator, some tasks were classified as *human delegated* (e.g., binning data into alert categories), and a small subset as *autonomous* (e.g., sensor stabilization functions, scan mode). All current mission commander tasks were classified as *fully human*. SMEs attempted to assign categories based on the current state of automation in unmanned aerial systems generally (as the current state of automation varies somewhat across platforms).

These SME classifications of relatively low automation support are echoed by recent findings by the Defense Science Board (DoD, 2012) that existing and proven autonomous capabilities are being generally underutilized in today's unmanned systems. Proven technologies are underutilized in vehicle fault detection and management, communications management, mission planning and decision support, and contingency planning.

How well are today's HMIs, systems, and available automation *supporting* the task needs of today's users specified in **Figure 5**? **Figure 7** provides a summary level assessment of the current state of task support, highlighting specific issues with *monitor*, *detect*, *assess*, and *decide* to tie back to the role-task matrix. Many of the HMI and human factors-related issues in unmanned systems identified in reports from almost 10 years ago (e.g., Tvaryanas, 2004; Williams, 2004) are still seen in the systems and HMIs of today. A common theme that emerged throughout the interviews was the burden and challenge for users to manage and compensate for these shortfalls (e.g., "*It feels like 90% of our training involves developing and teaching work-arounds to get the system to do what we need…*"). Work-arounds that current operators devise, teach, and employ include using dry-erase marker annotations (marked directly on HMI screens) to flag and draw attention to key indicators and to record starting values as comparisons for real-time values to help monitor. These work-arounds are strikingly similar to strategies used by nuclear plant operators when monitoring (Mumaw, Roth, Vicente, & Burns, 2000). The development and use of these strategies is indicative of the shortfalls of systems in both domains.

Compared to the descriptive model with *fully human* and *human delegated* indicated for most tasks, the prescriptive model assumes more allocation to automation, and specifies allocation across the full range of categories (see "future" columns in Figure 5). SMEs envision automation helping significantly with detection and assessment tasks for vehicle and sensor operators. The variations in task allocation categories across the "detect" tasks mainly reflect differences in management authority for handling the detections (consent vs. exception vs. independent) before being passed on to a human or other automation at the next step. SMEs anticipated needing more human involvement for tasks related to *deciding on courses of action*, as well as many of the mission commander tasks which tend to be more complex (e.g., detect events impacting or likely to impact customer satisfaction). SMEs also envisioned needing more human involvement or approval as the criticality of mission events increases.

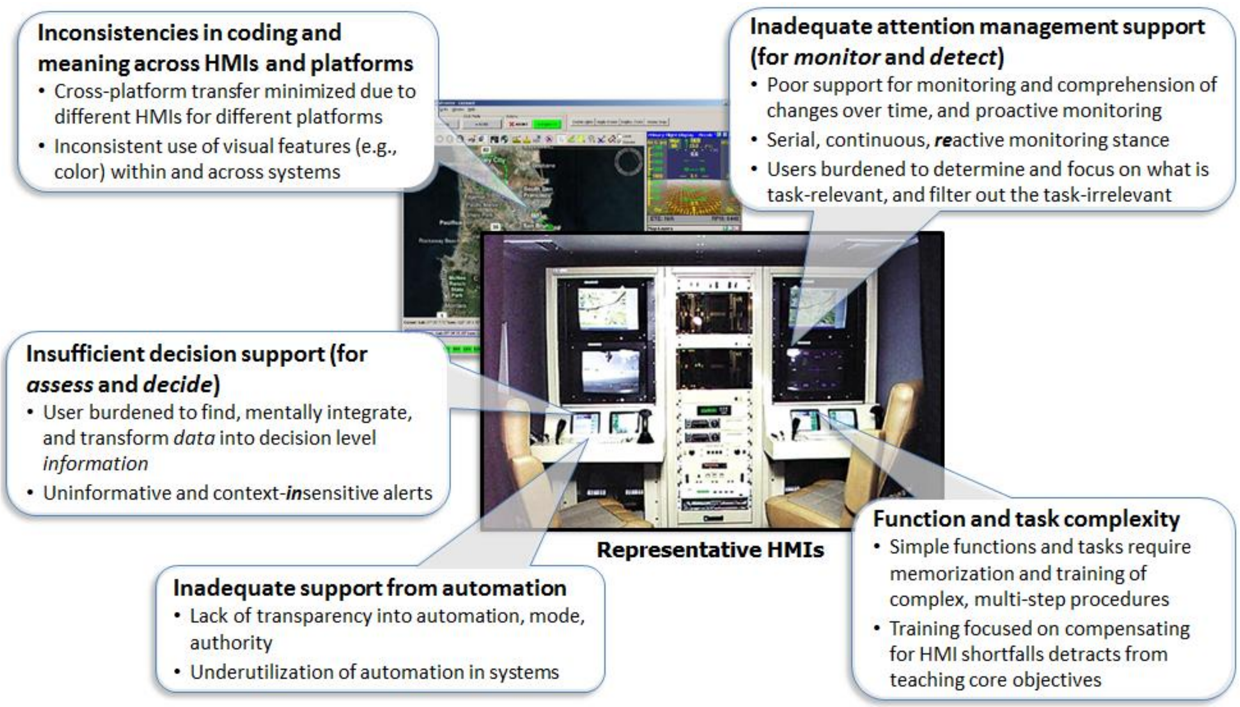


**Figure 7. Overview of shortfalls of current unmanned system HMIs and automation.**

This role-task matrix covers a wide range of tasks for which future decision support can be developed. How can the matrix and the SME assessments be used to guide the design of decision support for future autonomous systems supervisors? We envision the prescriptive role-task matrix as a helpful tool for scoping the type of task support needed for a wide range of future supervision tasks, as an initial step in the design of joint human-autonomous system decision support. The prescriptive allocations suggest a general human-automation interaction scheme for core tasks as a guide and useful starting point to enable designers to achieve robust designs.

Following Stage 2, we used the role-task matrix to inform the development of decision support for a subset of tasks related to problem detection for vehicles, environments, and sensors (see orange focus region in Figure 3). We chose to focus on the problem detection tasks because SMEs saw significant potential for assistance from automation for these kinds of detection tasks (see Figure 5), and several efforts are underway to develop and mature anomaly and problem detection automation. As outlined in Figure 2, we began by defining the workflow for these detection tasks, and specifying the necessary supporting information exchanges needed for users and automation to jointly perform these detection tasks. The workflow is shown below in Figure 8, followed by a brief description of the method we used to define information exchanges with SMEs.

*Stage 3: Approach to Defining Workflow and Information Exchanges*

Anomaly detection tasks lend themselves to assistance from automation, assuming normal performance and deviations from normal can be defined. Detection technologies are currently used to detect changes, problems, and anomalies in several work domains, including industrial process control and medicine. There is significant potential for these technologies to assist within unmanned systems, as highlighted by SMEs in their Stage 2 assessments. In this section, we provide an overview of how the Stage 2 assessments are being harnessed to concretely define HMI concepts for anomaly detection.

We began by specifying how tasks in the role-task matrix related to problem detection are currently performed by humans and automation, and how they should be performed in the future. We characterized monitoring and detection by sequencing their associated tasks into the workflows shown in **Figure 8**. We contrasted future practice (**Figure 8**, right), based on the prescriptive role-task matrix and ideal task support, with current practice (**Figure 8**, left), based on the descriptive role-task matrix and task support and deficiencies of current systems (see **Figure 7**). These workflows are also informed in part by interviews with industrial process control operators who monitor and supervise complex automation through information displays (Smallman & Cook, 2013). The relative strengths and weaknesses of the two approaches in **Figure 8** are discussed in detail in Smallman and Cook (2013).

Current problem detection is characterized by its *reactivity,* due to the practice of responding to system alerts, and diagnosing and addressing problems after they have surfaced. Anomaly detection does exist in today's unmanned systems but only in rudimentary form, manifesting as alerts for a limited set of vehicle and sensor health and status indicators. These alerts tend to be uninformative, un-prioritized, insensitive to and lacking in context, and based on a limited set of data. Paradoxically, the relevant information needed to interpret and prioritize the alerts is available within the system, but is not integrated or harnessed for effective alerting management. Users are left to initiate investigation of underlying causes, urgency, impact, and likely resolution (i.e., will they self-correct or not?).

For example, current-day *MQ-9 Reaper* pilots receive "aircraft not close to assigned altitude" alerts that can be triggered by different causes and require different responses. Pilots must investigate several other pieces of information (on separate HMIs) to understand, differentiate, prioritize, and resolve these altitude alerts. An aircraft in "speed preference mode" temporarily disregards altitude and *will* self-correct on its own, but an alert is triggered nonetheless; however, the same alert could be triggered for an aircraft whose speed lever in the ground control station is not fully forward (for fuel conservation) and *will not* self-correct. It is up to the operator to investigate and differentiate these alerts.

*Proactive* monitoring (shown in **Figure 8**, right), in contrast, stresses spotting deviations, problems, and anomalies before they become serious problems to allow time for diagnosis and intervention, which is critical in several domains including industrial process control (e.g., Burns, 2006), nuclear plant monitoring (e.g., Mumaw et al., 2000), and unmanned systems. Today's unmanned vehicle operators *strive* to monitor proactively, but are hindered by the shortfalls of current anomaly detection and HMIs (Smallman & Cook, 2013). Further, the information-dense, multi-window, real-time status displays typical of today's operational systems intensify these problems, further overwhelming users when they are stressed (e.g., Bransby, 2001). For example, alarm banners show status and anomalies, but lack context for anomaly interpretation, prioritization, and management.

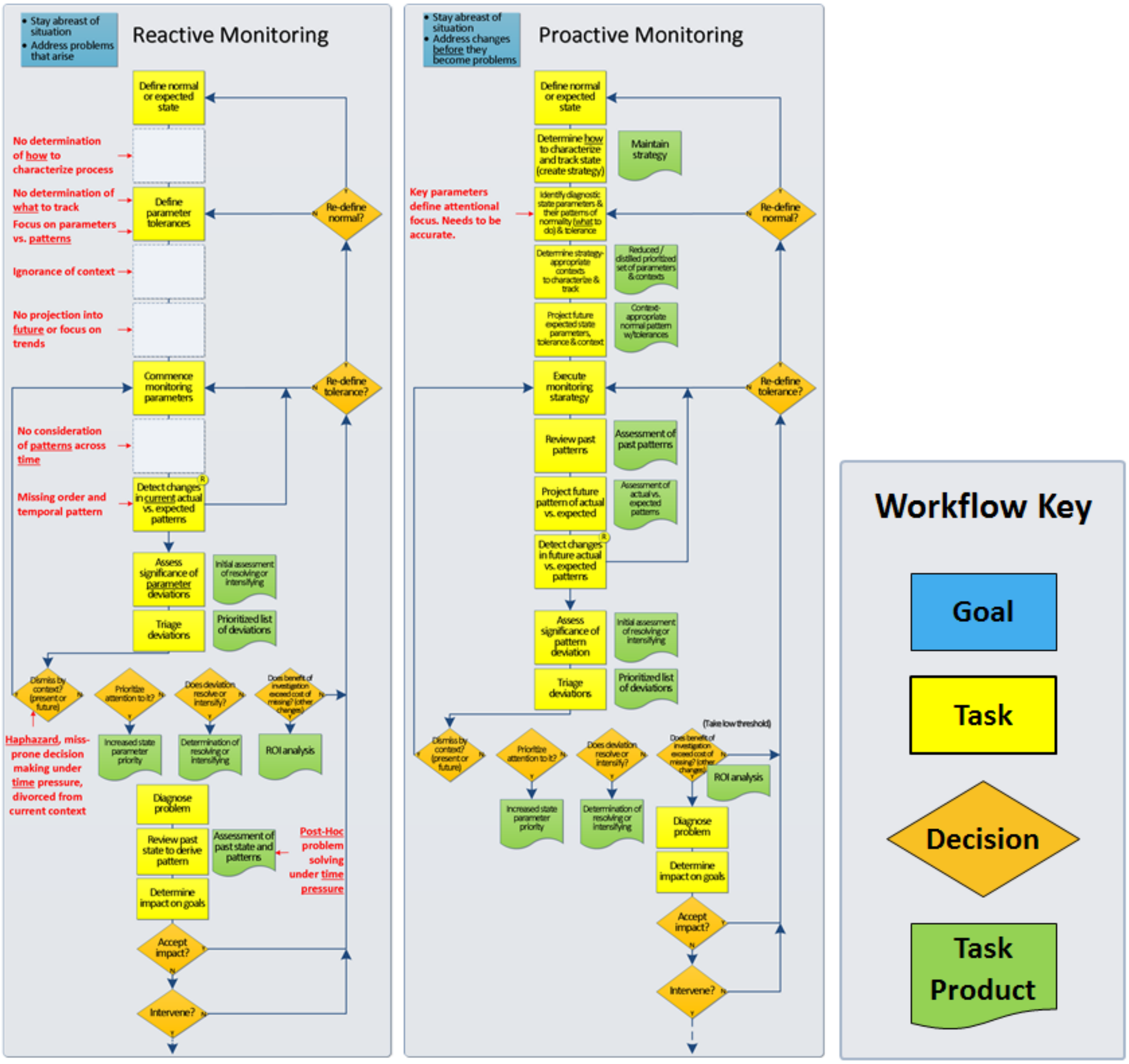


**Figure 8. Elaborated workflows contrasting reactive and proactive monitoring and detection, informed by descriptive and prescriptive role-task matrix (from Smallman & Cook, 2013).**

Anomaly detection is even more challenging in the multi-vehicle, multi-mission situation envisioned for the future. The number of detected anomalies is likely to increase, with the increase in vehicles and missions, potentially flooding the future supervisor with an unmanageable number of alerts and leading to slow, reactive responding (DoD, 2012; Errington, Reising, & Burns, 2009). Human cognitive abilities are relatively fixed, and cannot grow to accommodate such an increase in loading in the future. If not appropriately designed and tailored for this future scenario, anomaly detection technologies have the potential to *increase* rather than decrease workload, *worsen* rather than improve performance, and make monitoring and detection even more *reactive* vs. *proactive*. The results of the future anomaly detection automation must be presented to users in ways that help them quickly review and understand the results and prioritize them.

We must carefully tailor the design of anomaly detection to support proactive monitoring in the future, and avoid these potential pitfalls. To begin to address this, we focused a third set of interviews on identifying (1) what information such anomaly detectors would need to detect anomalies, and (2) what information users would need to know about the results of the anomaly detection to effectively supervise and manage it. With eight SME UAS trainers from a major US Air Force training facility, we reviewed and refined a set of information inputs that need to be considered by anomaly detection automation, to help inform automation and algorithm development, and the necessary information outputs to enable a user to understand results of the automation, to ensure the automation is functioning correctly, and be able to intervene when necessary. (Example information outputs include anomaly type, severity, impact, priority, etc).

We involved SMEs in a principled and systematic design process that leveraged their strengths in domain knowledge and avoided discussions of intuitions about specific HMI formats and designs for future tasks (e.g., Andre & Wickens, 1995; Smallman & Cook, 2011). We developed a novel procedure in which SMEs made *design-impactful* decisions based on their expertise and anticipated information needs for future anomaly detection supervision. Specifically, SMEs commented on their anticipated needs for *information availability* and *information detail* required to effectively supervise future anomaly detection automation. This process helped to identify the information access costs that SMEs envision accepting for accessing information in a future supervisory HMI (Wickens & Hollands, 2000). SMEs consistently anticipated needing immediate access to certain aspects of anomaly detection results, such as general categories of anomaly types and severity, and were willing to access other information on-demand only as needed, such as precise values for ongoing and expected problem duration. We have successfully employed a similar process with other SMEs in the support of HMI designs that are being implemented in submarine command and control systems and industrial process control software. The results from these interviews directly informed the design of low-fidelity initial prototype visualizations reported in Smallman and Cook (2013). The prototype visualizations support a trend-based approach to monitoring, to enable users to monitor and supervise proactively, with context incorporated to aid in understanding and interpretation of anomalies.

**Conclusions**

The DoD vision for the future of autonomy (DoD, 2011) is extremely ambitious. It envisions a massive increase in the number of autonomous systems, all functioning with an entirely different business process than today's teams of humans and unmanned vehicles. The role of the human will change from operators of single vehicles and systems to supervisors of swarms of autonomous and highly automated systems performing multiple simultaneous missions.

The DoD vision is multi-faceted**,** thus requiring a multi-faceted approach to achieve it. Currently, most effort is directed towards developing the technology and the supporting infrastructure for the autonomous capabilities. Although this is essential, alone it is not sufficient to achieve the vision. The notion of engineering humans out of the system is a science fiction (e.g., *Skynet*) that is neither viable nor helpful. Future autonomous systems and swarms, no matter how automated, will still be part of a complex system that ultimately includes and reports to human decision makers and arbiters. Our focus in the current effort has been on the work paradigm shift towards supervisory control and supporting the needs and increasing work demands on this future human decision maker.

Although the sophistication of future automation will undoubtedly increase in 20 years, the cognitive abilities of future human supervisors will not. Effectively supporting the future autonomous system supervisor requires careful definition of their future tasking, tools and HMIs that support it, and viable supervisory control mechanisms, all presented in a way that respects users' perceptual and information processing characteristics. Supporting the future supervisor also requires careful consideration of the display metaphors proposed to enable users to do their tasks. Current displays tend to promote a reactive monitoring stance, which is at odds with the needs of operators to monitor proactively. The importance of proactivity will grow as future supervisors monitor automation; they will need to understand what parts of the situation are beginning to trend away from normal, so that efforts can be focused on intervening and correcting before the situation deteriorates and cannot be remediated. New display metaphors to support the shift towards supervision are needed (Smallman & Cook, 2013). Through our UCD approach paired with expertise in perceptual and cognitive science and the supervisory control of automation, we have begun to make inroads into this complex problem.

The ambition and complexity of the DoD vision has required us to tailor classic UCD processes to the problem. Classically, UCD entails interviewing domain experts and building task models for the design of capabilities firmly grounded in today's realities (e.g., Norman, 1986). For the futuristic DoD vision, however, current users cannot definitively envision the future supervisor's job. They do not know what future mission types and requirements will be. They cannot foresee the vehicles and systems that will be employed, and they have little experience employing, trusting, and valuing automation (Lee & See, 2004). However, across the different roles that current users take, the different platforms and vehicles they operate, the different missions they conduct, and the experiences with different HMIs and automation that they accumulate, current users can usefully ground an understanding of future tasking.

We therefore approached and solicited input from a large sample of 27 SMEs selected to cover the requisite experiences in roles, mission types, vehicle types, and automation. Our constraints were significant. Individual SMEs had limited time to devote to a limited set of issues. We therefore employed a carefully scoped, staged, sequential, interactive UCD approach where the products resulting from one site visit with one SME group were progressively built upon in subsequent site visits with different SME groups. We scoped our analysis to the monitoring aspect of supervisory control, which is widely considered to be the most challenging (Sheridan, 2006). We staged the UCD sessions across four military and commercial industry sites in the US specializing in training, development, testing, and operation of unmanned vehicles.

The design artifacts resulting from these interviews include a descriptive model of today's monitoring and intervention tasks for unmanned vehicles, and a prescriptive model for tomorrow's vision of how those same tasks should be allocated to humans and automation working cooperatively, as well as the information exchanges needed for future supervisors to manage future automation. We used an existing framework for automation design (Parasuraman et al., 2000) and applied it in a novel way to task analysis with domain experts, providing an objective basis for SMEs to offer their expectations about the future role of automation. We balanced the roles of the different stakeholders in the UCD process, harnessing the strengths of the different stakeholders in a synergistic way, with the SMEs providing domain, task, and technology expertise, and the human factors scientists / designers applying expertise in perceptual and cognitive science and the supervisory control of automation.

By tackling these issues now, we can stay ahead of the autonomy revolution with solutions that guide the technology to support the users, rather than making the users "slaves to the technology."

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**References**

Anderson, J. R. (1983). A spreading activation theory of memory. *Journal of Verbal Learning and Verbal Behavior*, 22, 261-295.

Andre, A. D., & Wickens, C. D. (1995). When users want what's NOT best for them. *Ergonomics in Design*, 3, 10–14.

Bainbridge, L. (1983). Ironies of automation. *Automatica*, 19, 775–779.

Bennett, K. B., & Flach, J. M. (2011). *Display and Interface Design: Subtle Science, Exact Art*. CRC Press, Boca Raton, FL.

Billings, C. E. (1996). *Aviation Automation: The Search For A Human-Centered Approach*. Hillsdale, N.J.: Lawrence Erlbaum Associates.

Bloomberg, 17 June 2012. Drones most accident-prone U.S. Air Force craft. http://www.bloomberg.com/news/2012-06-18/drones-most-accident-prone-u-s-air-force-craft-bgov-barometer.html

Bransby, M. (2001). Design of alarm systems. In J. Noyes and M Bransby (Eds.), *People in control: Human factors in control room design* (pp. 207-222). London: IEE.

Burns, C. M. (2006). Towards proactive monitoring in the petrochemical industry. *Safety Science*, 44, 27-36.

Cook, M. B. & Smallman, H. S. (2010). When plans change: Task analysis and taxonomy of 3-D situation awareness challenges of UAV replanning. In *Proceedings of the 15th International Command and Control Research and Technology Symposium.* Santa Monica, CA.

Cooke, N. J. (1999). Knowledge elicitation. In. F.T. Durso, (Ed.), *Handbook of Applied Cognition*, pp. 479-509. John Wiley & Sons, Inc.: Sussex, UK.

Cooke, N. J., Rivera, K., Shope, S., & Caukwell, S. (1999). A synthetic task environment for team cognition research. In *Proceedings of the Human Factors and Ergonomics Society 43rd Annual Meeting* (pp. 303-307).

Cummings, M. L., Bruni, S., Mercier, S., & Mitchell, P. J. (2007). Automation architecture for single operator, multiple UAV command and control. *Massachusetts Institute of Technology Technical Report*.

Department of Defense (2009). FY2009-2034 Unmanned Systems Integrated Roadmap. Washington, DC: U.S. Department of Defense.

Department of Defense (2011). FY2011-2036 Unmanned Systems Integrated Roadmap. Washington, DC: U.S. Department of Defense.

Department of Defense, Defense Science Board. (2012). The Role of Autonomy in DoD Systems. Task Force Report, July, 2012.

Diaper, D., & Stanton, N. (2004). *The handbook of task analysis for human-computer interaction*. Lawrence Erlbaum Associates; Mahwah, NJ.

Drury, J. L., & Scott, S. D. (2008). Awareness in unmanned aerial vehicle operations. *The International C2 Journal*, 2, 1-10.

Errington, J., Reising, D., & Burns, C. (2009). *Effective Alarm Management Practices*. Minneapolis, MN: Abnormal Situation Management Consortium Books.

Fitts, P. M. (1951). *Human engineering for an effective air navigation and traffic control system.* Washington, D.C.: National Research Council Committee on Aviation Psychology.

Fleet Forces Command (2008). *Fleet Unmanned Aircraft Systems Concept of Operations*. Naval Network Warfare Command, 31 July 2008, Norfolk, VA.

Gugerty, L. (2004). Using cognitive task analysis to design multiple synthetic tasks for uninhabited aerial vehicle operation. In S. Schiflett, L. Elliott, E. Salas & M. Coovert (Eds.), *Scaled Worlds: Development, Validation, and Application*, (pp. 240-262). London: Ashgate Publishers.

Klein, G., Woods, D. D., Bradshaw, J. M., Hoffman, R. R., & Feltovich, P. J. (2004). Ten challenges for making automation a "team player" in joint human-agent activity. *Intelligent Systems, IEEE*, 19, 91-95.

Larkin, J., & Simon, H. (1987).Why a diagram is (sometimes) worth ten thousand words. *Cognitive Science*, 11, 65-99.

Lee, J. D., & See, K. A. (2004). Trust in automation: designing for appropriate reliance. *Human Factors*, 46, 50-80.

Mumaw, R. J., Roth, E. M., Vicente, K. J., & Burns, C. M. (2000). There is more to monitoring a nuclear power plant than meets the eye. *Human Factors*, 42, 36-55.

Nehme, C. E., Crandall, J. W., & Cummings, M. L. (2007). An operator function taxonomy for unmanned aerial vehicle missions. In *Proceedings of the 12th International Command and Control Research and Technology Symposium.* Newport, RI.

Nehme, C. E., Scott, S. D., Cummings, M. L. & Furusho, C. Y. (2006). Generating Requirements for Futuristic Heterogeneous Unmanned Systems. In *Proceedings of the 50th Annual Meeting of the Human Factors and Ergonomic Society (HFES)*, (pp. ), San Francisco, CA.

Newell, A., & Simon, H. A. (1972). *Human Problem Solving*. Englewood Cliffs, NJ: Prentice-Hall.

Nielsen, J. (1993). *Usability Engineering*. Academic Press, Boston, MA.

Nielsen, J. (2000). Why you only need to test with 5 users. Jakob Nielsen's Alertbox. Available on line from www. useit. com/alertbox/20000319. html.

Norman, D. (1986). Cognitive engineering. In D. Norman, & S. Draper (Eds.), *User centered system design: New perspectives on human-computer interaction* (pp. 31–61). Hillsdale NJ: Lawrence Erlbaum Associates.

Norman, D. A. (1988). *The psychology of everyday things*. Basic books.

Norman, D. A., & Draper, S. W. (1986). *User centered system design; new perspectives on human-computer interaction*. L. Erlbaum Associates Inc.

Office of the Under Secretary of Defense. (2012). *Unmanned Aircraft Systems (UAS) Ground Control Station (GCS) Human-Machine Interface (HMI) Development and Standardization Guide*. Washington, DC.

Osga, G. (2006). *Agile User-Centered Design Team Process*. SPAWAR System Center San Diego, CA. Unpublished Technical Memo, San Diego, CA, June 2006.

Parasuraman, R., & Riley, V. A. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors*, 39, 230–253.

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans, 30* (3), 286-297.

Rouse, W. B. (1988). Adaptive aiding for human/computer control *Human Factors*, 30, 431-438.

Scerbo, M. S. (1996). Theoretical perspectives on adaptive automation. In R. Parasuraman & M. Mouloua (Eds.), *Automation and human performance: Theory and applications* (pp. 37-63). Hillsdale, NJ: Erlbaum.

Scott, S. D., & Cummings, M. L. (2006). Cognitive Task Analysis for the LCS Operator. *MIT Humans and Automation Laboratory Technical Report.*

Sheridan, T. (2006) Supervisory Control. In Salvendy, G. (Ed.), *Handbook of Human Factors and Ergonomics*. 3rd ed. (pp. 1025 – 1052). John Wiley: New York, NY.

Sheridan, T. B., & Verplank, W. L. (1978). *Human and computer control of undersea teleoperators*. Cambridge, MA: MIT Man–Machine Laboratory.

Shneiderman, B. (1987). *Designing the User Interface: Strategies for Effective Human-Computer Interaction*. Reading, MA: Addison-Wesley Publishing Co.

Sibley, C. & Coyne, J. (2012). Fort Pickett trip report. *Naval Research Laboratory Technical Report.* Washington, DC.

Simons, D. J., & Rensink, R. A. (2005). Change blindness: Past, present, and future. *Trends in cognitive sciences*, 9, 16-20.

Smallman, H. S., & Cook, M. B. (2011). Naïve Realism: Folk fallacies in the design and use of visual displays. *Topics in Cognitive Science*, 3, 579-608.

Smallman, H. S., & Cook, M. B. (2013). Proactive supervisory decision support from trend-based monitoring of autonomous and automated systems: a tale of two domains. *HCI International (HCII)* 2013 Invited Paper, Las Vegas, NV, 21-26 July 2013.

Smallman, H. S., Cook, M. B., Beer, R. D., & Lacson, F. C. (2009). Concept of Operations (CONOPS) for Submarine-based Monitor and Control of Unmanned Aerial Vehicles for Over-The-Horizon Targeting Applications. San Diego, CA: *Pacific Science & Engineering Group, Inc., Technical Report*.

Smallman, H. S., & St. John, M. (2005). Naïve Realism: Misplaced faith in the utility of realistic displays. *Ergonomics in Design*, 13, 6–13.

Spillers, F. (2004). Task analysis through cognitive archeology. In D. Diaper & N. Stanton (Eds.), *The handbook of task analysis for human-computer interaction*. Mahwah, NJ: Lawrence Erlbaum Associates.

St. John, M., Cowen, M. B., Smallman, H. S., & Oonk, H. M. (2001). The use of 2D and 3D displays for shape understanding vs. relative position tasks. *Human Factors*, 43, 79–98.

Tvaryanas, A. P. (2004). USAF UAV mishap epidemiology, 1997-2003. Presented at the *Human Factors of Uninhabited Aerial Vehicles First Annual Workshop*, Phoenix, AZ, May 24-25, 2004.

Tvaryanas, A. (2012). Human Systems Integration: Focusing on the Means. *US Navy Aerospace Experimental Psychologist Society Call Signs*, 3(2), Winter, 2012, (pp. 2-4).

Tvaryanas, A. P., Thompson, W. T., & Constable, S. H. (2006). Human factors in remotely piloted aircraft operations: HFACS analysis of 221 mishaps over 10 years. *Aviation, Space, and Environmental Medicine*, 77(7), 724-732.

Vicente, K. J., & Rasmussen, J. (1992). Ecological interface design: Theoretical foundation. *IEEE Transactions on Systems, Man, and Cybernetics*, 22, 489–506.

Wickens, C. D. & Hollands, J. (2000). *Engineering Psychology and Human Performance*, 3rd Edition. Upper Saddle River, NJ: Prentice Hall.

Williams, K. W. (2004). A summary of unmanned aircraft accident/incident data: Human factors implications. Washington, DC: U.S. Department of Transportation, Federal Aviation Administration, Office of Aerospace Medicine. Technical Report Publication No. DOT/FAA/AM-04/24.

Woods, D. D., & Hollnagel, E. (2006). *Joint cognitive systems: Patterns in cognitive systems engineering*. Taylor & Francis, CRC: Boca Raton, FL.

Woods, D. D., & Roth, E. M. (1988). Cognitive engineering: Human problem solving with tools. *Human Factors,* 30, 415-430.