Evidence Report:

Risk of Inadequate Design of Human and Automation/Robotic Integration

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I. Risk of Inadequate Design of Human and Automation/Robotic Integration

The *Risk of Inadequate Design of Human and Automation/Robotic Integration* is identified by the National Aeronautics and Space Administration (NASA) Human Research Program (HRP) as a recognized risk to human health and performance in space. The HRP Program Requirements Document defines these risks. This Evidence Report provides a summary of the evidence that has been used to identify and characterize this risk.

II. Executive Summary

Successful integration of humans with automated and robotic systems is required to successfully accomplish both current and future NASA mission goals. Effective human automation/robotic integration (HARI) requires that automated/robotic systems and their human interfaces be designed to support all levels of human operation from direct manual control, to shared human-robotic control, or to human supervisory control. Integration of automated systems with their users requires that a variety of role allocations between the human and the automation be supported as it is expected that roles will vary based on contextual elements. Effective user interfaces, appropriately designed functional task allocations, and designs that adhere to a transparent system design philosophy ensure mission success and safety. The effects of an inadequate design of HARI may be immediate and direct or long-term and indirect. Poor design may measurably and negatively impact task time, workload, operator trust in the system, system state awareness, use of consumables, number of times repairs are required, and other performance-related measures. It may also lead to negative consequences by compounding interacting factors such as training, communication, fatigue or stress, and urgency and dynamics of the task. Multiple expert communities (design, accident investigation, and regulatory) have illustrated the need to develop methods, tools, and techniques to identify and address HARI vulnerabilities as early as possible in the design process. Risks from inadequate designs associated with human-technology interactions will increase as mission requirements become more demanding and as missions are carried out in unfamiliar circumstances substantially different from our experience base. Good design is not just implementing appropriate user interfaces, but considering how the operator integrates into the system that s/he is required to use. If effectively implemented and evaluated, good HARI design reduces integration risks, reduces costs, increases efficiency, and enhances safety. Future HARI research and design should be proactive and anticipate potential issues that may arise during future exploration missions. Four key contributing factors to the risk of inadequate HARI include: 1) Assignment of Human and Automation Resources, 2) Perceptions of Equipment, 3) Design for Automation, and 4) Human/Robotic Coordination.

III. Risk Statement

Given that automation and robotics must seamlessly integrate with crew, and given the greater dependence on automation and robotics in the context of long-duration spaceflight operations, there is a risk that systems will be inadequately designed, resulting in flight and ground crew errors and inefficiencies, failed mission and program objectives, and an increase in crew injuries.

IV. Risk Overview

National Aeronautics and Space Administration missions depend on humans interacting with automated and robotic systems to accomplish mission goals. Future missions will see an increase in this dependency for both near- and deep-space exploration missions, including near-Earth object and planetary surface operations. This dependency will be the case for crew in space and controllers on the ground.

In accordance with NASA's vision, operations involving crew-robot and crew-automation interactions will increase substantially relative to current operations. Automation is the use of machines or computers, generally for the purpose of increasing productivity and reducing human cognitive workload. In space systems, automation is required to support a highly diverse set of functions and operations that in turn, necessitate a variety of amounts and types of automation. The required automation systems will span ground and flight systems and will support functions from controlling the habitat to conducting science experiments. Beyond automation, there is robotics. Hancock, Billings, Schaefer, Chen, and Parasuraman (2011) characterize robots as mobile, having a human or animal form, and intended to "effect action at a distance;" the latter attribute being of significant importance for space and planetary exploration. Dexterous, heavy-lift, and mobility systems are the classes of robotic systems expected for near- and deep-space exploration missions.

Human-robot teaming will be a cornerstone of future operations. Robotic systems and their human interfaces must be designed to support all levels of human operation (direct manual control, shared control, and supervisory control). They must also support multiple robot operators in multi-agent team configurations, with those operators separated by time, space, or both. These mixed-initiative systems will have to support multiple operators, varying time delays, and increased reliance on high and variable levels of automation. Similarly, the integration of automated systems with their human users requires supporting a variety of role divisions: authority and autonomy can be differently allocated between human and automation, and that allocation may change dynamically depending on task or context.

Ineffective user interfaces, poor system designs, or ill-advised functional task allocation compromise mission success and safety. As a result, the design of effective human automation/robotic integration (HARI) is essential. There are gaps in our knowledge and experience for the expected level of complexity of future automated and robotic operations. Concerning robotics, risk arises because we have limited experience with teleoperation, time-delayed operations, and multi-robot operations. For example, poorly designed human interfaces can result in a loss of situation awareness, compromising mission safety and efficiency. Of special concern are losses of situation awareness that occur while a crewmember is in close proximity to a robot, with the consequent risk to crew safety. Crew must be able to ascertain and understand the state of a robot, affect or change its command, and override the system whenever necessary.

Currently, most work in space is performed by the crew, supported to some degree by on-board automated systems (e.g., for environment control) and to a larger degree by ground-based Mission Control, therefore human-automation integration will be critical in space as well as on the ground. In space, tasks will need to be completed by fewer people and with fewer external resources and support. In addition, crewmembers will have less training and experience in any particular activity compared to a ground team specialist. Further, ground control will need to provide different forms of support for the crew and vehicle, focusing more on longer-term projections, modeling, anticipatory troubleshooting, and monitoring health of systems and crew.

In short, mission complexity will increase as mission familiarity and experience decrease. This means that the challenges to effective design of automation and robotics also increase. A critical aspect to meeting automation design challenges is a focus on integration (Terwiesch and Ganz, 2009). Automation and robotics must be well integrated into the process and the workflow it is designed to support. As complex missions will require multiple automation systems, robots, and people, it is critical to design with an awareness of how multiple agents (people, automation, or robots) can and should be coordinated. Human-system integration that includes robotics and automation into mission design is not simply about reassigning tasks between people, automation and robotics. Changing the roles and assignments lead to changes in the work, shifts times of peak human workload, and creates new, often challenging tasks for humans such as supervisory responsibility. Hence, emphasis must be placed in integrated design of these complex systems.

A. Aerospace Examples of Ineffective HARI

In the space domain, the Mir-Progress collision is an example of a near-catastrophic accident that resulted from inadequate human-automation integration based on a poorly designed operations concept and insufficient needs analysis. The Russian spacecraft Progress 234 collided with the Mir space station, causing the Mir pressure hull to rupture, and nearly causing the space station to be abandoned (Ellis, 2000; Shayler, 2000). The original operations concept was that Progress would dock automatically with the Mir. Crew responsibilities were primarily to cancel the approach (if necessary) and limited crew displays were provided. Crewmembers were later tasked to perform the docking manually, following a decision not to install automatic docking systems for each Progress spacecraft. This change however was not followed up with an impact assessment of integrated human-system performance. It neglected consideration of the types of information crewmembers would need to remotely control another vehicle, and thus, no additional displays were provided. Future effective HARI must be included in the design process so as to minimize safety issues like that illustrated by the Mir-Progress collision.

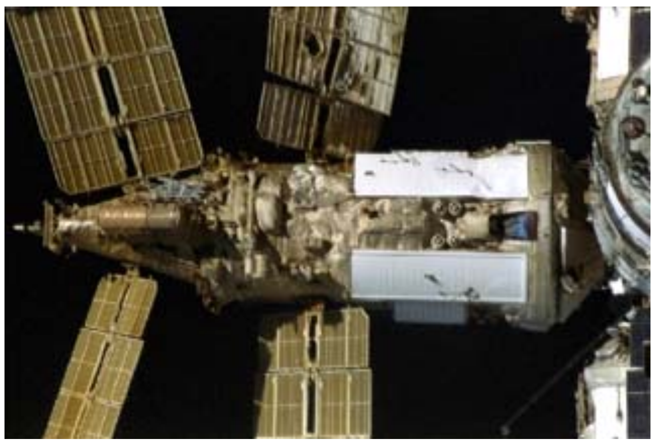

Figure 1: Spektr module showing the damaged radiator and solar array on Mir (NASA photograph)

In the aviation domain, many human-automation interaction difficulties for commercial aviation are attributable to inappropriate designs. The U.S. Federal Aviation Administration (FAA) and the European Joint Aviation Authority recognized an increase in accidents attributable to problematic interaction between flight crews and flight deck automation. The FAA released a report listing design deficiencies contributing to aviation incidents and accidents and made recommendations for improvement, including the need for new design and evaluation tools in 1996 (Federal Aviation Administration [FAA] Human Factors Team, 1996). Research from the following communities are important: the design (C. E. Billings, 1997; Curtis, 1981; Leveson, 1995), the accident investigation (Mellor, 1994; Sarsfield, Stanley, Lebow, Ettedgui, and Henning, 2000), and the regulatory (Australian Bureau of Air Safety Investigation [BASI]), 1999; The Interface between Flight crews and Modern Flight Deck Systems, 1996). These communities have also illustrated the need to develop methods, tools, and techniques to identify and address human-automation interaction vulnerabilities as early as possible in the design process. Mishaps due to design errors (i.e., mishaps where automated systems performed as designed but aspects of the design contributed to the accident) are increasing (Sarsfield et al., 2000).

B. Dependencies & Interrelationships

Good design of HARI must support effective execution of system functions under nominal and off-nominal conditions. Many factors affect the adequacy of designs of human and automation/robotic integration, and an inadequate design can produce many interrelated effects. Effective intervention to minimize risk from inadequate design requires a multi-faceted, systems-level approach.

The effects of an inadequate design of HARI may be immediate and direct, such as an operator selecting an unintended action or a robot harming an astronaut. They may also be long-term and indirect, such as an unusable design contributing to human stress or an unclear design resulting in operation of equipment in configurations that produce unnecessary wear. It is important to be able to measure the consequences of inadequate design beyond merely documenting the occurrence of rare, catastrophic accidents. Poor design may measurably and negatively impact task time, workload, use of consumables, number of times repairs are required, and other objective and subjective performance measures. The key point is that poor design can lead to many different types of negative consequences and can be caused by multiple, interacting factors. Effective risk reduction requires a systems-level analysis of HARI. This is needed to understand and intervene on multiple interacting causes.

The effects of an inadequate design of HARI may manifest in various ways, but it is important to understand that these effects could be caused by interacting operational factors. For instance, how controllers are trained, the amount of communication between ground and crew, the level of controller fatigue or stress to be supported, and the urgency and dynamics of the tasks being carried out are examples of interacting factors. These are all contextual factors that are not necessarily inherent to the system design itself, however, they can affect how the quality of the system is perceived or assessed. These factors may interact such that safety-reduction from one factor increases vulnerabilities from another.

It is important to understand and acknowledge the overlap between the HARI risk and the Risk of Inadequate Human-Computer Interaction (HCI). These two risks are virtually inseparable, given that human-automation and human-robot interactions are, in fact, human-computer interactions involving a user interface. Both areas are concerned with the interactions amongst humans and computer machines to affect a more productive and error-free system. HCI is the study and design of human computer interaction and interfaces. HARI is the study and design of the interactions between humans and automation and robotics. While for instance, HARI risk would focus on how humans operate robots, HCI considerations are necessary to enable effective communication between the human and the robotic agents. These risks are inherently overlapped due to the nature of working with complex human-systems.

For the purposes of classification within the Space Human Factors Engineering (SHFE) portfolio, if a project or topic explicitly involves a robot, focuses on interaction with automation, or the effects of automation, or deals with assignment of tasks to agents – it is considered a HARI risk, with a secondary risk of Inadequate HCI. If a project primarily focuses on the user interface, and not interaction with a robot or automation, it is assigned to the HCI risk.

An example from Apollo 13 illustrates how both HARI and HCI risks are important and interrelated. During Apollo 13, management of an equipment failure was compounded as the system state was provided in a form that did not facilitate anomalous error detection (e.g. difficulty in early diagnosis (Murray and Cox, 1990), cited in (Woods et al., 2010)). In this example, poor displays could be attributed to the HCI risk, while poor allocation of the function of detecting off-nominal data (to a person vs. automation) could be attributed to the HARI risk. Inadequate HCI and/or HARI can lead to errors and efficiencies, failed mission and program objectives, and an increase in crew injuries. Risks specific to HARI include, but are not limited to, stress, loss of situation or mode awareness, haphazard actions, robot harming an astronaut, and unnecessary wear on equipment.

In addition to being related to the Risk of Inadequate HCI, the Risk of Inadequate Human-Automation/Robotic Integration is related to two other Space Human Factors Engineering risks: the Risk of Inadequate Critical Task Design (TASK) and the Risk of Performance Errors Due to Training Deficiencies (TRAIN).

The HARI risk focuses on those issues that are specifically related to semi-autonomous systems – robotics and automation. The TASK risk is concerned with tasks, schedules and procedures. Many tasks are performed using automated or semi-automated systems or robotics, thus there is a heavy interaction between the TASK and HARI risks. The emphasis in TASK is on factors related to the flow of the work: operational tempo and workload; procedural guidance; training for specific procedural knowledge. Supervision or monitoring of automated or robotic systems can be an important component of task design, and especially when workload is considered (e.g., where monitoring of autonomous systems is performed simultaneously with other tasks) and where procedural guidance provides critical information about the modes, parameters, or limitations of automated or robotic systems.

The TRAIN risk interacts with HARI in that systems with poor HARI design may be non-intuitive, and require more training. The research under TRAIN addresses best methods of training for different purposes, including individual and team activities, for skills and knowledge.

C. Levels of Evidence

The levels of evidence presented in this chapter include case study, expert opinion, terrestrial data, expert data, and spaceflight incidents. Evidence presented in this chapter encompasses lessons learned from 50 years of spaceflight experience and ground-based research related to the risk of inadequate human and automation/robotic integration. A variety of evidence types is available, which differ both with respect to the method used to collect evidence and with respect to the context or domain of the evidence. Concerning method, evidence comes from both formal and informal methods. Informal methods include post-hoc reports of naturally occurring events (including incidents and accidents) and case studies. Formal methods include systematic logging or survey of naturally occurring events, and interviews with or surveys of experts. The most formal method of gathering evidence is controlled experimentation. Some evidence is reliant on simulated data from models of human behavior, of automation or robotic system behavior, or of human-system interaction, particularly for circumstances in which it is hard to directly observe and gather empirical data.

A summary of Levels of Evidence may include, but not be limited to:

- Post-hoc reports of naturally occurring events
- Case study
- Expert data
- Expert opinion
- Spaceflight incident data
- Terrestrial data
- Modeling
- Controlled experiments

Concerning context or domain, relevant evidence for HARI may come from space operations (both in-flight and on the ground), from aviation or other safety-critical work domains, or from other domains with extensive or advanced automation or robotics. Typically, it is difficult to conduct experiments in-flight, so experimental data is most likely to come from simplified tasks or related domains, while in-space data is more likely to come from case studies.

Portions of the evidence consist of summaries of subjective experience data, as well as non-experimental observations or comparative, correlation, and case or case-series studies. It should be noted that some evidence in this report is derived from the Flight Crew Integration (FCI) International Space Station (ISS) Life Sciences Crew Comments Database. Although summaries of ISS crew comments are presented as evidence, the raw comments in the Life

Sciences Crew Comments Database are protected and not publicly available, due to the sensitive nature of the raw crew data it contains.

V. Evidence

There is extensive evidence that poor HARI design produces safety-critical errors. Some evidence comes from in-space applications. There is also a large body of evidence from analog domains, such as aviation and medicine, in which highly-skilled users interact with complex technical systems. Evidence and information from analog mishaps is used to develop systems involving similar situations and skills. However, this reactive design stance primarily "chases old problems" rather than forestalling the new. A proactive design stance is particularly valuable because, unlike in aviation, the experience base in space is relatively small and circumstances of operations change from mission to mission. Thus, information from prior mishaps is only a partial guide to the many novel situations where we lack specific experience. Future research on HARI will need to investigate those circumstances where we lack direct knowledge. Research will also need to develop methods for extrapolating knowledge from known to less-understood conditions and to integrate the extensive, but sometimes fragmentary, knowledge we have.

The risk of inadequate HARI includes four core contributing factors: 1) Assignment of Human and Automation Resources, 2) Perceptions of Equipment, 3) Design for Automation, 4) Human/Robotic Coordination. Each is described subsequently.

A. Contributing Factor 1: Assignment of Human and Automation Resources

Human automation/robotic integration requires appropriately allocating functions among agents, be they people, automation, or robots, to drive efficient systems design. Inappropriate distribution of functions among humans and automation/robotics may result in inefficient and unsafe operations, threatening mission completion. Allocating tasks determines the role people must play in future complex, automated systems. Unsuitable allocations may have the repercussions of overwhelming or underutilizing humans under normal and/or emergency situations.

The idea of assigning functions or tasks to humans or automation/robotics has been around since the 1950s. Fitts (1951) proposed a set of human-computer role allocations based on the strengths and capabilities of each (summarized in Table 1). Fitts' list has been modified by many to develop other guidelines regarding task allocation and levels of automation. Systems differ, so it is difficult to establish exactly which tasks should be automated and to what degree of automation. de Winter and Dodou (2011) highlight that since its original inception, much in the human-automation world has changed, and hence, the list may be considered flawed, outdated, incomplete, and disregarding human-machine integration.

TABLE 1: FITTS HUMAN-COMPUTER ROLE ALLOCATIONS

Humans are better at:	Computers are better at:
Perceiving patterns	Responding quickly to control tasks
Improvising and using flexible procedures	Repetitive and routine tasks
Recalling relevant facts at the appropriate time	Reasoning deductively
Reasoning inductively	Handling many complex tasks
Exercising judgment	Fast and accurate computations.

An alternative allocation list is Sheridan and Verplank's Levels of Automation (LOA) of Decision and Action Selection coupled with Parasuraman and Sheridan's (2000) model of types and levels of automation (Table 2, Sheridan and Verplank, 1978; Sheridan and Parasuraman, 2005). Parasuraman and Sheridan (2000) determined that it is more practical to provide guidelines—rather than rigid rules—to assist in determining which tasks should be automated and at which levels of automation. Other frameworks to allocate human-automation functions are provided by Riley (1989) and Endsley and Kaber (1999). These further expand the amount of automation relative to specific types of functions. The authors of this report do not know of frameworks that describe guidelines for human-robotic allocation according to the type of task.

In some ways, these frameworks for function allocation among human and automation/robotic resources imply that a particular design operates at only one automation level. Visser, LeGoullon, Freedy, A., Freedy, E., Weltman, and Parasuraman (2008) cite Opperman (1994) in describing flexible automation that can adjust and respond to user needs, environmental demands, and context as being referred to as adaptable or adaptive automation. Under such circumstances, allocation between humans and automation/robotic resources could change depending on the context of the work. To successfully complete future space missions, we will need autonomous systems (e.g. unmanned vehicles, robots, rovers, habitats) that can adapt to unexpected events and endure extreme environmental conditions, through human or system-induced modifications. Visser et al. (2008) further discriminate between the adaptable and adaptive automation: they describe the former as cases where change is induced by the operator, while the latter covers cases where change is induced by the automated or robotic system. Adaptive automation may turn out to be critical for space exploration because of the many unknowns that exist in deep space and surface exploration.

TABLE 2: LEVELS OF AUTOMATION

Automation Level	Automation Description
1	The computer offers no assistance: human must take all decision and actions.
2	The computer offers a complete set of decision/action alternatives, or
3	Narrows the selection down to a few, or
4	Suggests one alternative, and
5	Executes the suggestion if the human approves, or
6	Allows the human a restricted time to veto before automatic execution, or
7	Executes automatically, then necessarily informs humans, and
8	Informs the human only if asked, or
9	Informs the human only if it, the computer, decides to.
10	The computer decides everything and acts autonomously, ignoring the human.

When considering adaptive automation, the LOA transitions need to be also taken into account. Transitions can be sequential or discontinuous (referred to as distance) and go from fully manual to fully automatic or fully automatic to fully manually (referred to as direction). Automation level transitions exhibit performance costs, particularly during the engagement and disengagement processes. When an operator changes from one level of automation to another, s/he must reorient to the current system status and operating level, which can decrease situational awareness and precipitate out-of-the-loop performance costs (see also Contributing Factor 3). Di Nocera, Lorenz, and Parasuraman (2005) maintain that the higher the current LOA (prior to LOA transition), the worse the "return-to-manual" performance. However, it is acknowledged that this may not be the case (Lorenz, Di Nocera, Röttger, and Parasuraman, 2002) so long as the interface is designed to facilitate information sampling, thereby maintaining operator situational awareness (Di Nocera, et al., 2005). Little research has been done on LOA transitions, and so we have only a limited understanding of the effects of distance and direction of LOA changes on the loss or maintenance of situational awareness.

While these frameworks describe options for human-automation/robotic allocations, determining which of these allocations works best for a particular system remains a challenge and hence, a contributing factor for the risk of inadequate HARI. There is limited guidance on how to apply any of these allocations. Parasuraman and Sheridan (2000) suggest first assessing the human performance consequences relative to the levels of automation flowchart to determine a range of appropriate degree of automation. From there, the options can be narrowed down upon further review. Human performance consequences include factors such as safety, mental workload, situation awareness, operator trust or distrust in automation, complacency, skill degradation, and mode awareness. Second, the reliability of automation and costs of decision or action should be evaluated. Methods to estimate reliability include fault and event tree analysis and methods for software reliability analysis.

In the space domain, task allocation for effective HARI is further complicated by the challenge of how to appropriately determine the complete set of required tasks and functions. This is, in part, because the work that is encompassed by human space missions has never been accomplished before and the required technology does not yet exist. As a result, a complete analysis of all tasks and functions is difficult. If there is not an adequate identification of the work functions needed, no partitioning of functions can be very satisfactory. Thus, effective allocation of function also depends on effective processes for needs analysis.

Typically, an analysis of all tasks and functions is called a needs analysis. This requires an understanding of mission operations, the particular functions that an automation/robotic system is supporting, and of how these functions coordinate with related functions. Many methods have been suggested: task analysis (Kirwan and Ainsworth, 1992), Work Domain Analysis (Vicente, 1999), and Contextual Inquiry (Beyer and Holtzblatt, 1997). Furthermore, effective HARI design needs to be integrated with process or workflow design (Beyer and Holtzblatt, 1997; Woods et al., 2010). Once an appropriate needs analysis has been conducted, this information must be linked to the design, development, and evaluation processes, which are typically handled as part of software or systems engineering. The assurance that a system meets the identified needs is particularly important for safety-critical systems.

Research in the appropriate human-automation functional allocation for specific tasks exist (e.g., Cummings and Bruni, 2009, Butler et al., 2007), however, additional research is needed to provide the empirical base from which generalizations can be made. A particularly challenging issue is developing the theoretical framework to guide how findings from one situation or task can be generalized to another. Furthermore, research is needed to understand how these frameworks must be adapted to include appropriate allocations in the context of robotics.

B. Contributing Factor 2: Perceptions of Equipment

The way operators view an automated system has a strong influence on how effectively the human-automation system functions. In this context, researchers have focused on the degree of trust and reliance that humans place on their automation.

Achieving an appropriate level of operator trust in automation and/or robotics is imperative for safety and successful mission completion. The operator must be cautious not to over or under-rely on automation or robot. Over-reliance will diminish the operator's situation awareness, placing all decision-making control in the hands of automation; under-reliance will inundate the operator's mental workload, relying solely on him/herself. An example of over-reliance on automation, with serious outcomes, involved failure to detect that the global positioning system component of the auto-navigation system on a cruise ship had failed. As a result, the Royal Majesty was run aground (Degani, 2004; Lee and See, 2004).

When trust is high, operators are likely to rely on automation, i.e., to act as indicated by alarms or hazard indicators, but may be too "compliant" and fail to respond to unidentified hazards or hazards incorrectly identified by the system (Sheridan and Parasuraman, 2005). Over-reliance is also considered a symptom of automation bias (Cummings, 2004; Mosier, Skitka, Heers, and Burdick, 1998; Skitka, Mosier, and Burdick, 1999). Automation bias is where the operator will have the tendency to disregard or search for contradictory information against the automation, potentially resulting in errors of commission and omission (Mosier and Skitka, 1996; Skitka, et al., 1999). On the other hand, under-reliance emerges when the user doesn't trust the automation because it has failed too often. As a result, under-reliance could lead to automation not being employed (de Vries, Midden, and Bouwhuis, 2003; Lee and Moray, 1994). Additionally, operator reliance on automation can be affected by workload (Kirlik, 1993; Wickens and Dixon, 2007), and by sudden change in automation performance (Lee and Seppelt, 2009).

Trust in automation and/or robotics is interweaved with functional task allocation (another contributing factor in HARI). For instance, issues may arise at the transition point between prior, manual control of a function to new, automated control, as this change typically requires a reorganization of the operator's tasks (Sarter, Woods, C. Billings, and Salvendy, 1997). Tasks that require automation, like those that are time-critical with little time for operator to response (Parasuraman and Sheridan, 2000), must be designed and built to be highly reliable in order to gain operators' trust.

Inadequate training also plays a role in trust, leading to automation biases, over or under-reliance on automation, increased operator workload, safety hazards, and failure of mission objectives. Within the domain of human-robotic interaction, Oleson et al. (2011) acknowledge the importance of training to reduce biases and educate the operator on how the robot operates, including "capabilities…behaviors…and risks." Similarly, other researchers (Billings, 1997; Oser, 1999; Sarter, 1996) believe that better methods of training should be developed to provide operators with a more thorough understanding of how the system works, why it works that way, and his/her overall role within the system (interrelating to the third HARI contributing factor). Wickens (1992) and Oser (1999) stress the importance of in-context training experience to supplement theory. A study that evaluated cross-training, suggests that human-robot cross-training "promotes predictable patterns of human and robot action sequences" in addition to greater satisfaction of the operators' expectancies by the robot (Nikolaidis and Shah, 2012).

According to Oleson, Billings, Kocsis, Chen, and Hancock (2011), trust is affected by "trust antecedents," which can be classified as human-related, robot-related, or environment-related. Personality traits and prior experiences, which establish people's expectations, would fall under the human-related category. In the robot-related category, examples include consistency in performance and degree of automation. Shared situation awareness and task complexity are traits that would be categorized as environment-related. In addition to these antecedents, Oleson et al. acknowledge the importance of training to reduce biases and educate the operator on how the robot operates, including "capabilities…behaviors…and risks." Each of these aspects (i.e. trust antecedents and training), and any combination thereof, should be considered in the design process of a robot and during training.

Effective HARI design should not be dependent on automation or robotics reliability because in the space domain, most systems are unique, one-of-a-kind, and are likely to be modeled incompletely or imperfectly. This makes it particularly challenging to design effective systems, and hence, focusing on understanding an operator's calibration in the system might be more useful. It is important to understand the operator's calibration with regards to the automation and/or robotic system in the context of trust. Calibration is the process by which the operator learns to modify his/her behavior based on the performance and reliability of the automated system (e.g. decision support tools, robotics) (McBridge and Morgan, 2010). For example, an operator's calibration may deal with how much time is spent on monitoring the automation, or how often the operator does what is recommended by the automation. The optimal calibration is not necessarily one in which the operator monitors or complies with the automation all the time: the operator may have other things that make demands on his or her time, and the operator may justifiably believe automation is not always to be relied upon.

McGuirl and Sarter (2006) convey that miscalibration of trust results in a mismatch between perceived and actual system performance. Trust calibration is a multi-faceted process because appropriately calibrating trust in automation and decision support tools strongly affects mission outcomes. There are multiple instances in which researchers provide methods to assist in calibrating trust: 1) Fan, Hyams, and Kucher's (1998) pilot decision-making study revealed that initially pilots rely on auxiliary information to validate an automated system's resolution, and with time, as system trust increases, the need for validation decreases; 2) Maes's (1994) interface agent model illustrates how time affects trust: the longer the operator spends with an automated system, the more knowledge s/he gains about how the system works, and thus increases his/her trust in the system; and 3) Cohen, Parasuraman, and Freeman's (1998) model of trust in decision aids communicates that the operator must understand the automated system's strengths and weaknesses, and the context in which each prevail (McBridge and Morgan, 2010). A few instances where miscalibration can occur include when automated systems' performance is unreliable, inconsistent, or not transparent, operator system knowledge is low, and operators have too much or too little confidence in their abilities.

C. Contributing Factor 3: Design for Automation

Operators using complex automation and/or robotics may find themselves confused about what the automated or robotic system is doing because of the complexity of the task or because the relevant information is not available to the operator. This lack of automation transparency is often attributed to a variety of effects, subsequently discussed. This is a contributing factor for HARI because understanding how and why automated systems, including robots, are working becomes an essential part of how operators react under off-nominal conditions and unexpected situations.

Lack of automation transparency has been attributed to operators' inappropriate knowledge acquisition (Glover, Prawitt, and Spilker, 1997) and inability to maintain mode awareness (Sarter and Woods, 1994). Mode-related errors are known contributors in aviation accidents and incidents. There are two types of problems: difficulty in telling what mode a system is in and difficulty telling what a mode will do. For example, pilot training may teach only a subset of possible modes, leaving out unusual modes or those not used in airline operations policy. Pilot performance has latent problems, revealed in non-normal situations (Sarter and Woods, 1994). Problems can result because the system was in an unexpected or unrecognized mode or because the pilot could not predict behavior in an unfamiliar mode, or both (Sarter et al., 1997). In 1994, an A300 airplane crashed at Nagoya Airport. Prior to the crash, the mode had been inadvertently changed to "Go Around" rather than land. The pilot fought against the autopilot and was unable to gain control. Lack of awareness that the mode had been changed and inability to predict how automation and human control would affect behavior in these conditions were both likely contributors (Sogame and Ladkin, 1996).

An Airbus flight test with very skilled crew also ended in a crash following a combination of conditions that produced both unexpected mode change and inability to compensate for the autopilot behavior in this mode (Aviation Week and Space Technology, 1995); also discussed in (Sarter et al., 1997). This case involved an automation-initiated mode change due to the extreme conditions of the test, and inadequate time to diagnose and recover from the control policy in this mode. Problems were compounded because automatic decluttering—designed to simplify the displays in an emergency—removed all flight mode enunciators from the display, leaving the pilot with no visible indicator of control mode. In another incident, unexpected effects of disengaging the autopilot led to Pilot Induced Oscillation resulting in passenger injury (Encounter with Wake Turbulence, Air Canada, Airbus A319-114 C-GBHZ, 2008); lack of understanding the effects of mode change was a probable contributor.

An example in the space domain where lack of transparency imposed a potential risk on safety can be found in Apollo 10. In this example, poorly communicated information about actions and state changes of both automation and crew potentially put safety at risk with accidental operations (Shayler, 2000). During Apollo 10, at the end of the second pass over lunar landing site 2, the two crewmembers were preparing to separate the two stages of the lunar lander and return to the command module in orbit around the moon when the mode of the guidance and navigation system was inadvertently changed by one of the crewmembers. A couple of seconds later, the other crewmembers reached up, without looking, and changed the mode of the guidance system, which canceled the change that had been made by the first crewmembers. As a result, the lunar module, Snoopy, began firing thrusters in all axes, pushing the gyroscopes into gimbal lock and making the navigation system useless until it was reset. The crewmembers then toggled the navigation system switch again and, although it was now put into the mode it should have been in to start with, the situation was made worse. At this point the crew overrode the computer and took manual control. The incident lasted about 15 seconds, during which Snoopy made eight complete rolls. It was estimated that if the crewmembers had not regained control within another 2 seconds, it would have been too late to avoid impact with the moon.

Sarter and Woods (1995) offer multiple solutions to alleviate the mode errors issue: reduce complexity of automated systems, find new training methods and train in context, develop new methods to facilitate mode awareness (e.g. displays that indicate current system state with justification and possible future states), forcing functions (prevents a change until the current problem is corrected), and “management by consent” (requires operators to approve changes before they take effect). Nunes (2003) instead emphasizes development of accurate mental models as a method to support mode awareness and hence, automation transparency.

Fundamentally, acquiring an accurate mental model of the automated system is critical for maintaining mode awareness. A mental model is the framework that manifests knowledge and understanding of a system's operating elements and processes to infer about its future behavior. Mental models are formed from past experiences, expectations, and system feedback, and requires time to develop. Nunes (2003) proposes a particular strategy to training for accurate mental models based on her experience studying air traffic controllers using decision support tools: 1) Develop methods to determine what underlying mental model the operator has, and methods to assess the effects that automation has on human performance; 2) Develop tools that decrease cognitive workload while keeping information processing high, and train operators on how the automated system works and why it works the way it does; and 3) Educate users on the benefits and drawbacks of automation. However, decreasing cognitive workload is not universally supported amongst researchers. Pea (1993), Salomon (1993), and Wickens (1992) have argued that decision support tools that decrease cognitive workload have the potential to jeopardize an operator's problem solving and learning ability, as a result of the operator's decreased cognitive effort in the processes taking place (Nunes, 2003).

Mental models are also essential for maintenance of situation awareness (SA); SA is not only perception of elements in current environment, but also the integration and comprehension of these elements, and the projection of future status based on comprehension (Endsley, 1995). Dependency on automation has been shown to lead to decreased SA (e.g., Strauch, 1997). Endsley and Kiris (1995) has shown that higher levels of automation are associated with out-of-the-loop syndrome, the consequence of complacency and degradation in skill and situation awareness resulting from prolonged supervisory control of automation. Kaber and Endsley (1997) conducted a study to examine the effects of the 10 levels of automation on operator performance and situation awareness. Results from this study reveal that participants were better able to recover from automation failures when the level of automation during the task involved human interaction (i.e., lower LOA). In the space domain—where operators conduct tasks in an extreme environment with high inherent safety risk—SA is essential.

A series of supervisory control pilot automation interaction studies within glass cockpit aircraft (Sarter and Woods, 1995) exposed further the relationship between mode awareness and automation complexity. Pilots were observed during their transition from a conventional to glass cockpit. Results from the field experiment revealed that the pilot's lack of mode awareness and incomplete understanding of how the various modes interrelate was related to the complexity in the automation. Automation complexity, including simultaneous use of the system by multiple operators can increase the time to detect an anomaly and time to recover from errors. One pilot, for example, followed through correctly with a task because he was following standard procedure, not because he understood how the automation modes interacted. Another set of pilots had difficulty detecting an anomaly and/or deducing its consequences. Other pilots made changes to the automation, but failed to activate them and did not understand why their changes did not take effect. Additionally, automation complexity can incite inadvertent mode changes, which may not bring about instant visible consequences (Sarter and Woods, 1995). In order to have automation transparency, the operator must understand how the various modes interrelate, have a high situational awareness of the current system state, past states, and possible future states, and be provided with appropriate feedback of system status and transitions.

Designing for transparency is very difficult for systems that are very complex and require many displays and controls. Kieras (1996) points out two strategies used for handling complexity: distributing displays and controls across physical space, as on older "switch and meter" systems, and distributing displays and controls across time, as with newer software-based systems, using multiple modes. Information can be spread across time with different information displayed in the same space at different times, depending on context. In older electro-mechanical systems, displays and controls were fixed physical devices, and instrumentation was spread over the surfaces needed to contain it. In these systems, inadequate design led to mode errors because information was often widely and awkwardly distributed. A critical factor in the Three Mile Island events was display layout: a distributed and awkward arrangement made the state of the system hard to grasp, and so failure diagnosis was difficult (Leveson, 1995).

Transparency in automation and/or robotics interacts with functional task allocation (another contributing factor in HARI). We have already mentioned the work interrelating situation awareness and the functionality allotted to automation. Additionally, Endsley and Kiris (1995) suggest the use of an intermediate level of automation keeps the operator in-the-loop. In a study of detection of changes in system dynamics, Kessel and Wickens (1982) compared detection performance between operators controlling and monitoring system dynamics. Participants were in one of three groups: 1) transferred from manual operation to automatic, 2) transferred from automatic operation to manual, or 3) control group for automatic. Results from this study indicate that detection is slower when an operator is in an automatic mode, than in a manual control mode. Additionally, there is a positive-transfer from the manual mode to the automatic mode, which implies that is it best to train operators in a manual level of automation because they will be more perceptive of system changes once they transfer to a more automatic level of automation. Parasuraman suggests that having operators intermittently assume manual control improves failure detection (as cited by Endsley and Kaber, 1999).

Risks from poor transparency concerning mode state and mode behaviors are most dangerous during unfamiliar conditions, frequently including operation in a less safe environment. While the conditions that trigger problems may be rare in aviation, unfamiliar mode combinations and unsafe environments will occur more frequently in space. Complex automation is powerful in part because it provides multiple control policies, which can be selected based on circumstances. Yet managing different modes is a key locus of ineffective integration. Understanding design and design trade-offs in managing complex control policies is essential to effective HARI.

D. Contributing Factor 4: Human/Robotic Coordination

Coordinating human and robotic activities for future space exploration creates challenges in many areas, but particularly for Human-Robot Interaction (HRI). Most research in this field is in its infancy, as evidenced primarily by the fact that human teleoperation, supervisory control and teaming have limited operational implementations in space, military, or industry. Currently, interaction with automation and robots relevant to space exploration is achieved through teleoperations, where one or multiple operators remotely control robots. During future space teleoperations, the operators and robots will be separated by an immense distance, so much that time delay associated with communicating over those distances may negatively affect performance if operators do not calibrate to it. In addition, the level of automation within the system will vary and undoubtedly, at one point or another, the operator will be involved in supervisory control of the system, or robot(s). Supervisory control can cause degradation in situational awareness and skill, system over-reliance or complacency, mode-related errors, and ultimately mission failure. Effective HARI must take these conditions into account for designing future HRI.

NASA's experience with in-space, robotic applications are limited to the Shuttle and Station robotic arms, and an experimental flight of the Autonomous Extravehicular Activity Robotic Camera Sprint robot in 1997 (Pederson, et al, 2003), all of which are controlled by on-orbit crew via direct teleoperation. Surface exploration robots such as Sojourner, Phoenix and the Mars Exploration Rovers have been used extensively for over a decade but their operations are open-loop, where the human must send sequences of commands rather than act on fed-back information in real-time due to the long signal time delays between Earth and Mars. We will be facing increasing complexity of future robotic systems as we move from direct teleoperation to supervised teleoperation and autonomous control, with both spatial and temporal distances between operator and robotic agent. Employing human-robot teams will require a level of coordination not previously realized among teams of robotic controllers, astronauts, and mission controllers. Without overcoming the complex and varied HRI challenges facing the system designers, we are at risk of not fulfilling the roles envisioned of NASA human-robot systems.

Risk is inherent due to our lack of knowledge and experience with how best to design HRIs to meet the capabilities required of future human-robotic systems. However, there have been many lessons learned from the years of Shuttle, Station and Mars robotic operations. McCurdy (2009) describes the iterative process that evolved the tools used by the Mars robot operators to plan and execute commands. After tactical processes were implemented, they found that they were not able to support the deadlines that the tasks demanded. Planning tools were developed to meet the necessary timelines, but these too suffered inefficiencies (Norris, et al., 2005). After applying human-centered principles, several interface issues were identified. For instance, they found that a large number of tools designed by different groups for differing purposes were inconsistent and non-cohesive, leading to steep learning curves as well as performance issues. Additionally, they found that the primary timeline tool was based on outdated legacy software and developed with a different user population in mind; this led to significant effects on their ability to make or miss an uplink deadline. As a result, tool design implementations were deployed for the next Mars mission, Phoenix Mars Lander.

Optimized robotics operations are critical for the successful execution of extravehicular activities (EVA) onboard the ISS. According to data contained in the FCI ISS Life Sciences Crew Comments Database, this includes the proper set up and configuration of the onboard Robotic Workstation (RWS) and subsequent actuation and execution of arm operations. The RWS for both the Space Shuttle Remote Manipulator System and Space Station Remote Manipulator System (SSRMS) consists of a laptop computer, translational and rotational hand controllers, three video monitors and a display and control panel. Robotics workstations onboard the ISS are currently located in the US Lab, Cupola and Japanese Pressurized Module. Although the workstation can be operated by a single crewmember, in practice, crewmembers prefer that RWS activities be conducted with two crewmembers. One person acts as the primary controller, and the second crewmember is dedicated to managing camera operations, observing procedures, and confirming the direction of motion. They report that this allows them to increase their situation awareness and maintain a system of checks and balances. They have noted that the second crewmember does not necessarily have to be another on-orbit crewmember and could be a ground crew operator. However this depends on maintaining real-time communication with Mission Control, which is not always possible. The crew has cited improvements that are needed to the Remote Manipulator System controls, including more camera views and assistive overlays.

Figure 2: European Space Agency astronaut Leopold Eyharts, STS-123 mission specialist, and astronaut Greg Johnson, pilot, perform work at the robotics workstation in the U.S. laboratory, Destiny.

Figure 3: Completing an EVA activity using the robot arm with a crewmember on the end from inside the shuttle requires careful allocation of functions and task planning.

Given the already strained robotics crew resources and the large number of robotic and EVA operations expected for ISS, utilizing ground control is an attractive option for off-loading on-orbit crew workload and maximizing the efficiency of end-to-end ISS operations (Coleshill, et al., 2009). In 2005 during STS-122/ISS 10A, the planned efficiencies were finally realized: the majority of pre- and post-operation configurations for SSRMS were allocated to ground control. Adjustments had to be made to reduce the constraints on the step size of arm motions allowing greater movement distances in less time. These were originally implemented by safety personnel to reduce the duration of each maneuver, thereby limiting the number of unplanned loss of communication signals between the ground and the ISS. Task analyses determined the best allocation of operations between the on-orbit crew and the ground. This type of coordination will be critical as control of remotely located robotic agents becomes more commonplace in an environment of increasing time delay and loss of signal (LOS) events (Aziz, et al., 2010).

For Shuttle and ISS operations and in cases where the time delay allows, ground control should be used to the greatest extent possible to reduce EVA time and increase the probability of completing EVA goals. For surface operations, this could involve a robotic operator in a habitat controlling an external robot to maximize the efficiency of surface EVAs. Currently, some barriers to extensive ground control exist because mission controllers place a high level of restriction upon the type and methods of operation allowed until more experience is gained. Additionally, the robotic systems along with their human interfaces were designed for on-orbit use and are not tailored to the needs and limitations of a remote operator. At present, the range of operations is limited and while crew on-orbit workload has been reduced, the overall timelines have not (Webb, et al., 2009).

The Special Purpose Dexterous Manipulator (SPDM), or Dextre is a two-armed manipulator mounted on the SSRMS as part of the Mobile Servicing System. It is designed to perform dexterous robotic maintenance, payload servicing, and other miscellaneous tasks. Even before the system was launched in 2008, it was determined that within the accepted operations constraints, the timelines associated with its use would be excessive and beyond the crew resources that were available. A Technical Interchange Meeting was convened in 2002 to look at the prohibitively long end-to-end timelines. They are due in part to robot design, wherein one arm is required for stabilization, resulting in tasks being reduced to single-arm tasks. There is also no direct operator viewing, large numbers of procedural steps, and robotic tool manipulation is required for almost all Removal and Replacement (R&R) situations (Caron, 2004). Additionally, procedures are entirely pre-planned and approved, leaving little to no ability to respond to real-time anomalies or contingencies. This plagued a recent SPDM activity in December 2010 wherein operations had to be halted for over a day while they re-planned based on an anomaly. Several enhancements such as auto-sequencing and targeting overlays are in the early stages of development to help mitigate these issues.

Figure 4: In June 2008, Dextre was moved atop the Destiny Laboratory Module of the International Space Station (ISS), completing tasks prior to the STS-124 mission's deployment of Japan's Kibo pressurized science laboratory.

Currie and Rochlis (2004) conducted a study using the SPDM trainer to assess the feasibility of ground control operations under a time delay, a condition that will become of primary concern for robotic operation as we move beyond Low Earth Orbit exploration. Astronaut test subjects conducted an Orbital Replacement Unit (ORU) R&R activity with simulated six and eight second telemetry and video time delays (LOS conditions were not modeled in this experiment). Crew found that they could easily adapt to the delays and all subjects were able to successfully complete the activity. Interestingly, more than fifty percent of the ground control operational time was spent not on motion command inputs via the hand controllers, but on manipulating displays, cameras, and controls to gain and maintain situation awareness. This implies that performance increases are to be gained from more effective interface designs (Currie and Rochlis, 2004).

Human interface improvements such as augmented reality have also been investigated (Maida, et al., 2007). Although a human-in-the-loop command mode is available for SPDM, it is operated almost exclusively using automated sequencing from the ground, where camera views and situation awareness information is at a minimum. Their results indicate that overlays improve performance in maneuvering an ORU in preparation for inserting it into a receptacle, and three performance metrics showed statistically significant improvements in prepositioning accuracy using overlays.

Display design can be modified various ways to improve human-robot interaction. Improvement in perception allows for better understanding of the environment, improved function (Chen and Joyner, 2009; Darken and Cervik, 1999), and decrease in operator workload (Park and Woldstad, 2000; Yeh and Wickens, 2001). Operators' field of view plays a role in human-robot interaction, where optimal views are likely to be determined per tasks (Smyth, Gombash, and Burcham, 2001). Additionally, research suggests that a third-person point of view during HRI (which is referred to gravity-based orientation) improves performance (Thomas and Wickens, 2000). In addition, auditory and tactile feedback improves operator performance when task complexity increases. Prewett, Johnson, Saboe, Elliott, and Coovert (2010) propose various ways of improving operator performance, while decreasing operator workload, which include: 1) increase the frequency at which the camera produces frames to an optimal human information processing level, 2) minimize system delays, and 3) provide naturalistic displays. Pazuchanics (2006) suggests incorporating contextual information into interface features can decrease operator workload.

While robotics operations conducted onboard the Space Shuttle and ISS involve ground crews supporting and monitoring all aspects of crew robotics tasks, future spaceflight missions will involve increased crew autonomy and, correspondingly, a decrease in ground support during robotics operations. Kadous, Ka-Man Sheh and Sammut (2006) highlight that teleoperation is a vital consideration for robotics activities and interaction with robots. Successful robotic operations rely on optimized design of user interfaces. This includes the development of user interfaces that allow for varying levels of autonomy, cooperation and interaction between humans and robots (Kadous, et al., 2006).

Systematic assessment of human-robotic interfaces and the methods and metrics used to do so are still emerging. While specific, agreed upon attributes for human-robotic user interfaces do not yet exist, Kadous, Ka-Man Sheh and Sammut (2006) highlight several guidelines to consider. These guidelines are derived from previous design principles developed by Scholtz (2004). They include awareness, efficiency, familiarity and responsiveness. Awareness involves the proper presentation of information to ensure operators have a complete mental model regarding the robot's internal and external state. This necessitates creating a balance to avoid overloading the operator with too much information. Efficiency involves requiring as little operator hand and eye movement as possible and ensuring focus of attention. Familiarity involves a focus on the inclusion of intuitive information and concepts that the operator is familiar with and an avoidance of the presentation of unfamiliar information. Finally, responsiveness guarantees an operator is receiving continuous feedback regarding operations.

Keyes et al. (2010) similarly contend that overall awareness is key for the successful completion of robotics tasks. Robotic operations will often occur outside of the human operator's line of sight. This requires the human to have acute knowledge of all aspects of the working conditions and environment that the robot will be operating in as well as the state of the robot (Keyes, et al., 2010). Drury, Keyes, and Yanco (2007) define this level of human-robot awareness by five individual characteristics, namely, human-robot awareness, human-human awareness, robot-human awareness, robot-robot awareness, and the human's overall awareness of the mission (Drury, et al., 2007). Kadous, Ka-Man Sheh and Sammut (2006) contend that robot operations should embody the operator, while the operator in turn should strive to imagine themselves as the robot (creating a sense of 'presence'), or in the same environment as the robot, during operations. However, this methodology can encounter barriers such as the varying morphologies between the robot and the operator, and issues with sensing and perception. Operators may encounter problems with control and interaction if they feel they cannot relate to or sense the robot's operations. Ensuring complete situation awareness is available through the HRI is critical.

Trafton, et al. (2005) also provide guidelines for the design of human-robot interfaces. They suggest a human-to-human interaction model, which involves using interactions between people as a guide to design the planned human-robotic interactions. While there are many aspects of human-to-human interaction, a desired characteristic of human-robotic interaction is a human's ability to apply alternative viewpoints and reason from this perspective, although it may vary from their day-to- day point of view. Various forms of perspective taking can apply to a multitude of tasks and situations. Although this seems to likely be a successful guideline for human-robot interface design, recent literature and research rarely address perspective taking and robots.

Trafton, et al. (2005) conducted research to attempt to understand how perspective taking is already used or could be applied to spaceflight EVA. They observed and analyzed EVA training activities at the NASA Johnson Space Center Neutral Buoyancy Laboratory and determined that spatial-perspective taking was occurring during these activities. This involves such examples as the meaning of the word "down" having a totally different definition in a six degree-of-freedom EVA environment (where one would have to know what "down" was in relation to) as opposed to on the ground. This weightless operational environment can create specific challenges from a spatial perspective. Based on this applied analysis, three guidelines were developed to assist with understanding and designing human-robotic interactions from a human-human interaction point of view. They include: 1) ensuring that all aspects of robotic representation and cognitive-like functioning (such as reasoning and perception) are as human-like as possible, 2) building cognitive systems for the interactions based on integrated cognitive architectures, and 3) applying heuristics and principles for collaborative activities that align with human expectations. Overall, similar to human-to-human perspective taking, a robot should be able to assume and adapt to multiple perspectives while performing tasks to allow for optimized human-robotic interaction. Lastly, the researchers discuss how the issue of collaboration between humans and robots is one of the most difficult aspects to study. Their analysis attempts to answer questions such as when to collaborate, when to ask for help, and how to respond to assistance.

Human-robot teammates must orchestrate if an effective team is to be desired. To build a successful human team, team members must share a common goal, share mental models, suppress individual needs for group needs, view affinity as positive, understand and achieve their role within the team, and have trust for each other (Groom and Nass, 2007). Robots, though, do not have mental models, individual values and beliefs to guide them, or even self-motivation; robots lack the essential qualities of a successful teammate. It is difficult to establish fixed criterion for operating teams of humans and robots because each human will bring their own prior experiences and knowledge, and the allocation of tasks between humans and robots will differ from mission to mission. To mitigate these issues, Groom and Nass (2007) developed fundamental questions to be addressed in order to determine accurate operating policies for human-robot teams:

- What are the restrictions of humanness that limit performance?
- Which inabilities of humans can be successfully implemented in robots?
- What organizational structure best optimizes both human and robot abilities?
- If an organizational structure familiar to humans is ideal, do robots have the potential to fulfill the social duties of roles within that structure, and is developing those abilities worth the effort?

McIntyre, et al. (2003) have focused their research on the nature of teams, their interrelations, and how they develop team cohesion. While this research is in reference to human teams, these concepts can apply to interactions within human-robotic teams. Team cohesion can be defined by both social and task cohesion. Social cohesion involves the desire to achieve team affiliation. Task cohesion involves the efforts of the team to achieve tasks and goals together as a team (Craig and Kelly, 1999). McIntyre, et al. (2003) highlight a teamwork process model known as the "Dickinson-McIntyre model" (Tedrow 2001) which can be mapped to the development of human-robotic teams. The model details seven components of teamwork which provide a framework that leads to optimized task performance. The elements include communication, team orientation, team leadership, monitoring, feedback, backup behavior, and coordination (Tedrow, 2001).

It is also critical to evaluate the dynamics of a human-robot team to determine its effectiveness. Olsen and Goodrich (2003) believe the goal of human-robot interactions is to minimize the amount of time an operator spends manipulating a robot (robot attention demand or RAD) so that s/he has time to focus on other tasks. RAD is derived from the following equation: $RAD = IE / (IE + NT)$; where IE (interaction effort) is the amount of time required to interact with a robot and NT (neglect tolerance) is the robot's autonomy. The difficulty lies in determining IE, since interaction may be cognitive, which is not as apparent as physical manipulation (Olsen and Goodrich, 2003). Other variables that must also be considered when determining operating policies for teams of humans and robots include the human's trust in the robot, task context and complexity, number of operators and robots, interface design, and goals (other contributing factors for effective HARI).

Ferketic et al. (2006) address NASA's "Vision for Space Exploration" (VSE) initiative established in 2004 and its primary goal of establishing a human-robotic program for future exploration. Unlike previous exploration programs, VSE places specific attention on human-robotic interaction capabilities and on integration to enhance exploration, safety and mission success. While new NASA programs are still being defined (as of 2013), the emphasis on human-robotic programs remains. The design of these missions that include human and robotic agents is significantly important and complex given potential long-duration and deep space missions that will involve increased crew autonomy, limited communication and minimized dependence on ground support. Increased reliance on human-robotic interaction in future mission objectives will lead to a significant change in the philosophy for the design and execution of missions. Crews will be expected to be comfortable and familiar with robotic user interfaces, and these interfaces must optimally support mission objectives (Ferketic, et al., 2006).

Similar to many other researchers, Ferketic et al. (2006) highlight the current lack and increasing need for establishing standards to define effective human-robotic interaction and design interfaces. While human engineering and human-centered design standards can apply, specific guidelines are needed based on the unique demands of long-duration spaceflight missions and the nature of interactions and objectives related to human-robotic operations. Developing HRI standards can be extremely complex as most robots are developed with customized interfaces and methods of interaction, and the level of coordination and control required is often highly task dependent. In order to standardize these types of operations and interactions, common metrics and measures must be developed. This includes fundamental commands, operations, and interfaces that lead to expected and similar responses from the robots. This will subsequently lead to increased consistency in robotic actions, operators' familiarization and comfort with control and operation of the robots, and decreased risk of errors and mission objective failures. In an effort to develop standards for human-robotic interactions during spaceflight missions, Ferketic et al. (2006) provide their guidelines, which include:

- define the capabilities and limitations of humans and robots
- develop user interfaces suited to the tasks at hand
- address any related challenges to efficiency and operations to allow for human-robotic collaboration

- establish prototyping and evaluation methods

These guidelines will allow for the evolution of human-robotic interaction, increased safety, and successful collaborative task completion.

VI. Computer-Based Modeling and Simulation

Understanding and predicting human-system performance and identifying risks that may be inherent in a concept or a design is often achieved via computer-based modeling or simulation. The use of human performance models can result in significant lifecycle cost savings as compared to repeated human-in-the-loop evaluations, but accurately modeling the human is extremely difficult. In the Space Human Factors Engineering domain, modeling and human-in-the-loop evaluations must be used in concert. We do not have high-fidelity human performance models, and most of those existing models have not been sufficiently validated or certified. Accordingly, models must be used in a limited fashion – i.e., to help determine the critical areas that should be addressed through the more costly, but more representative human-in-the-loop evaluations.

A variety of methods exist for testing existing or prototyped HARI designs. Direct assessment by observing people using the system is valuable. However this may be impractical or excessively expensive for some complex, safety critical systems. Modeling provides a complementary assessment approach. Operations can be modeled both at the level of a task analysis and at the level of human performance. Systems can be formally checked for specified properties, such as occurrence of a particular unsafe state (Clarke and Wing, 1996). Various modeling methods from cognitive science can simulate human performance (Card, Moran, and Newell, 1983; Gray, 2008; B. E. John, Prevas, Salvucci, and Koedinger, 2004). Modeling is primarily applicable for an existing design, as evaluation, and few models provide direct design guidance. However, modeling a system as it is being developed has provided formative feedback used by designers that substantially contributes to the effectiveness of the final design (Gray, B. John, and Atwood, 1993).

Man-Machine Integration Design and Analysis System (MIDAS) Function Allocation Support Tool (FAST) Development (Sebok et al. 2012) integrated Gore's MIDAS with the Basic Operational Robotics Instructional System (BORIS), which is a robot arm simulation training environment, and developed the MIDAS-FAST to predict operator performance in different robotic system automation conditions. BORIS is the primary instructional aide in the General Robotics Training program at JSC for training general robotic arm control concepts and camera manipulations. It consists of a six-joint generic robot arm in a simulated room with a table and latches for securing payloads. The MIDAS model and BORIS simulation are connected via a middleware application and accessed through a graphical user interface. The model and simulation produce three main types of output: a dynamic representation of arm movement in the BORIS environment; a dynamic visualization of predicted operator performance, including the operator's view cone and attention shifts, workload, situation awareness, camera selections, and major actions; and data files describing operator and simulation performance. At the time of this write up, experimental Human-in-the-Loop studies are being conducted to evaluate several conditions that were modeled. Although MIDAS-FAST is being developed for NASA space applications, many aspects of the tool also apply to other industries that use robotic technology. For examples, MIDAS-FAST can be used to predict operator performance for designing complex robotic systems, such as autonomous unmanned aerial vehicles, to identify which automation features will best (and most robustly) support performance. It could also be used to evaluate existing robotic systems to proactively identify potential problems and to plan targeted training interventions as needed.

VII. Risk in Context of Exploration Mission Operational Scenarios

Future exploration-mission scenarios will increase in duration and in distance from earth. This will require developing new technology, new work methods, and new ways of ensuring that these novel elements are suitably integrated. In particular, new automation and robotic technology and new ways of using technology to accomplish mission objects are needed. Missions carried out in space will need greater flexibility and less dependence on ground support, and new interaction between ground-based resources and crew will also be needed. Risks from inadequate design of human-technology interaction will increase as mission requirements become more demanding and as missions are carried out in unfamiliar circumstances substantially different from our experience base. Human factors principles will need to be extended and applied to reduce risk.

Good design is foundational to reducing integration risks, both of safety and of failure to complete missions due to inefficiency or ineffectiveness. While poor integration design may be partially mitigated by extensive training or other workarounds, good design reduces costs, increases efficiency, and enhances safety. Most space exploration missions are carried out through human use of technology (automation/robotics). Thus, the scope of impact of the design of human-automation/robotic integration is very large. In turn, applying effective design methods and implementing effective designs can have a very large, beneficial impact on operational success. Gaining the benefits of good design also requires effective implementation and evaluation.

VIII. Gaps

Potential research gaps related to HARI include, but are not limited to:

- Improved tools and techniques for allocating functions between humans and automated/robotic systems are needed.
- Metrics and methods for evaluating automation trust are needed. Particularly, it is important to determine an appropriate level of trust for a specific system design and to detect situations where human operators under- or over-trust automated and robotic systems.
- Design requirements, guidelines, and validation methods are needed to ensure that systems supporting human-automation and human-robotic interactions will provide adequate situational awareness by human crew, including information about the state and actions of automated and robotic systems.
- Design requirements, guidelines, and validation methods are needed to ensure that human interfaces for operation and control of automated and robotic systems accommodate the unique points of view and operating environments of human and robotic agents.

A summary of all SHFE gaps can be found in the Human Research Roadmap Content Management System at http://sa.jsc.nasa.gov/hrrcms/.

IX. Conclusion

The success of future exploration missions depends, even more than today, on effective integration of humans and technology (automation and robotics). This will not emerge by chance, but by design. Both crew and ground personnel will need to do more demanding tasks in more difficult conditions, amplifying the costs of poor design and the benefits of good design. This report has presented evidence for the importance of good HARI design and the risks from poor design from several perspectives:

1. If the relevant functions needed for a mission are not identified, then designs of technology and its use by humans are unlikely to be effective: critical functions will be missing and irrelevant functions will mislead or drain attention.
2. If functions are not distributed effectively among the (multiple) participating humans and automation/robotic systems, later design choices can do little to repair this: additional unnecessary coordination work may be introduced, workload may be redistributed to

create problems, limited human attentional resources may be wasted, and the capabilities of both humans and technology underused.

3. If the design does not promote accurate understanding of the capabilities of the technology, the operators will not use the technology effectively: the system may be switched off in conditions where it would be effective, or used for tasks or in contexts where its effectiveness may be very limited.
4. If an ineffective interaction design is implemented and put into use, a wide range of problems can ensue. Many involve lack of transparency into the system: operators may be unable or find it very difficult to determine a) the current state and changes of state of the automation or robot, b) the current state and changes in state of the system being controlled or acted on, and c) what actions by human or by system had what effects.
5. If the human interfaces for operation and control of robotic agents are not designed to accommodate the unique points of view and operating environments of both the human and the robotic agent, then effective human-robot coordination cannot be achieved.

X. References

Aviation Week and Space Technology. (1995). English Translation of the French Commission of Investigation Preliminary Report on the June 30, 1994 Airbus A330 Accident, In Six parts. New York, NY: McGraw-Hill Companies.

Aziz, S. (2020). Lessons learned from the STS-120/ISS 10A robotics operations. *Acta Astronautica,* ISSN: 00945765, Vol: 66, pp. 157-165

BASI (Australian Bureau of Air Safety Investigation). (1999). Advanced Technology Aircraft Safety Survey Report. Flight Safety Digest Special Issue. BASI. Retrieved from http://www.mtc.gob.pe/portal/transportes/aereo/aeronauticacivil/alar_tool_kit/pdf/fsd_jun_aug99.pdf

Beyer, H., and Holtzblatt, K. (1997). Contextual Design: Defining Customer-Centered Systems (1st ed.). Morgan Kaufmann.

Billings, C. E. (1997). Aviation automation: The search for a human centered approach. Mahwah, NJ: Erlbaum.

Keyes, B., Micire, M., Drury, J. L. and Yanco, H. A. (2010). Improving Human-Robot Interaction through Interface Evolution, Human-Robot Interaction, Daisuke Chugo (Ed.), ISBN: 978-953-307-051-3, InTech.

Butler, K., Zhang, J., Esposito, C., Bahrami, A., Hebron, R., and Kieras, D. (2007). Work-centered design: a case study of a mixed-initiative scheduler. Proceedings of the SIGCHI conference on Human factors in computing systems (pp. 747-756). ACM.

Card, S. K., Moran, T. P., and Newell, A. (1983). The psychology of human-computer interaction. Hillsdale, N.J.: L. Erlbaum Associates.

Caron, M. (2004). *SPDM OV M: Robotics Brownbag Class* [PowerPoint slides]. < http://google.jsc.nasa.gov>

Chen, J. Y. C., and Joyner, C. (2009). Concurrent performance of gunner's and robotics operator's tasks in a multi-tasking environment. *Military Psychology*, 21, 98-113.

Clarke, E. M., and Wing, J. M. (1996). Formal methods: state of the art and future directions. ACM Computing Surveys, 28(4), 626-643. doi:10.1145/242223.242257

Cohen, M., Parasuraman, R., and Freeman, J. (1998). *Trust in decision aids: A model and its training implications*. Paper presented at the Proceedings 1998 Command and Control Research and Technology Symposium.

Coleshill, E., Oshinowo, L., Rembala, R., Bina, B., Rey, D. and Sindelar, S. (2009). Dextre: Improving maintenance operations on the International Space Station, *Acta Astronautica* 64, pp. 869–874.

Craig, T.Y. and Kelly, J. R. (1999), Group cohesiveness and creative performance. *Group Dynamics, 3(4)*, 243-256).

Cummings, M. L. (2004). Automation Bias in Intelligent *Time Critical Decision Support Systems*. Paper presented at the AIAA 3rd Intelligent Systems Conference, Chicago.

Cummings, M. L., and Bruni, S. (2009). Collaborative Human Computer Decision Making. In S. Nof (Ed.), Springer Handbook of Automation (pp. 437-447). New York, NY: Springer.

Currie, N. and Rochlis, J. (2004). *Command and Telemetry Latency Effects on Operator Performance during International Space Station Robotics Operations* (Johnson Space Center, Document ID: 20040084079). NASA Technical Reports Server http://ntrs.nasa.gov/search.jsp.)

Curtis, B. (Ed.). (1981). Tutorial: Human Factors in Software Development. New York, NY: IEEE Computer Society Press.

Darken, R. P., and Cervik, H. (1999). *Map usage in virtual environments: Orientation issues*. Paper presented at the Proceedings of IEEE Conference on Virtual Reality.

de Vries, P., Midden, C., and Bouwhuis, D. (2003). The effects of errors on system trust, self-confidence, and the allocation of control in route planning. *International Journal of Human-Computer Studies,* 58, 719-753.

de Winter, J., and Dodou, D. (2011). Why the Fitts list has persisted throughout the history of function allocation. *Cognition, Technology and Work*, 1-11.

Degani, A. (2004). Taming Hal: designing interfaces beyond 2001. New York, N.Y.: Palgrave Macmillan. Retrieved from http://www.loc.gov/catdir/bios/hol053/2003054934.html http://www.loc.gov/catdir/description/hol041/2003054934.html http://www.loc.gov/catdir/toc/hol041/2003054934.html

Di Nocera, F., Lorenz, B., and Parasuraman, R. (2005). Consequences of shifting from one level of automation to another: main effects and their stability. In D. d. Waard, K. A. Brookhuis, R. v. Egmond and T. Boersema (Eds.), *Human Factors in Design, Safety, and Management* (pp. 363-376). Maastricht, the Netherlands: Shaker Publishing.

Department of Defense. (2005). Department of Defense human factors analysis and classification system, a mishap investigation and data analysis tool.Washington, D.C.

Drury, J., Keyes, B. and Yanco, H. (2007). LASSOing HRI: analyzing situation awareness in mapcentric and video-centric interfaces. In *Proceedings of the ACM SIGCHI/SIGART Conference on Human-Robot Interaction*, pages 279–286.

Ellis, S. R. (2000). Collision in Space. Ergonomics in Design: The Quarterly of Human Factors Applications, 8(1), 4-9.

Encounter with Wake Turbulence, Air Canada, Airbus A319-114 C-GBHZ (Aviation Investigation Report No. A08W0007). (2008). Washington State, United States: Transportation Safety Board of Canada.

Endsley, M. R. (1995). Toward a Theory of Situation Awareness in Dynamic Systems. *Human Factors*, 37(1), 32 - 64.

Endsley, M. R., and Kaber, D. B. (1999). Level of automation effects of performance, situation awareness and workload in a dynamic control task. Ergonomics, 42(3), 462-492.

Endsley, M. R., and Kiris, E. O. (1995). The out-of-the-loop performance problem and level of control in automation. *Human Factors,* 37(2), 381-394.

Fan, T., Hyams, D., and Kuchar, J. K. (1998). Preliminary study of in-flight replanning performed on the flight deck: National Center of Execllence in Aviation Operations Research (NEXTOR).

Ferketic, J., Goldblatt, L., Hodgson, E., Murray, S., Wichowski, R., Bradley, A., Fong, T., Evans, J., Chun, W., Stiles, R., Goodrich, M.A., Steinfeld, A., King, D., Erkorkmaz, C. (2006). *Proceedings of AIAA Space 2006: Toward Human-Robot Interface Standards II: A Closer Examination of Common Elements in Human-Robot Interactions across the Space Enterprise,* San Jose, CA.

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

Glover, S. M., Prawitt, D. F., and Spilker, B. C. (1997). The influence of decision aids on user behavior: Implications for knowledge acquisition and inappropriate reliance. *Organizational Behavior and Human Decision Processes,* 72(2), 232 - 255.

Gray. (2008). Cognitive modeling for cognitive engineering. In R. Sun (Ed.), The Cambridge handbook of computational psychology. New York: Cambridge University Press. Retrieved from http://www.rpi.edu/~grayw/pubs/papers/2008/OUP-chptr/gray-070829.pdf

Gray, W., John, B., and Atwood, M. (1993). Project Ernestine: Validating a GOMS analysis for predicting and explaining real-world task performance. Human Computer Interaction, 8(3), 237-309.

Groom, V., and Nass, C. (2007). Can robots be teammates?: Benchmarks in human–robot teams. *Interaction Studies*, 8(3), 483-500.

Hollnagel, E., Woods, D., and Leveson, N. (Eds.). (2006). Resilience engineering : concepts and precepts. Aldershot England; Burlington VT: Ashgate.

Human Health and Performance Risks of Space Exploration Missions: Evidence Reviewed by the NASA Human Research Program (No. SP-2009-3405). (2009). . Houston, TX: NASA Johnson Space Center. Retrieved from http://humanresearch.jsc.nasa.gov/files/HRP_EvidenceBook_SSP-2009-3405.pdf

John, B. E., Prevas, K., Salvucci, D. D., and Koedinger, K. (2004). Predictive human performance modeling made easy 10.1145/985692.985750. Proceedings of the SIGCHI conference on Human factors in computing systems (pp. 455-462). Vienna, Austria: ACM.

Kaber, D. B., and Endsley, M. R. (1997). Out-of-the-loop performance problems and the use of intermediate levels of automation for improved control system functioning and safety. *Process Safety Progress*, 16(3), 126-131.

Kadous, M. W., Ka-Man Sheh, R., and Sammut, C. (2006). Proceedings of the 1st ACM SIGCHI/SIGART Conference on Human-Robot Interaction: *Effective User Interface Design for Rescue Robotics*, Salt Lake City, UT

Kessel, C. J., and Wickens, C. D. (1982). The transfer of failure-detection skills between monitoring and controlling dynamic systems. *Human Factors,* 24(1), 49-60.

Keyes, B., Micire, M., Drury, J. L. and Yanco, H. A. (2010). Improving Human-Robot Interaction through Interface Evolution, *Human-Robot Interaction,* Daisuke Chugo (Ed.), ISBN: 978-953-307-051-3, InTech.

Kieras, D. (1996). A Guide to GOMS Model Usability Evaluation using NGOMSL. Retrieved April 1, 2003. from University of Michigan. Electrical Engineering and Computer Science Department FTP site: ftp://www. eecs. umich. edu/people/kieras/GOMS/NGOMSL_Guide. pdf.

Kirlik, A. (1993). Modeling strategic behavior in human-automation interaction: Why an“ aid” can (and should) go unused. Human Factors: The Journal of the Human Factors and Ergonomics Society, 35(2), 221-242.

Kirwan, B., and Ainsworth, L. K. (1992). A Guide to task analysis. London ; Washington, DC: Taylor and Francis.

Lee, J., and Moray, N. (1994). Trust, self-confidence, and operator's adaptation to automation. *International Journal of Human-Computer Studies*, 40(153 - 184).

Lee, J. D., and See, K. A. (2004). Trust in computer technology: Designing for appropriate reliance. Human Factors, 46, 50-80.

Lee, J. D., and Seppelt, B. D. (2009). Human factors in automation design. In S. Nof (Ed.), Springer Handbook of Automation. New York, NY: Springer.

Leveson, N. (1995). SafeWare : system safety and computers. Reading, Mass.: Addison-Wesley.

Lorenz, B., Di Nocera, F., Röttger, S., and Parasuraman, R. (2002). Automated fault- management during simulated space flight. *Aviation, Space, and Environmental Medicine, 73*, 886-897.

Maes, P. (1994). Agents that reduce work and information overload. *Communications of the ACM, 37*(7), 30-40.

McBridge, M., and Morgan, S. (2010). *Trust calibration for automated decision aids* (Online): Institute for Homeland Security Solutions.

McGuirl, J. M., and Sarter, N. B. (2006). Supporting trust calibration and the effective use of decision aids by presenting dynamic system confidence information. *Human Factors, 48*(4), 656–665.

Mosier, K., and Skitka, L. J. (1996). Human decision makers and automated decision aids: Made for each other? In R. Parasuraman and M. Mouloua (Eds.), *Automation and Human Performance: Theory and Applications* (pp. 201-220). Hillsdale, NJ: Erlbaum.

Mosier, K., Skitka, L. J., Heers, S., and Burdick, M. D. (1998). Automation bias: decision making and performance in high-tech cockpits. *International Journal of Aviation Psychology, 8*(1), 47 - 63.

Maida, J. C., Bowen, C. K., and Pace, J. (2007). Improving robotic operator performance using augmented reality. In *Proc. 51st Annu. Meeting Human Factors Ergonom. Soc.*, Baltimore, MD, pp. 1635–1639.

McCurdy, M. (2009). Planning Tools for Mars Surface Operations: Human-Computer Interactions Lessons Learned. IEEE ACM.

McIntyre, R.M., Strobel, K., Hanner, H., Cunningham, A., and Tedrow, L. (2003). *Toward an understanding of team performance and team cohesion over time through the lens of time series analysis*. United States Army Research Institute for the Behavioral and Social Sciences.)

Mellor, P. (1994). CAD: computer-aided disaster. High Integr. Syst., 1(2), 101-156.

Murray, C., and Cox, C. B. (1990). Apollo: Race to the Moon. Touchstone Books.

Nikolaidis, S., and Shah, J. (2012). *Human-Robot Interactive Planning using Cross-Training: A Human Team Training Approach*. Paper presented at the AIAA Infotech@Aerospace.

Norris, J., Powell, M., Vona, M., Backes, P., and Wick. J. (2005). "Mars Exploration Rover Operations with the Science Activity Planner." In *Proceedings of the IEEE Conference on Robotics and Automation,* Barcelona, Spain, April 2005.

Nunes, A. (2003). *The impact of automation use on the mental model: findings from the air traffic control domain*. Paper presented at the Proceedings of the Human Factors and Ergonomics Society 47th Annual Meeting.

Oleson, K. E., Billings, D. R., Kocsis, V., Chen, J. Y. C., and Hancock, P. A. (2011). *Antecedents of trust in human-robot collaborations*. Paper presented at the Proceedings of the IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support.

Olsen, J., D.R., and Goodrich, M. A. (2003). *Metrics for Evaluating Human-Robot Interactions*. Paper presented at the PERMIS.

Opperman, R. (1994). *Adaptive user support*. Hillsdale, NJ: Erlbaum.

Oser, R. L. (1999). *Using automation to support decision making: challenges and training research requirement*. Paper presented at the Proceedings of the Human Factors and Ergonomics Scoiety 47th Annual Meeting.

Parasuraman, R., and Sheridan, T. B. (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.

Park, S. H., and Woldstad, J. C. (2000). Multiple two-dimensional displays as an alternative to three-dimensional displays in telerobotic tasks. *Human Factors, 42*(4), 592–603.

Pazuchanics, S. L. (2006). *The effects of camera perspective and field of view on performance in teleoperated navigation*. Paper presented at the Proceedings of the Human Factors and Ergonomics Society's 50th Annual Meeting.

Pea, R. D. (1993). Practices of distributed intelligence and designs for education. In G. Salomon (Ed.), *Distributed Cognitions: Psychological and Educational Considerations* (pp. 47-87). Cambridge, UK: Cambridge University Press.

Pederson, L. Kortencamp, D., Wettergreen, D. and Nourbakhsh, I. (2003). "A survey of space robotics," in *7th International Symposium on Artificial Intelligence, Robotics, and Automation in Space*, Munich, Germany.

Prewett, M. S., Johnson, R. C., Saboe, K. N., Elliott, L. R., and Coovert, M. D. (2010). Managing workload in human-robot interaction: a review of empirical studies. *Computers in Human Behavior, 26*(10), 840-856.

Riley, V. (1989). *A general model of mixed-initiative human-machine systems*. Paper presented at the Proceedings of the Human Factors and Ergonomics Society 33rd Annual Meeting. Sarsfield, L., Stanley, W., Lebow, C., Ettedgui, E., and Henning. (2000). Safety in the Skies: Personnel and Parties in NTSB Accident Investigations: Master Volume (?Rand? Corporation Report No. MR-1122/1-ICJ). The Institute for Civil Justice.

Salomon, G. (1993). No distribution without individuals' cognition: a dynamic interactional view. In G. Salomon (Ed.), *Distributed Cognitions: Psychological and Educational Considerations* (pp. 111-138). Cambridge, UK: Cambridge University Press.

Sarter, N. B. (1996). Cockpit automation: From quantity to quality, from individual pilot to multiple agents. In R. Parasuraman and M. Mouloua (Eds.), *Automation and Human Performance* (pp. 267-280). Mahwah, NJ: Erlbaum.

Sarter, N., and Woods, D. (1994). Pilot Interaction With Cockpit Automation II: An Experimental Study of Pilots' Model and Awareness of the Flight Management System. The International Journal of Aviation Psychology, 4(1), 1-28. doi:10.1207/s15327108ijap0401_1

Sarter, N. B., and Woods, D. D. (1995). How in the world did we ever get into that mode? Mode error and awareness in supervisory control. *Human Factors, 37*(1), 5-19.

Sarter, N., and Woods, D. (2000). Team Play with a Powerful and Independent Agent: A Full-Mission Simulation Study. Human Factors, 42(3), 390-402.

Sarter, N., Woods, D., Billings, C., and Salvendy, G. (1997). Automation surprises. Handbook of human factors and ergonomics (2nd ed., pp. 1926-1943). New York: Wiley.

Scholtz, J. (2004). Human-Robot Interaction. Presented at the *RoboCup Rescue Camp*, October-November, Rome, 2004.

Sebok, A., Wickens, C., Gacy, A., Brehon, M., Scott-Nash, S., Sarter, N., et al. (2012). MIDAS-FAST: A modeling and simulation-based tool to predict operator performance in human-robotic automation systems. Paper presented at the 4th International Conference on Applied Human Factors and Ergonomics (AHFE).

Shappell, S.A., and Wiegmann, D.A. (2000)"The Human Factors Analysis and Classification System – HFACS", Report DOT/FAA/AM-00/7, February 2000. (http://www.nifc.gov/fireInfo/fireInfo_documents/humanfactors_classAnly.pdf).

Shayler DJ. (2000) Lunar module checkout-mode error. In: Mason J (Ed.), *Disasters and accidents in manned spaceflight*. Springer-Praxis, Chichester, U.K., pp. 216–220

Sheridan, T. B., and Parasuraman, R. (2005). Human-automation interaction. Reviews of Human Factors and Ergonomics, 1(41), 89-129.

Sheridan, T. B., and Verplank, W. L. (1978). Human and Computer Control of Undersea Teleoperators (No. ADA057655). MASSACHUSETTS INST OF TECH CAMBRIDGE MAN-MACHINE SYSTEMS LAB. Retrieved from http://handle.dtic.mil/100.2/ADA057655

Sherry, L., and Ward, J. (Eds.). (1995). Formalism for the specification of operationally embedded reactive systems. Proceedings AIAA/IEEE Digital Avionics Systems Conference (DASC). Cambridge, MA.

Singer, S. M., and Akin, D. L. (2009). Role Definition and Task Allocation for a Cooperative EVA and Robotic Team. Proceedings of the 39th International Conference on Environmental Systems. Savannah, Georgia.

Skitka, L. J., Mosier, K., and Burdick, M. D. (1999). Does automation bias decision-making? *International Journal of Human-Computer Studies*, 51, 991 - 1006.

Smyth, C. C., Gombash, J. W., and Burcham, P. M. (2001). *Indirect vision driving with fixed flat panel displays for near-unity, wide, and extended fields of camera view* (Technical Report): Army Research Laboratory, Aberdeen Proving Ground, MD.

Sogame, H., and Ladkin, P. (1996). Aircraft accident investigation report 96-5. Japan: Ministry of Transport. Retrieved from http://sunnyday.mit.edu/accidents/nag-4-7.html

Strauch, B. (1997). *Automation and decision making -- lessons from the Cali accident*. Paper presented at the Proceedings of the Human Factors and Ergonomics 41st Annual Meeting.

Tedrow, L. B. (2001). The Effects of Training in Teamwork Skills on Intact Student Teams. Unpublished master's thesis, Old Dominion University, Norfolk, VA.)

Terwiesch, P. G., and Ganz, C. (2009). Trends in Automation. In S. Nof (Ed.), Springer Handbook of Automation (pp. 127-143). Berlin: Springer-Verlag.

Federal Aviation Administration Human Factors Team. (1996). The Interfaces between Flight crews and Modern Flight Deck Systems. (1996). . Federal Aviation Administration. Retrieved from http://www.faa.gov/aircraft/air_cert/design_approvals/csta/publications/media/fltcrews_fltdeck.pdf

Thomas, L. C., and Wickens, C. D. (2000). *Effects of display frames of reference on spatial judgments and change direction* (Technical Report): Army Research Laboratory, Aberdeen Proving Ground, MD.

Trafton, G.J., Cassimatis, N. L., Bugajska, M.D., Brock, D.P, Derek P., Mintz, F. E. and Schultz, A. C. (2005). *Enabling Effective Human–Robot Interaction Using Perspective-Taking in Robots.* 35(4), 460-470.

Vicente, K. J. (1999). Cognitive work analysis : toward safe, productive, and healthy computer-based work. Mahwah, N.J.: Lawrence Erlbaum Associates. Retrieved from http://www.loc.gov/catdir/enhancements/fy0740/98031670-d.html

Visser, E. J., LeGoullon, M., Freedy, A., Freedy, E., Weltman, G., and Parasuraman, R. (2008). *Designing an adaptive automation system for human supervision of unmanned vehicles: a bridge from theory to practice*. Paper presented at the Proceedings of the Human Factors and Ergonomics Society 52nd Annual Meeting.

Webb, S. Whitley, J., Winters, A. (2009). *Generic Ground Rules and Relevant Information: End to End Maintenance Scenario Development* [PowerPoint slides]. <http://google.jsc.nasa.gov>

Wickens, C. D. (1992). Process control and automation. In C. D. Wickens (Ed.), *Engineering Psychology and Human Performance* (2nd ed., pp. 504-551). New York, NY: Harper Collins.

Wickens, C. D., and Dixon, S. (2007). The benefits of imperfect diagnostic automation: A synthesis of the literature. Theoretical Issues in Ergonomics Science, 8, 201-212.

Wickens, C. D., Rice, S., Keller, D., Hutchins, S., Hughes, J., and Clayton, K. (2009). False alerts in the air traffic control traffic conflict alerting system: Is there a cry wolf effect? Human Factors, 51(4), 446-462.

Woods, D., Dekker, S., Cook, R., Johannesen, L., and Sarter, N. (2010). Behind Human Error (2nd ed.). Ashgate Publishing.

Yeh, M., and Wickens, C. D. (2001). Display signaling in augmented reality: Effects of cue reliability and image realism on attention allocation and trust calibration. *Human Factors,* 43(3), 355–365.

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XII. List of Acronyms

BASI	Bureau of Air Safety Investigation (Australia)
BORIS	Basic Operational Robotics Instructional System
EVA	Extravehicular Activities
FAA	Federal Aviation Administration
FCI	Flight Crew Integration
HARI	Human Automation/Robotic Interaction
HCI	Risk of Inadequate Human-Computer Interaction
HRI	Human Robot Interaction
HRP	Human Research Program
IE	interaction effort
ISS	International Space Station
LOA	Levels of Automation
LOS	Loss of Signal
MIDAS	Man-Machine Integration Design and Analysis System
MIDAS-FAST	Man-Machine Integration Design and Analysis System Function Allocation Support Tool
NASA	National Aeronautics and Space Administration
NT	neglect tolerance
ORU	Orbital Replacement Unit
R&R	Removal and Replacement
RAD	robot attention demand
RWS	Robotic Workstation
SA	Situational Awareness
SHFE	Space Human Factors Engineering
SPDM	Special Purpose Dextrous Manipulator
SSRMS	Space Station Remote Manipulator System
TASK	Risk of Inadequate Critical Task Design
TRAIN	Risk of Performance Errors Due to Training Deficiencies
VSE	Vision for Space Exploration