NASA/TM-2006-214504

Adaptive and Adaptable Automation Design: A Critical Review of the Literature and Recommendations for Future Research

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September 2006

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Abstract

This report presents a review of literature on approaches to adaptive and adaptable task/function allocation and adaptive interface technologies for effective human management of complex systems that are likely to be issues for the Next Generation Air Transportation System, and a focus of research under the Aviation Safety Program, Integrated Intelligent Flight Deck Project. Contemporary literature retrieved from an online database search is summarized and integrated. The major topics include the effects of delegation-type, adaptable automation on human performance, workload and situation awareness, the effectiveness of various automation invocation philosophies and strategies to function allocation in adaptive systems, and the role of user modeling in adaptive interface design and the performance implications of adaptive interface technology.

The main finding of the review is that adaptable system designs requiring human delegation of task and function authority to automation during performance may pose an additional workload on operators leading to degradations in situation awareness and performance, as compared to adaptive automation. In adaptively automated systems, dynamic task/function allocations are typically managed by a computer based on real-time monitoring of operator workload states and decision making regarding the allocation of system control is not an additional responsibility for operators. It is also revealed that approaches to adaptable system design may only be effective for addressing finite operating states of systems and that such automation may only produce performance comparable to manual control under variable environmental conditions. Beyond this, the findings on adaptive interfaces for implementing adaptive automation include the need for consideration of multiple user characteristics, preferences and behaviors in the design process. It is also observed that adaptive interface feature/components must be linked to specific task requirements to promote performance and that it is necessary to maintain some consistency in interface design across modes of system operation to allow operators to effectively apply mental models.

In general, the findings of this review motivate further exploration of adaptively automated systems for managing complex system operator workload states and attempting to promote situation awareness, as compared to design of adaptable system alternatives. This includes: (1) exploration of types and levels of adaptive automation that are easiest for operators to work with in different task contexts, (2) development of more integrated and robust approaches to operator state monitoring, (3) development of highly accurate methods for operator state classification and computer triggering of adaptive task/function allocations, and (4) development of on-line methods for assessing adaptive automation effectiveness for operator workload management and maintenance of situation awareness.

1. Introduction

1.1. Defining Automation

Automation refers to "...systems or methods in which many of the processes of production are automatically performed or controlled by autonomous machines or electronic devices" (Parsons, 1985). Automation is a tool, or resource, that the human operator can use to help perform some task that would be difficult or impossible without machine aiding (Billings, 1997). Therefore, automation can be thought of as a process of substituting the activity of some device or machine for some human activity, fully or partially; or it can be thought of as a state of technological development. Automation does not have to be an “all or none” option, but can take forms varying in the type and level of aiding provided to operators, as shown in Tables 1 and 2.

Table 1. Sheridan’s (1987) Levels of Human-Automation Interaction.

1. The computer offers no assistance; the human must do it all
2. The computer offers a complete set of action alternatives
3. The computer narrows the selection down to a few
4. The computer suggests a selection, and
5. Executes that 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 the human, or
8. Informs the human after execution only if he asks, or
9. Informs the human after execution if it, the computer, decides to
10. The computer decides everything and acts autonomously, ignoring the human

Table 2. Endsley and Kaber’s (1999) Levels of Automation Taxonomy.

	ROLES			
LEVEL OF AUTOMATION	MONITORING	GENERATING	SELECTING	IMPLEMENTING
1. Manual Control	Human	Human	Human	Human
2. Action Support	Human/Computer	Human	Human	Human/Computer
3. Batch Processing	Human/Computer	Human	Human	Computer
4. Shared Control	Human/Computer	Human/Computer	Human	Human/Computer
5. Decision Support	Human/Computer	Human/Computer	Human	Computer
6. Blended Decision Making	Human/Computer	Human/Computer	Human/Computer	Computer
7. Rigid System	Human/Computer	Computer	Human	Computer
8. Automated Decision Making	Human/Computer	Human/Computer	Computer	Computer
9. Supervisory Control	Human/Computer	Computer	Computer	Computer
10. Full Automation	Computer	Computer	Computer	Computer

Many researchers have questioned whether automation should be viewed as a substitution of one agent for another; that is, whether machines designed by humans can or should be the ideal replacement for humans. This is the idea of "apparent simplicity, real complexity" advocated by some involved in human-automation research (e.g., Woods, 1996). Nevertheless, because many tasks performed by humans can be decomposed superficially into a myriad of task components, humans have sought to define what the human and machine can respectively do best. Such an approach to function allocation dates back to the "Fitts' List" concept of the 1950s. However, as technology has advanced, the capability of machines to emulate human functions, sometimes inappropriately, has enabled engineers and systems designers to effectively automate most, if not potentially all, human functions.

Today, the presence of automation has pervaded almost every aspect of modern lives. From the wheel to the modern jet aircraft, humans have sought to improve the quality of life. We have built machines and systems that not only make work easier, more efficient, and safe, but also give us more leisure time. The advent of automation has further enabled us to achieve this end. With automation, machines can now perform many of the activities that we once had to do. Our automobile transmission will shift gears for us. Our airplanes will fly themselves. All we have to do is turn the machine "on" and "off". It has been suggested that one day there may not even be a need for humans to do so "through" the proverbial switch.

1.2. The "New" Problems of Automation

> "During the 1970s and early 1980s...the concept of automating as much as possible was considered appropriate. The expected benefit was a reduction in pilot workload and increased safety...Although many of these benefits have been realized, serious questions have arisen and incidents/accidents that have occurred which question the underlying assumptions that a maximum available automation is always appropriate or that we understand how to design automated systems so that they are fully compatible with the capabilities and limitations of the humans in the system."
>
> -- Air Transport Association of America (ATA), 1989

The real question is not "…whether one or another function can be automated, but, rather, whether it should be" (Wiener & Curry, 1980, p.2). "Although aviation has become a remarkably safe way to move people and goods, preventable accidents continue to occur. To an increasing extent, these accidents involve both human operators and their machines, because the humans and machines have become more *interdependent*…. Automation is now a central element in that system. It has been extremely successful in improving the reliability and productivity of the system. Like all technology, its successes have brought with them new problems to solve" (Billings, 1997, p. 297).

Automation is "...a wrapped package -- a package that consists of many different dimensions bundled together as a hardware/software system. When new automated systems are introduced into a field of practice, change is precipitated along multiple dimensions" (Woods, 1996). As a consequence, automation increases the burdens and complexities for those responsible for operating, troubleshooting, and managing systems resulting in "new" problems, including:

1. adding to or changing the nature of the task, such as device setup and initialization, configuration control, and operating sequences;
2. changing and/or adding cognitive demands;
3. changing the roles of people in the system, often relegating people to supervisory controllers who watch over the automation potentially leading to "out-of-the-loop" performance issues;

4. increasing coupling and integration among parts of a system often resulting in data overload and lack of "transparency" leaving operators to wonder "what is it [the automation] doing now?"; and
5. lack of appreciation of the impact of automation on humans by those who advocate for the use of the technology.

These issues are not singular to aviation alone. Research has shown that these new problems have had significant effects on human operators, who work in a variety of high technology environments, which include effects of reduced job satisfaction (e.g., automation may dehumanize human roles), lowered vigilance, fault-intolerant systems, silent failures, an increase in cognitive workload, automation-induced failures, over-reliance, complacency, decreased trust, manual skill erosion, false alarms, and a decrease in mode awareness (e.g., Parasurman, Molloy & Singh, 1993a; Shiff, 1983; Sarter & Woods, 1995). These are in addition to numerous fatal accidents, directly attributable to poor human-automation interaction, which serve as testimony to the need for new approaches to human-automation design. Two very promising approaches are adaptable and adaptive automation systems.

1.3. Overview of Memorandum

This report presents a review of literature on approaches to adaptive and adaptable function allocation, and adaptive interface technologies, for effective human management of complex systems that are likely to be issues for the Next Generation Air Transportation System, and a focus of research under the Aviation Safety Program, Integrated Intelligent Flight Deck Project.. Adaptive automation has been defined as the dynamic allocation of complex system control to a human or computer controller, based on system-state variables, with the objective of optimizing performance, reducing operator workload and promoting situation awareness (Rouse, 1977; Parasuraman, 1987; Scerbo, 1996; Kaber & Riley, 1999). In adaptive systems, the overall degree of autonomy or the number of functions operating under automation can be modified in real time (Scerbo, 1996) in order to best address workload demands. In adaptive systems, authority over function allocations typically remains with the computer, which mandates the role of the operator. However, it is possible that the human operator and a computer may share authority in invoking automation of specific functions. Adaptable systems differ from adaptive systems in that the automation invocation authority remains with the human operator. The human is responsible for initiating changes between modes of automation and may also have control over system interface settings (Bailey, Scerbo, Freeman, Mikulka & Scott, in press). Prior research (Scerbo, 1996) has suggested that there may be performance differences among adaptive and adaptable systems and some recent work has made direct comparison of human functioning with adaptive versus adaptable systems (Bailey et al., in press).

The objective of this review was to detail the state of research on the design and implementation of adaptive and adaptable automation systems. This included identifying effective approaches for promoting operator performance with complex systems and managing workload, making general recommendations on adaptive automation and adaptive interface design, and projecting future research needs in the area. A literature search was conducted on research on human performance with adaptable systems, adaptive task and function allocation in automated systems, and the design of adaptive interface technologies for delivering adaptive automation. The search involved use of an on-line reference database, and reviews of references used in prior technical reports on adaptive automation research were also completed. The online research database includes all articles published in registered archival journals dating back to 1945. The review summarizes the advantages and disadvantages of adaptable and adaptive automation for complex systems control and identifies benefits and limitations of approaches to adaptive interface design for providing users with access to adaptive automation.

2. Adaptable Systems

Scerbo (1996) formally defined adaptable automation and empirical work on truly adaptable systems (versus adaptive automation involving some human invocation authority over dynamic function allocations) has only recently appeared in the literature (e.g., Bailey et al., in press; Miller, 2003; Parasuraman, Galster, Squire, Furukawa & Miller, 2005; Squire, Trafton & Parasuraman, 2006). These studies have yielded mixed results on the potential utility of adaptable systems for promoting performance and managing operator workload, as compared to adaptive automation, high-level static automation and manual control.

Bailey et al. (in press) investigated performance, situation awareness and workload effects of an adaptive system in which dynamic function allocations were based on operator workload states measured using an EEG-based index of engagement with an adaptable system in which control allocations were invoked by operators without suggestions from a computer. They used a modified version of the multi-attribute (flight) task battery (MAT-B) that included additional simulated aircraft gauges, which served as a basis for situation awareness assessment. In one experiment, the authors found no significant effect of the adaptive automation condition on task performance, as compared to a condition in which dynamic function allocations occurred at random. However, in a second experiment, they found the adaptable system condition (i.e., subjects could invoke automation or manual control, at will) to worse performance than the arbitrary automation condition in resource management task performance. They also found a significant reduction in workload for subjects exposed to arbitrary automation versus adaptable automation. When subjects were not responsible for managing dynamic control allocations, their ratings of subjective workload were lower. Unfortunately, there was no comparison of the adaptive or adaptable system results with completely manual or fully automated control conditions. However, Bailey et al. did compare the results of their first and second experiments and they found that the adaptive condition yielded lower subjective ratings or workload than the adaptable system. The authors attributed this to the requirement for subjects to manage control allocations as part of the adaptable condition.

Miller and Parasuraman (2003) presented a new approach to flexible automation for complex systems to extend beyond the historical taxonomies of levels of automation (e.g., Sheridan and Verplank, 1987) and use of stages of human information processing as a basis for defining types and levels of automation (Parasuraman, Sheridan & Wickens, 2000). They said that automation could be applied to every subtask to be addressed by a system as part of larger parent tasks. They argued for fine-grained models of tasks that could be shared between human operators and automation in adaptable systems. They introduced an approach to adaptable automation called the “playbook” approach involving operator selection of predefined automation behaviors to respond to changing environmental and task demands. The human operator is required to delegate tasks to the automation. Miller and Parasuraman (2003) presented an example application of the playbook approach to unmanned aerial vehicle (UAV) mission planning to illustrate how specific control subtasks could utilize different combinations of human and automation control. However, the study did not present any empirical results.

On the basis of the research by Miller and Parasuraman (2003), Parasuraman, Galster, Squire, Furukawa & Miller (2005) conducted an empirical study of adaptable automation (involving use of the playbook approach) for human supervision of multiple robots in team performance of a flag capture task against an opponent robot team. In three experiments, they made comparison of human use of an interface for delegating tasks to the robots with manual control or with a combination of delegation automation and manual control. Other independent variables manipulated in the study included the number of robots being controlled and the postures of the opposing robot team (defensive, offensive or variable). In the first experiment, the playbook approach to automation allowed for some response to variable opponent robot behavior, but performance was never as good as when adaptable automation was applied to fixed opponent behaviors (defense, offense). Beyond this, contrary to the authors' hypothesis, there was no evidence that the playbook approach led to differences in perceived workload when subjects were posed with variable or fixed opponent behavior. Interestingly, the authors noted that operators tended to revert to manual control under high workload circumstances in order to deal with variable opponent robot behavior versus relying on automation to implement predefined robot behaviors. In their second experiment, Parasuraman et al. (2005) made comparison of completely manual control, fixed automation and flexible automation (the playbook approach). Surprisingly, the mode of control did not affect robot mission success rate and the flexible automation approach was no different from manual control in terms of task time. The fixed automation produced the worse performance, suggesting a "clumsy" implementation (Riley & Parasuraman, 1997). Most importantly, and related to the results of Bailey et al. (in press), the flexible automation produced the highest workload ratings and situation awareness was better for the manual control condition. The authors attributed decrements in operator situation awareness when using the playbook automation to increased workload. In their third experiment, Parasuraman et al. manipulated the degree of task automation available to operators and the number of robots being controlled. The forms of automation ranged from manual mode, to playbook automation, to a playbook approach with high-level behaviors (e.g., sending robots on the offensive). They found that use of automated control with fewer robots led to workload reductions compared to manual control. However, there was no affect of the automation on operator situation awareness compared to manual control. In general, manual control of multiple robots appeared to be no worse than the flexible automation in terms of workload and performance. Even though there was no conclusive evidence of workload reductions attributable to the flexible automation, the authors concluded by saying that automation was needed for high workload conditions in multiple robot control, but for novel task circumstances, manual control may be necessary.

In another study, Squire, Parasuraman and Trafton (2006) used the same task, the same forms of automation and automation interfaces, as Parasuraman et al. (2005), in order to assess the performance costs of operator task switching in the robot flag capture. They made comparison of performance involving manual control of multiple robots with adaptable automation, specifically the playbook approach, involving computer control of low- or high-level robot functions. They found that manual control generally produced shorter task times than static automation, again suggesting a "clumsy" implementation of the automation (cf., Riley & Parasuraman, 1997), and the flexible/adaptable automation was no better than manual control. One advantage of the flexible automation they observed was that there were significantly fewer interface actions required of operators when they performed the task following a single strategy (e.g., offensive robot behavior), as compared to manual control and static automation. However, when operators were required to switch strategies/tasks during the robot flag capture, manual control produced the shortest task times followed by adaptable automation and then static automation. In general, the adaptable automation appeared to be no better than manual performance and only superior to "clumsy" static automation. Unfortunately, the authors did not record workload ratings, as a basis for further comparison of the adaptable (delegation-type) automation with manual control and the work of Parasuraman et al. (2005).

2.1. Summary on Adaptable Systems Research

On the basis of Bailey et al. (in press) research, it appears that adaptable systems may actually produce worse performance results than arbitrary automation of tasks in real-time. Adaptable automation may also lead to higher workload than adaptive automation, which yields performance no worse than arbitrary automation and better that adaptable automation. These are not promising observations for use of adaptable automation in complex task performance, like aircraft piloting, air traffic control, or human control of multiple robotic systems. With respect to the latter application, Parasuraman et al. (2005) work generally showed that adaptable systems, using a playbook-type approach to automation, appear to be suited to rule-based task performance under which task circumstances are known and predefined behaviors can be applied. When task circumstances are dynamic and workload is high, operators tend to revert to the use of manual control (versus adaptable automation) in exhibiting knowledge-based behaviors. Related to Bailey et al. (in press) findings, Parasuraman et al (2005) found that adaptable automation performance may not be better than manual control and use of the playbook approach may lead to higher workload and worse situation awareness than manual control. (The authors' interpretations of results were more liberal than this.) In addition, in one experiment by Parasuraman et al (2005), human manual control of multiple complex systems (simultaneously) appeared to be no worse than adaptable automation in terms of workload and performance, and it actually improved operator SA. This study provides evidence that human delegation of task automation (adaptable automation) may impose additional workload on operators potentially degrading SA; however, this was not one of the conclusions of Parasuraman et al. (2005). Finally, with respect to Squire et al. (2006) research, adaptable automation does not appear to improve performance over manual control, but it may reduce the number of interface actions for operators. This may translate into workload reductions, but no evidence was provided of such an effect. When operators are required to use multiple strategies in controlling complex systems and to switch between tasks, adaptable automation does not appear to provide a significant benefit over manual control, but it may offer some advantage relative to static, technology-centered automation.

3. Adaptive Systems

Human factors research on adaptive automation began in the early 1990s with a number of seminal works by Parasuraman and colleagues (e.g., Parasuraman, 1993; Parasuraman, Bahri, Deaton, Morrison & Barnes, 1992; Parasuraman, Mouloua, Molloy & Hilburn, 1993). The first studies to use the terminology adaptive task allocation and adaptive function allocation appeared shortly after this (e.g., Rencken & Durrant-Whyte, 1993; Scallen, Hancock & Duley, 1995). In complex systems, high-level functions may include, for example, information analysis and decision making. Such functions may encompass multiple tasks to be addressed by an operator in system control (e.g., monitoring subsystem states, tracking a defined navigation path with a vehicle). Opposite to this, complex system tasks may involve multiple low-level functions. For example, a tracking task may involve the functions of compensatory tracking along a vertical axis or a horizontal axis. Research on adaptive automation has addressed both high- and low-level function allocation as well as adaptive task allocation.

Many different approaches to adaptive task and function allocation have been developed. Early work investigated performance and workload implications of switching "on" or "off" automation of specific types of tasks based on predefined schedules or models of human and computer control in multiple task scenarios (Parasuraman, 1993). Similar studies assessed performance-based approaches to adaptive automation in which computer assistance was provided to operators in, for example, monitoring tasks if their performance fell below a specified criterion (e.g., Parasuraman, Mouloua and Molloy, 1996). Other work has investigated workload-based approaches in which automation of tasks or functions occurs on the basis of operator workload states measured using secondary-task performance (Kaber & Riley, 1999) or physiological indicators of cognitive load and arousal (e.g., Prinzel, Freeman, Scerbo, Mikulka & Pope, 2000 (electro-encephalogram signals (EEG)); Wilson & Russell, 2003 (electro-cardiogram signals (ECG), electro-oculography (EOG), and respiration intervals)). Beyond this, other work has suggested that adaptive function allocation should occur on the basis of critical system states requiring human or automated handling of specific functions (see Scerbo (1996) for a thorough review of approaches).

Adaptive automation can be applied to many different types of tasks and functions in complex systems in order to moderate operator workload yet maintain sufficient levels of task engagement for achieving situation awareness. Historical research has used the MAT-B to assess the affects of adaptive automation on human monitoring and tracking task performance (e.g., Parasuraman et al., 1996; Hilburn et al., 1993), as compared to completely manual or fully automated performance. This research concentrated on potential benefits of adaptive automation for psychomotor task/function performance. Only in more recent work has the potential impact of adaptive automation on cognitive task workload and performance been assessed. Hilburn, Jorna, Byrne and Parasuraman (1997) conducted a study on adaptive automation in the context of air traffic control. They examined whether decision-aiding automation could be used to reduce operator workload and optimize overall system performance. Experienced air traffic controllers were required to perform an airport arrival traffic simulation with or without the assistance of the automation. An automated Descent Advisor tool was simulated, which calculated aircraft trajectories, dynamically developed flight plans, detected planning conflicts, or projected separation conflicts. The tool offered the human operator advice to resolve conflicts. Hilburn et al. (1997) used three automation schemes including constant manual control, constant automation and the adaptive automation condition (under which the automation was invoked only during high traffic to simulate workload relief). They found that the adaptive automation condition resulted in the smallest increase in mental workload across trials. This research provided support for the use of automation and/or adaptive automation in cognitive (decision-making) tasks. However, the authors did not make comparison of adaptive automation of psychomotor tasks as part of air traffic control with adaptive automation of decision functions in order to determine the relative effectiveness of automating various information processing functions.

Even more recently, Kaber, Wright, Prinzel and Clamann (2005) conducted a study to determine whether there are differential performance and workload effects of adaptive automation applied to various aspects of human information processing in a simulated air traffic control task. They investigated types of automation similar to those defined by Parasuraman et al. (2000), including information acquisition, information analysis, decision making and action implementation, adaptively applied to tasks performed in terminal radar approach control. Kaber et al. (2005) implemented adaptive automation using a workload-based approach in which automation of a single aspect of information processing occurred when operator performance in a secondary task fell below a specified criterion (i.e., the air traffic control workload increased substantially). They found that humans are generally better able to adapt to adaptive automation when applied to lower-order sensory and psychomotor functions, such as information acquisition and action implementation, as compared to adaptive automation applied to cognitive (planning and decision making) tasks. Like the prior investigations of adaptive automation of psychomotor functions, they also observed that any adaptive automation of information processing produced better performance than no automation whatsoever. With respect to operator workload, reductions also primarily occurred when adaptive automation was applied to psychomotor functions, including information acquisition and action implementation, in the air traffic control task. Adaptive automation of information analysis and decision making functions appeared to not only degrade performance under automated periods but it increased objective workload (measured with a secondary task) as well.

The findings of the research by Hilburn et al. (1997) and Kaber et al. (2006) demonstrate benefits of adaptive automation, including model- and workload-based approaches, for supporting human performance of psychomotor and cognitive functions in complex systems control compared to manual control and static automation. There is also substantial evidence demonstrating workload reductions attributable to adaptive automation, as compared to manual control and static automation. These findings differ substantially from the contemporary results on adaptable systems.

3.1. Automation Invocation Authority in Adaptive Systems

As mentioned earlier, adaptively automated systems typically assign automation invocation authority to computers; however, some experimental setups have investigated forms of shared authority involving human and computer management of function allocations. Investigations of automation invocation authority in adaptive systems also began around the early 1990s (e.g., Hilburn, Molloy, Wong & Parasuraman, 1993) and several studies have followed (e.g., Scerbo, 1996; Bubb-Lewis & Scerbo, 1997; Clamann & Kaber, 2003). Hilburn, Molloy, Wong and Parasuraman (1993) evaluated human versus computer managed allocation of functions in the context of the MAT-B with the possibility of applying automation to the monitoring and tracking tasks of the simulation in real-time. They found that performance in the tracking subtask of the MAT-B was significantly better when the computer determined manual and automated control allocations. In general, adaptive automation was found to produce better monitoring performance than purely manual monitoring. Hilburn et al. (1993) stated that performance degradations under adaptive automation observed during the experiment were due to operators frequently cycling between full automation and manual control (at will) and that excessively short automation cycles (2 min or less) compounded this effect. These results are in-line with the contemporary findings on adaptable automation reviewed above. When humans are required to manage function allocations at the same time they perform mission-related tasks, this may lead to workload increases and performance degradations.

Kaber and Riley (1999) used a workload-based approach to adaptive automation to investigate the affects of computer mandated versus human elected function allocations on performance and workload in a radar-monitoring task. They used observations on secondary task performance (simple gauge monitoring) as a basis for mandating or suggesting to operators control allocations in aspects of the radar monitoring. Adaptive automation involving shifts between manual control and partial automation (a shared decision making mode) of the primary task were mandated for one group of operators and merely suggested for another. Kaber & Riley (1999) found significantly improved manual, primary task performance and enhanced secondary-task monitoring under automation for the mandated-adaptive automation group, with the opposite results occurring for non-mandated adaptive automation subjects. The average subject workload marginally exceeded an objectively established criterion by using the secondary task measure to direct adaptive automation of the primary task. This work demonstrated that adaptive automation could be used to effectively manage operator primary task workload within a defined range. It also provides additional evidence that computer decisions of whether and when automation should be invoked for certain system functions produces superior performance to requiring human operators to perform function delegation. This is consistent with other historical research (Scerbo, 1996) demonstrating that humans might not be the best judges of dynamic function allocations.

In a more recent investigation, Clamann and Kaber (2003) assessed the performance and workload effects of applying adaptive automation to different stages of human-machine system information processing, including information acquisition, information analysis, decision making and action implementation, and facilitating dynamic function allocations through two levels of computer authority. The research was to provide insight into any interaction between these aspects of adaptive automation design. They hypothesized that adaptive automation of the higher-order information processing functions, including information analysis and decision making, would be more compatible with computer mandated allocations, while adaptive automation of lower-order functions, such as information acquisition and action implementation, would be more effective with partial human control (computer suggestion and human veto) of function allocations. Clamann and Kaber's (2003) results demonstrated the effectiveness of adaptive automation to be dependent upon both the type of automation and the type of invocation authority designed into the system. Like the findings of Kaber et al. (2006), performance with adaptive automation of information acquisition was superior to performance under decision automation. However, contrary to the results of Kaber and Riley (1999), when using automated assistance, human invocation authority produced superior performance to computer mandates. The authors noted that subjects tended to remain under the automated control mode, which provided some advantage over manual control. Related to this, Clamann and Kaber (2003) observed that such control behavior might ultimately undermine any benefit of adaptive automation for operator situation awareness over the long run. In general, the results of this study suggested that a "blended" form of authority, involving humans invoking automation and computer mandates of returns to manual control as part of adaptive automation, may improve the potential for performance and workload benefits in complex systems.

The findings of the studies on automation invocation authority in adaptive systems generally support the use of computer mandated function allocation over human delegation of tasks to a computer. Like the adaptable systems research, the main observation is that human responsibility for decisions on dynamic function allocations may contribute to workload and cause task performance problems. There is some data supporting the implementation of shared human and computer authority over function allocations depending upon the current mode of system control, but such findings may be highly system dependent. Beyond this, the scenario of a human operator invoking automation, only for a computer to subsequently mandate manual control may not be a form of blended invocation authority acceptable to operators in real-world systems.

3.2. Adaptive Task Allocation Research

The literature search revealed only six studies in the online research search database using the terminology adaptive task allocation to describe approaches to the design and implementation of adaptive automation in complex systems. Early work in this area studied the use of model- and performance-based approaches to adaptive task allocation and focused on supporting psychomotor task performance. In the majority of studies, entire system subtasks are allocated to either a human operator or automation and the degree of task responsibility is not defined at a lower, functional level. Parasuraman et al. (1996) examined the effect of such approaches to adaptive task allocation on human monitoring performance using the MAT-B during long duration tests. They required manual performance of the tracking and fuel management tasks and developed an automated engine status task. Under the adaptive automation strategies, manual control of the engine status task was periodically allocated based on when monitoring performance was expected to be at its worst (model-based adaptive automation) or if individual monitoring performance in previous automated periods did not meet criterion levels (performance-based adaptive automation). Automation failure detection was compared across the adaptive automation conditions and a static automation condition. In general, their results revealed that both adaptive automation approaches enhanced monitoring performance over static automation during long duration tests.

Even prior to the work by Parasuraman et al. (1996), Rencken and Durrant-Whyte (1993) developed an approach to adaptive task allocation in a complex system involving the use of an adaptive human-computer interface for a security area surveillance task. They developed a quantitative model of human task performance in identifying and classifying targets to facilitate adaptive task allocation between the operator and a computer serving as a backup decision maker when workload was high or the operator was unable to perform a task. Like Parasuraman et al. (1996), they used a performance-based approach to the adaptive task allocation by continually monitoring human and computer errors rates during task performance. The model of human performance developed by Rencken and Durrant-Whyte (1993) was used to estimate changes in operator ability to address target classifications in real-time. It was also capable of predicting future human and computer performance levels and recommending appropriate task allocations. The model was programmed to make a task allocation prediction every time a new target arrived in the physical area under surveillance. The computer then decided what new targets the human was capable of classifying, given the current task load (i.e., the computer managed the task allocations). If the computer determined that operator workload was already too high (based on the human performance model), then automation was activated to aid the operator in the new tasks. The system developed by Rencken and Durrant-Whyte (1993) functioned in a closed-loop manner in which an explicit task allocation between the human and computer was initially determined by the computer, tasks were assigned, and performance was measured in real-time and used as a basis for establishing future allocations. With respect to the adaptive interface, the computer display was broken-down into modules (a graphical image of the room under surveillance, system messaging, system activation controls, target labeling controls, display parameter controls) to present different tasks and the behavior of each module was defined separately based on operator workload assessments. The study demonstrated that the use of the adaptive interface for task allocation was an effective approach to addressing operator workload and ability to perform surveillance tasks in a desired manner. The adaptive interface was implemented in an actual surveillance system and compared with manual or unaided human target classification under low and high event rates. Human performance and overall system performance were enhanced by the interface aid. The system prevented operators from becoming overwhelmed with targets and significantly reduced the mean target service time.

There have been a number of more advanced approaches to adaptive task allocation in complex systems presented in the literature, including using physiological variables as a basis for decisions about whether and when automation should be invoked. In very recent research, Berka, Levendowski, Cvetinovic, Petrovic, Davis, Lumicao, Zivkovic, Popovic and Olmstead (2004) assessed the utility of real-time monitoring of operator cognitive states, alertness and memory states using EEG signals as a basis for intelligent allocation of tasks between humans and autonomous agents in a complex system. They used a warship commander task simulation (a navy command and control simulation) involving multiple, simultaneous subtasks requiring the use of various cognitive resources. Subjects were exposed to multiple levels of workload in a cognitive task as part of the simulation. They demonstrated that EEG indices could be reliably associated with varying levels of cognitive workload and the indexed responses changed as a function of subject training and learning and memory requirements as part of task performance. The authors said the systems showed good promise for adaptively augmenting cognition in military environments.

Prior to the work by Berka et al. (2004), Pope, Bogart & Bartolome (1995) developed a closed loop system to evaluate human-automation interface design, based upon a criterion of mental engagement derived from EEG activity. They argued that optimal adaptive task allocation between a human and automation is achieved when closed-loop system control is stable, reflecting stable mental engagement of the operator. The purpose of this study was to evaluate the usefulness of several different candidate EEG indices for reflecting mental engagement. Six subjects performed the MAT-B. The monitoring, communication, and resource-management tasks of the battery remained under automated control throughout all trials. The tracking task was performed by the subject when in manual mode and monitored by the subject when in automated mode. EEG activity was measured at seven scalp sites and total EEG power was computed over three frequency bands at each site. Each trial consisted of time spent under ‘negative’ feedback and time spent under ‘positive’ feedback conditions. Under negative feedback, the tracking task was switched to (or remained under) manual control when the engagement index was decreasing. Under positive feedback, the tracking task was switched to (or remained under) automated control when the engagement index decreased. Each trial was 16 minutes long, with alternating 4-minute blocks of positive and negative feedback. Each candidate EEG/mental engagement index was judged on the basis of its strength in producing the expected feedback control system phenomena; that is, stable operation under negative feedback and unstable operation under positive feedback. The authors determined that of all the indices examined, beta/(alpha + theta) reflected task engagement best and was most sensitive to changes in task demand. They concluded that their approach represented a dynamic, interactive method of adjusting a system design to optimize operator engagement. It is important to note here that the automation cycle times observed in this study were even shorter than those observed or examined in other adaptive automation research (Hilburn et al., 1993; Scallen et al., 1995) around the same period of time. Pope et al. (1995) stated that no condition combination (e.g., manual mode and negative feedback) was operative for a continuous interval of more than a few seconds, and they defined their run durations for examining EEG activity as the number of 2-second epochs for which the tracking task remained in one mode, either manual or automated.

Although Pope et al. (1995) results showed promise for designing adaptive automation around EEG measures, there remained a need for research to demonstrate the utility of physiological-based adaptive aiding for managing complex system operator workload and performance. Prinzel, Freeman, Scerbo, Mikulka and Pope (2000) sought to replicate and expand the experiment conducted by Pope et al. (1995). They developed a closed-loop system to examine the utility of physiological indicators of cognitive states as a basis for driving adaptive task allocation between human operators and automation in a complex system and to determine whether such an approach could regulate operator performance and workload. They developed a system in which an original EEG-based index of operator arousal was used as a basis for determining whether and when automation should be applied to tasks as part of the MAT-B to assist operators and moderate workload. Subjects were required to perform either a single task or multiple tasks as part of the flight simulation. In the setup by Prinzel et al. (2000), a computer system made task allocation decisions based on operator engagement, as indicated by the EEG signal, following either a negative or positive feedback control strategy. The study demonstrated that it is possible to manage operator workload within a range through a closed-loop system driven by an operator's own EEG. The authors also found the approach to adaptive task allocation to significantly impact operator perceived workload measured using the NASA Task Load Index. Participants found the multiple task condition with adaptive aiding to be more taxing than the single task condition.

In a related study, Prinzel, Pope & Freeman (2002) examined the efficacy of psychophysiological self-regulation during performance of adaptively automated tasks by assigning groups to either a self-regulation condition, false feedback condition, or control condition. Six subjects were assigned to each test condition and participants performed the monitoring, resource management and compensatory tracking tasks of the MAT-B. Only the tracking task was adaptively automated, and it was done so using an EEG engagement index similar to those investigated by Pope et al. (1995) and Prinzel et al. (2000). Return-to-manual-control performance was assessed on the tracking task 3 seconds after a change was made in the tracking task mode, and was found to be poorer for subjects in the control and false feedback conditions, as compared to subjects in the self-regulation group, who were provided with biofeedback regarding their task engagement level. These subjects could use this biofeedback information as a type of "cue" to better prepare for and respond to automation state changes compared to those subjects receiving no feedback or irrelevant information. These results provide some evidence that advance cueing of automation state changes may serve to reduce adaptive automation-induced performance deficits. Further, subjects in the self-regulation condition were better able to maintain their task engagement level within a narrow range, thereby reducing the need for many task mode changes. The effect of this was an increase in task performance as well as a decrease in reported workload.

Finally, related to the historical research on automation invocation authority in adaptive systems, some recent research has provided insight into the effectiveness of computer management of task allocation in distributed systems. Galstyan & Lerman (2005) developed an approach to the distribution of tasks across multiple autonomous agents/robots as part of a single system in order to address environmental demands and to promote performance. Such robot systems may operate under human supervisory control, as in Parasuraman et al. (2005) research, or they may function autonomously. Galstyan and Lerman (2005) designed a computer algorithm to choose among multiple tasks to be performed by multiple robots. The robots were then to function collaboratively to achieve the mission of the system. The computer decision making regarding the task allocation was based on sensing of local environmental circumstances. The results on computer authority over the automation invocation showed improvements in individual robot performance and collective robot behavior. The authors said their approach could be used as an algorithm or model for adaptive task allocation across multiple autonomous agents. Such models may also apply to integrated human-robot systems in which the human acts as another agent working with the robots.

3.2.1. Summary of Adaptive Task Allocation Research

Early work in this area provided strong evidence of the potential benefits of adaptive automation for supporting human psychomotor performance, even when using simple automation invocation approaches based on task workload models or operator performance histories (e.g., Parasuraman et al., 1996). Rencken and Durrant-Whyte's (1993) research effectively integrated a performance-based approach to adaptive task allocation with an adaptive interface technology to accommodate human ability to perform complex control system tasks and to moderate operator workload. They showed that a model of human performance combined with a computer algorithm for managing dynamic task allocations was useful for reducing human error rates and improving overall system performance. This was one of the first adaptive task allocation and adaptive interface design investigations.

More advanced approaches to adaptive task allocation have been explored in the recent literature. The study by Pope et al. (1995) was critical in the history of adaptive automation research because it demonstrated the potential for EEG signals to be used in indices of operator task engagement and to serve as a basis for dynamic task allocations to a human operator and computer. The research by Prinzel et al. (2000) was important because it was one of the first studies to reveal the effectiveness of a biocybernetic closed-loop system for facilitating adaptive task allocation to regulate workload and promote performance. Berka et al. (2004) study also demonstrated that EEG signals may be a useful basis for assessing operator cognitive states in real-time in order to drive adaptive task allocations in complex automated systems and manage levels of operator engagement. Berka et al. (2004) demonstrated that it is possible to use EEG indices for regulating human workload in complex system control under multitasking conditions. The findings of the Prinzel et al. (2000) study were extended by the Prinzel et al. (2002), who revealed that complex system operators could effectively use biofeedback for self-regulation of task engagement states and to better prepare for system control mode changes, as compared to groups receiving no feedback. In general, the physiological self-regulation work that has been conducted demonstrates how adaptive automation can be used as a practical approach for managing operator workload states. Self-regulation approaches may also prevent problems with fast-cycle automation (frequent switching among control modes), as observed by Hilburn et al. (1993), and address performance loses due to the need for human invocation authority in some systems and increased workload.

Contemporary work in this area by Galstyan and Lerman (2005) has demonstrated that it is possible to adaptively allocate tasks across multiple autonomous agents in a complex system in order to achieve higher levels of group behavior. Related to Prinzel et al. (2000) study, Galstyan and Lerman's (2005) computer algorithm or model for managing task allocation proved to be highly effective for performance. Such algorithms for multi-agent task allocation may be useful for adaptively prescribing tasks in integrated human-robot systems.

In general, the adaptive task allocation research shows that several approaches to automation invocation philosophy and strategies to task allocation are effective for promoting complex, automated system performance and for regulating operator workload. The work also lends support to the design of adaptive systems in which a computer makes decisions about task allocations over adaptable systems in which the human operator is taxed with managing function allocations, in addition to performing mission-related tasks.

3.3. Adaptive Function Allocation Research

Of the relevant studies identified through the literature search, only two (Scallen & Hancock, 2001; Scallen et al., 1995) used the terminology adaptive function allocation in referring to the implementation of adaptive automation in complex systems. Adaptive function allocation research has primarily examined the performance effects of distribution of low-level system functions, such as controlling one or more dimensions of a tracking task, between humans and computers. The studies by Scallen and colleagues have specifically focused on determining how pilot performance and workload can be improved through dynamic allocation of aircraft functions or tasks based on real-time monitoring of behavior. On a more general level, they have sought to assess the efficacy of adaptive automation for multitasking situations in the aviation domain.

In the study by Scallen et al. (1995), they used a low-fidelity aviation simulation to examine pilot responses to rapid cycling automation applied to a flight path tracking task while aircraft systems monitoring and fuel management tasks were performed manually in all trials. The adaptive automation in this research was implemented using a model-based approach with manual and automated control of the tracking task cycling every 15, 30 or 60s. Contrary to the findings of Hilburn et al. (1993), Scallen et al. (1995) initially observed significant improvements in tracking task performance with automation cycles every 15s as compared to every 60s in the piloting tasks. Performance in the secondary tasks under manual control (monitoring and fuel management) was unaffected by the adaptive automation of the tracking task. It is important to reiterate that the dynamic function allocations in this study followed a predetermined time schedule. The dynamic function allocations in Hilburn et al. (1993) study were truly adaptive in nature and based on operator performance levels. In an additional analysis of manual tracking performance immediately following the 15s of automation, Scallen et al. (1995) found a different pattern of results indicating task performance to be highly sensitive to difficulty manipulations. They concluded that excessively short cycles of automation in multitasking situations could prove disruptive to overall performance.

Hadley, Prinzel, Freeman and Mikulka (1999) conducted a study to further investigate the affects of short cycle automation on operator performance and workload in complex systems control. In general, they found that reversions to manual control after short periods of automation had a negative effect on subsequent performance and appropriate cognitive resource allocation to tasks. They said there might be greater manual performance problems associated with shorter cycle automation. They observed that participants found it more difficult to reorient to, and sustain, manual control of a compensatory tracking task as the duration of a preceding automated control period decreased. (A P300 evoked response potential was significantly smaller for shorter-cycles indicating reduced perception of the mode transition and new information processing needs.) There was also a significant increase in workload for shorter cycle automation. However, this study and the research of Scallen et al. (1995) only addressed the problem of return-to-manual performance problems for automation applied to psychomotor functions as part of complex systems control and not cognitive functions.

In general, the studies of adaptive automation examining the influence of automation cycle time on operator performance have revealed longer periods of automated control, offset with manual control, to better support performance, as compared to short cycle automation. Long duration automation cycles also appear to facilitate workload reductions.

In more contemporary research, Scallen & Hancock (2001) sought to provide additional information on the effects of adaptive function allocation on pilot performance and workload by manipulating the approach to automation invocation in tasks and the underlying function allocation strategy. In the STARFIRE flight simulation, automation of the tracking task occurred at the time of critical events (surface targets appearing) and on the basis of operator performance, and the automation was applied to either both dimensions of 2-D tracking or one dimension (vertical or horizontal). Pilots were also required to manually perform aircraft systems monitoring and fuel management in all trials. The adaptive automation conditions evaluated in the experiment all appeared to be effective for sustaining tracking performance compared to manual control, even under high workload. Furthermore, adaptive automation of the tracking task appeared to benefit secondary monitoring and fuel management task performance. Interestingly, the effect of the semi-automated tracking task allocations was equivalent to the fully automated allocation; therefore, a complete shift in tracking control from human to automation was not necessary to achieve performance benefits. However, Scallen and Hancock (2001) did note increased variability in pilot performance with partial automation of the tracking task, as compared to the other conditions. The authors suggested that pilots could be retained in the control loop by using a part-task allocation strategy to maintain high performance in the cockpit, without compromising manual skill over the long term. The authors also advocated the use of adaptive automation for a wide range of pilot functions, such as task prioritization, mission segmenting, task initiation and cessation, risk identification, and workload management.

This research was important because it demonstrated that adaptive automation could be effectively applied to specific low-level functions of a task versus automating an entire task in order to achieve performance benefits. It is possible that adaptive automation of low-level functions (instead of tasks) may provide greater flexibility for managing operator workload states and, at the same time, support the achievement of situation awareness.

4. Adaptive Interface Technology

Of the search terminology used for this review, adaptive interface(s) generated the largest number of references, approximately 42; however, only 16 of the studies proved to have relevance to the design of adaptive automation for complex systems. Furthermore, some of the studies considered relevant to this research were found to target desktop computing applications versus complex interfaces used to control machine systems in dynamic real-world environments.

The terminology adaptive automation has historically been used to refer to dynamic allocation of control between human and computer servers in real-world systems, based on predefined function allocation schemes and various system-state variables. The adaptation of automation implies changes in machine behavior, including functional responses to operator commands and the type of feedback provided by a system to the user. It also implies changes in the task responsibility of operators ranging from monitoring to control action implementation. Adaptive automation may be considered in the development of software design when changes in application states amount to more than simple transitions from one interface display configuration to another and include activation or deactivation of specific software subroutines for handling data input from users, facilitating information processing, and presenting output.

Adaptive interface technologies may be used to support, or provide access to, adaptive automation programmed in software applications. Different instances of a display interface and controls may allow users to exploit specific software functions available under different modes of automation. In this way, the adaptive interface technology is critical for presenting and promoting the effectiveness of the adaptive automation, as in the early research by Rencken and Durrant-Whyte (1993). However, in some cases, the design of an adaptive interface does not necessarily imply adaptation of underlying system functionality to user needs.

Research on adaptive interface technologies for supporting human-machine system performance appeared in the engineering literature as early as the 1980s (e.g., Innocent, 1982; Mason & Thomas, 1984; Hancock & Chignell, 1988), slightly more than five years after the development of the personal computer. These studies focused on developing self-adapting interfaces for man-machine systems, mental workload responses associated with the use of adaptive interface technology, and potential applications of adaptive interfaces in information systems. Additional studies occurred in the 1990s and focused on developing new approaches to interface design for software applications to create intelligent and adaptive technologies (Sukaviriya, 1993). The basis for these technologies was to create descriptive user models by observing task behaviors with applications. The models were integrated with interface adaptation strategies specifying detailed changes in interface features. One of the main challenges identified through this research was the need to relate specific instances of a user interface to certain user states. Sukaviriya

(1993) worked to identify high-level links between aspects of user tasks and the activation of interface components/features (e.g., how to sequence dialogs, how to generate help information).

4.1. User Modeling as a Basis for Adaptive Interface Design

Several subsequent studies (Debevc, Meyer, Donlagic & Svecko, 1996; Gong & Salvendy, 1995; Arai, Fukuda, Yamamoto, Naito & Matsui, 1996; Yoshida & Motoda, 1996) identified the need to consider user needs for specific applications, individual differences in the ability to use software, personal differences and preferences, and individual behaviors in designing user-adapted interfaces. Therefore, one major thrust of this research area has focused on individual user modeling as basis for implementation of adaptive interfaces. Debevc et al. (1996) explored how to adjust computer display features and software use procedures to support individual patterns of work. They assessed adaptive icon toolbars that allowed for addition or removal of icons in real-time (controlling function access) based on a model of user usage history and task needs, for supporting desktop computing tasks. An important aspect of this technology was that users had to agree to or veto adaptive interface features as they became available during task performance. The authors observed that in the use of the adaptive toolbar there was a need for certain aspects of the overall software interface to remain consistent to allow users to apply a general model of the system for performance. The adaptive interface was found to effectively support user performance.

Gong and Salvendy's (1995) research was similar in that they developed adaptive menu and command interfaces that could be modified based on changing levels of user skill due to task learning. They conducted an experiment with subjects revealing performance to be significantly improved with the adaptive interface versus static menus or command interfaces. Interestingly, there was no impact of the adaptive interface technology on perceived memory load or satisfaction ratings relative to the conventional, static interfaces.

Arai et al. (1996) took a more complex approach to adaptive interface design considering the interactive relationship between a user and computer and how each adapts to the other. Factors they considered in modeling this interaction included characteristics of the task, the state of the user (individual characteristics, skill level and behaviors), and physical/environment conditions. They developed an adaptive virtual reality (VR) simulation interface that changed states based on user performance of the VR game and galvanic skin response, as an indicator of arousal level. They presented results demonstrating that the VR interface adaptation accommodated different user states for performance improvements over a static interface.

Yoshida and Motoda (1996) conducted a study with a premise similar to that of the Debevc et al. (1996) work. They emphasized the need for elaborate user models for adaptive interface development. The main problem identified by Yoshida and Motoda (1996) was that prior research had created models largely based on activity/command sequences and behaviors at interfaces. They said that such an approach was inadequate for predicting user behavior under different task circumstances. They presented an approach to user modeling that not only considered command sequences but also the aspects of cognition activated as part of the sequences in order to create more elaborate models. They used a simple desktop computing application (the ClipBoard) to present an adaptive interface and to demonstrate the adequacy of their model for predicting user performance and as a basis for adaptive interface design.

In the last study on adaptive interfaces (identified by the literature search) to occur in the 1990s, Miller (1999) discussed the limitations of existing approaches to adaptive interface design and recommended a new method to ensure the "fit" of interfaces to operator information demands. He said that prior work had offered simple approaches based on pattern matching rules associating a few instances of an interface with a limited set of parameter settings defining user needs. His approach was to formally identify information requirements of user tasks and to associate these requirements with the capability of different interface features for conveying information. The interface design approach was demonstrated through prototyping of an adaptive interface for military attack helicopters.

4.2. Performance with Adaptive Interfaces and Extensions of User Models

With the new century, several investigations were conducted to assess the utility of adaptive interfaces for supporting human performance in complex systems control, including adaptive displays and controls for Air Force pilot performance (e.g., Haas, Nelson, Reppberger, Bolia & Zacharias, 2001; Bennett, Cress, Hettinger, Stautberg & Haas, 2001). In the Bennett et al. (2001) study, the authors initially presented theoretical background on dynamic adaptive interfaces (DAIs) (interfaces involving changes in both displays and control of a system in real-time) and they compared them to forms of automation and decision aiding. They said that the goal of such interfaces is to anticipate the needs of an operator and to provide necessary information without requiring explicit control actions. This is different from the adaptive interface design approach presented by Debevc et al. (1996) for desktop computing applications where users were required to accept or veto changes in an adaptive interface in real-time. Bennett et al. (2001) laid-out a conceptual framework for design and evaluation of DAIs to explore specific design issues. They said that if adaptive interfaces are designed poorly, they have the potential to increase workload and degrade human performance. They identified different types of information that could serve as bases for triggering adaptive automation/interface changes for decision support in aviation tasks, including variability in the task environment (significant events), data on the human operator states (real-time assessments of workload and performance), and on-line assessment of operator activities (the tasks being performed and operator intent). They used a low-fidelity (F-16) flight navigation simulation to test experienced pilots in a waypoint following task in short trials. They developed and tested three types of interfaces including: a standard interface with basic throttle and joystick controls and a standard heads-up display (HUD); a candidate interface with a force-reflecting joystick and configural HUD; and an adaptive interface incorporating aspects of both of the former conditions (dynamically). Under the adaptive condition, pilots could alternate between use of the standard and candidate interfaces. Bennett et al. (2001) also manipulated workload through simulated turbulence conditions. They observed subject performance measures, including aircraft position relative to the pre-planned flight path, and they used deviation from the path as a basis for adaptation of the interface content. They found the workload manipulation to significantly effect performance and the candidate and adaptive interfaces to improve performance quality relative to the standard condition. However, they did not find the adaptation capability of the interface to promote performance beyond that achievable with the candidate interface alone. Furthermore, subjects generally found the adaptive interface to produce higher workload.

Other research at this same time returned to the need to make elaborate consideration of user characteristics in developing adaptive interface technologies (Duvallet, Boukachour & Cardon, 2000) and some studies also focused on Air Force applications (Hudlicka & McNeese, 2002). The research by Duvallet et al. (2000) was focused on developing adaptive interfaces for information systems to support decision making. They said that for an interface to be adapted to individuals, many characteristics need to be considered, including ways of perceiving information, patterns of interface behavior, and how environmental factors affect behavior. Duvallet et al. (2000) said there remains a need for user models to take into account these factors for adaptive interface design. This line of thinking is very similar to the elaborate user modeling approaches advocated by Arai et al. (1996) and Yoshida and Motoda (1996). Duvallet et al. (2000) also said that with respect to implementing adaptive interface technologies, addition or subtraction of components/features should occur without making the overall design of the interface uncertain for operators. This notion is similar to the observation by Debevc et al. (1996) that there is a need to maintain some consistent features in an adaptive interface from one mode to another in order to allow users to apply a general system model for performance.

Similar to the Bennett et al. (2001) research, Hudlicka and McNeese (2002) presented a framework for adaptive interface design incorporating different user factors, including emotional states and active beliefs. They provided an approach for assessing user states, including knowledge elicitation, self-reports of stress states, performance on diagnostic tasks and physiological sensing, and relating states to user interface adaptation strategies varying based on content and format. They said that the implementation of adaptive interfaces to accommodate user needs involves sensing and inferring states and beliefs about a system, identifying the potential impact of user states on system performance, selecting an adaptation strategy for the user state, and implementing the strategy through specific interface features. In general, the approach takes into account user emotional states and the knowledge requirements of a task for interface adaptation. Hudlicka and McNeese (2002) also demonstrated the use of their framework for prototyping an interface for use in an Air Force combat task simulation. The interface was able to adapt to different pilot anxiety levels in the simulation and belief states by modifying specific cockpit instrument displays in response to detected pilot state changes.

In the most recent research on adaptive interface technology, studies have focused on design for Internet-based tasks (Ji & Salvendy, 2002; Narayanan, Koppaka, Edala, Loritz & Daley, 2004). Narayanan et al. (2004) were concerned with developing approaches to define how displays and available controls in an interface could be automatically adjusted to the current goals and abilities of a user by assessing (in real-time) user status, the system task, and working context. This work is similar to the historical approach to adaptive interface design advocated by Duvallet et al. using elaborate user models. Narayanan et al. (2004) said that with adaptive interfaces not only the format but the content must be adaptable for supporting user knowledge acquisition tasks. They offered that the requirements for designing adaptive interfaces to support these tasks can be identified through knowledge elicitation with users and looking at patterns of user behavior. (It is important to recall here that Yoshida and Motoda (1996) said that simply inspecting patterns of user behavior is not sufficient for developing complex user models to drive adaptive interface design.) Narayanan et al. (2004) said that observing patterns of user behavior is particularly useful for developing models of how people search for information and accomplish knowledge discovery. They suggested that another approach to modeling users is to analyze the type and content of feedback they are able to elicit from applications and to use this as a further basis for establishing a user profile and information needs. The profile can be used as a basis for appropriately structuring content for users during information search tasks. Obviously, the results of this research are most applicable to database application or Internet search engine use. There could be extensions of this work for designing adaptive interfaces for real-world automated systems that may require human operators to perform information acquisition tasks collaboratively with automation aids.

4.3. Summary of Adaptive Interface Research

Most research on adaptive interfaces has been conducted in the context of desktop computing applications concentrating on flexible menu design, toolbar design, etc. (e.g., Debevc et al., 1996; Gong & Salvendy, 1995). One major limitation of this work, relative to design of adaptively automated systems, is that desktop applications are typically self-paced, unlike real systems in which operators may not have complete control over the pace of interaction with the automation. Early empirical evidence with desktop systems revealed that simple adaptive interface technologies may provide performance benefits over conventional, static interfaces, even when humans need to make decisions about changes in interface features in real-time. Of course, there may be an increase in task workload with this type of interface that should be considered on top of the cognitive load imposed by mission-related tasks, and any potential for performance decrements should be identified. According to Miller (1999), good adaptive interface design starts with the identification of user goals in a task and user information requirements for achieving goals. Any instance of an adaptive interface should be evaluated against the user's goal set and objective approaches should be used to quantify the "fit" of an interface to user information requirements during task performance. Related to Miller's (1999) research, the study by Hudlicka and McNeese (2002) provided evidence that there may be a need to consider user emotional states for effective adaptive interface design in addition to goal states and information requirements for task performance. Related challenges include the quantification of emotional states and the development interface features that address specific states, like anxiety.

Beyond user goals and emotions, many historical studies have advocated elaborate user models as a basis for designing adaptive interfaces. The majority of research on adaptive interface technology has focused on consideration of user behavior patterns (sequences of interface actions) and preferences as bases for design. In constructing adaptive interfaces, Yoshida and Motoda (1996) said that elaborate user models are needed that describe the aspects of information processing required for performance of different tasks. This is relevant to the design of interfaces for adaptive automation applied to various stages of information processing in complex systems control, as discussed above. The models must be capable of predicting what the user's behavior will be with the system interface during information acquisition, information analysis, etc. Interfaces should then be designed based on the model in order to best accommodate specific user behaviors. Duvallet et al. (2000) reinforced this point by saying that many user characteristics need to be incorporated in models as a basis for adaptive interface design. The Narayanan et al. (2004) work also emphasized the need for elaborate user models based on real-time assessments of user status, system or task states, and the environmental context for adapting interfaces to user needs. Beyond looking at patterns of detailed user behavior with interfaces, examining the type of output being generated by systems for users may provide another basis for profiling users for future use in interface adaptation strategies (Narayanan et al., 2004).

With respect to real-time assessment of user states for triggering adaptive interface changes, the research by Arai et al. (1996) may have been one of the first investigations to use physiological response measures for real-time characterization of operator stress states and use in driving adaptive interface settings. This is akin to the adaptive task allocation research using physiological variables for indicating cognitive workload states and prescribing appropriate allocations of tasks to a human or computer in complex systems control with the objective of promoting overall performance (e.g., Prinzel et al., 2000; Wilson & Russell, 2003). In addition to adapting interfaces to operator stress or workload levels, Gong and Salvendy (1995) observed that as users become more familiar with systems over time, there may be an additional need for adaptive interfaces to be designed to accommodate skill changes. This is particularly relevant to adaptive automation systems for which learning curves may be steep.

With respect to implementing interfaces changes to accommodate operator states, Duvallet et al. (2000) offered that the addition or subtraction of features in dynamic adaptive interfaces should not lead to user uncertainty about the overall design of the interface. Some elements should remain consistent from mode to mode as references for operators. Prior to this Debevc et al. (1996) said there is a need for some consistent features in adaptive interfaces, as an operator transitions from one state of the interface to another, in order for them to apply some general task model for use of the system.

In regard to supporting human performance with adaptive interface technologies in complex systems control, Bennett et al. (2001) demonstrated that there may be new advanced interface technologies for supporting operator performance (e.g., contemporary HUDs for fighter aircraft cockpits) that are superior to conventional interfaces and can be adaptively applied based on task circumstances. However, the reasons for making the technology adaptable and the manner in which the adaptation occurs is critical to promoting performance over static use of new technologies. In designing adaptive interfaces to, for example, provide pilots with the flexibility to shift between standard controls and advanced controls, it is important to ensure that the switching capability has meaning with respect to the flight tasks to be performed. Otherwise, the adaptation may not yield benefits beyond advanced control use, alone. Each mode of an adaptive interface should have some benefit for specific aspects of a task.

Related to Bennett et al. (2001) research, Bubb-Lewis and Scerbo (2002) conducted an empirical investigation demonstrating that adaptive interface technologies can provide flexibility in human-computer interaction that may promote performance over conventional static interfaces. They said that restrictions in human-computer communication due to traditional interface design can lead to performance decrements. However, they also observed that in adaptive systems, when automation assumes greater control of a task, there are increased restrictions on communication between the human and automation and performance on simple tasks may decline. This is another negative implication of adaptive interface technology that should be considered in design.

5. Discussion

One of the main findings of this review is that adaptable system designs requiring human delegation of task and function authority to automation during performance may pose additional workload on operators leading to degradations in situation awareness and performance, as compared to adaptive automation. Based on the review of literature, current approaches to adaptable system design (e.g., the playbook approach) may only be effective for addressing finite operating states of systems or facilitating rule-based operator behaviors. However, such automation may ultimately only produce performance comparable to manual control under variable environmental conditions. Furthermore, when workload is high and environmental dynamics occur, operators may revert to manual control for effecting knowledge-based behaviors. The one advantage that has emerged in research on adaptable automation is that the number of interface actions required to performance certain tasks with complex systems may be significantly reduced, as compared to manual control. One would expect this to translate into reductions in perceived workload but there is currently no evidence to support this. Beyond this, when system operators are required to switch between control strategies or tasks on a regular basis, adaptable automation appears to provide some advantage over static automation but it is not superior to manual control.

In contrast to adaptable systems, adaptively automated systems provide for dynamic task/function allocations mandated by a computer based on real-time monitoring of operator workload states. Decision making regarding the allocation of system control is not an additional responsibility of operators and, consequently, overall workload may be lower. Based on the review of literature, numerous approaches to adaptive automation (model-based, performance-based, workload-based, etc.) have been shown to improve operator performance in both psychomotor and cognitive tasks and to facilitate workload reductions in comparison to completely manual control and static automation. These findings are far more promising than the current results on adaptable systems performance. Studies of automation invocation authority in adaptive systems have also revealed an advantage of computer mandates of function allocation over human delegation of tasks to a computer because of potential workload issues. Shared approaches to function allocation in adaptive systems may also be appropriate depending on the control mode under which the human makes decisions about task delegation.

Research on adaptive task allocation has shown that sophisticated approaches to real-time assessment of operator states (e.g., EEG signals) can be useful for implementing adaptive automation and for promoting operator performance in single and multitasking scenarios. Biofeedback also appears to be a useful basis for physiological self-regulation in adaptively automated systems control. The research in this area also supports the use of multiple automation invocation philosophies and function allocation strategies for managing operator workload. Results also support computer management of adaptive task allocation in complex systems.

Research on adaptive function allocation has extended some of the findings on adaptive task allocation by demonstrating that adaptive automation can be applied to specific low-level functions as part of larger information processing tasks in complex systems control. Research in this area has also provided insight into appropriate durations of automated and manual control as part of adaptive automation for supporting performance.

Research on adaptive interfaces represented the largest body of work covered by this review. Adaptive interface technology is important to the implementation of adaptive automation in terms of providing operators with displays and controls for access to relevant system functions during different tasks or modes of operation. Several studies have identified users characteristics that need to be taken into consideration in the design adaptive interfaces. The list includes goal states, information requirements, emotional states, skill level, perceptual preferences, interface behavior patterns, information processing requirements associated with tasks posed to an adaptive system, etc. The general approach to adaptive interface design presented in the literature involves creating elaborate user models and using them as a basis for prototyping modes of displays and controls that can address user needs under various task and environmental circumstances. For DAIs (dynamic adaptive interfaces), these considerations need to be combined with real-time assessment of operator states and the use of galvanic skin response for identifying stress states has been demonstrated as an effective measure for adaptive interface changes.

One major recommendation that can be made based on the adaptive interface research is that some features of interfaces should remain consistent across modes of system operation to allow operators to rely on, or apply, general mental models of a task or system in using the interface. This is in-line with established basic principles of screen design for human-computer interaction tasks (Tullis, 1997). The other major recommendation is that when it is possible to provide complex system operators with adaptive interfaces, one should ensure that each mode of an interface has relevance to a certain task or functional requirement. It is also important for operators to understand which interfaces to use when (and why) from performance and workload perspectives.

6. Conclusions and Future Research

In general, the findings of this review motivate further exploration of adaptively automated systems for managing operator workload states and attempting to promote situation awareness, as compared to design of adaptable system alternatives. There is a substantial body of research on adaptive automation demonstrating performance and workload benefits over manual systems control and traditional, technology-centered approaches to automation. Unfortunately, the same cannot be said for adaptable systems and there is mounting evidence of negative performance, workload and situation awareness implications associated with requiring human operators to manage dynamic task or function allocations in complex systems control. Further research is needed in this area, however, to evaluate different approaches to adaptable system design, extending beyond those tested in recent research, and to confirm performance decrements of adaptable automation relative to adaptive automation across a range of applications.

The main adaptive automation research directions that need to be explored in the future include:

(1) Identification of types and levels of adaptive automation that are easiest for operators to work with in different task contexts – In general, there is a need for additional investigations on the differential effectiveness of adaptive automation applied to various information processing functions in complex systems control. Studies need to be conducted on a broad range of applications and should make use of high-fidelity simulations when field implementations are not possible.

(2) Development of more integrated and robust approaches to operator and system state monitoring for triggering task/function allocations – There is a need for evaluation of new approaches to automation invocation in adaptive systems considering multiple operator and system-state variables (simultaneously) as a basis for triggering dynamic task or function allocations. For example, combination of performance and workload-based approaches to adaptive automation should be considered for making more accurate function assignments in real-time in order to manage operator workload and promote performance. Beyond this, EEG-based approaches for assessing operator workload states must be refined to rely on a small set of signals for computing indices of arousal that can be related to automation states.

(3) Development of highly accurate methods for operator state classification and computer triggering of adaptive task/function allocations – Beyond identifying operator and system variables that may be useful for characterizing workload and performance conditions in real-time, there is a need to develop advanced computational method to integrate data on large sets of variables for effectively classifying system states (e.g., "underloaded", "overloaded"). Neural network-based approaches have historically proved useful for this purpose (Wilson & Russell, 2003); however, they provide little basis for explanation of the relationship between, for example, operator physiological responses (ECG, EEG, and EOG data) and objective measures of task load.

    Related to this, one of the most important research needs in the adaptive automation area is to establish objective human performance and workload criteria for making decisions about whether and when to turn "on" or "off" automation of a particular task or function. Previous investigations have used preliminary experiment data or statistical measures for establishing workload criteria to identify operator "underload" or "overload" states (e.g., Kaber & Riley; Kaber et al., 2005). New criteria expressed in terms of information processing limitations would be far more useful across applications and systems (e.g., visual overload (Mackworth, 1976); working memory limitations (Miller, 1956)). Another approach would be to develop computational cognitive models of users (e.g., GOMSL models, ACT-R models) for use in predicting potential information requirements and automation assistance needs in real time. These predictions could be used as a basis for dynamic function allocations managed by a computer.

(4) Development of on-line methods for assessing adaptive automation effectiveness for operator workload management and maintenance of situation awareness – There remains a need to establish the efficacy of adaptive automation in complex systems and the capability for such human-centered approaches to automation to control operator workload and to support achievement of situation awareness. Recent research on the performance, workload and situation awareness implications of adaptive automation (Kaber & Endsley, 2004) has demonstrated that dynamic allocations of lower-order information processing functions (e.g., information acquisition, information analysis) between humans and machines may have negative effects on operator situation awareness (over the long-term), as compared to short-term benefits for performance and workload. This is an issue that needs further empirical investigation and should be considered carefully by adaptive system designer. Developing methods for collecting real-time speed and accuracy data on operators during complex systems control will allow for assessment of the magnitude and timing of effects of adaptive automation on operator behavior and overall system performance.

7. References

Arai, F., Fukuda, T., Yamamoto, Y., Naito, T. & Matsui, T. (1996). Concept and realization of interactive adaptation interface using recursive fuzzy reasoning. JSME *International Journal Series C-Mechanical Systems Machine Elements and Manufacturing*, 39(4), 721-727.

Bailey, N.R., Scerbo, M.W., Freeman, F.G., Mikulka, P.J. & Scott, L.A. (in press). A comparison of a brain-based adaptive system and a manual adaptable system for invoking automation. To appear in *Human Factors*.

Bennett, K.B., Cress, J.D., Hettinger, L.J., Stautberg, D., & Haas, M.W. (2001). A theoretical analysis and preliminary investigation of dynamically adaptive interfaces. *The International Journal of Aviation Psychology, 11*(2), 169-195.

Berka, C., Levendowski, D.J., Cvetinovic, M.M., Petrovic, M.M., Davis, G., Lumicao, M.N., Zivkovic, V.T., Popovic, M.V., & Olmstead, R. (2004). Real-time analysis of EEG indexes of alertness, cognition, and memory acquired with a wireless EEG headset. *International Journal of Human-Computer Interaction*, 17(2), 151-170

Bubb-Lewis, C., & Scerbo, M. W. (1997). Getting to know you: Human-computer communication in adaptive automation. In M. Mouloua, & M. Koonce (Eds.), *Human-automation interaction: Research and practice* (pp. 92-99). Mahwah, NJ: Erlbaum.

Bubb-Lewis, C. & Scerbo, M.W. (2002). The effects of communication modes on performance and discourse organization with an adaptive interface. *Applied Ergonomics*, 33(1), 15-26.

Clamann, M. P. and Kaber, D. B. (2003). Authority in adaptive automation applied to various stages of human-machine system information processing. In *Proceedings of the 47th Annual Meeting of the Human Factors and Ergonomics Society* (pp. 543-547). Santa Monica, CA: Human Factors and Ergonomics Society.

Debevc, M., Meyer, B., Donlagic, D. & Svecko, R. (1996). Design and evaluation of an adaptive icon toolbar. *User Modeling and User-Adapted Interaction*, 6(1), 1-21.

Duvallet, C., Boukachour, H. & Cardon, A. (2000). Intelligent and self-adaptive interface. *Intelligent Problem Solving: Methodologies and Approaches, Proceedings Lecture Notes in Artificial Intelligence*, 1821, 711-716.

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

Galstyan, A. & Lerman, K. (2005). Analysis of a stochastic model of adaptive task allocation in robots. *Engineering Self-Organising Systems: Methodologies and Applications, Lecture Notes in Computer Science*, 3464, 167-179.

Gong, Q. & Salvendy, G. (1995). An approach to the design of a skill adaptive interface. *International Journal of Human-Computer Interaction*, 7(4), 365-383.

Haas, M.W., Nelson, W.T., Reppberger, D., Bolia, R. & Zacharias, G. (2001). Applying adaptive control and display characteristics to future Air Force crew stations. The *International Journal of Aviation Psychology*, 11(2), pp. 223-235.

Hadley, G. A., Prinzel, L. J., Freeman, F. G. & Mikulka, P. J. (1999). Behavioral, subjective and psychophysiological correlates of various schedules of short-cycle automation. In M. W. Scerbo & M. Mouloua (eds.), *Automation Technology and Human Performance* (pp.139-143). Mahwah, NJ: Lawrence Erlbaum Assoc., Inc.

Hancock, P.A. & Chignell, M.H. (1988). Mental workload dynamics in adaptive interface design. *IEEE Transactions on Systems Man and Cybernetics*, 18 (4), 647-658.

Hilburn, B., Jorna, P., Byrne, E. A., & Parasuraman, R. (1997). The effect of adaptive air traffic control (ATC) decision aiding on controller mental workload. In M. Mouloua & J. M. Koonce (eds.), *Human-automation interaction: Research and practice* (pp. 84-91). Mahwah, NJ: Lawrence Erlbaum Associates.

Hilburn, B., Molloy, R., Wong, D., & Parasuraman, R. (1993). Operator versus computer control of adaptive automation. In R. S. Jensen & D. Neumeister (eds.), *Proceedings of the 7th International Symposium on Aviation Psychology* (pp. 161-166). Columbus, OH: Department of Aviation, The Ohio State University.

Hudlicka, E. & McNeese, M.D. (2002). Assessment of user affective and belief states for interface adaptation: Application to an Air Force pilot task. *User Modeling and User-Adapted Interaction*, 12 (1), 1-47.

Innocent, P.R. (1982). Towards self-adaptive interface systems. *International Journal of Man-Machine Studies*, 16 (3), 287-299.

Ji, Y.G. & Salvendy, G. (2002). Development and validation of user-adaptive navigation and information retrieval tools for an intranet portal organizational memory information system. *Behaviour & Information Technology*, 21(2), 145-154.

Kaber, D. B. & Endsley, M. R. (2004). The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task. *Theoretical Issues in Ergonomics Science*, *5(2)*, 113-153.

Kaber, D. B. & Riley, J. (1999). Adaptive automation of a dynamic control task based on secondary task workload measurement. *International Journal of Cognitive Ergonomics*, *3(3)*, 169-187.

Kaber, D. B., Wright, M. C., Prinzel, L. P. and Clamann, M. P. (2005). Adaptive automation of human-machine system information processing functions. *Human Factors*, 47(4), 730-741.

Mackworth, N. H. (1976). Stimulus sensitivity limits the useful field of view. In R. A. Monty & J. W. Senders (Eds.), *Eye Movements and Psychological Processes*. Hillsdale, NJ: LEA.

Mason, M.V. & Thomas, R.C. (1984). Experimental adaptive interface. *Information Technology-Research Development Applications*, 3(3), 162-167.

Miller, C.A. (1999). Bridging the information transfer gap: Measuring goodness of information fit. *Journal of Visual Languages and Computing*, 10(5), 523-558.

Miller, C. and Parasuraman, R. (2003). Beyond levels of automation: An architecture for more flexible human-automation collaboration. In *Proceedings of the 47th Annual Meeting of the Human Factors and Ergonomics Society* (pp. 182-186). Santa Monica, CA: Human Factors and Ergonomics Society.

Miller, G. A. (1956). The magic number seven, plus or minus two: Some limits on our capacity for processing information. *The Psychological Review*, 63, 81-97.

Narayanan, S., Koppaka, L., Edala, N., Loritz, D. & Daley, R. (2004). Adaptive interface for personalizing information seeking. *Cyberpsychology & Behavior*, 7(6): 683-688.

Parasuraman, R. (1987). Human-computer monitoring. *Human Factors*, *29*, 695-706.

Parasuraman, R. (1993). Effects of adaptive function allocation on human performance. In D. J. Garland & J. A. Wise (eds.), *Human factors and advanced aviation technologies* (pp. 147-158). Daytona, Beach, FL: Embry-Riddle Aeronautical University Press.

Parasuraman, R., Bahri, T., Deaton, J., Morrison, J., & Barnes, M. (1992). *Theory and design of adaptive automation in aviation systems* (Progress Rep. No. NAWCADWAR-92033-60). Warmister, PA: Naval Air Warfare Center, Aircraft Division.

Parasuraman, R., Galster, S., Squire, P., Furukawa, H., & Miller, C. (2005). A flexible delegation-type interface enhances system performance in human supervision of multiple robots: Empirical studies with RoboFlag. *IEEE Transactions on Systems Man and Cybernetics*, 35(4), 481-493.

Parasuraman, R. Molloy, R. & Singh, I. L. (1993a). Performance consequences of automation induced complacency. International Journal of Aviation Psychology, 3(1), 1-23.

Parasuraman, R., Mouloua, M., Molloy, R., & Hilburn, B. (1993b). Adaptive function allocation reduces performance costs of static automation. In R. S. Jensen & D. Neumeister (eds.), *Proceedings of the 7th International Symposium on Aviation Psychology* (pp. 178-185). Columbus, OH: Department of Aviation, The Ohio State University.

Parasuraman, R., Mouloua, M., & Molloy, R. (1996). Effects of adaptive task allocation on monitoring of automated systems. *Human Factors*, *38(4)*, 665-679.

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model of types and levels of human interaction with automation. *IEEE Transactions on SMC*, *30*(3), 286-297.

Pope, A.T., Bogart, E.H. & Bartolome, D.S. (1995). Biocybernetic system evaluates indices of operator engagement in automated task. *Biological Psychology*, 40, 187-195.

Prinzel, L.J., Freeman, F.C., Scerbo, M.W., Mikulka, P.J., & Pope, A.T. (2000). A closed-loop system for examining psychophysiological measures for adaptive task allocation. *International Journal of Aviation Psychology*, 10(4), 393-410.

Prinzel, L.J., Pope, A.T. & Freeman, F.G. (2000). Physiological self-regulation and adaptive automation. *International Journal of Aviation Psychology*, 12(2), 181-198.

Rencken, W.D. & Durrant-Whyte, H.F. (1993). A quantitative model for adaptive task allocation in human-computer interfaces. *IEEE Transactions on SMC*, 23(4), 1072-1090.

Riley, V. & Parasuraman, R. (1997). Humans and automation: use, misuse, disuse, abuse. *Human Factors*, 39(2), 230-253.

Rouse, W. B. (1977). Human-computer interaction in multi-task situations. *IEEE Transactions on Systems, Man and Cybernetics*, *SMC-7,* 384-392.

Sarter, N.B., & 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.

Scallen, S.F. & Hancock, P.A. (2001). Implementing adaptive function allocation. *International Journal of Aviation Psychology*, 11 (2): 197-221.

Scallen, S. F., Hancock, P. A., & Duley, J. A. (1995). Pilot performance and preference for short cycles of automation in adaptive function allocation. *Applied Ergonomics*, 26, 397-403.

Scerbo, M. W. (1996). Theoretical perspectives on adaptive automation. In R. Parasuraman & M. Mouloua (Eds.), *Human performance in automated systems: Theory and applications* (37-64). Mahwah, NJ: Lawrence Erlbaum Associates.

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

Shiff, B. (1983). *An experimental study of the human-computer interface in process control*. Unpublished thesis, University of Toronto, Toronto.

Squire, P., Trafton, G. & Parasuraman, R. (2006). Human control of multiple unmanned vehicles: Effects of interface type on execution and task switching times. In *Proceedings of the 2006 ACM Conference on Human-Robot Interaction* (pp. 26-32). New York: ACM.

Sukaviriya, P. (1993). From user-interface design to the support of intelligent and adaptive interfaces - an overhaul of user-interface software infrastructure. *Knowledge-Based Systems*, 6(4), 220-229.

Tullis, T. (1997). Screen design. In M. Helander, T. K. Landauer, and P. Prabhu (Eds.), *Handbook of Human-Computer Interaction* (pp. 503-531). Amsterdam: Elsevier Science.

Wilson, G.F. & Russell, C.A. (2003). Real-time assessment of mental workload using psychophysiological measures and artificial neural networks. *Human Factors*, 45(4), 635-643.

Yoshida, K. & Motoda, H. (1996). Automated user modeling for intelligent interface. *International Journal of Human-Computer Interaction*, 8(3), 237-258.

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 0704-0188*

1. REPORT DATE *(DD-MM-YYYY)*
01- 09 - 2006

2. REPORT TYPE
Technical Memorandum

3. DATES COVERED *(From - To)*

4. TITLE AND SUBTITLE
Adaptive and Adaptable Automation Design: A Critical Review of the Literature and Recommendations for Future Research

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Kaber, David B.; and Prinzel, Lawrence J., III

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER
609866.02.07.07

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
NASA Langley Research Center
Hampton, VA 23681-2199

8. PERFORMING ORGANIZATION REPORT NUMBER
L-19255

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
National Aeronautics and Space Administration
Washington, DC 20546-0001

10. SPONSOR/MONITOR'S ACRONYM(S)
NASA

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
NASA/TM-2006-214504

12. DISTRIBUTION/AVAILABILITY STATEMENT
Unclassified - Unlimited
Subject Category 03
Availability: NASA CASI (301) 621-0390

13. SUPPLEMENTARY NOTES
An electronic version can be found at http://ntrs.nasa.gov
Kaber: North Carolina State University; Prinzel: Langley Research Center

14. ABSTRACT
This report presents a review of literature on approaches to adaptive and adaptable task/function allocation and adaptive interface technologies for effective human management of complex systems that are likely to be issues for the Next Generation Air Transportation System, and a focus of research under the Aviation Safety Program, Integrated Intelligent Flight Deck Project. Contemporary literature retrieved from an online database search is summarized and integrated. The major topics include the effects of delegation-type, adaptable automation on human performance, workload and situation awareness, the effectiveness of various automation invocation philosophies and strategies to function allocation in adaptive systems, and the role of user modeling in adaptive interface design and the performance implications of adaptive interface technology.

15. SUBJECT TERMS
Adaptive automation; Automation; Aviation safety; Human-computer interaction

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
					STI Help Desk (email: help@sti.nasa.gov)
					19b. TELEPHONE NUMBER *(Include area code)*
U	U	U	UU	32	(301) 621-0390